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Systematic Categorisation of 3,091 Smartphone Applications From a Large-Scale Smartphone Sensing Dataset

DATA PAPER

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ABSTRACT

Practically all user activities on a smartphone depend on self-contained software applications, so-called apps. Due to the large number and diversity of available apps, the analysis of app usage behaviour in social science research requires elaborate pre-processing of app data. Therefore, we present a categorisation scheme and a dataset of 3,091 manually categorised apps used by a representative quota sample within a large-scale smartphone sensing study conducted in Germany over several months in 2020. For the categorisation, we report values for inter-rater agreement between two independent raters. We provide the freely available dataset as a CSV and we invite other researchers to use and modify the categorisation for their specific research questions and to extend it for the mobile sensing research community.

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KEYWORDS:
Smartphones; Mobile sensing; App usage; App categorisation; Behavioural data

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BACKGROUND

The interaction with smartphones is mediated through small application software packages commonly referred to as "apps." Apps enhance the smartphone's functionality with specific tasks like calling, texting, sending emails, surfing the web, navigating on maps, taking photos, shopping, listening to songs, and so on. The variety of daily behaviours enabled by apps has made app usage an interesting subject of social science research. Even more so since novel mobile sensing approaches allow for an objective and unobtrusive collection of app usage data in the field (e.g., Chittaranjan et al., 2013; Ferreira et al., 2015; Harari et al., 2019; Reeves et al., 2019; Schoedel et al., 2019; Stachl et al., 2020; Yang et al., 2019) filling the lack of behavioural data in psychology (Baumeister et al., 2007; Rozin, 2001). Previous studies successfully associated app usage with personality traits (e.g., Harari et al., 2019; Schoedel et al., 2019; Stachl et al., 2017, 2020), cognitive ability (Gordon et al., 2019; Stachl et al., 2017), psychological well-being (Gao et al., 2016) and chronotype (Peng & Zhu, 2020). These studies demonstrate how app usage can be interpreted as media usage behaviour, but also serve as a proxy of real-life behaviours that are difficult to access directly (e.g., alarm clock app usage in the morning as indicator for awakening times; Schoedel et al., 2020).

While it is possible to inspect app usage at the level of individual apps (e.g., Montag et al., 2015), most researchers are interested in analysing mobile app usage at an aggregated category level. Thereby, functionally interchangeable or similar apps are grouped in meaningful behavioural categories. For example, the apps Spotify and Deezer, both of which enable music listening, are labelled as music listening apps, and their usage is considered music listening behaviour. The majority of previous research on app usage relied on the default categorisation provided by leading app distribution platforms (e.g., Böhmer et al., 2011; Gordon et al., 2019; Malmi & Weber, 2016; Mehrotra et al., 2017a & b; Morrison et al., 2018; Ram et al., 2020; Rauber et al., 2019). However, commercially used category systems are too general, and the developers category assignments are often inconsistent (Frey et al., 2017; Stachl et al., 2017). For example, the Google Play Store distinctly classifies the app Tinder as a Lifestyle app, while other apps with dating functionality are classified into a more granular "Dating" category. Accounting for these limitations, few studies manually refined the default categorisation (Böhmer et al., 2012; Frey et al., 2016; Stachl et al., 2017) or developed their own category system (Stachl et al., 2020). However, to our knowledge, there is no systematically developed and transparently documented app category system to date.

Therefore, we developed and validated a categorisation of smartphone apps for social and psychological research purposes. Based on a smartphone sensing dataset of 850 participants, we created 26 distinct app categories and assigned the apps used in our sample accordingly. While the process of defining categories and labelling apps is inevitably somewhat subjective, our procedures were not biased by any specific research question because our only aim was a category system that was as general and objective as possible. Furthermore, the definition of categories and the labelling of apps were conducted by separate researchers to ensure the intuitive usability of the app categories. We believe that our procedure produced a high-quality app categorisation valuable for a wide range of research applications.

METHODS

STUDY DESIGN

The basis of our app categorisation was a collection of apps used by Android users of a representative German quota sample during a longitudinal panel study. The overall aim of our Smartphone Sensing Panel Study (SSPS) conducted by LMU Munich and the Leibniz Institute for Psychology (ZPID) was to create a benchmark dataset for the scientific community, including longitudinal and high-dimensional behavioural and situational sensing data and in and ex situ self-report data about a broad range of psychological phenomena (Schoedel & Oldemeier, 2020). For this purpose, our purely observational study combined smartphone sensing (i.e., the unobtrusive logging of smartphone usage data) with different survey methods (i.e., online surveys and experience sampling). The study lasted three (study group 1) or six months (study group 2) depending on a randomised grouping, that was necessary for financial reasons only. The list of used apps for categorisation was extracted from the resulting smartphone sensing dataset.

TIME OF DATA COLLECTION

The data collection, including the app data we used as starting point for our categorisation, took place between May 2020 and December 2020.

LOCATION OF DATA COLLECTION

Data were collected throughout Germany. Therefore, our categorisation is focused on apps that are frequently used in this geographic region. However, we believe that the categorisation can still be transferred to other countries for the majority of categories, except for apps that have a specific geographic reference. For example, the categories *Transportation* and *News* are very likely to contain different apps depending on the study region. We encourage researchers using our category system to enhance the list of apps by adding labelled apps that are currently not covered. The presented category definition scheme (s. ***Table 1***) allows researchers to adapt our categorisation with only minor efforts.

#	CATEGORY	DEFINITION
1	Audio Entertainment	*Audio Entertainment* describes apps serving acoustic-only entertainment. This category includes apps providing music, podcasts, audiobooks, or radio. The usage of *Audio Entertainment* apps can be seen as media consumption behaviour limited to the auditory channel (i.e., excluding the visual channel).
2	Career	*Career* describes apps allowing users to promote their professional career. The category contains apps for job search, career-related networking, career planning, or counselling.
3	Communication	*Communication* describes apps specifically designed for all sorts of communication behaviours. The category includes traditional calling and text messaging apps, but also apps for web-based instant messaging, email access or face-timing. While other apps may also contain communication functionalities as a secondary feature (e.g., *Social Media* or *Dating* apps), apps in the *Communication* category are only used for communicative purposes.
4	Creativity	*Creativity* describes apps that enable creative activities such as drawing, playing instruments, singing, recording sounds, or creative writing. This category explicitly excludes photography apps, which are contained in the category *Photo*.
5	Dating	*Dating* describes apps specifically designed for dating activities ranging from browsing potential partners to communicating with them to arranging meetings. Thereby, the category excludes general *Communication*, which, of course, may also serve dating purposes.
6	Finance	*Finance* describes apps related to financial and monetary issues. This category includes, for example, banking apps, apps for earning money, stock trading apps, apps for donating money, apps for comparing prices, or for checking currencies. From a behavioural perspective, the use of *Finance* apps indicates behaviours dealing with money, like making, spending, or monitoring money.
7	Food	*Food* describes apps facilitating a range of behaviours related to food and eating. The category contains, for example, apps for ordering food or groceries online, for sharing food with others, for finding cooking recipes or for making meal plans. Apps related to diets (e.g., calorie counting apps) are excluded here and are featured in the *Health* category.
8	Gaming	*Gaming* describes apps for gaming behaviours ranging from playful strategy games to serious gambling or making bets.
9	Health	*Health* describes apps related to the user's engagement with (their own) health. This category includes, for example, apps providing physical exercises, as well as apps for improving and/or monitoring physical and mental health, sleep, or diets.
10	Internet	*Internet* describes apps for browsing the internet, including search engines such as Google or Yahoo. Even though this category is unambiguously and narrowly defined, the behavioural implications of using *Internet* apps are various as surfing the web can fulfil a myriad of purposes.
11	Knowledge	*Knowledge* describes apps for the acquisition of knowledge or the seeking of specific information. This rather broad category includes apps providing general knowledge or specific information, as well as apps for learning new skills (e.g., languages). This category excludes general search engines and browser apps, which are featured in the category *Internet*. Furthermore, the *Knowledge* category does not contain apps related to the consumption of news, which are featured in the separate category *News*.
12	News	*News* describes apps explicitly meant for the seeking of and consumption of daily news. These apps contain digital newspapers or news blogs. In contrast, the categories *Visual Entertainment* or *Social Media* may also contain news-related content, which, however, cannot be determined without assessing the within-app usage behaviour.
13	Orientation	*Orientation* describes apps that help the user find their way in the surroundings. This rather narrow category includes, for example, apps with maps and for navigation.
14	Photo	*Photo* describes apps for making, editing, or inspecting one's own photos and videos. This category does not include apps for posting or viewing posted photos or videos, which are featured in the category social media.
15	Reading	*Reading* refers to apps providing textual media sources like books, comics, magazines, or blog articles, whose consumption indicates reading behaviour. This category explicitly excludes the consumption of news-related textual media (e.g., newspapers), which is featured in the separate category *News*.
16	Security	*Security* describes apps that increase the user's security both online and offline, e.g. by concealing the user's identity when surfing the web via VPNs, by scanning websites for viruses or by tracking the user's way home. From a behavioural perspective, the use of *Security* apps can be interpreted as diligence.
17	Settings	*Settings* describe apps that are used to change the smartphone's settings, to monitor and optimise functions (e.g., monitoring the smartphone's usage time or battery consumption), or to personalise the smartphone. Unlike *System* apps, *Settings* apps involve active interactions (e.g., changes) made by the user. From a behavioural perspective, the usage of *Settings* apps may be seen as maintenance work done by the user.

(Contd.)

#	CATEGORY	DEFINITION
18	Shopping	*Shopping* describes apps for buying and selling things both online and offline. This category includes, for example, apps of online shops, thrifting apps, apps providing brochures or membership apps for stores. The *Shopping* category explicitly excludes apps related to food shopping, which are featured in the category *Food*.
19	Social Media	*Social Media* describes apps for sharing, browsing & interacting (i.e., liking or commenting) with content (e.g., texts, pictures, videos) within an online community. This app category is rather heterogeneous, because social media apps often enable secondary functionalities like *Communication*, *Shopping* or *Dating*, and provide content from the categories *Visual Entertainment* (e.g., movie trailers), *Health* (e.g., food or fitness posts), *Knowledge* (e.g., science posts) or *News*. Nevertheless, all *Social Media* apps have content sharing as main functionality and their usage can be interpreted as social media usage behaviour.
20	Spirituality	*Spirituality* describes apps related to spiritual behaviours or beliefs ranging from religion to esotericism. This rather broad, but rare category contains, for example, apps for bible study, but also horoscope apps.
21	System	*System* describes apps that enable the basic functionality of the phone and its apps. *System* apps are not consciously accessed and actively interacted with. As they run in the background of the device, they have no informative power for behavioural analyses. Oftentimes, removing *System* apps facilitates further analyses of app usage.
22	Time	*Time* describes apps with a time-structuring function like clocks or timers or calendars. From a behavioural perspective, *Time* apps can fulfil different purposes ranging from planning (e.g., planning meetings) to monitoring actions (e.g., setting a timer for boiling eggs).
23	Tools	*Tools* describe apps for the organisation of everyday life. This category is rather heterogeneous as it includes, for example, apps for creating notes or to-do lists, for managing files (e.g., scanning, printing, opening, editing, downloading), for calculating or programming, or for managing own devices. In addition, *Tools* include provider services (e.g., contract service, parcel service) unless they can be clearly assigned to one of the more content-related categories (e.g., food delivery apps in the category *Food*). Due to the breadth of this category, *Tools* apps can have various behavioural meanings ranging from private organising behaviour (e.g., making a shopping list) to more office-related behaviours (e.g., working with documents).
24	Transportation	*Transportation* describes apps that assist the user with utilising or planning the use of different means of transport ranging from local and long-distance public transport to cars. This category includes, for example, apps for informing oneself about departure times of public transport, for doing research on best routes and for purchasing car-sharing services.
25	Visual Entertainment	*Visual Entertainment* describes apps serving audiovisual entertainment. This category includes apps for viewing videos, for streaming movies or TV. Using *Visual Entertainment* apps can be interpreted as media consumption behaviour including (but not exclusive to) the visual channel. In contrast to Social Media apps, apps in this category lack the sharing and community aspect.
26	Weather	*Weather* describes apps for checking the local or international weather, including weather forecasts.

Table 1 Definition of app categories in alphabetical order.

SAMPLING, SAMPLE AND DATA COLLECTION

Recruitment

The SSPS was conducted in cooperation with a German panel provider that managed the recruitment and compensation of participants. The recruitment of participants started on April 30th, 2020 and the joint study start date for all participants (i.e., the day PhoneStudy app started data logging) was set to May 15th, 2020. However, because the targeted number of participants for the start sample had not been reached at the start date, recruitment continued until May 28th, 2020.

To be eligible for the study, participants had to be the sole user of a private smartphone running on Android 5 or higher (e.g., no business phone). Furthermore, participants were required to be between 18 and 65 years old and to have fluent German language skills. In addition, we aimed to collect a quota sample representing the German population in terms of gender, age, education, income, confession, and relationship status.

Data collection

After completing an onboarding questionnaire informing about the study's GDPR compliance and giving informed consent, participants were instructed to download the PhoneStudy app, a custom research application developed at LMU Munich, on their private smartphones. During the study, the PhoneStudy app continuously logged data from the background while participants used their smartphones as usual. If a WiFi connection was available, the sensing data were synchronised hourly with our backend server using SSL-encryption. The PhoneStudy app automatically recorded a broad range of smartphone usage behaviours including, for example, connectivity status, calling, and text messaging, notifications, camera usage, and, most relevant for the current paper, app usage. In particular, the app retrieved a full list of all apps installed on participants' smartphones at the beginning of the study (i.e., app adoption) and, in addition, continuously collected timestamped app usage events (i.e., app usage).

The sensing data collection was complemented by monthly online surveys and one (study group 1) or two (study group 2) experience sampling periods. Here, we refrain from giving more detail on these self-report measures because they are not relevant to the app categorisation. For a detailed description of all study procedures, including the inventories used, please refer to our preregistration protocol (Schoedel & Oldemeier, 2020).

Sample

Due to the independent parts of the study (i.e., smartphone logging, experience sampling & online questionnaires), it is difficult to determine a general sample size. Because our categorisation is based on the app usage data, we focus on the availability of logging data here: A total of 850 participants installed the PhoneStudy app for at least 1 week. Participants of study group 1 (n = 191) installed the app for on average *M* = 83 days (*SD* = 20) and participants of study group 2 (n = 659) for on average *M* = 150 days (*SD* = 57). Of these 850 participants, N = 740 also answered the starting online questionnaire. The mean age across these participants was *M* = 42.1 (*SD* = 12.9) ranging from 18 to 65 years. Our sample was composed of 54.7% males, 45.1% females, and one person who specified their gender as diverse. All levels of education were represented in our sample with 0.8% having no school-leaving qualification, 16.9% elementary school or equivalent qualification, 35.5% secondary school or equivalent qualification, 28.1% technical college or general higher education qualification (Abitur), 18.0% university/college degree, and 0.7% doctorate or habilitation.

Compensation

The different parts of the study (i.e., smartphone logging, experience sampling, & online questionnaires) were compensated independently. In sum, study group 1 received up to 44.50€ and study group 2 up to 131.50€ if all study activities were completed. Participants were excluded from the study, if they revoked permissions for smartphone logging for more than two (group 1)/three (group 2) times on seven consecutive study days or omitted two out of three monthly online surveys during month 1 to 3 and month 4 to 6 (group 1 only).

MATERIALS

Raw material: Collection of apps

The SSPS provided us with a collection of 19,361 apps used over all participants and the entire study period. We used both, the list of adopted apps and the app usage events to categorise apps as they both contained the official app names. To reduce the dimensionality of app adoption or usage data, we decided to manually sort these apps into different, psychologically meaningful categories. However, the excessive total app count was practically infeasible for manual categorisation, so we filtered for apps used by at least 1% of participants who had installed the PhoneStudy app. This filter seemed legit as the majority of the remaining apps were used by only one or very few participants. This restriction left us with 3,091 apps to categorise (see ***Figure 1***).

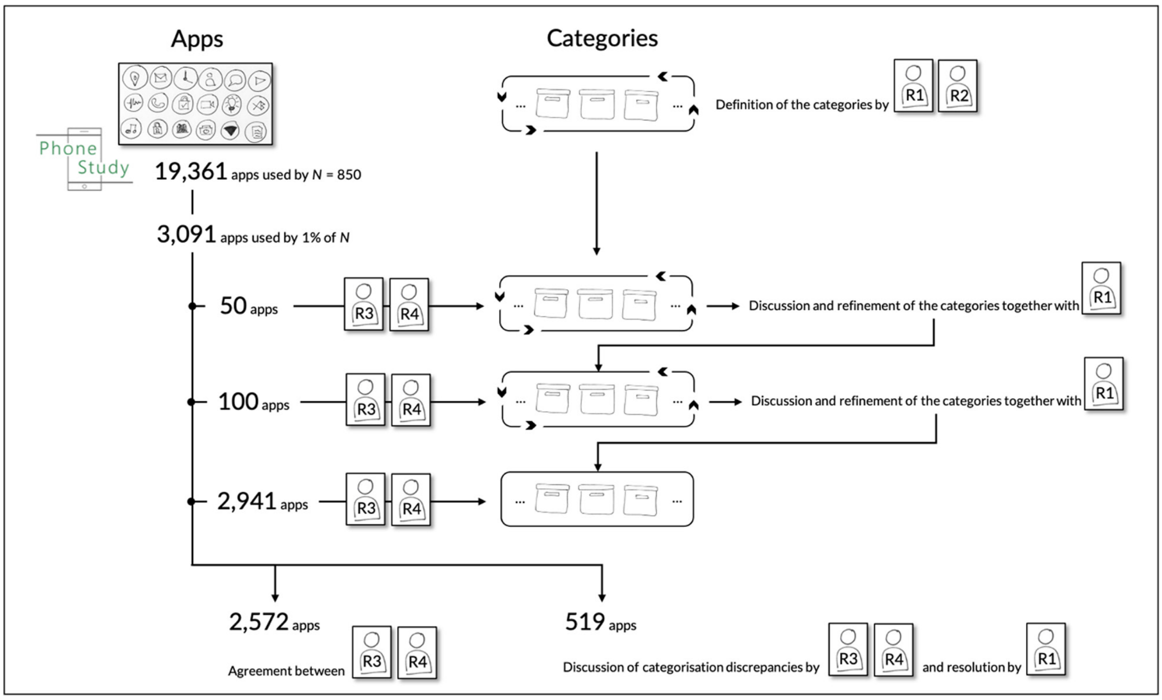

Figure 1 Scheme for visualising our process of categorisation. The left side of the scheme illustrates the assignment of the apps and the right side the development of the app categories by R(esearcher) 1 to 4.

Process of app categorisation

First, the authors designed an initial draft of the category system based on their extensive prior experience analysing app usage data. We created detailed category definitions describing the activities that can be pursued with a respective group of apps. These definitions contained references for differentiation from other categories, but they did not contain any app examples to not bias raters. This initial category system was consequently tested and refined in three iterations based on our empirical collection of apps. Therefore, two independent raters, who were not previously involved with the category definition, applied the category system to our app collection to test if all apps could be assigned unambiguously to a single category. The raters used the apps' descriptions featured in the Google Playstore to inform themselves about apps they did not know. If there was no Google Playstore entry for an app, the raters used descriptions from the manufacturers or read forum entries in which the respective app was discussed. In the first step, these raters categorised 50 randomly chosen apps from our collection. The raters commented whenever categories were ambiguously defined or missing. Any discrepancies between the raters were discussed and resolved. Afterward, we refined the app category definitions based on the raters' comments and added new, previously neglected categories. In the second round, the raters used the modified category system to assign categories to 100 new randomly chosen apps. Again, the raters commented on any problems when categorising apps, and the category system was refined. Finally, the remaining 2,941 apps were categorised by both raters. All discrepancies between the two raters were discussed and resolved by a third rater. Based on the results of the joint discussion, the third rater additionally performed some checks to resolve single remaining inconsistencies. For example, ad blocker apps were inconsistently assigned to the categories *Security*, *Settings*, or *Tools*. The third rater made a unification by assigning them into the category *Security*. To get a better overview, ***Figure 1*** summarizes the process of app categorisation.

Principles of categorising apps

We decided to categorise each app exclusively into one category to facilitate statistical analyses of app usage behaviour. Thus, whenever an app offered several functionalities, raters focused on the app's main theme (i.e., its selling point). For example, the app "Instagram" was categorised as a social media app because its main purpose is sharing content, even though the app also allows for taking photos or communicating via direct messages. We acknowledge that a single category system may understate the full scope of technological affordances provided by a given app, but we believe an app's main functionality does, on average, represent participants' app usage behaviour even if individual users exploit more rarely used side functionalities. If the main theme of the app was not clearly identifiable, raters were instructed to place the app in a more general category such as *Knowledge* or *Tools*.

Several apps could have been labelled rather unspecifically as service apps, for example, apps for controlling external devices (e.g., headphones). As the category of "service apps" would have been rather meaningless from a psychological perspective, we decided to assign these apps to the category of the respective device or service they enable (e.g., headphone management apps as music apps).

Categorisation scheme

Table 1 provides an overview of our final app categories.

QUALITY CONTROL

Our representative quota sample with behavioural data over 3 to 6 months ensured that our categorised apps are representative of app usage in everyday life and, thus, a good basis for our category system. We also made several efforts to control the quality of the app categorisation itself. For a strong empirical rooting of the category system, we developed the categories iteratively based on the list of commonly used apps (see Process of app categorisation for details). To ensure the highest possible objectivity in the categorisation, the definition of app categories and the categorisation of the apps were conducted by separate researchers. In addition, two raters independently categorised each app and we report the concurring judgments in our dataset. All cases of disagreement were resolved by a third independent rater. We present the interrater agreement according to app categories between the two principal raters in ***Table 2***.

DATA ANONYMISATION AND ETHICAL ISSUES

The SSPS from which the app data originated received ethical approval of the data collecting institution and complied with the EU-GDPR. Participants gave informed consent prior to data collection, which they could withdraw at any time without giving a reason. Upon request, data already collected could also be deleted. In the dataset presented here, anonymity is guaranteed because data are already aggregated over the entire sample (i.e., app usage across all individuals and the entire study period). Personal data is therefore not included in the dataset.

EXISTING USE OF DATA

These data are the preliminary work for the publication of several planned articles around the Smartphone Sensing Panel Study (Schoedel & Oldemeier, 2020), but these articles are still work in progress. Corresponding preregistrations are available via *https://doi.org/10.23668/psycharchives.2901*.

#	CATEGORY	COHEN'S KAPPA [95% CI]		NUMBER OF ASSIGNED APPS	NUMBER OF DISAGREEMENTS
1	Audio Entertainment	0.87	[0.80;0.94]	50	5
2	Career	0.80	[0.57;1.03]	7	1
3	Communication	0.71	[0.62;0.80]	66	16
4	Creativity	0.64	[0.40;0.87]	13	6
5	Dating	0.94	[0.83;1.06]	9	1
6	Finance	0.88	[0.85;0.91]	203	13
7	Food	0.66	[0.49;0.84]	30	16
8	Gaming	0.96	[0.94;0.98]	204	5
9	Health	0.76	[0.68;0.84]	70	16
10	Internet	0.82	[0.70;0.95]	21	3
11	Knowledge	0.65	[0.54;0.76]	53	15
12	News	0.93	[0.87;0.99]	42	2
13	Orientation	0.92	[0.84;1.00]	24	2
14	Photo	0.81	[0.75;0.86]	135	24
15	Reading	0.74	[0.50;0.97]	10	3
16	Security	0.72	[0.62;0.82]	62	23
17	Settings	0.66	[0.60;0.71]	195	45
18	Shopping	0.78	[0.72;0.84]	114	20
19	Social Media	0.63	[0.45;0.82]	21	8
20	Spirituality	0.40	[–0.28;1.08]	1	0
21	System	0.83	[0.81;0.85]	1231	173
22	Time	0.81	[0.70;0.92]	25	1
23	Tools	0.75	[0.71;0.79]	394	97
24	Transportation	0.80	[0.69;0.90]	39	10
25	Visual Entertainment	0.62	[0.50;0.74]	43	11
26	Weather	0.93	[0.85;1.00]	28	3

Table 2 Interrater agreement according to app categories in alphabetical order.

DATASET DESCRIPTION AND ACCESS

REPOSITORY LOCATION

http://doi.org/10.23668/psycharchives.5680

OBJECT/FILE NAME

Data: app_categorisation_2020_v2.csv
Codebook: app_categorisation_2020_codebook_v2.Rmd, app_categorisation_2020_codebook_v2.pdf

DATA TYPE

Interpretation of data

FORMAT NAMES AND VERSIONS

CSV

LANGUAGE

English

LICENCE

The data were published under a CC-BY Attribution 4.0 International (CC-BY 4.0) licence.

LIMITS TO SHARING

No embargo.

PUBLICATION DATE

January 28th, 2022

FAIR DATA/CODEBOOK

We use PsychArchives to publish the dataset. PsychArchive's service allows us to annotate the dataset with all relevant metadata and upload a codebook.

REUSE POTENTIAL

We systematically developed a categorisation that classifies over 3000 commonly used apps into 26 psychologically meaningful categories. Thereby, we opted for a high-level categorisation that differentiates apps into rather broad but unambiguous categories to accommodate as many research purposes as possible. For more specific research questions (e.g., differential effects of different types of social media usage or the influence of stress relief apps on wellbeing), we encourage researchers to further expand our category system by differentiating the broad categories into more narrow behavioural units. For example, the category *Health* may be subdivided into apps targeting mental vs. physical health, or *Social Media* apps may be divided based on the type of content (e.g., pictures vs. text) one can share. Here, we refrain from taking this step as more narrow categories often induce stronger overlap between categories and require theoretically derived categorisation decisions, which should be preregistered for each individual study.

While our categorisation is based on apps running on the Android system, it may easily be applied to app usage data from other operating systems as we provide not only Android's APK name but also the generic name of all apps. Please note, however, that the generic app names were annotated manually and may differ slightly between countries or app versions. To facilitate matching generic app names via regular expressions, we provide only the short title without details on content or version number.

To our knowledge, we present the first freely available categorisation for (smartphone) apps developed specifically for research purposes with the goal of objectivity in mind. In mobile sensing research, the categorisation of apps is an essential first step for analysing app usage behaviour. Even though this step may appear to be only a tiny part of the data pre-processing, it can still be very time-consuming and have a tremendous impact on the results after further data aggregation and modelling. Therefore, we consider our app categorisation as a valuable foundation for app research that may, however, very well be extended by future researchers. We explicitly encourage all readers and post-users to contribute to the further extension of this dataset, for example, by differentiating the app categories we suggest or by adding country- or system-specific apps. We also want to note that the current state of our categorisation represents a snapshot of apps popular in 2020. Thus, future researchers may want to add newly emerging apps to our category system. In this fashion, our ready-to-use categorisation facilitates app research and contributes to more objectivity. The mobile sensing community can thrive as we create a common understanding of app use.

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COMPETING INTERESTS

The authors have no competing interests to declare.

AUTHOR CONTRIBUTIONS

Ramona Schoedel: Conceptualization, Data Curation, Writing – Original Draft, Writing – Review & Editing
Michelle Oldemeier: Data Coding
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