The hidden image of mobile apps : geographic, demographic, and cultural factors in mobile usage

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The Hidden Image of Mobile Apps: Geographic, Demographic, and Cultural Factors in Mobile Usage

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ABSTRACT

While mobile apps have become an integral part of everyday life, little is known about the factors that govern their usage. Particularly the role of geographic and cultural factors has been understudied. This article contributes by carrying out a large-scale analysis of geographic, cultural, and demographic factors in mobile usage. We consider app usage gathered from $25,323$ Android users from 44 countries and $54,776$ apps in 55 categories, and demographics information collected through a user survey. Our analysis reveals significant differences in app category usage across countries and we show that these differences, to large degree, reflect geographic boundaries. We also demonstrate that country gives more information about application usage than any demographic, but that there also are geographic and socio-economic subgroups in the data. Finally, we demonstrate that app usage correlates with cultural values using the Value Survey Model of Hofstede as a reference of cross-cultural differences.

ACM Classification Keywords

500 Social and professional topics: Cultural characteristics; 500 Information systems: Mobile information processing systems; 300 Human-centered computing: User studies

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INTRODUCTION

Smartphones have become an integral part of modern society[1]. This is particularly evident in the popularity of mobile apps, which support practically any kind of everyday activity, such as well-being, education, health, and leisure. Thanks to wide pricing options, smartphones are popular in practically all countries and afforded by a large percentage of the population. These developments have resulted in smarphones becoming an unprecedented opportunity for studying people's behavior and activities through information garnered through smartphones.

While the importance of apps has been widely established, the factors governing application usage are currently understudied. Indeed, existing research on mobile usage has predominantly focused on characterizing usage patterns [4, 33, 36] without examining the factors that result in differences or similarities. Particularly the role of *geographic* and *cultural* factors has thus far not been taken into account, with questions such as how application usage differs across countries, and to what extent usage reflects cultural and geographic boundaries remaining unanswered. Answering these types of questions would enable researchers, e.g., in human-computer interaction and social sciences to understand how similarities and differences in application usage would influence their studies, what possible differences running studies in different countries could reveal, and how that would influence the adoption of their applications. Beyond academic interest, answering these questions would be relevant to several practical applications. For example, the findings can be used to enrich app recommendation systems and better tailor app markets, including advertisements, for the users. While some popular app marketplaces, such as Google

[1]Newzoo ranked top 50 countries by the number of smartphone users, with average smartphone penetration of 39.4% or total 2.4 bn smartphone users https://newzoo.com/insights/rankings/top-50-countries-by-smartphone-penetration-and-users/.

Play, provide localized recommendations based on user location and other attributes, they are predominantly limited to app level differences across countries (e.g., local news agency, bank, or transportation service) and may not consider the full spectrum of app usage variations resulting from demographic, geographic, and cultural value differences.

In this article, we contribute by rigorously studying and analyzing geographic, cultural, and demographic factors in mobile application usage. We carry out our analysis through a large-scale data set that is collected by 25,323 Android users from 44 countries in Asia, Europe, Americas, and Oceania. This data as county-based aggregated vectors is also published on our project website[2]. The scale of the data is several orders of magnitude of larger than in previous studies and considers actual application usage across a wide spectrum of countries [16, 18]. The data set we use in this study has been created for autonomous, technical analysis of mobile devices. While this data provides a rich real-life source of mobile usage, it also imposes a variety of challenges related to extraction of demographic features from machine oriented data. To mitigate potential biases, we supplement this data with responses from a user survey that focuses on user demographics and values. In total, responses from 3,293 participants are considered.

The results of our analysis reveal geographic differences to have an influence on application usage, and that these differences reflect cultural boundaries between countries. We demonstrate that country information has a stronger influence than other demographic factors with socio-economic factors being second most important, but only half as important as country information. To obtain further insights into the potential role of geographic factors, we study the relationship between application usage and cultural values using the value survey model of Hofstede [14], an established and widely used model of cross-cultural differences. To avoid language and marketing biases, we consider applications through the categories they belong to, such as communication, social apps, and different game genres. Our approach extends the typical characteristics of application usage to the evaluation of the demographic, geographic, and cultural factors behind application choices. To complement these observations, we explore usage differences within geographic and demographic groups, demonstrating that specific sub-groups can be identified where country and socio-economic factors together are determining.

The contributions of our work are summarized as follows:

1. We show that statistically significant relationships can be found between features of a country and app usage.
2. Within the 44 countries considered, geographic clusters can be identified based on differences in mobile app usage.
3. We show that app usage constitutes an external societal factor that correlates with Hofstede's Cultural Values Model.
4. Comparing the information gain from different geographic and demographic attributes we show that the app usage reflects country of an individual. We also compare countries together with information of different demographic features, such as occupation and educational background.

[2] http://carat.cs.helsinki.fi/research/

RELATED WORK

Academic research on analyzing app usage has predominantly focused on characterizing dominant usage patterns and the contexts where usage occurs without examining demographic and geographic factors or cultural values influencing it. In particularly, differences across countries have been understudied. The previous studies, while essential for understanding how individuals use apps, provide no insights about the collective dynamics of the usage. For instance, Xu et al. [36] analyze network traffic caused by apps. The authors find app usage to follow diurnal patterns, as well as to be dependent on spatial context. In a related study, Verkasalo [33] show location to have significant correlation with app usage. Falaki et al. [9] study installation and usage patterns, showing that the number of apps installed and those actually used contains significant variation. Böhmer et al. [4] also demonstrate strong diurnal variations in app use. They show that usage session times tend to be short, and that they depend on contextual factors. Hintze et al. [13] report average of 60 interactions with a smartphone during a day, lasting 107 seconds on average with a median of 57 seconds. Ferreira et al. [10] investigate characteristics of short-term usage sessions, finding social and spatial context to have strong influence, in addition to app functionality.

Instead of usage, analysis of application *installation* patterns garnered from marketplaces has been an active research area. Petsas et al. [23] demonstrate that user preferences are highly clustered, and that users generally show interest in a small set of app categories at a time. Zhao et al. [37] demonstrate that clusters with salient features can be extracted and that specific user demographics can be associated to each cluster. Examples of clusters include "evening learners", "young parents", and "night communicators". Also, Rahmati et al. [26] show that socio-economic status results in differences among iPhone users. Lim et al. [18] analyze factors affecting app download decisions (instead of usage) across countries, finding the importance of pricing, reviews, and app descriptions to vary across countries. Our work extends these studies by considering actual app usage across countries instead of limiting to installation patterns. This is a fundamental difference as research has shown that over a quarter of installed apps are only used once[3], and even apps that are used for longer than a day are unlikely to stay relevant longer than a fortnight [30]. Consequently, installation patterns are heavily biased by applications that are not actually used and thus do not reflect true differences in mobile usage patterns. Besides differing in terms of data source, we focus on overall effect of geographic, socio-economical, and value-based factors instead of looking merely at temporal and functional patterns.

To summarize, the focus of our work is on uncovering regional dynamics from data collected on mobile devices. To the best of our knowledge, our work is the first to study mobile app usage across countries from around the world with the goal of understanding the underlying demographic and geographic factors, as well as their relationship with cultural values. Existing projects of this area have predominantly focused either on analyzing mobility patterns extracted from

[3] http://info.localytics.com/blog/app-user-retention-improves-in-the-us

Data set	Attributes	Date	Size
Mobile usage data set	user id, apps, timezone, timestamp	3/2016 – 4/2017	25,323 users
Background questionnaire	user id, gender, age, occupation, education, household situation, income, debt, savings, location	6/2016 – 5/2017	3,293 users
Google Play categories	1-2 categories for each application	10/2016	54,776 apps
Cultural Values Model (VSM)	6 cultural factors	2015, downloaded 9/2016	111 countries
VSM questionnaire	VSM questionnaire (24 items)	6/2016 – 5/2017	634 users

Table 1: Summary of the data sources.

cellular data records (CDR) obtained through network operators or information acquired through location-based social media. For example, Silva et al. [31] uncover geographic differences from FourSquare check-ins to restaurants. Instead, Kendall et al. [11] study cultural effects of social media on consumer decision-making. They show that information sources that influence online purchase decisions strongly vary by culture. Reinecke et al. [27] study usage of the Doodle scheduling software worldwide and present differences in response times. Qiu et al. [25] study usage of Facebook and a Chinese app with similar functionality called Renren, and find cultural differences, naming the Renren community more collectivist. Kang et al. [16] study mobile usage differences in the USA and South Korea, but limit their analysis in these two countries. In our work, we analyze application usage in 44 different countries distributed around the world.

MOBILE USAGE DATA SETS

We investigate how application category usage reflects geographic and demographic factors among Android users considering large-scale application usage data collected through a popular mobile application, and survey data consisting of responses to a demographic questionnaire. Table 1 summarizes different data sources used in our analysis and their collection periods. In the following we discuss them in detail.

Mobile Application Data

To collect application usage data, we leverage the Carat collaborative platform [21, 22] for smartphone data gathering and analysis. The data gathering part of the platform is open source. Originally designed for energy consumption research, the platform takes a sample every time 1% of battery has been drained. Each sample contains a list of currently running apps, and several other features, the following of which are relevant for this work: user specific identifier, timestamp, time zone, and mobile country code (MCC). Carat collects data by registering to battery change events provided by the OS, which means the resulting data is sparse and can miss events, e.g., when the device is in deep sleep mode, or when the application is terminated either manually by the user or by the OS. We

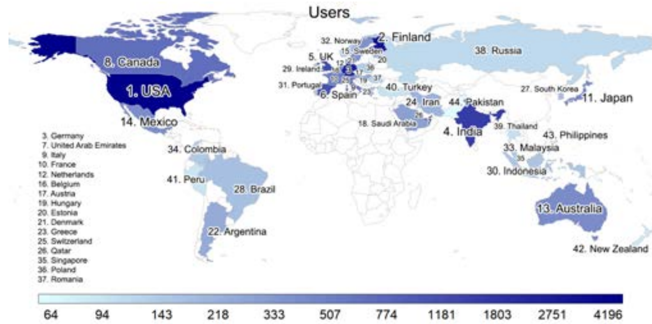


Figure 1: User distribution of the mobile usage data. The colors scale indicates number of users.

overcome issues arising from data sparsity through careful preprocessing of the data; see the next section for details.

We consider only samples from Android devices due to the list of the running applications no longer being available on iOS[4]. In total, we consider 5.65 million samples, in which the time zone and MCC match ($\approx$ 97% of all Android samples). The MCC is obtained from the cellular network, and automatically converted to a two-character country code. We compare MCC with the country that the city of the time zone field corresponds to. This procedure increases the reliability of detecting the country of the user, when GPS is not available. The subset contains 25,323 Android users associated with 114 country codes, from which 44 countries have a significant number of users (100 or more). Figure 1 shows user distributions over the countries. The majority are based in the USA, with strong user bases also in Finland, India, Germany, and the UK among others. As Carat has been designed to support energy-awareness, there is an inherent bias towards users interested in their smartphones' energy consumption. Carat is only available in three languages (Finnish, English, Italian), and hence the sample is likely biased to people with sufficient knowledge of one of these languages. Note that we have no reliable way to identify user's language as application names are mostly in English, e.g., due to branding, desire to appeal to a wider audience, or lack of suitable translations. For this reason we do not consider language information as part of our analysis. We discuss these limitations at the end of the article.

For each app in the data set, we fetch its categorization from Google Play, and map the app to corresponding categories. In October 2016, there were 55 categories on Google Play. The data set contains 97,000 different apps including system processes, from which 54,776 apps are available from Google Play with at least one category assigned. Countries' aggregate usage vectors for each Google Play category are available for research purposes at http://carat.cs.helsinki.fi/research.

User Demographic Questionnaire

To obtain demographic information, a survey has been conducted with the users of the mobile usage data set. The survey was pushed through the Carat app. Answers can be linked

[4]iOS 9.3.4 released on Aug 4, 2016: https://www.macrumors.com/2016/08/04/apple-releases-ios-9-3-4-with-security-fix/

to the app usage through the same user id. The questionnaire includes the following questions (single choice): gender, age group, current occupation, highest completed education, household situation (such as, living alone, or with kids), yearly income compared to their country average, debt as percentage of monthly income, savings as a number of months possible to live off, and current location if the user consents to sharing it. The questionnaire received 3,293 individual answers from 44 countries. This corresponds to 14.3% of active users that have the latest version of the Carat app and thus the questionnaires available. Comparing to an earlier study [1], the demographic distributions are similar with the exception of user locations, where the peak had shifted from the US to Finland due to changes in the maintenance of the Carat platform.

In the questionnaire, the most represented are professionals (34%), technicians or associate professionals (14%), students (12%), and managers (10%), i.e., our respondents are mostly employed. The distribution of respondents' education also reflects this: 35% have undergraduate degree, 30% Master's degree or equivalent, and 5% PhD or research graduate degree. 10% of respondents are female and 87% men, which, while unfortunate, is similar to gender biases of other mobile application studies [2]. 36% of the respondents report their yearly salary is higher than average and 7% that it is much higher. On the other hand, age groups are evenly distributed: 12% of age 18 – 24, 30% of age 25 – 34, 28% of age 35 – 44, 27% of age 46 – 64 and 4% 65 years or older.

In addition to the demographic questionnaire, a 24-item Value Survey Model questionnaire was also presented to the users who had already answered the demographic questionnaire. In total, 634 users answered this questionnaire. Finally, 1153 users agreed to share their location and we have GPS coordinates (latitude and longitude) for these users. We compare these locations to the MCC codes in user's sample history. In 97% of cases the coordinates match to the most common MCC among all samples. This indicates that these people have been inside a single country for most of the time, and thus we can trust MCC as a country information source.

Ethical Considerations: We only consider aggregate-level data that contains no personally identifiable information, following the privacy protection mechanisms of the Carat platform [21]. Data collection is subject to the IRB process of the University of California, Berkeley. The mobile users are informed about the collected data and give their consent from their devices. The user questionnaire performed for this work have been approved on 14 June 2016 by the IRB process of the University of Helsinki, Finland. Participation in the study has been voluntary and the users have been informed about the data collection and management procedures.

Cultural Value Survey Model

Hofstede's Cultural Value Survey Model (VSM) is used in a wide variety of empirical research [17] to present cultural differences between countries. The VSM model has been previously used, for example, to study culture in IT corporations [24], evaluate tourist services [7], study international ethics [3], evaluate consumer decision making [11], Doodle scheduling responses [27], and model emoji usage in different countries [19]. The VSM model has also been criticized. McSweeney [20] questions the validity of defining culture boundaries based on politically agreed national areas. The VSM model does not include minorities or subcultures, or take into account immigration and emigration in the global world, previously referred to as transnational mobility [35]. VSM has been validated earlier for the study of country differences [28, 29]. In this work we analyze relationships between the VSM model, as an established and widely used model of cross-cultural differences, and mobile usage.

The public version of the VSM data set[5] consists of six cultural factors from 111 countries. The VSM data set contains partial factors for Saudi-Arabia and Qatar, which are observed in the mobile usage data set. For the rest of the countries in the mobile usage data the VSM data set contains a full set of cultural factors. The six factors are defined as follows: **Power distribution (PDI)** describes whether unequal power distributions are expected and accepted in the population. **Individualism vs collectivism (IDV)** describes how much members of the population are supposed to care themselves or stay integrated to a group, such as family. **Masculinity vs femininity (MAS)** describes strength of masculine and feminine roles in the population. **Uncertainty avoidance (UAI)** describes whether members of the population feel either comfortable or uncomfortable in new, unstructured, or unpredictable situations. **Long vs short-term orientation (LTO)** describes how members of the population accept delays in either social, material, or emotional gratification. **Indulgence vs restraint (IVR)** describes whether any gratifications are allowed to be relatively free or regulated by norms of the population.

In addition to the general VSM model, we consider the 634 responses received through the VSM survey. In total, 20 countries had more than 10 respondents. Hofstede uses Cronbach's α to test reliability of the factors among the countries. We follow this procedure and calculate Cronbach's α of the VSM factors produced by the questionnaire answers. The results are presented in Table 2. To compare, also Cronbach's α calculated for the published VSM model are included.

From Table 2 we note that four factors gain α larger than 0.75 which is generally considered as acceptable reliability [8]. For *Uncertainty avoidance* and *Long versus short-term orientation*, we receive excellent reliability that is also in line with the original VSM model. For the factors *Power distribution* and *Indulgence versus restraint* we get only moderate reliability, which might be caused by the small number of respondents, and by a bias in the limited set of 20 countries for which sufficient amounts of responses were present in the data set. The high reliability of the majority of constructs, combined with moderate reliability for two of the constructs, shows that our responses are generally representative of cultural differences and in line with Hofstede's VSM model.

COMPARING APPLICATION USAGE

Comparing app usage directly is not meaningful as countries tend to have different apps for banking, news, sports, and many

[5] http://www.geerthofstede.nl/dimension-data-matrix

Factor name	Quest.	VSM Model
Power distribution (PDI)	0.55	0.91
Individualism vs collect. (IDV)	0.77	0.85
Masculinity vs femininity (MAS)	0.79	0.94
Uncertainty avoidance (UAI)	0.91	0.95
Long vs short-term orient. (LTO)	0.94	0.91
Indulgence vs restraint (IVR)	0.61	0.86

Table 2: Reliability test (Cronbach's α) for 1) the questionnaire conducted for mobile users and 2) the VSM model.

other purposes. To avoid these kinds of trivial differences influencing our results, we perform our analysis on category level to understand how usage differs in terms of application *functionality*. To determine the functionality of an app, we extract the category of the app from Google Play (55 were available at the time of writing) and use the corresponding categories as basis for our analysis. While not perfect, the categorization on Google Play is sufficient for our purposes as the number of misclassified apps has been shown to be below 2% for main categories with higher error rates occurring only on subcategory level [32]. In the data set, every user has at least one app from category *Tools* and almost everyone uses *Communication*, a sign of basic functionalities of smartphones. Also, categories of *Productivity*, *Social*, and *Travel and Local* are popular among the examined countries. In turn, certain games and minor categories have less users.

For each user, we consider all applications that have been running on the user's device. We consider both foreground and background applications, but ignore applications that are (pre-)installed but never opened. This latter step is necessary to ensure certain apps, most notably manufacturer specific apps and highly popular apps, such as Facebook or Gmail, are not overrepresented. We map the apps to their representative Google Play category. If the app belongs to two different categories, we consider it twice, once in each category. Finally, we create a binary category vector for each user considering whether a category is used or not. Binarization of category usage information is necessary to cope with sparsity resulting from the sampling mechanism used by Carat. Users with heavier battery drain or that open the Carat app more often will contribute more samples, and there are periods where samples may be missing (e.g., due to app being terminated or device being in deep sleep state). The use of binary vectors treats all users equally, reducing biases resulting from differing sample counts. To compare users across countries, we map the usage vectors into probability distributions of category usage within the country. Each distribution represents the fraction of users in the country using apps belonging to a specific category. Formally, for each category $c_i \in C, C = c_1, c_2, ..., c_k$ where k is the number of categories, we define the probability of its use within a country n as

$$c_{i,n} = \frac{\sum_j u_{i,j} \in U_n}{|U_n|},$$

where U_n is the set of users in country n and $u_{i,j}$ is 1 if user j used category i and 0 otherwise. Now $C_n = c_{1,n}, c_{2,n}, ..., c_{k,n}$ is the category use probability vector for country n.

We use symmetric Kullback-Leibler divergence (KL) to measure the similarity of the probability distributions of different countries. Given two probability vectors C_n and C_m, their Kullback-Leibler divergence is defined as

$$KL(C_n||C_m) = \sum_{i=1}^{k} C_n(i) \log\left(\frac{C_n(i)}{C_m(i)}\right).$$

Their symmetric KL-divergence is given by:

$$dist(C_n, C_m) = \log\left(KL(C_n||C_m) + KL(C_m||C_n)\right).$$

In the remainder of the article, we consider the terms KL-divergence and symmetric KL-divergence exchangeable while referring to the symmetric variant of KL-divergence.

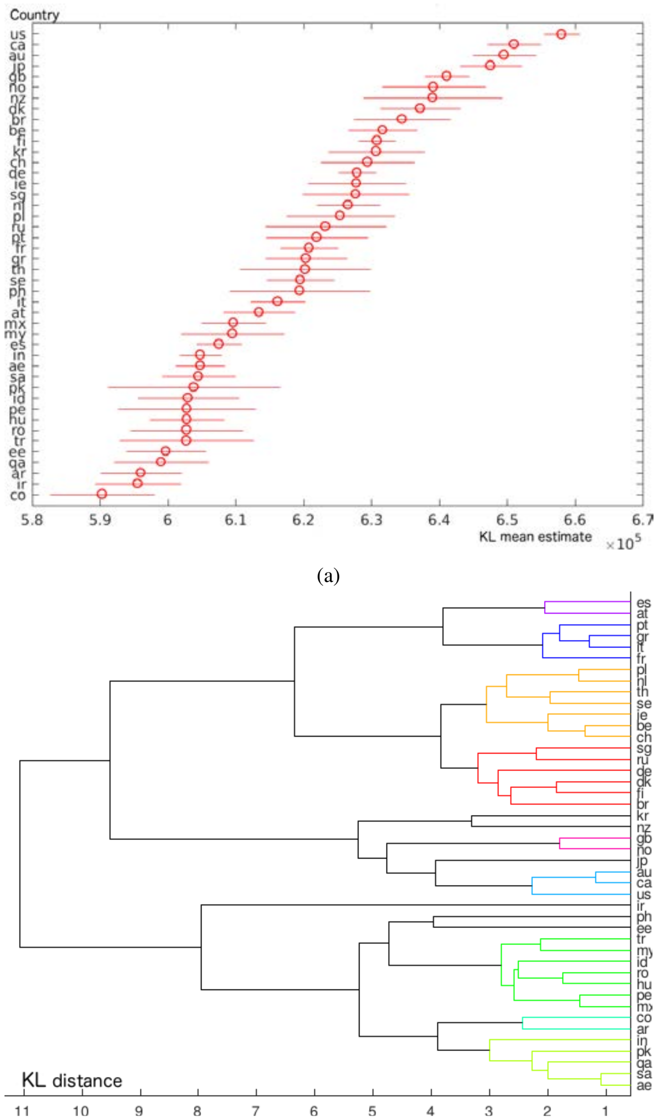
GEOGRAPHIC FACTORS AND CULTURAL VALUES

We begin our analysis by investigating the *overall* effect of geographic and demographic factors, and cultural values. We consider 44 countries presented in the mobile usage data set. First, we compare countries using their app category usage aggregates and find groups of countries with similar mobile usage. Second, we analyze app usage differences across countries, and find possible reasons behind them. Third, we compare the importance of geographic and demographic factors by measuring the information they provide about app usage. Our results demonstrate that the country of the participant has almost twice the information gain than any demographic factor in explaining app usage. We proceed to examine the relationship between cultural values and app usage through the value survey model (VSM). We show that differences in mobile usage partially explain cultural values, as explained by the VSM model, but also have important differences. Finally, we demonstrate that, country and socio-economic information can be used to identify dedicated subgroups where application usage is similar. For example, professionals in English speaking countries have similar app usage patterns while students have differing application usage patterns across countries.

Geographic Groups in Mobile Usage

We first show that there are statistically significant differences between application category usage of different countries. To demonstrate this, we consider binary usage vectors of users in a country, and compare the distributions using Kruskal-Wallis non-parametric ANOVA and post-hoc tests. We find that, indeed, there are significant differences in application category usage across countries (χ^2 = 6792.4, df = 40, $p < .001$, η^2 = 0.309). Figure 2a shows post-hoc comparisons for the median estimates and their standard errors for each country. With significance level $\alpha = 0.05$ (using Tukey-Kramer correction), the differences in the medians are statistically significant for most countries, as can be observed from the small amount of overlap for each of the countries in the figure.

In addition to differences, we are interested in understanding similarities between countries. We perform this comparison by clustering the countries using (symmetric) KL divergence



(a)

(b)

Figure 2: App usage comparison: (a) the multiple comparison of the country means and standard errors by the Kruskal-Wallis test; (b) visualization of KL divergence between countries.

as similarity measure. Figure 2b illustrates the similarities between countries through a dendrogram. The closer the branches are in the figure, the closer the countries are in terms of app usage. The main three branches of the dendrogram are also visualized on the world map in Figure 3.

The similarities reflect cultural boundaries to a large degree, with few exceptions. The topmost branches, blue color in the map of Figure 3, consist of mostly continental European countries, all relatively close to each other in terms of the distance metric. Spain (es) and Austria (at) are found together, and also close to some other Southern and Central European countries: Portugal (pt), Greece (gr), Italy (it), and France (fr). The next branch contains countries from Central and Northern Europe, including Poland (pl), Netherlands (nl), Sweden (se),

Country	o/a ν	1.	ν	2.	ν	3.	ν
ee	0.85	fi	0.80	se	0.15	de	0.11
ch	0.82	de	0.45	fr	0.26	it	0.20
th	0.73	fi	0.18	de	0.16	us	0.15
se	0.72	fi	0.48	de	0.16	dk	0.12
cz	0.69	de	0.37	fi	0.16	it	0.16
fr	0.66	de	0.25	gb	0.16	be	0.14
no	0.64	fi	0.23	se	0.20	dk	0.13
nl	0.62	de	0.28	be	0.19	fr	0.15
dk	0.60	de	0.25	fi	0.17	se	0.17
at	0.60	de	0.38	it	0.11	fi	0.10
cn	0.60	us	0.19	jp	0.16	hk	0.13
be	0.59	nl	0.22	fr	0.21	de	0.19
ie	0.57	gb	0.28	us	0.14	de	0.13
pl	0.54	de	0.27	fi	0.12	it	0.09
pt	0.53	de	0.20	es	0.15	gb	0.13

Table 3: Ratios of visited countries: overall ratio, and ratios of three most visited countries.

Ireland (ie), Belgium (be), and Switzerland (ch). Thailand (th), a popular holiday destiny for Europeans is part of this group. The third sub-branch contains Russia (ru) and another Asian country, Singapore (sg). The last group consist of Nordic countries Denmark (dk) and Finland (fi) together with Germany (de). However, also Brazil (br) is close to these countries.

The next large branch in the dendrogram (located in the middle, red color in Figure 3) consists of English-speaking countries such as the USA (us), Australia (au), Canada (ca), New Zealand (nz), the United Kingdom (gb), and other countries with early adopters of the data collection app, such as South Korea (kr) and Japan (jp). The Asian countries fall into the same cluster as the English speaking countries likely because the data collection app has not been translated to the local language and hence usage is likely biased towards the English-speaking people in these countries. Countries of this group have the highest usage in almost all app categories. This is likely due to the fact that almost all apps have an English version, and many services, retailers, restaurants, and public places in Europe and the USA have dedicated apps. Some categories, such as *Food and Drink*, *Medical*, and *Shopping* are almost equally popular in most of the countries, but surpassed by the "English-speaking" group.

The remaining countries fall within the third main branch (yellow in Figure 3) where the similarities are less obvious, though some meaningful cultural and geographical groups can be identified. Examples include Columbia (co) and Argentina (ar) in South America, and the Arab Emirates (ae), Saudi Arabia (sa), Qatar (qa), Pakistan (pk) and India (in) in Asia. Iran (ir), the Philippines (ph) and Estonia (ee) were not grouped close to other countries. This group can be characterized by lower app usage across the board, but higher than the other two categories in *Sports* and *Racing games*.

The mobile data set only contains information about the user's country whenever a sample is taken without uniquely identified the home country of the user. Thus, users can contribute usage data to different countries depending on their mobility.

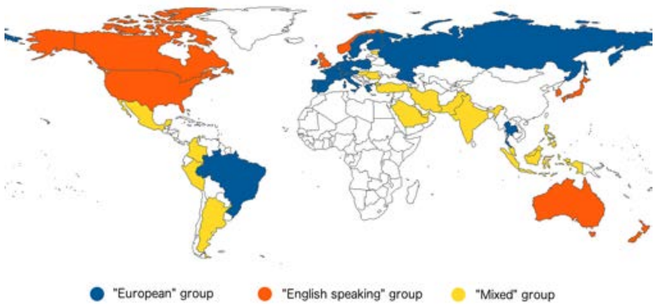


Figure 3: Countries colored by main clusters in the KL divergence analysis (see Figure 2b).

To understand the degree at which this affects our results, Table 3 shows the degree of mobility for the 15 countries with highest overall mobility. There results help to explain some of the inconsistencies in the clustering of countries. As an example, we observe 73% of measurements for Thailand being contributed by people visiting other countries, with Finland and Germany being the highest contributors. As there is little mobility from countries neighboring Thailand, and the visits are split among many countries with no clear main contributor, we can safely conclude tourism to be the main reason for Thailand to be associated with Western countries in the dendrogram. Other countries where we can observe strong tourism patterns include Estonia, Switzerland, and, to a lesser degree, Portugal. We can also observe high degree of mobility between neighboring countries within Europe, which further enforces results about their closeness.

To summarize, our analysis shows that similarities between countries, to a large degree, reflect geographical and cultural boundaries. The few exceptions, most notably Thailand and Brazil, result from of a combination of mobility, small sample population from the corresponding countries, and the data collection app being only available in English, Finnish, and Italian, potentially biasing data from these countries to expatriates and people visiting the country. Similarly, all countries within the third main branch have relatively small sample-size and high number of cross-country mobility, which are the most likely reasons for lack of strong structure amongst them.

Influential Geographic and Cultural Factors

We next assess the relative importance of country information and different demographic factors on app usage. As measure of importance we consider information gain between the attribute and application usage. We sort users' application categories alphabetically and view them as a vector of ones and zeros, corresponding to the user having used that category, or not, respectively. Thus, we can detect information gain for each demographic factor and country against the category vectors.

Figure 4 presents attributes in the background questionnaire sorted by their information gain. From the figure we can see that country attribute has the highest information gain compared to the other attributes. Indeed, the effect of country is

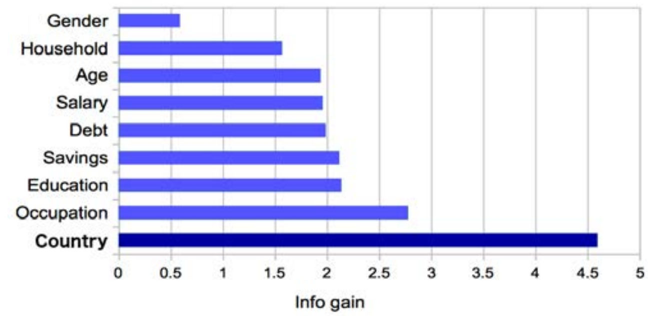


Figure 4: Demographic attributes sorted by information gain against application usage.

much higher than other features, such as age or gender. The second highest contributors are demographic factors related to socio-economic level, including occupation, education, savings and dept levels. Household size and gender had only a modest relationship with app usage, suggesting that socio-economic factors are more important in explaining mobile app usage than common demographic factors. This observation is in-line with previous studies considering importance of socio-economic factors in smartphone usage [26]. However, the effect of country information has not been previously established, and our results suggest it to be almost twice as important than other attributes.

Association between Mobile Usage and Cultural Values

As we have shown, the country of the user has a significant impact on mobile usage. Next, we examine whether the effect is cultural or purely demographic by considering the Value Survey Model as a reference for cultural differences. For each of the six factors in VSM, we compute a difference matrix and correlate the entries of the matrix with app usage similarity as given by KL divergence. Following the Mantel test procedure, we calculate the Pearson correlation coefficient between the VSM factor matrices and our mobile usage matrix using $100,000$ permutations of the order of countries. All the VSM factors have a 0.3 - 0.4 correlation coefficient with the category use matrix, indicating intermediate correlation.

Next, we correlate application category and VSM factor pairs separately to identify which relationships are significant. We find power distance (indicates hierarchy in the culture) to have a significant negative correlation (PDI $\rho = -0.53$) to the use of *Entertainment* applications and other leisure related categories, such as *Travel and Local* (PDI $\rho = -0.42$), *Sports* (PDI $\rho = -0.42$), *Health and Fitness* (PDI $\rho = -0.48$), and *Music and Audio* (PDI $\rho = -0.53$). These same categories are mostly related to individualist cultures. Collectivist cultures, those with higher power distance, and cultures considered feminine seem to value family related categories, such as *Family create* (IDV $\rho = -0.46$), *Education games* (PDI $\rho = -0.33$), *Family pretend* (MAS $\rho = -0.43$), and *Parenting* (MAS $\rho = -0.27$).

Regarding other VSM factors, masculine cultures correlate with high use of *Personalization* apps (MAS $\rho = +0.38$). Long-term oriented cultures seem to prefer leisure-related categories, such as *Sport* (LTO $\rho = -0.41$), *Casual* (LTO $\rho = -0.34$) and *Word games* (LTO $\rho = -0.36$), as well as *Social* apps (LTO $\rho = -0.35$). In short-term oriented cultures, there is a preference for *Role playing games* (LTO $\rho = +0.37$) and a need for *Weather* apps (LTO $\rho = +0.42$) as well as *Comics* (LTO $\rho = +0.46$). It is noticeable that categories with high correlations differ from those with the highest usage in general, indicating that cultural differences in app usage are more sophisticated and complex in nature.

Reversely, categories that do not correlate with any of the VSM factors can provide insights to apps that are equally important across the studied countries. We take a closer look at the categories that correlate less than $\rho = 0.2$ (or $\rho = -0.2$, respectively) with the VSM factors. There are nine categories which correlate less than the given threshold with at least five VSM factors. The category *Dating* correlates only slightly more (IDV $\rho = +0.26$) to the Individualism versus collectivism, and the category *Events* to the Masculinity versus femininity (MAS $\rho = +0.21$). *Game role playing* has very low impact against five factors, but gains more correlation (LTO $\rho = +0.36$) to Long versus short-term orientation. Additionally, the category *Beauty* and many types of games have low correlation against every factor: *Game arcade*, *Game casino*, *Game music*, *Game simulation*, and *Game strategy*. To summarize, certain categories, particularly different types of games, are generally more independent of the VSM factors than categories with other types of functionality.

Our results have demonstrated that both country and cultural values, as measured through the Value Survey Model, have clear impact on mobile usage. We also found strong correlations between certain app categories and VSM factors, but neither country nor the VSM factors can explain mobile usage as a whole. We also found some categories, most notable different types of games, that were popular across all countries. To summarize, our results indicate that mobile app usage has a *significant* cultural dimension, but that the overall relationship between culture and app usage is sophisticated and complex.

Combined Effect of Geographic and Economic Factors

The previous sections demonstrated that both country and cultural values correlate with mobile usage, and that the geographic effect is more significant than the effect of demographic factors. However, certain application categories are popular across all countries, for example, *Communication*, *Productivity*, and *Social* apps. To gain better understanding of worldwide mobile usage, we consider also use cases where socio-economic factors and countries together are examined in detail. We study *occupation* and *education*, which have the highest information gain against application category usage after country. We also include *household status* to highlight some common demographic and geographic clusters and to endorse the view that societal and economical factors are also important determinants in app usage.

Out of all questionnaire answers, we consider those that with ten or more responses. Also, countries with less than 10 respondents are excluded. In Figure 6, we show the comparison between the best represented educational levels (vocational education, Bachelor's, Master's, and PhD equivalent degree)

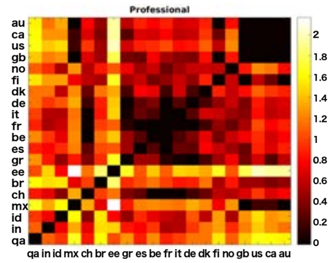


Figure 5: Professionals' category usage in different countries.

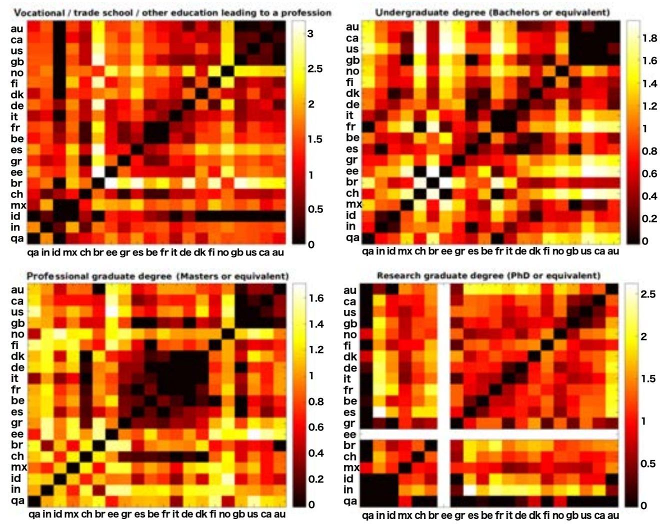


Figure 6: Colormaps of the KL differences in category usage in different countries and education groups. As far as the PhD degree is concerned, the values for Estonia (ee) are missing.

within 21 countries. Darker color indicates closeness (symmetric KL divergence between countries close to 0) and lighter color farther distance (high symmetric KL divergence).

As seen in Figure 6, professionals in Australia, Canada, the USA, and the UK use application categories similarly, indicated as a dark cluster in the North-Eastern corner of the colormap. The results suggest that highly educated people or those working as professionals (see Figure 5) seem to use their mobile devices similarly in these countries. For professionals and Master's degree holders there is also a cluster in the middle of the colormaps. This cluster includes continental European countries: Denmark (dk), Germany (de), Italy (it), France (fr), Belgium (be), Spain (es), and Greece (gr). The app category usage of this group is different from the previously mentioned English-speaking cluster, as seen in Figure 2b. Also Zhao et al. [37] note in their study a special cluster of people focusing on *Financial* and *Navigation* on weekdays, that possibly indicates highly-educated professionals.

One more cluster is visible in the bottom left corner of the colormaps, including Qatar (qa), India (in), and Indonesia (id). Undergraduate students and PhDs are presented in this cluster, indicating similarities in app usage of academic people in these countries. It is possible that these groups also have

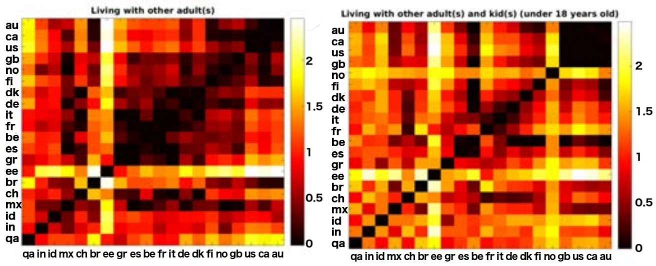


Figure 7: Colormaps of the KL differences by category usage in different countries and household statuses.

a higher smartphone penetration. While clear clusters can be found for professionals, for other occupations, such as students, retired, and technicians or assistant professionals no meaningful groups can be identified. This may be a result of personal preferences affecting typical set of apps, as indicated also in previous studies [23], instead of adopting new ones as a group. In addition, students visited other countries more than country average, except students from the US and Canada.

Respondents who report their household status are also similar to others with the same status (see Figure 7). Similarly, previous studies [37] have noted a tendency of parents using their smartphones in a parallel pattern. Most household statuses have a cluster of English-speaking countries in the upper right-hand corner of the figure, with a larger cluster of similar application usage for respondents living with other adults within European and English-speaking countries. The darker area encompassing Finland, Norway, and the UK may also be interpreted as its own cluster.

To summarize, when both country and socio-economic information is taken into account, we can identify clear usage subgroups. People in the same socio-economic group, especially professionals and well-educated people, tend to have similar patterns in their app usage, and these similarities are strongest in English-speaking countries and, on the other hand, continental European countries.

DISCUSSION

Geographies vs. Cultures: Differences of app usage between countries may be influenced by many external factors. Firstly, language can have a strong impact, such as English in the USA, Canada, and Australia, and Arabic languages in Qatar, Saudi-Arabia, and the Arab Emirates. These clusters are in line of previous study that classifies them to societal clusters "Anglo Cultures" and "Arab Cultures" [12]. On the other hand, the questionnaire we used for collecting data has only been available in English, and the data collection application is available only in English, Finnish, and Italian. Hence, the respondents as a whole are probably biased towards those familiar with three languages. This may have reduced the number of questionnaire respondents in some countries. Second, close geographical and political relationships may also bring app usage closer between countries. Finally, especially within Europe, cultural boundaries are likely to affected by free movement between countries.

Our respondents have a bias towards males and professionals, which may be indicative of people interested in energy consumption analysis apps in general, or it could be due to the distribution of Android users in general. Similar biases to male dominance in sample population has been noted is previous research on smartphone usage [34]. Nevertheless, our study covers 44 countries, data from over 25,000 users and a wide array of other demographic and socio-economic factors, such as age and household status, making our research the largest study of mobile app usage to-date. Our work also paves way for analyzing more fine-grained differences in app usage, e.g., by correlating app usage patterns with weather or climate data, or economic indicators such as GDP.

Individual vs. Group Usage: We found that certain user groups, most notably educated professionals, form strong clusters across countries. This is in line with previous research noting educated males focusing, for example, on finance and transportation apps [37]. Conversely, some groups do seem to use apps similarly across countries. Most notably, students' app usage does not follow country boundaries, perhaps due to mobility during studies, or using the apps they are familiar with also when studying abroad, or due to desire to maintain ones cultural identity. To validate this assumption, we calculated the degree of mobility for students, and found mobility to be higher among them than with the general population. We can observe patterns that do not reflect geographic boundaries while examining respondents by age. Younger respondents (under 25 years) are dissimilar between countries, while within age groups from 25 to 64 years, clusters within central Europe and the English-speaking group form, and grow similar. However, respondents over 65 years of age break this pattern, and clusters form between country pairs such as Germany and Denmark, Estonia and Greece, and Switzerland and Brazil, possibly indicating immigration or retirement destinations.

Some findings in our analysis were tied to specific demographic subgroups. For example, household status had a significant impact in some cases as apps can be targeted to singles, couples, or families, which are not present in the data of respondents with a different household status. Parenting, dating, and family apps have a high information gain for household status. Also other Google Play *Family* subcategories see higher usage in households with children. These findings are in line with previous studies, especially Zhao et al. [37] who find clear clusters for young parents. The similar app usage of members of the same age, household, education, or profession group also motivates studying app category usage in more detail. Together with these societal, economical, and demographical factors, it can provide groupings across country boundaries.

Cultural Values and Effects: Our analysis used Hofstede's Value Survey Model to capture cultural differences across countries. One of the most poignant criticisms of VSM is that it oblivious to immigration and multiculturalism, as well as to values that are based on religion or other sub-culture within a country [20, 35]. On the other hand, VSM gives us an insight to value-based boundaries between countries in addition to geographical and historical similarities, which are hard to capture otherwise, especially in studies of smartphone usage [19]. Fine-grained subpopulations are difficult to identify reliably from mobile app usage data, which further motivates the decision to limit on country level granularity.

Our analysis uncovered natural interconnections between app usage and the VSM factors. For example, we found countries with collectivist and feminine values to prefer family-related applications. Countries with low power distance, indicating a shallow hierarchy, were found to have higher preference for leisure-related apps such as *Music and Audio*, *Entertainment*, and *Travel and Local*. These categories are also popular in countries that attach high value to individualism. These findings are in line with the cultural differences identified by Hofstede [15], which suggests that app usage indeed serves as a cultural indicator. However, we stress that our claim is not that mobile usage is the dominant, or even a major, factor in explaining cultural differences, but one of the factors that influence it, together with religion, language, and other.

Sample Representativeness: Studies on mobile app data, including ours, are necessarily biased by the population installing the application [5, 6]. Additionally, there are differences in demographic and geographic factors between iPhone and Android users with Android being more popular than iPhone in Western Europe, developing countries, continental Asia and Africa, and iPhone being more popular in the US, the UK, Japan and few other developed countries. The iPhone is generally considered more popular among women and high-income earners, suggesting there is a slight gender and socio-economic bias in the data also due to the selection of platform. In our case we sought to mitigate these biases through resampling and careful statistical analysis. Moreover, our data set is several orders of magnitude larger than what has been considered in previous research [19, 36], offering better generalizability to our results. However, we acknowledge there being also some omissions. Most notably, since we relied on Google Play, we were not able to access users who use other marketplaces as their primary source of applications (most notably in China, Japan and South Korea).

App Functionality: We considered categories as given by Google Play to determine the functionality of an app. The categorization in Google Play is done by the developer and can contain errors, which can influence the results of our analysis. While some efforts at automatic categorization have been developed, their accuracy has not been validated, making these approaches unsuited for our purposes. Surian et al. [32] investigated errors on Google Play marketplace and found the categorization error to be typically within 2% with the most conservative estimate of 5% applying only on subcategory level. Most of the errors are attributed to classifying different mobile games and thus the primary functionality of the apps would remain unchanged for the purposes of our analysis. The sole exception was the category *Tools* which was excluded from analysis due to being too broad.

Design Implications: Our results showed that there is a strong relationship between app category usage and geographic and socio-economic factors, suggesting that these different factors should be taken into account when studying mobile data. Our results can be used to better target mobile apps in different countries and for personalization. As category popularities varies across countries and category usage correlates well to the Value Survey Model, it is possible to build a value-aware recommendation engine that recommends apps from categories more likely to be used in the target country's value profile. Previous research is in-line with the need for understanding app usage in different countries [18] in terms to help developers target their products in highly competitive app markets. In addition, thin cultures could yield commonalities in terms of app usage. For example, adults living with children choose different apps because of their household status, but do they choose the same apps across countries and cultures? We considered category-level differences, which sets the stage for studies focusing on specific app-level differences.

SUMMARY AND CONCLUSIONS

In this work, we analyzed mobile app usage on category level across 44 countries and $25,000$ smartphone users. The results of our analysis demonstrate that there are significant differences in app usage across countries, and that these differences to a large degree reflect geographic boundaries. For example, there are marked close relationships between the *non-English speaking European* countries (Russia and most of Europe), a clear cluster of the *English-speaking* countries (the USA, Canada, Australia, the UK), and groupings between the countries of South America, Middle East, and South-East Asia. Particularly, the English-speaking group uses all categories in a more diverse fashion compared to the other groups, while the non-European, non-English-speaking countries use more sports and racing games than the others.

We have also used information theoretic tools to explore the relative importance of different factors on mobile usage. Our analysis revealed the country attribute to have the highest information gain among all demographic factors, with twice as high importance than with the other attributes. We also demonstrated that socio-economic factors have a strong relationship with app usage, even if their overall influence is smaller than that of country. Based on this finding, we demonstrated how dedicated subgroups can be found by comparing both country and socio-economic attributes. For example, educated people and professionals in Australia, Canada, the USA, and the UK use app categories in a similar fashion, while the other groups are more diverse in their app usage. Finally, we demonstrate that application category usage also correlates with cultural values, suggesting that app usage has emerged as part of everyday culture, together with a number of other factors.

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