A First Look at SIM-Enabled Wearables in the Wild

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ABSTRACT

Recent advances are driving wearables towards stand-alone devices with cellular network support (e.g. SIM-enabled Apple Watch series-3). Nonetheless, a little has been studied on SIM-enabled wearable traffic in ISP networks to gain customer insights and to understand traffic characteristics. In this paper, we characterize the network traffic of several thousand SIM-enabled wearable users in a large European mobile ISP. We present insights on user behavior, application characteristics such as popularity and usage, and wearable traffic patterns. We observed a 9% increase in SIM-enabled wearable users over a five month observation period. However, only 34% of such users actually generate any network transaction. Our analysis also indicates that SIM-enabled wearable users are significantly more active in terms of mobility, data consumption and frequency of app usage compared to the remaining customers of the ISP who are mostly equipped with a smartphone. Finally, wearable apps directly communicate with third parties such as advertisement and analytics networks similarly to smartphone apps.

CCS CONCEPTS

• **Networks → Network measurement**; **Mobile networks**;

KEYWORDS

Wearables, IoT, Mobile Networks

ACM Reference Format:
Harini Kolamunna[*‡], Ilias Leontiadis[★], Diego Perino[★], Suranga Seneviratne[°], Kanchana Thilakarathna[°‡], Aruna Seneviratne[*‡]. 2018. A First Look at SIM-Enabled Wearables in the Wild. In *2018 Internet Measurement Conference (IMC '18), October 31-November 2, 2018, Boston, MA, USA.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3278532.3278540

1 INTRODUCTION

Smart wearable devices of various kinds such as smartwatches, fitness trackers, and smart headsets are becoming increasingly popular. Recent Gartner reports [4] indicate that over 500 million smart wearables will be sold by 2021, which is approximately twice the number of wearable sales in 2016. To date the smart wearable market is dominated by smartwatches and fitness trackers [16]. In 2017 over 100 million units of these two types of smart wearables were sold, that contributed to a 44% of the total sales of wearables. In addition to being fitness tracking devices and complementary devices to smartphones, wearables find applications in a number of other domains that include healthcare, finance, sports, and transportation. While the majority of today's wearables rely on a paired smartphone for communication, there is an increasing trend towards stand-alone wearables with mobile network communication to facilitate higher mobility, especially for fitness tracking by eliminating the need of carrying the smartphone [8].

Despite being a new breed of SIM-enabled devices and showing a significant growth in the recent past, a little has been studied on their traffic and usage characteristics, and on understanding differences with respect to smartphones. Furthermore, wearables are designed to be always attached to the human body; thus has the potential of providing even more interesting insights into user behavior and mobility at a large scale than smartphones. Finally, modern wearables also support a range of functionalities and thereby many third-party smartphone apps are including companion wearable apps to provide services such as notifications (e.g. weather, news, and location-based alerts), micro-interactions with the smartphone or cloud (e.g. voice commands), and handling payments (e.g Apple and Android pay): such services would benefit from a better understanding of wearable users behavior.

To this end, this paper presents five month summary statistics and seven weeks of detailed analysis of SIM-enabled wearable network traffic of a large European mobile ISP. To the best of our knowledge, this is the first such analysis at this scale. Our analysis includes application network usage, popularity characteristics, user mobility, and network traffic. We also compare SIM-enabled wearable patterns to the other customers of the ISP (mostly equipped with a smartphone), and to a fraction of wearable devices relaying traffic through a smartphone (Through-Device wearables). We make the following main observations:

- SIM-enabled wearable usage is constantly growing at a rate of 1.5% per month for a total of 9% over five months. However, only a small fraction of users (34%) actually use cellular connectivity.
- SIM-enabled wearable users are significantly more mobile (70% higher entropy), consume 26% more data, and generate 48% more transactions than the remaining users of the ISP.
- *Communication, Shopping, Social, Weather*, and *Music & Audio* are the top-5 frequently used app categories leveraging cellular network. Also, these categories dominate the data consumption.
- Just like the smartphone apps, wearable apps directly communicate with third-party advertising and analytics networks. The volumes of data exchanged with those services are in the same

IMC '18, October 31-November 2, 2018, Boston, MA, USA

ACM ISBN 978-1-4503-5619-0/18/10…$15.00
https://doi.org/10.1145/3278532.3278540

order of magnitude as the volumes exchanged with application service providers.

2 RELATED WORK

Traffic analysis in mobile networks: A plethora of work studied smartphone traffic characteristics in mobile networks to understand the user, device, app, and protocol behaviors [2, 5, 14, 15] through active and passive measurements. Nonetheless, only a limited amount of work focused on the traffic generated by non-smartphone devices connecting to mobile networks. Shafiq et al. [18] studied the Machine-to-Machine (M2M) traffic characteristics in a tier-1 US mobile operator whereas Andrade et al. [1] studied the network traffic created by connected cars in the US. Kolamunna et al. [7, 8] studied the performance of various encryption protocols in wearable devices through active measurements and analyzed the performance trade-offs between relayed communication and direct Internet communication. *In contrast, our work focuses on identifying and characterizing network traffic generated by SIM-enabled wearable devices through a large scale passive network measurement. Also, in contrast to M2M, connected vehicles, or other IoT devices, wearables support a range of functions through first and third party apps and as such traffic characteristics can be expected to be different.*

Wearable user behavior studies: Several work carried out participatory sensing based data collections to understand behaviors of wearable users [9, 10, 13]. For example, Liu et al. [9] collected data from 27 Android smartwatch users over a period of 106 days and characterized the usage patterns, energy consumption, and network traffic. Similarly, in [10] and [13] the authors analyzed the power consumptions of smart-watches. *Our work differs from these as we focus on analyzing SIM-enabled wearable users' behaviors from the data collected at the vantage points of mobile networks. As such, we study a much larger number of users compared to participatory sensing based approaches.*

Wearable apps: Multiple work studied availability and adoption of wearable apps [3, 11, 12] by analyzing app metadata, source codes and binaries, app-store reviews and permissions. *In contrast, we focus on the network communications initiated by SIM-enabled wearables and use the traffic characteristics to study user and app behaviors.*

3 METHODOLOGY

We focus on wearables with cellular connectivity that we define as *SIM-enabled* wearables. For comparison, we also consider the traffic of the remaining customers of the ISP: this is generated by all devices (mostly smartphones) equipped with a SIM. Finally, in the conclusion section we present a preliminary comparison of SIM-enabled wearable traffic with a fraction of the wearable traffic that is relayed through the paired smartphone (*i.e.,*Through-Device wearables). In the following, we first present the measurement infrastructure and the dataset. Then, we describe how we identify the SIM-enabled wearables and their apps for traffic collection and analysis. Finally, we discuss limitations and ethical considerations related to data collection and analysis.

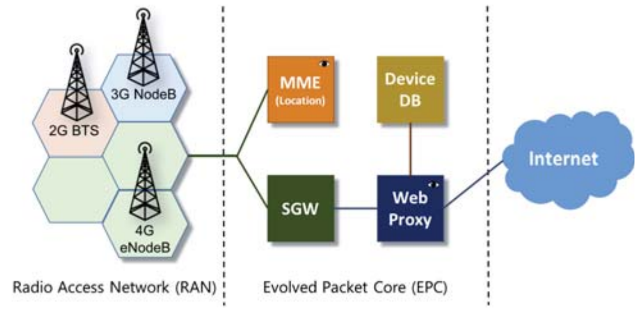


Figure 1: Data collection architecture.

3.1 Measurement infrastructure and dataset

We analyze passive traces collected in a large European mobile ISP with tens of millions of subscribers. Fig. 1 shows the main elements of the measurement infrastructure on the mobile network. There are three separate main data collection elements providing different statistics useful to our analysis: i) *a transparent Web-proxy* used by the ISP to optimize the mobile traffic but also logs performance metrics about each HTTP/HTTPS transaction; ii) the *Mobility Management Entity (MME)* that keeps track of the *sector* (*i.e.,* antenna/tower) where the subscribers are at any given time; iii) the *Device database* providing up to date information binding a deviceID (*i.e.,* IMEI) with a specific device model, OS, and manufacturer (e.g., iPhone7, iOS, Apple).

We collect summary statistics for a period of five months (between mid-December 2017 and mid-May 2018) from the MME and Transparent web proxy logs to analyze the user adoption trends in Section 4.1. The rest of results presented in the paper are obtained by leveraging the full MME and transparent Web-proxy logs of the last seven weeks of the observation period.

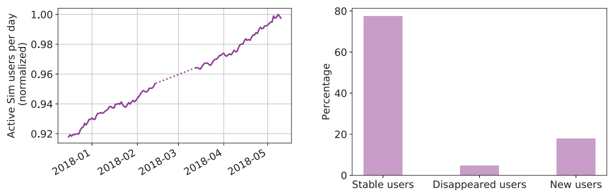
3.2 Identifying SIM-enabled wearables

We first prepared a list of all SIM-enabled wearable device models that are available in the country. These primarily include Android and Tizen-based wearables (mostly Samsung and LG); note that this operator does not yet support the SIM-enabled Apple Watch 3. Afterward, we leverage the DeviceDB to associate these models with their respective IMEI ranges and finally, we search for these IMEIs in the traffic logs extracted at other two vantage points. Overall, we count in the order of thousands active SIM-enabled devices during these five months.

3.3 Identifying apps from the traces

For each connection, the transparent HTTP proxy log contains the SNI for HTTPS traffic and the full URL for HTTP. We used this information to map a set of connections in the same timeframe with a given app. These mappings are based on the experimental data on app Internet communication performed with different devices (e.g., Samsung Gear S, Nexus5) and the information reported by Androlizer.[1]

[1]https://www.androlyzer.com



(a) SIM-enabled users. (b) First week vs last week.

Figure 2: Studying active users with SIM-enabled wearables.

3.4 Scope and limitations

All results and claims presented in the paper are valid for SIM-enabled wearable users when connected to cellular networks. Indeed, the goal of this work is to look at this emerging category of wearable users through the lens of an ISP. Therefore, we are interested in their mobility and network traffic patterns when connected to the cellular network, and not on providing a general characterisation of wearable activity and usage. WiFi wearable traffic characterization is also outside the scope of this paper. Finally, our preliminary analysis presented in the conclusion, suggests wearable users relaying traffic via smartphones (Through-Device users) have very similar patterns to SIM-enabled users. However, we leave a full analysis of this category of wearable users as future work.

3.5 Ethical considerations

The data collection and short-term retention at network middleboxes are in accordance with the terms and conditions of the ISP and the local regulations. The terms also include data processing for research and publications as allowed usages of collected data. Our data analysis process is approved by *Data61, CSIRO's Human Research Ethics Committee under the reference number 009/18.*

4 USER BEHAVIOR

In this section, we provide early insights of user adoption trends of SIM-enabled wearables over a five month period (cf. Sec. 4.1). Then, we investigate SIM-enabled devices usage patterns and user mobility averaged over a 7 weeks period for which we can retain detailed statistics.

4.1 User adoption

We first analyze user adoption trends. We report in Fig. 2(a) the daily number of SIM-enabled users that were connected to the cellular network (*i.e.,* registered with the MME). Note that we show the normalized values of the number of users (i.e. divided by the latest number of users) for confidentiality reasons. We observe that there is a constant rise in the numbers of SIM-enabled users at a rate of approximately 1.5% per month for a total of 9% in 5 months, and we expect that this rise will be sharper once the Apple watch is supported by this ISP. Currently, most users are using LG and Samsung SIM-enabled watches.

Interestingly, only 34% of those users are actually generating any traffic during this period. This can be attributed to three potential reasons. First, SIM-enabled wearables have a limited set of apps transmitting data directly via the cellular network (cf. Sec 4.3). Second, about 60% of SIM-enabled users consume cellular data from a single location (cf. Sec. 4.3): we expect that the majority of these people are connected to WiFi access points. Finally, a large percentage of these users have not subscribed for mobile data subscription and their wearable is only registered with the MME when they connect to check if it is allowed to transmit data.

In Fig. 2(b) we compare the users that were connected to the cellular network at least once during the first week to the ones that were connected during the last week. We observe that only 7% of the initial users were not present and 77% of the users were still active.

Takeaway: *The adoption of SIM-enabled wearables keeps increasing at a rate of 1.5% per month (9% in 5 months) and 7% of the users abandon them after a five-month period. Notably, only 34% of users actually transmit any data over the cellular network.*

4.2 Macroscopic daily/weekly pattern

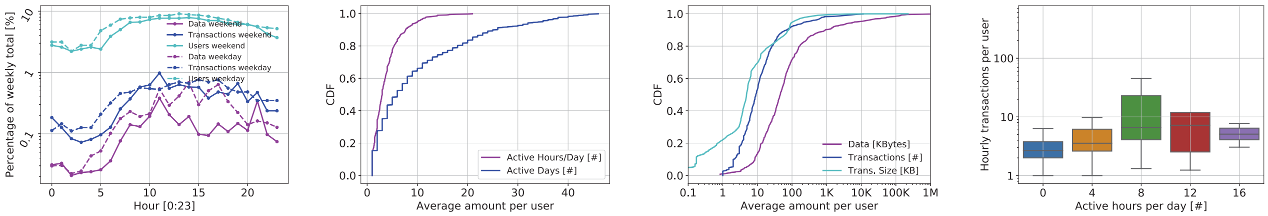
We now present a high-level analysis of average daily and weekly usage patterns. Specifically, we report in Fig. 3(a) the average percentage of active users (i.e., users that performed at least one transaction during a week on average), amount of transferred data and the number of transactions over hours. The three metrics are normalized over the total number of distinct active users, the total amount of data and the total number of HTTP/HTTPS transactions of a week on average. This figure highlights that the only difference between weekdays and weekends are in the early hours of the morning (*i.e.,* 4am-9am) and evening (4pm-8pm) that are commuting hours.

Although not shown, we do not observe a clear weekly pattern as all metrics are almost constants across days. Specifically, we observe 35% of the users that have performed a transaction within a week are active on a given day, and transactions and data are evenly spread across days of the week. However, when we look at the wearable traffic in comparison with the overall traffic of the ISP, we observe that the relative usage of wearables is slightly higher on weekends and evenings. We conjecture this could be attributed to their demographics (possibly younger more tech-oriented subscribers, compared to the average population containing all ages and demographics).

Takeaway: *Activity levels of SIM-enabled wearable users do not change significantly between weekdays and weekends, besides the commuting hours when they are slightly more active. When compared to the remaining customers of the ISP, SIM-enabled wearable users are more active over weekends and evenings.*

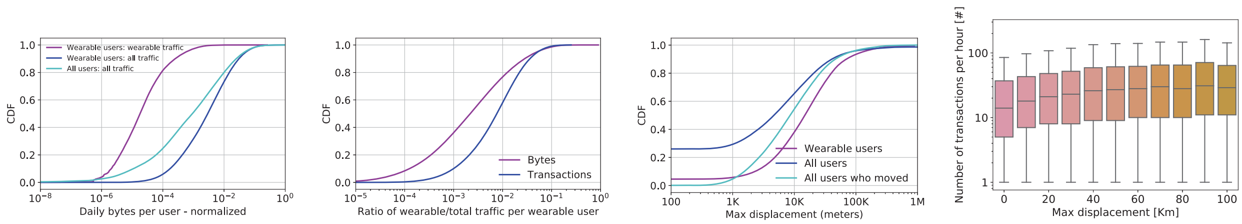
4.3 Microscopic user activity analysis

We now present a detailed user activity analysis. We start by looking at the active number of days per week and hours per day for wearable users (Fig. 3(b) blue and purple lines respectively). On average, users are active about 1 day a week and 3 hours per day. Only 7% of users are active for more than 10 hours a day, while 80% of them use wearables for less than 5 hours.



(a) Hourly usage. (b) Active days and hours. (c) Transactions analysis. (d) Transactions-active hours.

Figure 3: User activity analysis. Metrics in (a) are normalized over the average weekly total.



(a) Bytes transfered. (b) Ratio of wearable over total traffic. (c) Max Displacement. (d) Max displacement vs user hourly activity.

Figure 4: (a-b-c) Comparison among users that have wearable devices and all the data-active customers of the ISP normalised by value of the maximum user. (d) Mobility and data usage.

The distribution of the size of transactions is reported in Fig. 3(c) (cyan line). We observe it is sharply centered around 3 KB as wearable traffic is mostly composed by notifications and synchronization of collected statistics with remote servers (cf. Sec. 5). As shown in [5], smartphone users also have an average transaction size of 3 KB, but the distribution is not as skewed as wearables because smartphone traffic includes a larger variety of apps with different traffic characteristics. Fig. 3(c) also reports the average hourly amount of data and transactions per user.

Furthermore, we analyze in Fig. 3(d) the relation between the amount of data transactions performed by a user within an hour and the number of active hours per day. We observe there is a clear correlation between those metrics. This highlights the fact that the more a user is active during the day the more is the number of transactions the device generates per hour as well, and users do not have a bursty behavior, *i.e.,* they are not connected for short time transferring a large amount of data for each transaction. This is also confirmed by Fig. 3(c) showing that 80% of transactions carry less then 10 KB (3 KB on average).

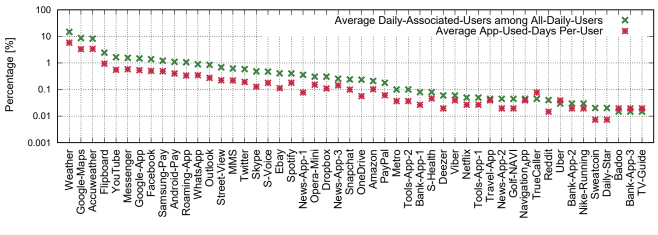
In Fig. 4, we compare the traffic of SIM-enabled wearable users to the remaining users of the ISP. To guarantee ISP confidentiality we have to normalize some of the plots with the traffic of the maximum usage. Firstly, we observe the users that use wearable devices generate on average 26% more data (Fig.4(a)) and 48% more transactions (not shown) than the remaining customers of the ISP. We conjecture this might be attributed to the fact that customers who have wearables are typically more technology-oriented people that are likely to contain multiple devices and gadgets. The general population (tens of millions of users) contains all age groups and demographics. Furthermore, if we compare the traffic of the wearables-themselves, we observe that it is on average three magnitudes smaller than their overall traffic (Fig.4(b)). Having said that, we do note that for 10% of the users, 3% of their traffic originates exclusively from the wearables.

Finally, note that users have 8 apps requiring Internet access on average on a wearable, while 90% of the users have less than 20 of such apps. Interestingly, there are some heavy users with more than 100 of those apps installed, and most users (*i.e.,* 93%) run only one of those apps per day. Overall, wearables have very few apps installed that require Internet connectivity and a very limited number of them run every day.

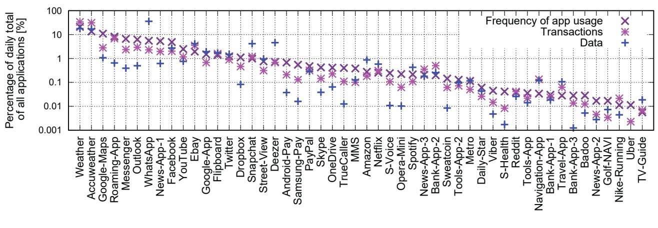
Takeaway: *On average SIM-enabled wearable users are active one day a week and three hours per day and the more a user is active the more she generates data/transactions. Also, users have very few apps installed on average requiring Internet connectivity (i.e., 8), and only a very limited number is used every day (i.e., 1-2 apps). Furthermore, we observed that the users who own a SIM-enabled wearable consume more data and generate more transactions. However, we conjecture this may mostly be attributed to their demographics rather than the wearable traffic that is three times of magnitude smaller than their overall traffic.*

4.4 User mobility

We now investigate SIM-enabled wearable users average daily mobility patterns and compare it to remaining users of the ISP. In Fig. 4(c), we plot the max displacement: the distance between the furthest two antennas that a user connects to during a day. On average, these SIM-enabled wearable users move 20 km a day, and 90% of them move less than 30 km. Further, we observe in Fig. 4(d) that users generating more transactions per hour are also the ones



(a) App used days and daily associated users over the week.



(b) Frequency of app usage, transactions and data per day.

Figure 5: Application popularity.

traveling a longer distance. However, despite being highly mobile, 60% of these users generate transactions from a single location.

In Fig. 4(c) we also compare max displacement of the users with SIM-enabled wearables to all the users of the ISP. At the first glance, we observe that these users exhibit almost double the max displacement distance (31 km vs. 16 km) when compared to all the customers in the country. We also compute the Shannon entropy of visited location (normalized by the time a user stays in a single location) and observe the SIM-enabled wearable users have 70% higher entropy values than smartphone and other wearable users. Finally, we evaluate the max displacement of users that are non-stationary (*i.e.,* max displacement greater than 0). The results indicate that SIM-enabled wearable users are still more mobile than the rest of the customers. We conjecture this can be also attributed to the demographics of these users (e.g., young and tech-savvy) compared to the whole subscribers base that might include a large portion of the country's population.

Takeaway: *On average, SIM-enabled wearable users move 20 km a day, and 90% of them move less than 30 km. Also, users traveling a longer distance are the ones generating more transactions and data per hour. These users are significantly more mobile than the remaining customers of the ISP. Again, we conjecture this may be attributed to customer demographics. However, 60% users perform actual data transfer from a single location only.*

5 APPLICATION BEHAVIOR

In this section, we analyze SIM-enabled wearable apps that leverage direct cellular connectivity. We focus on a 7 weeks period that we retain detailed statistics over which results are averaged.

5.1 Macroscopic application analysis

We analyze in Fig. 5(a) apps popularity in terms of the number of users using apps at least once a day, and the number of days where each app has generated at least one transaction across all users. Those metrics are normalized over the average daily total amount of all apps.

We observe *Weather*, *Google Maps* and *Accuweather* are the most popular apps in terms of the number of associated users, and app popularity decreases exponentially. Interestingly, we observe that two major wearable based payment systems *Android Pay* and *Samsung Pay* are at the top of the rank, indicating that users are adopting the easy *tap-and-go* payment methods as one of the major use cases for wearables. Note that we have anonymized some app names due to confidentiality reasons (E.g. News-App-1 and Bank-App-1). Also, it is observed that the average number of app used days per user follows the trend of associated users.

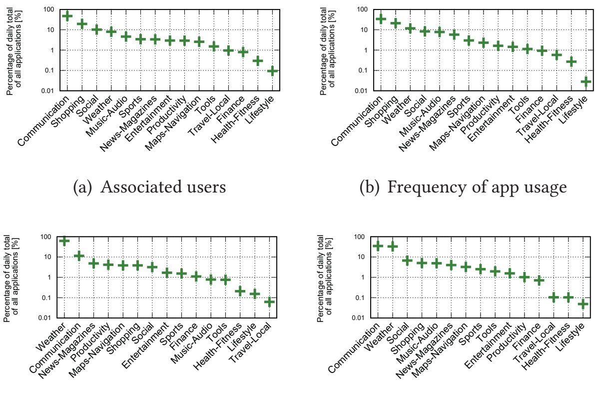
For some apps such as social networking, video streaming, and news streaming, the duration engaged with the app is also an indication of the popularity in addition to the frequency of use. Therefore in Fig. 5(b), we plot the average number of time an app is used per day, the number of internet transactions made by the app within a single usage (*i.e.,* until when the two consecutive transactions are made at least one minute apart), and the amount of transferred data per day. In general, for highly used apps such as *Weather* and *Accuweather*, high usage is associated with a higher number of transactions as well as high data usage. On the one hand, notification based apps such as *Messenger* and *Microsoft-outlook* use less data despite having a higher number of transactions. On the other hand, communication and data streaming apps such as *WhatsApp*, *Snapchat* and *Deezer* show high data usage compared to the number of connections.

Next, we consider the popularity of app categories according to the Google Play Store app categorization. In Fig. 6, we show the category-wise daily averages of the number of users, frequency of use, number of transactions and volume of transferred data. According to Fig. 6(a), the majority of the users are associated with *Communication* and *Shopping* apps followed by *Social* and *Weather* apps. Surprisingly, the *Health & Fitness* category does not seem to be popular among the users when connected to the cellular network. However, this could be due to the app configurations where some apps are designed/configured to synchronize data with the Internet servers only when the WiFi access is available. We observe a very similar trend and rank in Fig. 6(b), Fig. 6(c) and Fig. 6(d), where we report the frequency of app usage, the rank of apps per number of transactions, and the rank of apps per data exchanged.

Takeaway: *The most popular app categories using cellular connectivity include Communication, Shopping, Social, and Weather. Notification based apps dominate the number of transactions, while multimedia and communication apps generate the majority of data.*

5.2 Microscopic application characteristics

To further investigate the data usage behaviours of apps, we show the number of transactions and data per single usage in Fig. 7. We observe that the apps in the categories of *Communication*, *Social*, and *Music & Audio* have the maximum data consumption during one usage even when the number of transactions are lower. This behavior is observed due to the longer duration of usage and the



(a) Associated users (b) Frequency of app usage

(c) Transactions (d) Data

Figure 6: Daily popularity of different categories of apps over a week.

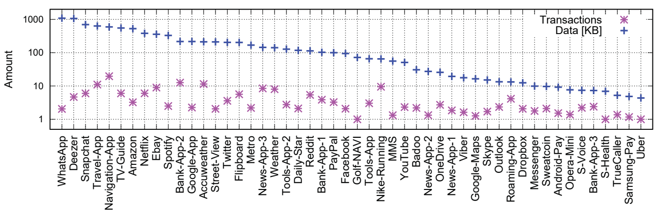


Figure 7: Data and transactions during a single time of app usage.

larger file transfers, which corroborates the observation in Section 5.1. The long tail of apps that have a low data usage majorly consists of messenger apps, payments apps, and other notification based apps.

We next study the types of transactions made by wearable apps. As highlighted in previous work [3], similar to smartphone apps, wearable apps also connect to different types of domains in addition to the first party domains. We categorize these transactions into three categories, similar to the categorization done by Seneviratne et al. [17] for smartphone apps. The three categories are; **i) Utilities** - *Generic domains such as CDNs*, **ii) Analytics** - *Domains belonging various analytics services such as audience characteristics, user engagement, and revenue performance*, and **iii) Advertising** - *Domains belonging to advertisement networks*. The fourth category **Applications** represents the first party domain names (i.e. the servers belonging to the app developer or the services provided by the apps).

In Fig. 8 we show the number of unique users, frequency of usage, and the amount of data usage for each transaction category for all the apps as a percentage of the daily total. It is interesting to observe that data transfers with third party domain categories are in the same order of magnitude as the data transfers with the first party app servers. Such a large relative volume of analytics and advertising traffic has been observed in smartphone apps and many work showed that such traffic consumes significant portion from user's mobile data plan [6, 20] and can cause the smartphone battery to drain quickly [14, 19]. When it comes to wearables, the consequences can be even more acute due to the limited battery

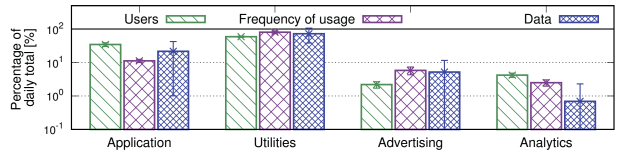


Figure 8: Applications and the services.

power and potentially less data allowance in the mobile plan for wearables.

Takeaway: *Majority of the frequently used apps do not consume significant amount of data due to their nature of communications such as notifications, messages, and micro-interactions in the likes of payments. Nonetheless, there exists a limited number of communication and multimedia wearable apps that consume significant amount of bandwidth. Finally, our analysis of domains of the transactions shows that volume of data exchanged with third party analytics and advertising services are in the same order of magnitude as the volume of data exchanged with first party servers.*

6 CONCLUSION

In summary, we provided insights on the behaviors of *SIM-enabled wearable* users, characterized their app usage, and compared those characteristics with the rest of the customers in the network (mostly equipped with a smartphone). Our analysis showed that SIM-enabled wearable users are highly active, more mobile, consume more data, and generate more transactions compared to ordinary users. We provided a detailed characterization of SIM-enabled wearable app usage and showed that *Communication*, *Shopping*, and *Weather* are the most frequently used app categories while consuming the largest amount of data. We also showed that similar to smartphones apps, SIM-enabled wearable apps also frequently communicate with third-party advertisers and analytics networks.

Finally, we showed that SIM-enabled wearable usage is constantly growing at a rate of 1.5% per month for a total of 9% over five months. On the one hand, this rate of growth is significant and we expect an even sharper increase once the Apple watch is supported by this ISP. On the other hand, most of the wearables available in the market current relay their traffic through smartphones. We expect those *Through-Device* devices will likely support direct cellular connectivity in the future. A detailed analysis of traffic and users of those devices is left as future work, but to get a sense of their potential impact on the presented results we preliminary identified a set of hundreds of thousands users covering ∼16% of total Through-Device users (this fraction is estimated from market reports). Specifically, we first fingerprint wearable traffic for *Fitbit* and *Xiaomi* devices that can be directly attributed to wearables. We also fingerprint more general *Android* and *Apple* wearables through the traffic of three popular applications *AccuWeather, Strava, Runtastic* for which we were able to extract signatures that can safely indicate that the user has an active wearable device. While this preliminary dataset covers ∼16% of total Through-Device users only, we observe they have similar macroscopic behavior and mobility patterns to SIM-enabled users. Also, we observe that Through-Device users typically have relatively modern smartphones when compared to the overall population.

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