JTrack: A Digital Biomarker Platform for Remote Monitoring of Daily-life Behaviour in Health and Disease

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Abstract

Health-related data being collected by smartphones offer a promising complementary approach to in-clinic assessments. Despite recent contributions, the trade-off between privacy, optimization, stability and research-grade data quality is not well met by existing platforms. Here we introduce the JTrack platform as a secure, reliable and extendable open-source solution for remote monitoring in daily-life and digital-phenotyping. JTrack is an open-source (released under open-source Apache 2.0 licenses) platform for remote assessment of digital biomarkers (DB) in neurological, psychiatric and other indications. JTrack is developed and maintained to comply with security, privacy and the General Data Protection Regulation (GDPR) requirements. A wide range of anonymized measurements from motion-sensors, social and physical activities and geolocation information can be collected in either active or passive modes by using JTrack Android-based smartphone application. JTrack also provides an online study management dashboard to monitor data collection across studies. To facilitate scaling, reproducibility, data management and sharing we integrated DataLad as a data management infrastructure. Smartphone-based Digital Biomarker data may provide valuable insight into daily-life behaviour in health and disease. As illustrated using sample data, JTrack provides as an easy and reliable open-source solution for collection of such information.

1 Introduction

Neurological and psychiatric diseases typically present with symptoms that are complex, atypical, fluctuant in disease progression, and display high variability between patients (Lyketsos et al., 2007). Current diagnostic and efficacy evaluation methods often rely on in-clinic visits and subjective evaluation by patients, caregivers or clinicians. In-clinic evaluation methods are often costly, time-consuming and limited in their quality and quantity of observations (Zhan et al., 2016). In addition, they are often prone to high inter- and intra-rater variability (Rovini et al., 2017). The aforementioned drawbacks of traditional diagnosis methods may affect the diagnostic process especially in the early stage of the disease where there is a lag between the onset of the pathological process and the onset of symptoms (Balogh et al., 2015).

Psychiatric and neurological diseases are typically long-term illnesses that cause significant fluctuations in symptoms over time. Therefore, recall and reporting biases are the key difficulties in evaluating respective diseases in episodic in-clinic visits. Remote monitoring of patients in their everyday-life using sensor-based at smart technologies is rapidly evolving and may assist clinicians in facilitating early diagnosis and evaluating and adjusting interventions. There has been an evolving interest in using newly emerged smart sensor technologies for monitoring of patients (Rahlf et al., 2019; Orlowski et al., 2017; Hasegawa et al., 2019; Skodda et al., 2013; Cancela et al., 2014; Serra-Añó et al., 2019).

Modern smartphones and wearables are equipped with various sensors including motion (i.e. acceleration, gyroscope), location (i.e. Global Positioning System (GPS)), environment (i.e. barometer, temperature, light) and health sensors (i.e. heart rate) (Bandodkar and Wang, 2014; Khan et al., 2016). This rich combination of sensors along with their ability to collect ecological momentary assessments (EMA), and information about social interaction (i.e. social media, messaging and phone calls) have made smartphones a potential alternative to in-clinic evaluation for various types of assessments (Kraft et al., 2020; Harari et al., 2016). Such health-related information being collected in clinical trials are often referred to as digital-biomarkers (DB) (Insel, 2017). DBs can provide objective, ecologically valid, and invaluable information for better understanding of specific diseases. In addition, DBs enable frequent assessments from larger target populations over longer periods of time and may thus provide detailed insight into inter- and intra-individual disease variability in daily-life (Swan, 2012).

Several contributions enabling the use of smartphones as an assessment tool have been recently introduced. The first set are commercial devices such as Fitbit[1], Garmin[2], Apple[3] and Samsung[4] devices. The main focus of these applications is to provide feedback on the daily activity of users by visualizing and showing notification regarding their heart rate, number of steps and kind of activity. However, most of these devices provide limited access to the raw data and do not support high-frequency data collection. A second type are applications and platforms developed by researchers such as AWARE (Ferreira et al., 2015), RADAR-base (Ranjan et al., 2018), Beiwe (Torous et al., 2016), mCerebrum (Hossain et al., 2017), mPower(Bot et al., 2016) and many others. The main focus of these mostly open-source platforms is to enable data collection for research applications as well as to facilitate data sharing and reproducibility. Yet, these software packages are often limited by an often

[1] https://www.fitbit.com/global/us/home [Accessed November 23, 2020].

[2] https://www.garmin.com/en-US/ [Accessed November 23, 2020].

[3] https://www.apple.com/ [Accessed November 23, 2020].

[4] https://www.samsung.com/us/ [Accessed November 23, 2020].

narrow focus to some specific clinical indications or with respect to privacy aspects. Also, these once in a while updated platforms make some of them unstable for the rapidly growing smartphone ecosystem.

Whilst there are several platforms that are able to collect context-driven data, the trade-off between privacy, optimization, stability and research-grade data quality is not well met yet. Thus, we aim to fill this gap by introducing the JTrack platform. JTrack was developed as an Android-based application for smartphones and an online server-side dashboard. JTrack application comprises the following main categories of components: sensor data, location data, Human Activity Recognition (HAR), and smartphone and application usage monitoring. Each component has the option to be used for active (with user interaction) and passive (without user interaction) monitoring. The dashboard side is an online platform to create and manage studies, integrating DataLad (Halchenko et al., 2019) infrastructures to facilitate management and sharing of collected data. JTrack is a modular open-source with a high level of optimization, security and privacy making JTrack a practical solution for clinicians and researchers to collect, manage, and share digital biomarker data.

2 Methods

[Figure 1]

[Figure 2]

[Figure 3]

2.1 General description

Here we introduce the main components of the JTrack platform (Figure 1) comprised of the JTrack app (Figure 2) and an online dashboard interface (Figure 3). The smartphone application JTrack was developed for smartphones with the Android operation system (OS). The reason for selecting Android was a wider range of users[5] (73%) and fewer restrictions which were necessary for technical aspects of application development.

JTrack enables passive 7/24 data collection running in the background. Active data collection is enabled through simple interaction (i.e. start and stop recording, i.e. before and after execution of a specific task). All collected data are recorded locally in the application and then synchronized on a periodic basis (i.e. connection to the Internet, have enough battery charge). All local data are deleted from the phone storage upon successful data transfer. To minimize the risk of data loss, we implemented auto-start functionality (without user interaction) to resist unwanted application crashes or operating system reboots, and all the crashes are reported via the Firebase dashboard[6].

On the server side, the JTrack dashboard was developed as an online web-application where study owners can create and manage studies. The dashboard consists of a front-end interface and a back-end API which is integrated with DataLad (Halchenko et al., 2019) as a data-management tool. The dashboard provides an overview of received data including sanity checks such as MD5 for received data, and embedded validity checking methods.

[5] https://gs.statcounter.com/os-market-share/mobile/worldwide [Accessed August 19, 2020].

[6] https://firebase.google.com [Accessed November 23, 2020].

2.2 QR-Code authentication

To provide a convenient and secure way of activation we implemented a QR-code method. The QR-code for each subject is generated as a pdf file from the dashboard. Each QR-code contains all the necessary information such as user ID, Study ID, and address of the target server or an optional authentication method (e.g. OAuth2). To join a study, the one-time QR-code needs to be scanned using the QR-scanner embedded in the JTrack app. Additional backup QR-codes are provided for scenarios in which users may want to leave and re-join or need to switch their device.

2.3 Location service

Location service provides an update on visited location data such as longitude, latitude, and altitude. This service operates as a part of the passive recording. The location data can be inquired based on pre-defined periods (i.e. 10 minutes). To ensure anonymization, for each user, a random value is generated during activation on the phone, which shifts the latitude to a random place on the globe. In addition, all recorded coordinates are rotated using a randomly generated fixed degree around this initial coordinate to ensure that even if the true installation location is known no other coordinates can be derived. These values remain on the phone throughout the study and are deleted upon deinstallation of the app. To keep a high accuracy, each data point is first transferred from WGS-84 to Cartesian coordinates. After the transformation using the generated value, the coordinates are transferred back to their native space. Since this transformation occurs before actual recording, all the collected data is relative and cannot be used to recover the user's actual location. Furthermore, we used a fused method that provides more accurate data (median accuracy of 14 meters) by combining GPS and network information.

2.4 Human Activation Recognition (HAR)

Inertial Measurement Unit (IMU) sensors of smartphones or wearables can be used to differentiate between human activities. Several studies described reliable algorithms for HAR (Littman, 2005; Wan et al., 2020). Nowadays, these algorithms are routinely deployed in commercial devices, as well as in a wide range of research areas from medicine to military. JTrack uses the Google Play Activity Recognition Service[7] for HAR, which recognizes up to six types of activity (walking, running, still, on bicycle, on vehicle or tilting). JTrack can record the detected activity and the assigned certainty with a pre-specified frequency of five minutes. The HAR module is computationally lightweight, optimized and does not require direct access to raw sensor data.

2.5 Application usage statistic

JTrack can collect the statistic of user's interactions with the smartphone. This data includes the name of the application and the amount of time it is used in the foreground since the previous midnight. Phone calls and SMS are treated as applications with same usage statistics being collected as above. No content of the applications, messages or phone calls (including phone numbers) is collected at any stage.

2.6 Sensors

Various sensors are embedded in any modern smartphones which are classified as hardware implementation (i.e. accelerometer, gyroscope, barometer) or software implementation (i.e. rotation

[7] https://developers.google.com/location-context/activity-recognition [Accessed June 23, 2020]

sensor). JTrack enables collection of data from most of the available sensors depending on the device model and version of Android. Among these, accelerometer, gyroscope and gravity sensors are the most important sensors for researchers focusing on motion analysis (Cho et al., 2018; Mundt et al., 2020; Schlachetzki et al., 2017; Orlowski et al., 2017; Moore et al., 2013; Rodríguez-Martín et al., 2020). As a default, JTrack provides recording of accelerometer and gyroscope data in the passive collection mode. Other sensors can be added upon the researcher's choice by using the provided template module which requires minimal coding effort. For each sensor, sampling frequency in Hz can be adjusted using the dashboard when creating a new study.

2.7 Dashboard

When creating a new study in the dashboard, all aspects of a study such as study name, duration, number of subjects, recording frequency, and categories of data to be collected can be customized. After creating a study, the dashboard will generate QR-codes which are used for enrolment into the study. The dashboard also provides management tools on an ongoing study producing information such as a number and time of received data for each sensor/modality and status (i.e. active, not active) of each participant in a particular study. We also implemented several quality controls including highlighting of missing data.

Furthermore, to assist study managers to establish further interaction with participants, we embedded a messaging method in the dashboard which allows to send a push notification directly to the participants' phone, either by selecting specific subject numbers or all participants within a particular study. Layered design (backend, frontend and data management layer) also makes the Dashboard flexible and extendable for further interaction and integration with third-party applications.

2.8 Performance, Security and Privacy

At all stages of the development, attention was paid to security and privacy as a main priority. In this context, we designed the JTrack platform to comply with GDPR and Google Developer Policies[8]. No sensitive data such as name, phone number, phone contacts or actual location are recorded at any stage. All the collected data transferred via Hypertext Transfer Protocol Secure (HTTPS) protocol and checked for any inconsistency using MD5 sanity checksum.

Concerning patient privacy, all users using JTrack are provided with clear information on what is been recorded and why. Permission requests for each module need to be approved during installation and activation. All participants may also stop and leave a study at any time directly from the app. Also, remote configuration and one-step recording allow clinicians to gain optimum control over the collected data without the need to collect any identifying information.

To reduce battery and memory usage, we provided several built-in optimizations such as:

- Detecting still period of the phone to pause recordings
- Delete locally stored data right after synchronization with the server
- Scheduled synchronization based on predefined criteria such as access to a Wi-Fi connection
- Detect and provide a possibility to bypass performance optimizations (i.e. battery and memory) policies of phone manufacturers introduced on-top of the Android OS.

[8]https://developer.android.com/distribute/play-policies [Accessed December 2, 2020].

To reduce data loss due to crashes or reboots, automatic re-starting is implemented alongside with Firebase integration to obtain performance and crash reports. Information about phone manufacturer, model, and OS version are among the optional recorded data (not active by default), which can be used to analyse and handle cross-sensor variability.

2.8 Pilot study

In a pilot experiment, we collected in a cohort of healthy volunteers (N=21, age: 26.1±6.9, 7 female) for 2 weeks on a daily basis passively recorded data for application usage, location and activity recognition aside with self-reported estimates for these parameters (for application usage: time spent (in minutes) with the phone: total, social media and messenger); for location and activity: walking/running distance in meters). To test for associations between passively recorded and self-reported measures, we computed Pearson correlations across all subjects and time-points to compare both types of measures (i.e. merging location and activity recognition co compute distance covered by foot).

3 Results

[Figure 4]

[Figure 5]

To illustrate the utility of the JTrack application sample data were collected in the beta testing phase. Figures 4 and 5 display such sample data collected for a single subject for different modalities. We provided sample data for each modality (i.e. location data, activity recognition, application usage and raw sensors data) also we further show a possible combination of the recorded data (i.e. location data with activity recognition data) in Figure 4c. Other combinations such as time and location (e.g. extracting amount of time spend outside of common residual place), location and application usage (e.g. extracting pattern of social interaction and applications used in-home condition) and activity and raw sensor data (e.g. extracting driving behaviour) are among the possible ways of making inference. Figure 5b also shows the daily phone and application usage (i.e. social media, phone calls, and online messaging platform) for a pilot participant.

In a pilot experiment, we further tested for associations between these passively recorded measures and self-reported estimates of specific behaviours. The self-reported distance covered by walking/running per day significantly correlated ($r=.53$; $p<001$) with the information derived from passive monitoring (Figure 6a). Similarly, the time spent with the phone in total, communication and social platform significantly correlated with the passively-recorded estimates of respective phone usage measures ($r=.38$-$.49$; all $p<.001$) (Figure 6b).

[Table 1]

3.1 Comparison to other platforms

Table 1 shows how the JTrack platform compares to other similar and related platforms in terms of some key features such as security and privacy, activation, management and also stability. AWARE (Ferreira et al., 2015) is a platform for remote assessment of a wide range of phone sensors, activity and self-reported data. AWARE also supports additional plugins for external sensors and new data.

However, this ability also requires a further declaration of permissions which limits control over privacy. mCerebrum (Hossain et al., 2017) is another platform for remote assessment supporting a wide range of high-frequency sensors with a focus on energy-optimization. However, this platform has not been updated in while (latest update is May 2018 in their GitHub repository), questioning its performance on new versions of Android-OS. Beiwe (Torous et al., 2016) is the next platform supporting remote monitoring and DBs assessments which has a flexible study portal, modelling and data analysis tools. Nevertheless, this platform does not have local data storage and makes use of Amazon Web Services (AWS) cloud computing infrastructure. Such public cloud-based solutions are often more cost effective and convenient to use since as they simplify the build and maintenance process (this is particularly evident when the number of users and the data collected are small to medium sized), yet they may also raise data privacy questions and require additional deployment procedures. Another drawback of this platform is the collection of identifiable data such as phone number, media access control (MAC) address of WIFI and Bluetooth devices. RADAR-base (Ranjan et al., 2018) is the last open-source platform in the list. It has a well-organized structure which is using Confluent and Apache Kafka services and flexible study portal. Nevertheless, the deployment and adaptation of this platform require heavy configuration. Concerning the convenient registration, it requires text-based registration. Location data being collected in background is considered as a big concern in terms of privacy which is also frequently regulated by Google Developer Policies[9] and restricted by recent updates in Android OS. Among all the compared platforms only RADAR-base provides relative location. There are several alternative variants of these platforms that may strengthen some of the basic capabilities, such as Health Outcomes through Positive Engagement and Self-Empowerment (HOPES) which is based on the Beiwe platform (Wang et al., 2021) and AWARE-Light which is based on the aware framework. While these additional enhancements may address some of the shortcomings of the specific underlying platform, here we only focused on the comparisons to the core versions.

Easy one-step registration and authentication via QR-Code, as well as remote configuration, make JTrack more practical in both the usage and management aspects. Battery and memory optimizations offered by Android OS or phone manufacturers can affect the stability and consistency of data collected, JTrack provides built-in detection and circumvention methods for better stability that are not provided by comparator platforms at this level.

4 Discussion

We developed JTrack as an open-source, smartphone-based platform for digital phenotyping. JTrack consists of a smartphone application and an online dashboard enabling remote data collection and study management. JTrack provides a flexible and modular environment for collection of various types of sensor and smartphone usage data with particular attention being paid to patient privacy as well as compliance with GDPR regulations.

From the functionality perspective, most of the solutions described above were developed with the focus on specific applications, i.e. a specific disease (i.e. RADAR-base(Ranjan et al., 2018) and Beiwe (Torous et al., 2016)). Their application is therefore limited to the respective primary context. In contrast, some other platforms were developed to collect as much information as possible with little attention to data privacy (i.e. AWARE (Ferreira et al., 2015)). Such frameworks violate GDPR and Google Play Store policies limiting their deployment for many clinical applications. JTrack aims to fill this gap by providing a customizable platform that can be deployed across different indications whilst

[9] https://developer.android.com/distribute/play-policies [Accessed December 2, 2020].

paying large attention to privacy and security policies. JTrack aims to comply with GDPR regulations as well as with the Google Play Store policies. It only requires minimal access to the device information and avoids collection of identifiable or sensitive data.

Developing an application for smartphones always requires dealing with variation in devices (e.g. manufacture, screen size, available sensors) as well as the variation of operation systems (OS) versions. Different manufacturers may add further OS optimizations such as limiting background processes. This may cause inconsistencies in performance of monitoring applications. We introduced several layers to detect, report and prevent the side effects of these variations. JTrack is actively maintained and covers up to 84.9 % of Android smartphones (Minimum Software Development Kit (SDK) 23) dealing currently with Android optimizations from eight main Android smartphone manufactures. Although the JTrack platform is now only available for the Android environment, which may introduce selection bias and limit participants to having an Android smartphone, an iOS version of JTrack is currently in development, with similar capabilities and will be made publicly available in the same GitHub repository and under the same open-source license.

Potential applications for JTrack include but are not limited to monitoring of motion information in diseases associated with alterations of gait and other motor functions affecting phone use. Similarly, the ability to track phone usage allows for monitoring of different types of behaviour, i.e. phone-based social interaction. As such, JTrack may be useful to track such behaviours in healthy participants as well its alterations by specific disorders.

Finally, to facilitate the reusability, JTrack is released under open-source Apache 2.0 licenses. All modules including online-management dashboard can be adopted and extended. It has been designed with modular structure to enable flexibility and customization to support new data and sensors.

Variations in device model, Android version, network quality, and other technical features may have negative effects on the performance of JTrack. Despite the effort to minimize crashes and data loss, there is no guarantee for such. During the development process, we used different third-party services (e.g. Google Play Service), any change or deprecation in these services, or Android policies may also affect the functionalities of JTrack partly or as a whole. Lastly, JTrack was designed and tested for smartphones. It may be used on other devices such as wearables (i.e. smartwatches) or tablets but further tests should be considered beforehand.

JTrack is an active and open-source project which is continuously maintained. We consistently improve and add new features to the platform. The features described here are part of the v1 release. Newer versions may differ and include additional functionalities at the time this article is published.

5 Data availability

For the most updated and previous versions please visit the public repository accessible at https://github.com/Biomarker-Development-at-INM7 .

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7 Author Contributions

MSF wrote the android-based application and performed all analysis. MSF wrote the manuscript with support of JD. MS and JF wrote the dashboard online application. JD designed the overall study. SBE contributed to the overall design of the study. All authors reviewed and commented on the manuscript.

8 Conflict of Interest

JD is a former employee and received consultancy fees on another topic from F. Hoffmann-La Roche AG. All authors report no conflicts of interest with respect to the work presented in this study.

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Table 1. Comparison of existing frameworks with JTrack.

Framework	Location Anonymization	Official app Stores	Data Management	Remote Configuration	Activation	Customized OS Detection

AWARE (Ferreira et al., 2015)	NO	NO	SQL	YES	Text-based	NO
RADAR-base (Ranjan et al., 2018)	YES	YES	MongoDB	YES	QR-Code	NO
Beiwe (Torous et al., 2016)	NO	YES	PostgreSQL	NO	Text-based	NO
mCerebrum (Hossain et al., 2017)	NO	NO	MySQL	NO	Text-based	NO
JTrack (this study)	YES	YES	DataLad	YES	QR-Code	YES

Figure 1. JTrack Platform overview.

Figure 2. JTrack Application Environment. a) opening page of the application, b) requesting for camera permission, c) QR-Code scanner, d) requesting for location permission, e) requesting for an activity detection permission, f) referring to ask for usage permission which is used for application usage module, g) detecting a custom optimization and asking for disabling it, h) the main menu of the application, where users may access the administration menu, leave a study, get information about the application and do manual synchronization, i) administration menu, here we have access to the main setting of application, the information provided here is for further administration from study owners and most of the information is catch from sever during Installation.

Figure 3. JTrack Dashboard Environment. a) main menu, b) here a new study can be created by specifying its details such as duration of the study, number of users, and list of data categories to be collected, c) currently ongoing studies and details of the selected study can be found here. Also, the generated QR-Code can be downloaded here, d) to accomplish more interaction with users participated in a particular study, a message as a push notification can be sent to a target user(s), e) details of received data, date of registration, date left, duration within in study and quality control by colour-labelling for sent data for users in a selected study can be monitored here.

Figure 4. Data sample for activity and location modules. a) travelled distance and relative geolocation information for different days, b) distribution of different physical activates during a different time of different days, c) type of activity data combined with geolocation information.

Figure 5. Data sample for application usage module and sensors. a) amount of time spent in different application types for a day, b) distribution of different type of application usage during a study. c) raw data recorded from the acceleration sensor, d) raw data recorded from the Gyroscope sensor.

Figure 6. Results of the pilot study comparing self-reported and passively recorded measures of daily behaviour. a) Correlation plot between self-reported distance walking/running and distance estimates derived from fusion of location and activity recognition data. b) Correlation matrix comparing self-reported measures of different smartphone usages and estimates derived from passively recorded app usage information.

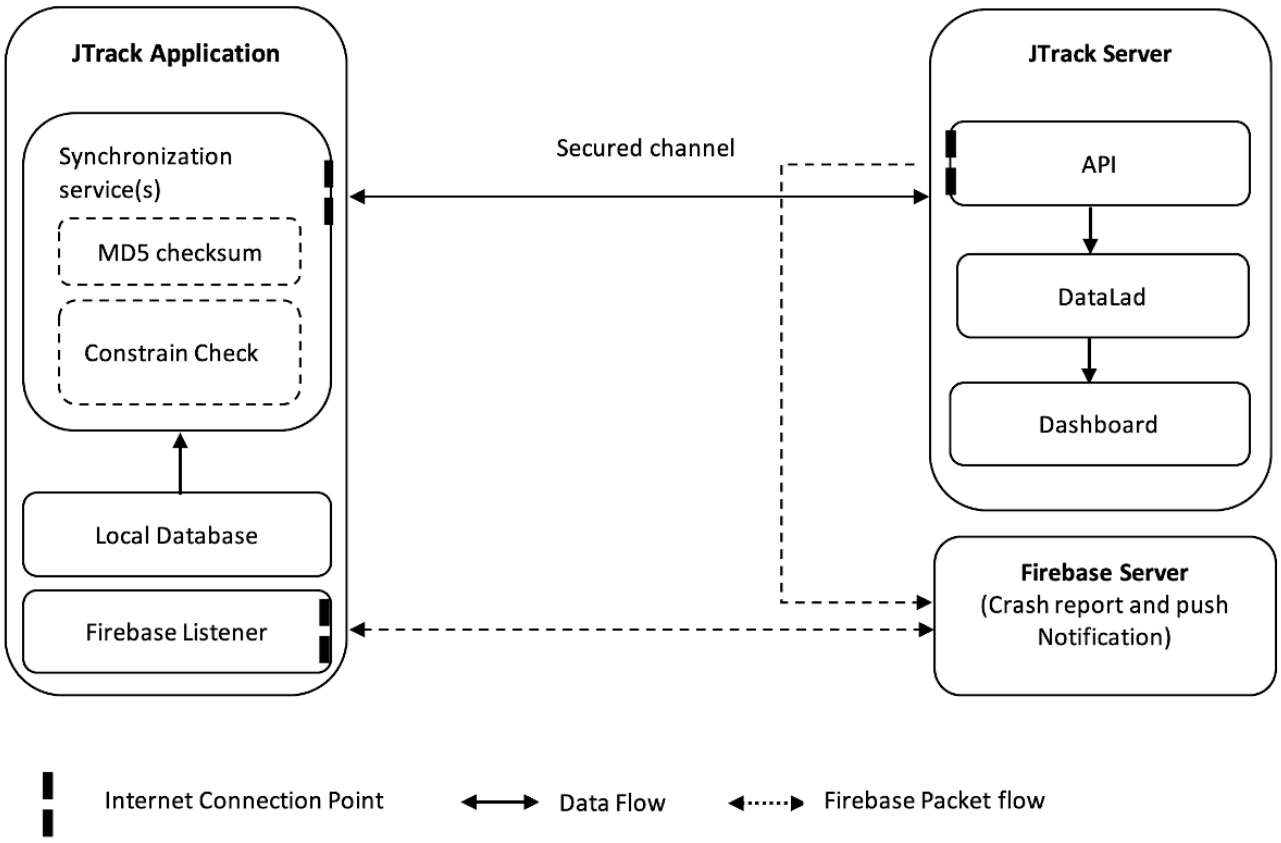


Figure 1

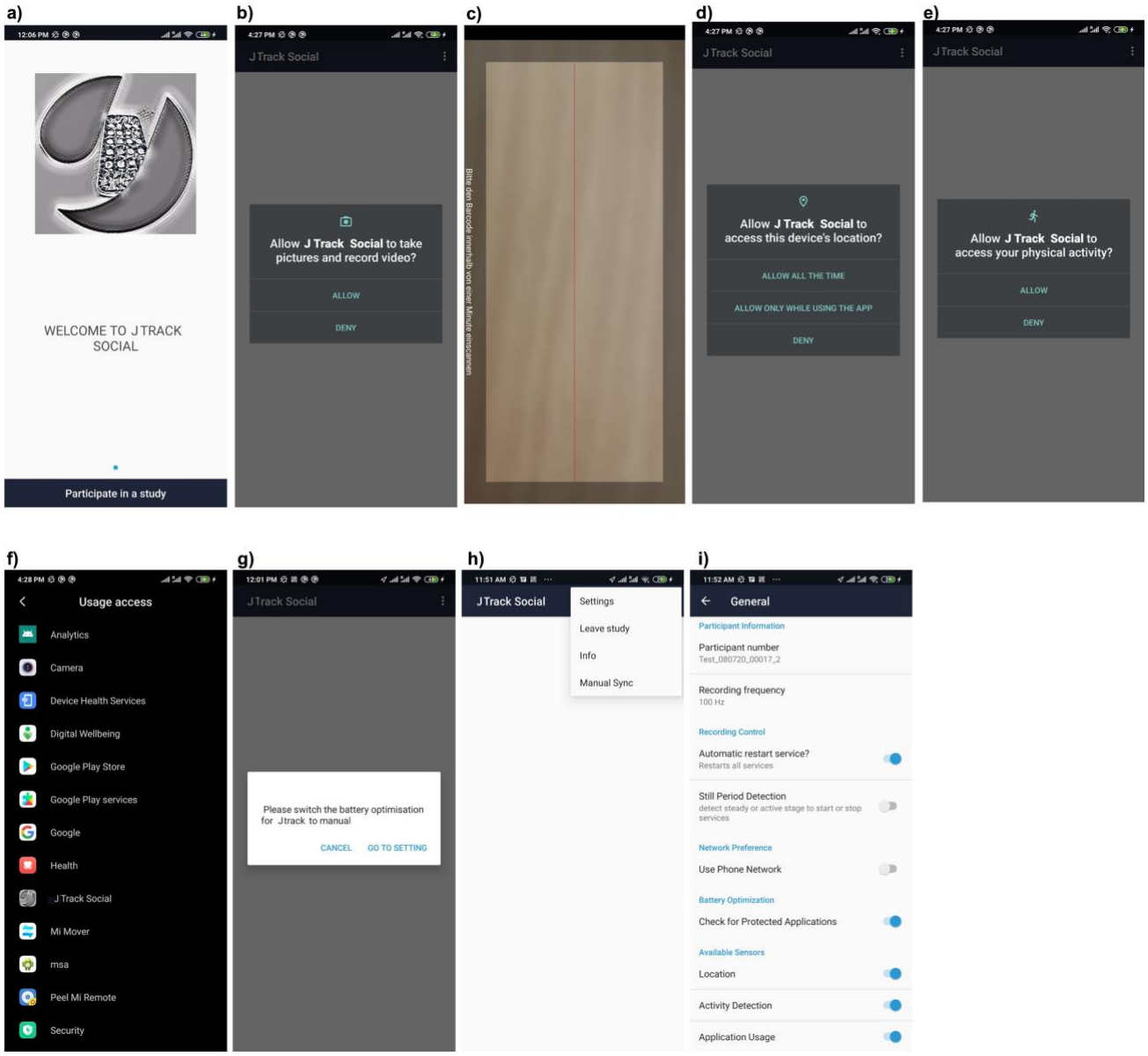
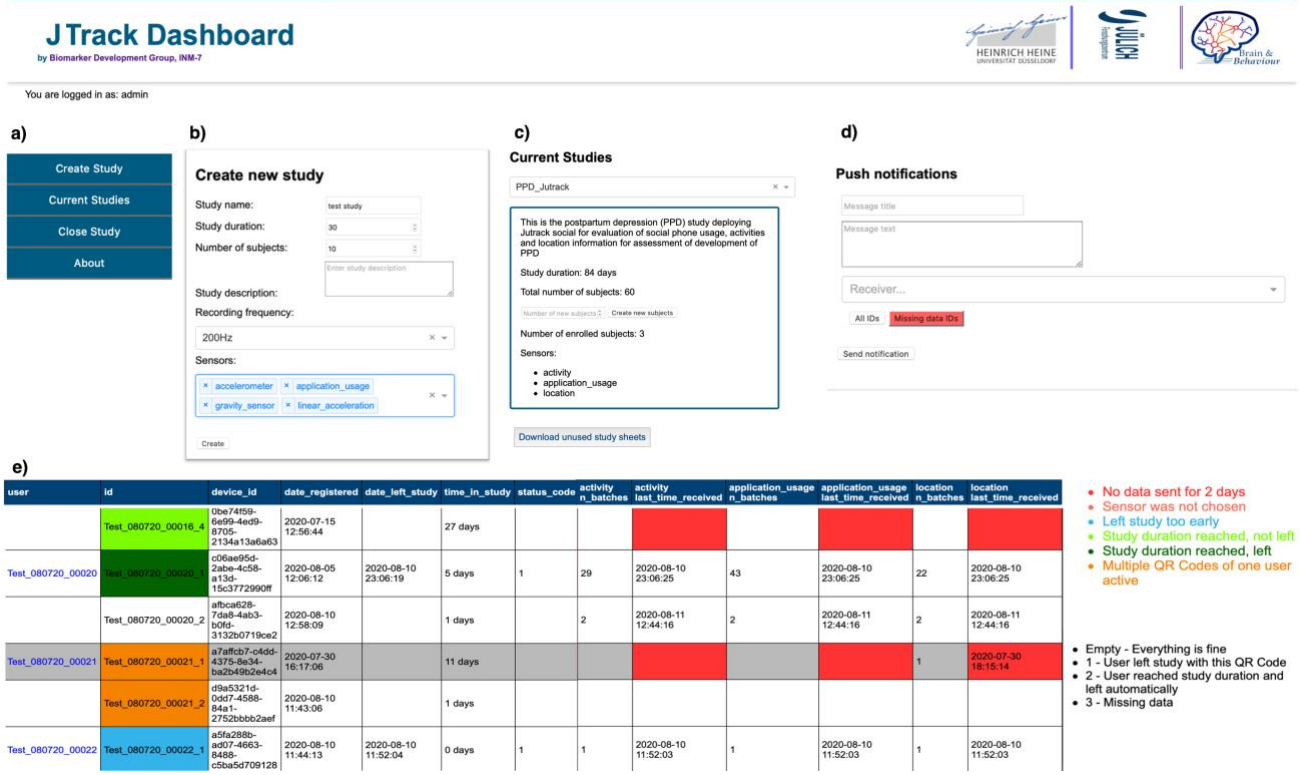

a)
WELCOME TO J TRACK SOCIAL
Participate in a study
b)
J Track Social
Allow J Track Social to take pictures and record video?
ALLOW
DENY
c)
Bitte den Barcode innerhalb von einer Minute einscannen
d)
J Track Social
Allow J Track Social to access this device's location?
ALLOW ALL THE TIME
ALLOW ONLY WHILE USING THE APP
DENY
e)
J Track Social
Allow J Track Social to access your physical activity?
ALLOW
DENY
f)
Usage access
Analytics
Camera
Device Health Services
Digital Wellbeing
Google Play Store
Google Play services
Google
Health
J Track Social
Mi Mover
msa
Peel Mi Remote
Security
g)
J Track Social
Please switch the battery optimisation for Jtrack to manual
CANCEL
GO TO SETTING
h)
J Track Social
Settings
Leave study
Info
Manual Sync
i)
General
Participant Information
Participant number
Test_080720_00017_2
Recording frequency
100 Hz
Recording Control
Automatic restart service?
Restarts all services
Still Period Detection
detect steady or active stage to start or stop services
Network Preference
Use Phone Network
Battery Optimization
Check for Protected Applications
Available Sensors
Location
Activity Detection
Application Usage

Figure 2



user	id	device_id	date_registered	date_left_study	time_in_study	status_code	activity n_batches	activity last_time_received	application_usage n_batches	application_usage last_time_received	location n_batches	location last_time_received
	Test_080720_00016_4	0be74f59-6e99-4ed9-8705-2134a13a6a63	2020-07-15 12:56:44		27 days							
Test_080720_00020	Test_080720_00020_1	c06ae95d-2abe-4c58-a13d-15c3772990ff	2020-08-05 12:06:12	2020-08-10 23:06:19	5 days	1	29	2020-08-10 23:06:25	43	2020-08-10 23:06:25	22	2020-08-10 23:06:25
	Test_080720_00020_2	afbca628-7da8-4ab3-b0fd-3132b0719ce2	2020-08-10 12:58:09		1 days		2	2020-08-11 12:44:16	2	2020-08-11 12:44:16	2	2020-08-11 12:44:16
Test_080720_00021	Test_080720_00021_1	a7affcb7-c4dd-4375-8e34-ba2b49b2e4c4	2020-07-30 16:17:06		11 days						1	2020-07-30 18:15:14
	Test_080720_00021_2	d9a5321d-0dd7-4588-84a1-2752bbbb2aef	2020-08-10 11:43:06		1 days							
Test_080720_00022	Test_080720_00022_1	a5fa288b-ad07-4663-8488-c5ba5d709128	2020-08-10 11:44:13	2020-08-10 11:52:04	0 days	1	1	2020-08-10 11:52:03	1	2020-08-10 11:52:03	1	2020-08-10 11:52:03

Figure 3

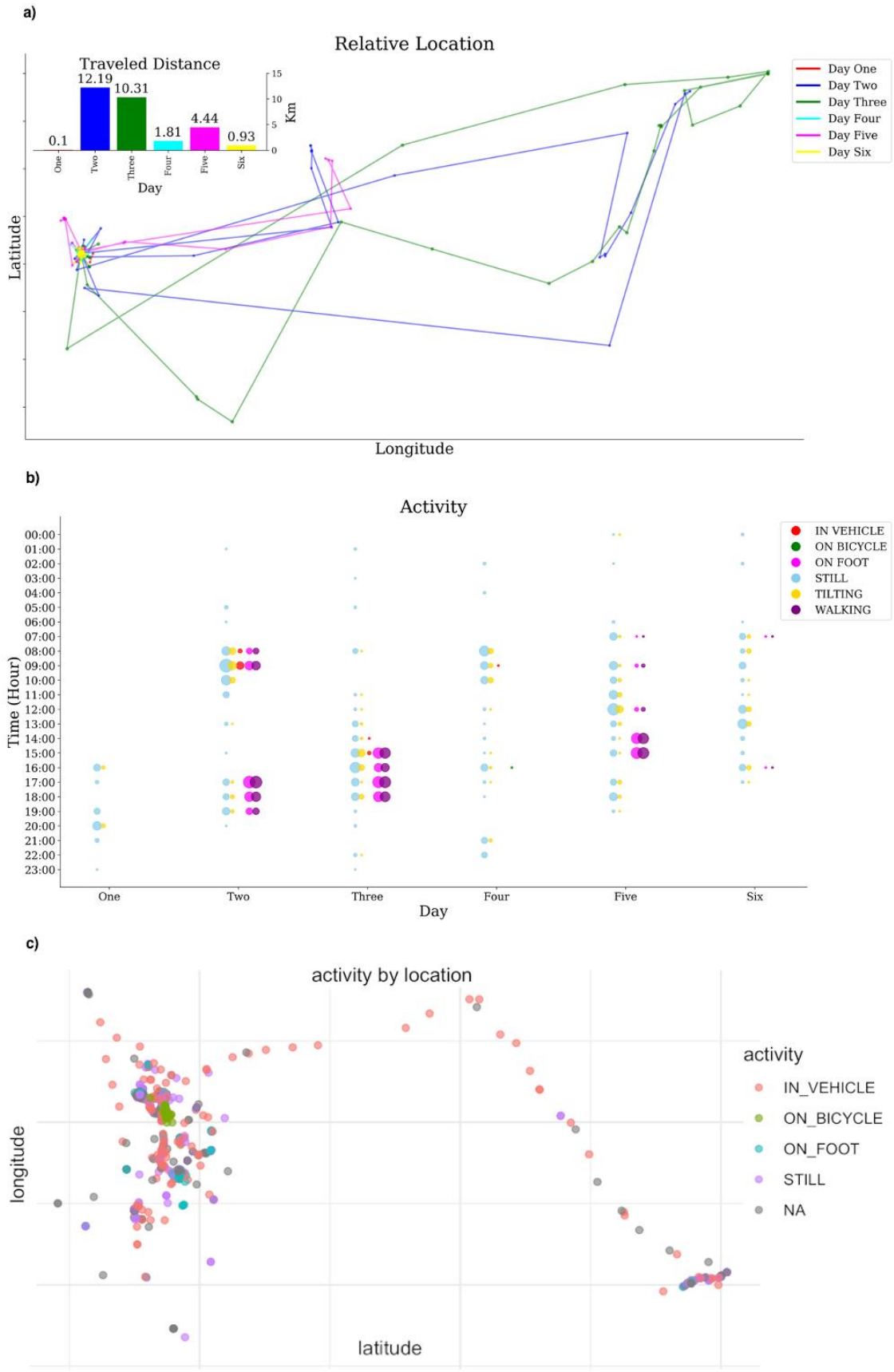

a)
Relative Location
Traveled Distance
12.19
10.31
0.1
1.81
4.44
0.93
One
Two
Three
Four
Five
Six
Day
Km
Latitude
Longitude
Day One
Day Two
Day Three
Day Four
Day Five
Day Six
b)
Activity
Time (Hour)
Day
IN VEHICLE
ON BICYCLE
ON FOOT
STILL
TILTING
WALKING
c)
activity by location
longitude
latitude
activity
IN_VEHICLE
ON_BICYCLE
ON_FOOT
STILL
NA

Figure 4

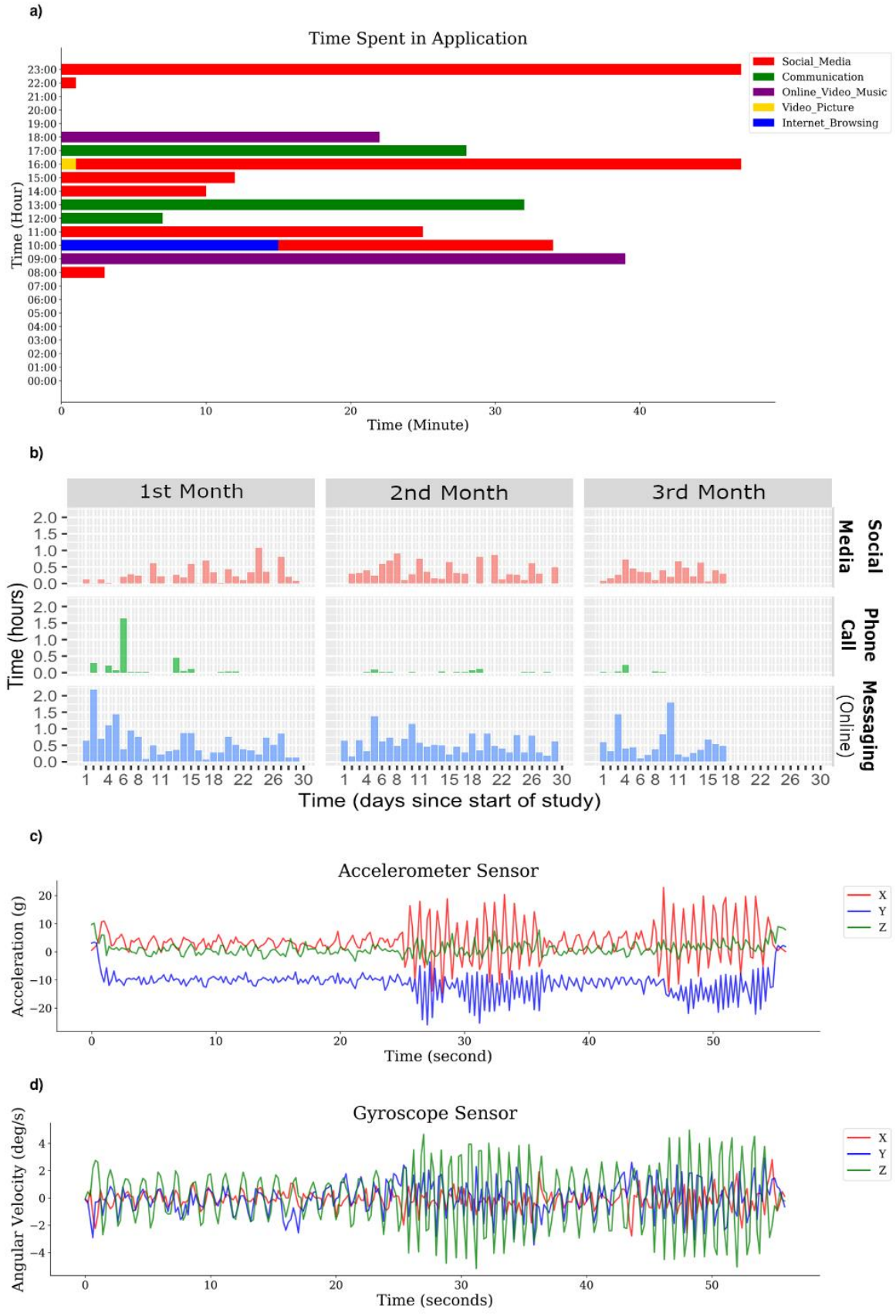

a)
Time Spent in Application
Social_Media
Communication
Online_Video_Music
Video_Picture
Internet_Browsing
Time (Hour)
Time (Minute)
b)
1st Month
2nd Month
3rd Month
Social Media
Phone Call
Messaging (Online)
Time (hours)
Time (days since start of study)
c)
Accelerometer Sensor
Acceleration (g)
Time (second)
X
Y
Z
d)
Gyroscope Sensor
Angular Velocity (deg/s)
Time (seconds)
X
Y
Z

Figure 5

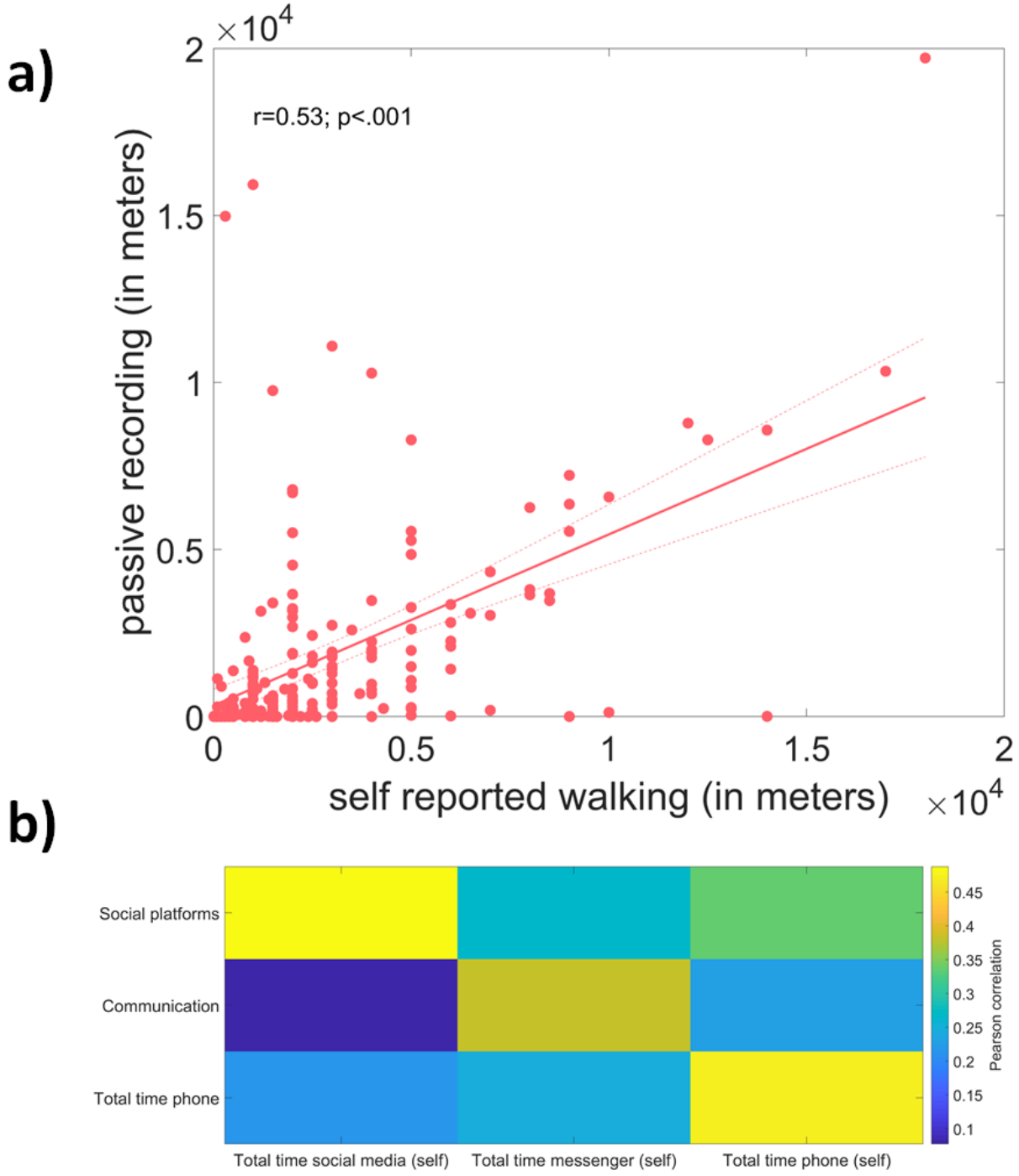

a)
×10^4
2
1.5
1
0.5
0
r=0.53; p<.001
passive recording (in meters)
0
0.5
1
1.5
2
self reported walking (in meters)
×10^4
b)
Social platforms
Communication
Total time phone
Total time social media (self)
Total time messenger (self)
Total time phone (self)
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
Pearson correlation

Figure 6