Chapter 23
The Importance of Smartphone Connectivity in Quality of Life

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Introduction

The World Health Organization (WHO) has defined Quality of Life (QoL) as an "individual's perception of their position in life in the context of the culture and value systems in which they live and in relation to their goals, expectations, standards, and concerns." The WHO expands this definition across several domains, namely physical and psychological health, social relationships, and the environment. In this chapter, we focus on one facet of the environmental domain: the physical environment. We explore the availability of mobile network connectivity in one's environment without considering other variables that contribute to this environment, such as noise, pollution, climate, and the general aesthetic. Determining the impacts of connectivity on an individual's QoL is important for considering improvements or adverse effects on their day-to-day life.

Wireless networks have been present in our physical environment since the invention of over-the-air transmission of information (ALOHAnet [1]) in 1970. Recent developments in communication technology have now made it affordable to own a powerful, ubiquitous, network-enabled device. Today, wireless networks are present throughout the shared physical environment, especially in the developed world and in areas with high population density. Indeed, the accelerated

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digitalization of the population can be attributed to the global adoption of smartphones. The number of smartphone users reached 3.2 billion worldwide in 2019 and will continue to grow [2]. Likewise, the networks that support them have been deployed at a similar pace and are continuously updated to cover larger areas and upgraded to utilize new technologies (e.g., from 3G to 5G).

The majority of mobile applications require an Internet connection, and in this study we focus on connectivity to mobile networks, whereby human-to-human interaction is enabled by computer-based networks. Networks support instant information transfer in various formats, including text, image, and video, and enable the necessary interaction between nodes (i.e., people or machines). Furthermore, they provide access to a number of services that can be used to improve an individual's decision-making capabilities and ultimately their QoL. A 2018 study by Chan et al. [3] found that smartphone use predicts relationship quality and subjective well-being, while Kim et al. [4] suggested that the use of information and communication technology, such as smartphones, in old age generally plays a positive role in enhancing the psychological, mental, and social aspects of one's QoL.

This chapter presents features of mobile network connectivity derived from smartphone use data collected from different cohorts in the Geneva area (Switzerland) between 2015 and 2020. We explore four connectivity features and examine the evolution of connectivity during the last 5 years as derived from data gathered unobtrusively from the consented mQoL (mobile QoL) Living Lab participants.

This chapter is structured as follows. We present the literature review in section "Related Work". In section "Mobile Network Connectivity Study: Methods", we provide the study parameters, describe the collected data, and outline the studied connectivity features. In section "Mobile Network Connectivity: Results", we report the results obtained from the analysis of the features. In section "Discussion", we discuss the limitations of the study and different approaches to connectivity quantification. Finally, in section "Conclusion", we describe the lessons learned and provide recommendations for future areas of work, especially the quantification of the impact of mobile connectivity on QoL.

Related Work

Mobile Network Connectivity and QoL

Previous work has shown the benefits of deploying mobile networks in rural and developing areas (e.g., Ghana, Nigeria, Kenya, and Tanzania) [5]. Researchers have found that it facilitates improved communication between the local population and distant services such as health and governance. The same authors have documented income growth in the Southeast Asia region in the last 10 years due to the rising usage of mobile applications and voice calls as the population gained access to new services and information relating to the weather, agriculture, finance, and music, for example. The income growth has only been reported in low-income countries, but surprisingly, in 2018, the GSM Association [6] found that the top reason to use mobile instant messaging was the same for low, middle, and high-income countries. This indicates that the benefits of messaging applications are not the prerogative of high-income countries. In recent years, messaging applications have created new markets and services that are available on their platforms. For instance, WeChat (est. 2011), Facebook Messenger (est. 2011), and WhatsApp (est. 2009) have all integrated payment functions into their applications in selected countries including China (WeChat Pay), Brazil, and the USA. Before the prevalent use of smartphones, the development of mobile payment solutions using a fast and reliable network was stagnant. Today, mobile networks are a critical gateway to the digital economy, as these solutions have been widely adopted to simplify the exchange of money and goods. Overall, 90% of Chinese tourists claim that they would use WeChat Pay overseas if given the opportunity [7].

The direct impact of broadband network access on GDP per capita has also been studied; one investigation found that a 10% increase in broadband penetration has a notable impact on GDP per capita, increasing it from 0.9 to 1.5 percentage points on average for OECD economies. Furthermore, the authors explained that if digital services are established alongside a reliable infrastructure, new services will be created [2].

In recent years, the Asia-Pacific region has been improving its environmental QoL through connectivity and will continue to do so particularly by way of smart city initiatives [8]. Such initiatives are described as cross-sector endeavors that link people to public and private infrastructures. Connectivity is crucial for smart city services, from the use of Internet of Things devices and a cloud-based platform to monitor and analyze air quality at street level, to the publishing of open data by public authorities to enable faster development of online-based services. In summary, a link between mobile connectivity and QoL around the world has been proven to exist—to such an extent that connectivity has a direct impact on a country's GDP.

Smartphone Apps and Their Impacts on QoL

The revolution in mobile devices, which have evolved from basic cell phones to smartphones, has created a new market for mobile applications. New application types were created for those devices, and as of November 2020, the Google Play Store hosted 2.56 million different applications across 32 application categories and 17 game categories [9]. Two application categories that may have a direct impact on users' health are (1) health and fitness, including personal fitness, workout tracking, dieting and nutritional tips, health, and safety applications, and (2) medical, including drug and clinical references, calculators, medical journals, news, and handbooks for healthcare providers.

Health and fitness applications such as food diaries allow users to track their food intake for multiple purposes. These applications connect to a central database that contains nutritional information about various foods (e.g., calories, carbohydrates, fat, and vitamin content). Users have to scan the barcode on a food item or use the search box to find and manually add the specific food and item weight, and the application computes its total nutritional value. Chen et al. [10] reported that users' quality of experience is much higher with smartphone application diaries than with pen and paper diaries. They also found that diabetic patients using application diaries reported a better food intake control than those using pen and paper diaries. Furthermore, a recent study by Bracken et al. [11] demonstrated that non-patient users wishing to lose weight (e.g., managing pre-obesity) and others wishing to gain weight (e.g., building muscle) utilize diary applications to attain their nutritional goals.

Medical applications are oriented towards health workers and healthcare practitioners. These professionals can use these applications as a productivity tool in their work, which enables them to automate necessary tasks [12]. Recent work [13] has indicated the advantages of medical applications: they increase access to point-of-care tools, thus improving patient outcomes that stem from better clinical decision-making. Wattanapisit et al. [14] investigated whether a medical smartphone-based application can replace a general practitioner. They praised the use of an application for tasks such as recording medical history, making diagnoses, promoting health, performing some physical examinations, and assisting in urgent, long-term, and disease-specific care. However, the application was unable to support clinicians in performing medical procedures, appropriately utilizing other professionals, or coordinating a team-based approach. A recent literature review by Wattanapisit et al. [15] focused on medical counseling for physical activity and returned mixed findings regarding the usability and utility of medical applications. The review suggested that technical issues and the complexity of programs were barriers to usability, thereby implying the possibility of unfavorable patient outcomes such as inaccurate advice and diagnoses.

Mobile network connectivity plays a significant role in always-online smartphone applications. These applications may help to enhance an individual's decision-making and thus result in an improved QoL through connectivity to the Internet. However, such applications can also lead to the reverse effects. One example is smartphone addiction. According to the observations of Kwon et al. [16], "the overuse of smartphones can be easily seen in today's society." The examples provided in the study include physical impacts (e.g., car accidents caused by smartphone use) and mental impacts that create issues for smartphone-addicted children (e.g., a loss of concentration in class). The authors proposed the Smartphone Addiction Scale (SAS) to quantify this addiction. The SAS consists of 48 items relating to smartphone usage in distinct contexts, such as taking the smartphone to the toilet or feeling stressed when the smartphone is not connected to a network. Also derived from this scale is the Smartphone Addiction Scale for Adolescents (SAS-SV) [17], evaluated by the same authors. The SAS-SV was used by Haug et al. [18] in a study on young people in Switzerland, which found that social networking applications were the applications most closely associated with smartphone addiction.

Smartphone addiction has also been attributed as a source of loneliness, poor bonding, and lack of integration, as shown by Bian et al. [19]. Samaha et al. [20] observed the relationships between smartphone addiction, stress, academic performance, and satisfaction with life. Through the use of multiple surveys, the SAS-SV, the Perceived Stress Scale, and the Satisfaction with Life Scale, they found addiction risk to be positively related to perceived stress. Finally, a large study by Carbonell et al. [21] demonstrated a substantial overlap between smartphone use, Internet addiction, and social media use in a student population. Smartphone addiction also has physical effects. For instance, Akodu et al. [22] described higher scapular dysfunction found in a population of students who are addicted to their devices.

A considerable amount of literature has been published on the influence of smartphones and has found that smartphone applications may influence users' QoL. Applications can contribute to users' well-being both positively and negatively, depending on the applications used and the user profile.

Smartphones as Sensors of Daily Life

Research by Dey et al. [23] established that smartphones are within arm's reach of their users an average of 88% of the time. Therefore, they are a beacon of one's presence. Indeed, smartphones have been used during the COVID-19 pandemic as a proximity sensor for contact tracing [24]. In recent years, smartphones have become a critical tool for researchers in all fields, as one of the greatest challenges to conducting a study is collecting participants' data. To solve this problem, a set of applications and software libraries have been developed to collect raw sensor data from smartphones as proxies for their users. These libraries collect similar data in different ways, although iOS devices are more restricted than Android devices.

Smartphone data can be collected from the following onboard sensors: accelerometer, location, proximity, barometer, gravity, light, magnetometer, audio, and temperature. Communication data can also be recorded from Bluetooth, SMS, telephony, and social applications. Tools such as AWARE exist to simplify the data collection process [25]. However, AWARE is often unable to integrate with other software platforms, while other tools such as Sensus [26] have customization issues. Meanwhile, libraries such as SensingKit [27] cannot support data collection alone. Furthermore, other software platforms like the CARP Mobile Sensing framework [28] propose a multi-platform approach (Android and iOS) with a reusable UI (Flutter) and support sensing for numerous features, but they lack low-level, hardware-based, detailed information.

Smartphone data collected with such tools have been successfully used in human studies [29]. For example, Ciman et al. [30] and De Ridder et al. [31] leveraged data collected from smartphone sensors to propose a stress assessment method. The first study used the data generated by finger swipes on the screen to detect stress, while the second paper showed through a meta-analysis that a tailored smartphone application can directly extract the heart rate variability (HRV), which is a stress indicator, from images of the subject's finger as it touches the smartphone's camera under illumination from the smartphone's flashlight. This process is called photoplethysmography. Smartphones are also used as sleep duration sensors, which was explored by Ciman et al. [32], and can predict users' intimacy, as claimed by Gustarini et al. [33].

In summary, smartphones are a proven source of daily-life data in multiple research domains, and their output has been validated experimentally.

Mobile Network Connectivity Study: Methods

QoL Lab was established in 2010, and since 2011, our research group has collected smartphone-based datasets for various human-based research studies and has used its own logging software for research into human activity recognition [34], mobility [35], and intimacy [33], among the other areas of study. The goal of this prior research was to quantify those aspects of human behavior with the use of smartphone sensors (i.e., gathering data using accelerometers, gyroscopes, and networking information, for example) and participants' self-reported inputs. We now focus on human subject studies "in the wild" and the practical aspects of smartphone data collection [36] through various research topics such as Quality of Service (QoS) [37], Quality of Experience (QoE) [38], and behaviors such as sleep [32] or stress assessment [39]. Smartphone data is collected in these different studies using the same framework (mQoL-Log), and it is tailored for each study. The mQoL-Lab application [40] enables background data collection through the mQoL-Log framework and implements surveys and remote notification to support human and smartphone-based research studies. Updates are necessary as the target system (Android OS) is always evolving. This section presents the tools used to acquire the data as well as their characteristics and discusses the selection of the derived features that are important for modeling individuals' day-to-day mobile network connectivity. Furthermore, we detail the processes used for feature engineering and data filtering.

Data Collection Periods and Overall Summary of the Collected Data

We investigated participant connectivity with the use of mQoL-Log data records. We focused on the networking data collected through different studies conducted in Geneva over three time periods, which is presented in Table 23.1. Each participant was only present during their period. P1 was aggregated from a mQoL-Lab Living

Table 23.1 Data collection periods

Period ID	Period Years	Study focus	References	Number of participants (N) Pre/post-filtering	
P1	2015–2017	QoS, mQoL LLab	[41]	53	50
P2	2018–2019	QoE, PeerMA	[42, 38, 39]	63	55
P3	2020	QoE	[forthcoming]	5	5
Total				121	110

Table 23.2 Participation statistics for the filtered datasets in each data collection period

Period ID	Avg number of measurement days/ participant	Standard error	Min	Q1 days (25%)	Q2 days (50%)	Q3 days (75%)	Max	Missing days avg ± std. err
P1	168.6	15.4	6	79	187	270	322	59 ± 10
P2	30.4	2.2	4	24	29	32	98	22.8 ± 1
P3	32.6	1.6	30	31	31	32	39	0 ± 0
Total	93.3	9.66	13.33	27	32.5	170	153	27 ± 3

(mQoL LLab) observational study that focused on people's smartphone usage. P2 studies were also "observational" and focused on quantifying the QoE of smartphone applications. They also focused on stress assessment via peers (PeerMA [39]). The P3 study was the first "interventional study of smartphone application category recommendations made based on the QoE model", where the intervention aimed to maximize user QoE in any context.

The presented meta-study focuses on participants' mobile connectivity throughout their days. The 121 participants collected a total of 69,761,823 samples. A *sample* is a piece of timestamped network-related information that was collected automatically via the mQoL-Log either when mQoL-Log requested information (i.e. by pulling the network state every 60 s for P1) or when an event occurred, such as a handover between different network connection types (e.g. 4G to WiFi, network connection or disconnection for P2 and P3) being *pushed* to the logger. The different ways of collecting the networking data (push/pull) were dictated by the Google API changes over the years. A "*day of the collection*" is a calendar day (midnight-to-midnight) for which at least one sample exists. On average, each participant collected data for 85 days (± std. err 9), 21 days for the 25th percentile (Q1), 31 days for the 50th percentile (Q2), and 128 days for the 75th percentile (Q3). We observed outliers in the aggregated dataset: one participant recorded 322 days of collection (max), while another only submitted one day of collection (min). Filtering was applied to the dataset following two exclusion criteria: (1) a participant collected less than ten samples, or (2) a participant collected less than three consecutive days of recording. The filtered dataset contained 110 participants; the filter removed 11 participants and 18,550,170 randomly distributed samples. The remaining 51,211,653 samples were retained for further analysis. Table 23.2 presents the participation statistics for the filtered datasets collected in each period. A "*day of measurement"* is defined as any sample collected in a 24 h period during the collection period; this is valid for P1, P2, and P3. Contrary to a "*day of the collection*", this new metric is not based on a calendar day but on the availability of samples in a 24 h period (defined as a moving window or 24 h from a previous sample).

For example, for the P1 participant who recorded 322 days of collection (max), we have defined 322 days of measurement, meaning that the time difference between any two samples was less than 24 hours and that at least one sample per calendar day (Monday, Tuesday, …) was available. On average, each participant collected data for 93.3 days of measurements (± std. err 9.66), 27 days for the 25th percentile (Q1), 32.5 days for the 50th percentile (Q2), and 170 days for the 75th percentile (Q3).

Given that a *sample* is a piece of timestamped network-related information, if n > =1 samples are generated at a specific *minute* (hh:mm), we classified this as *one minute of data collected*. Table 23.3 details the total number of minutes of data collected per period. We computed the mean rate of minutes acquired to understand how much data was collected per collection period overall. This rate differs from the days of data collection and the days of measurement, as it is minute based. We compared each sample acquired at a minute level to the possible number of data collection minutes during the collection period, assuming zero data loss, i.e., with data for all the minutes available. The last column of the table shows the overall acquired minute rate over the three data collection periods. Compared to P2 and P3, as explained above, the data collected in P1 was acquired more frequently.

Measurement Framework: mQoL-Log

In 2011, within the context of the mQoL Living Lab, we developed the first version of a smartphone logger for the Android operating system, and we implemented a cloud-based infrastructure to collect smartphone data. The smartphone application was composed of two modules: the data logger (mQoL-Log) and the user interface (mQoL-Lab). The user interface contained the participant's communication medium to complete the study and provide the possibility to contact the study's principal

Table 23.3 Number of minutes of data collected for the three periods

Period ID	Avg [min]	Standard error	Min	Q1 (25%)	Q2 (50%)	Q3 (75%)	Max	Mean acquired minute rate ± std.err [%]
P1	86,148	9387.8	855	15,769	89,008	138,676	224,684	34 ± 2
P2	1499	151	189	634	1202	2021	5559	4 ± 0.2
P3	1370	286	546	1017	1232	1992	2045	3 ± 0.5
Total	39,970	5858	536	1088	2471	75,339	77,429	17 ± 1.8

investigator. A cloud-based (our university-hosted) component was able to trigger surveys remotely and control the quality of the data collected on the smartphone, for integrity purposes.

mQoL-Log collected the data from the smartphone as mentioned previously (see section "Smartphones as Sensors of Daily Life"). Table 23.4 presents data collected from the smartphone's sensors through mQoL-Log. Table 23.5 presents in detail the

Table 23.4 Data collected by mQoL-Log

Variable name	Definition	Study period	Trigger and frequency of collection
Screen activity	The status of the smartphone screen and the user interaction.	P1, P2, P3	Changes in screen events (on, off, user presence, rotation) (push)
Touches	Number and duration of user touches on the screen during a usage session.	P1, P2, P3	Screen event-based: Each smartphone session (push)
Active app name	Application name on the user screen	P1, P2, P3	Changes in the application on-screen (push)
Background app	Application services running in the background (list)	P1	Every 60 s (pull)
Connectivity and network	WiFi level, WiFi BSSID, WiFi SSID, WiFi interface speed, cell ID, cell operator, cell strength, cell radio access technology (RAT), cell network code, Internet connection status, cell bandwidth up and down stream, number of packets and bytes sent and received on wireless interfaces	P1	Every 60 s (pull)
		P2, P3	Changes in network connection state and during user app usage (push)
Round Trip-Time [ms]	The RTT is the time needed for a ping to be sent by a smartphone to a server, plus the amount of time taken for an acknowledgment to be received. A ping is an active probing connection to a specific server via its address. A ping is executed six times; the first is discarded to remove any noise from DNS resolution time. We derived statistics (mean, stdev, and variance) from five executions.	P1 (always unige.ch server)	Every 60 s (pull)
		P2 (app server)	When the app usage session starts (pull)
Battery	Battery status (e.g., charging, full, discharging), battery level, battery temperature	P1, P2, P3	Changes in battery state (push)
Physical activity	Physical activity of the user from Google Play Services activity (still, tilting: between two states, in-vehicle, on a bicycle, on foot, running).	P1, P2, P3	Changes in the user activity (push)

Table 23.5 mQoL-log network data

Name	Description
Network type	Type of cellular or WiFi network (RAT).
Signal strength	The signal strength is defined as the received power present in the WiFi and cellular radio in dBm (RSSI). dBms were transformed into the representation used in the Android OS, i.e. bars, as the participant would see this information on-screen.
Operator	The name of the cellular network operator.
Unique identifier (ID)	Cellular network tower ID (cell ID) or WiFi basic service set identifier (BSSID).
Network name	WiFi network name.
Handover	Flag indicating a change in network type, cell ID, or BSSID.
Total downloaded data	Cumulative sum in bytes of downloaded data since the last smartphone reboot.
Total uploaded data	Cumulative sum in bytes of uploaded data since the last smartphone reboot.

connectivity and network data collected. The logger included an energy policy to preserve the participant's smartphone battery life by stopping all data collection at a threshold of 30% battery capacity. Collection resumed once the smartphone was charging or when the battery capacity was above the threshold.

Final Dataset

As we wished to compare the connectivity of participants for the given data collection periods, we resampled the acquired P1, P2, and P3 datasets to one sample per minute, and completed the missing data points with the last known connectivity value. This method interpolates the missing points between two samples (upsampling), thus enabling a minute-based analysis of the smartphone's connectivity. The following assumption was made to validate this dimension change (i.e., to discretize it to 1 min frequency): if no data is present between two samples, this means that no event occurred. With this, we propagate the last known value to the next minute until a different event-generated sample is found. However, we are fully aware that this process does not allow us to make generalizations about a representative sample of the population.

Theoretically, P1 should have been sampled at one-minute frequency, since the pull method was leveraged for collecting the data every minute. However, we observed a skew in the pulling time, due to the Android OS giving lower priority to the collection process; the mean acquired pull rate was not 100% at 1 min period. Following the resampling process, the P1 was hence resampled to a one-minute frequency. As for P2 and P3, the resampling process generated a time series from

Table 23.6 Average measurement minutes collected post resampling, per participant in a period

Period ID	Avg [min]	Standard error	Min [min]	Q1 (25%)	Q2 (50%)	Q3 (75%)	Max [min]	Mean acquired minute rate ± std.err [%]
P1	241,832	22,261	7245	113,091	267,415	388,762	462,466	100 ± 0
P2	42,171	3144	3931	33,402	39,637	45,089	139,726	100 ± 0
P3	45,122	2473	41,448	42,447	42,930	43,902	54,885	100 ± 0
Total	109,708	9292	17,541	62,980	116,660	159,251	219,025	100 ± 0

the discrete events collected by the push method. The total size of the resampled dataset is 234 million samples as presented in Table 23.6.

Features Derived from Mobile Network Connectivity

In this subsection, we describe the four features derived from the raw dataset: (1) network access technology, (2) signal strength, (3) data consumption, and (4) user's physical mobility.

Network access technology or radio access technology (RAT) is defined as the physical connection system for a radio-based communication network. Smartphones support several RATs, such as WiFi, Bluetooth, GSM, UMTS, LTE, or 5G NR (New Radio). The focus of this analysis lies on RATs that enable Internet connection, so the Bluetooth standard is out of scope.

The *signal strength* is defined as the received power present in the WiFi and cellular radio signal. The signal strength feature directly impacts a user's network context and provides an insight into the connectivity level at that moment to the current Internet provider (i.e., a cell tower or WiFi access point).

Data consumption is defined as the amount of data (bytes) transferred from and to the smartphone through upload and download. The amount of data transferred during a specific time window provides information about the immediate network bandwidth. Some types of smartphone applications consume more data than others; for example, a video call application sends and receives more bytes than a text-based chat application.

The fourth feature is the *user's physical mobility*. Smartphones are used on the move, and their small size allows users to keep them in their pockets. In this way, they are a proxy for the user's mobility. Mobile connectivity is dependent on the physical network infrastructure around the user. Therefore, we analyzed the mobility aspect registered in the dataset. Mobility is defined as the number of cell towers and/or WiFi access points with unique identifiers that a participant passes through during a specific time window.

Network Access Technology

Wireless network access technology on a smartphone consists of two Internet-enabled subtypes: WiFi and cellular. WiFi allows smartphones to connect to a wireless local area network (WLAN). Often these local networks are also routed to provide Internet access. A smartphone's WiFi interface connects to an access point (AP) to provide an Internet connection, which has a network name and a unique identifier. In contrast to a cellular connection, WiFi enables a smaller coverage range depending on the generation used (on the scale of meters rather than the kilometers of a cellular connection). For this reason, WiFi is primarily used to connect to the Internet from home, work, or university. Various generations of cellular networks have been developed (e.g., 3G, 4G, 5G) with the evolution of access technology (see Table 23.7).

A cell tower offering Internet connectivity also has a unique identifier, but the main differences between cell-based technologies generation are the speed of the connection and their coverage range from the antenna. A smartphone's baseband processor is the chip on its motherboard, which manages all radio functions. This processor is separated from the main smartphone processor for three reasons: (1) radio performance: the main processor is too slow to handle the type of work done by the baseband processor, such as encoding and modulation; (2) legal: authorities require the software that manages radio transmission to be certified; and (3)

Table 23.7 Generation of cellular network access technologies

Generation	Acronym	Full name	Max download speed	Estimated download time for a 3 min 1080p YouTube video (75 MB)
2G	GPRS	General Packet Radio Service	0.0125 Mbit/s	800 min
	EDGE	Enhanced Data Rates for GSM Evolution	0.0375 Mbit/s	27 min
3G	UMTS	Universal Mobile Telecommunications System	0.0375 Mbit/s	27 min
	HSPA	High Speed Packet Access	0.9 Mbit/s	11 min
	HSDPA	High Speed Downlink Packet Access	14 Mbit/s	1.1 min
	HSUPA	High Speed Uplink Packet Access	14 Mbit/s	1.1 min
	HSPA+	Evolved High Speed Packet Access	42 Mbit/s	13.8 s
4G	LTE (Cat4)	Long-Term Evolution	150 Mbit/s	0.001 s
5G	NR	New Radio	400 Mbit/s (sub-6Ghz) 1.8 Gbits/s (mmWave)	1.5 s

reliability: the OS or new application versions should not interfere with the baseband processor functions. The baseband processor is the component that manages the handover between network access technologies. When a tower is located too far from a smartphone, the signal may drop and end the user's connectivity. The baseband processor then automatically connects to a closer antenna to provide network access. If an antenna is not available in the same RAT, the baseband processor, selects a lower technology RAT, as older RAT often provide a larger range of coverage. For instance, if a 4G signal is unavailable because the user is on the move, and no other 4G link can be established, the smartphone will attempt to connect to a 3G antenna.

The type of network access technology is important because it is directly linked to the quality of connectivity. As Table 23.7 shows, an EDGE-based connection theoretically has a maximum download speed of 0.0375 Mbit/s, which is not enough to watch a YouTube video [43]. WiFi technologies have also undergone several stages of evolution with different maximum download speeds, i.e., WiFi type (e.g., a, b, g, n, ac). However, this information was not available during dataset collection, so information regarding WiFi speed is not included in this analysis. Connection to a WiFi network is not automatic, as the user must enter credentials to connect to the network. These credentials ensure the encryption of the communication between the smartphone and the wireless AP. The credentials exchange is transparent on a cellular connection, in which case the baseband processor communicates with the Security Information Management (SIM) card and the operator network to authenticate the smartphone on the network.

Signal Strength

We examined the overall network connectivity signal strength over the collection periods. Signal strength is always presented on the smartphone screen and is located in the upper right-hand corner on Android and iOS. Icons represent the signal strength sensed by the onboard antennas for both WiFi and cellular networks in a human-readable format. The mQoL-Log application was able to collect that information in decibel-milliwatts (dBm). To utilize this information, we determined how the Android OS presented this data to the end-user, and mapped the dBm to the number of bars (0 to 4) shown on-screen. The signal strength represents the power present in the received radio signal. For smartphones, this directly impacts the QoE of smartphone services such as video streaming and online games. The minimum signal strength needed to achieve a "good" experience when watching an online video on the move depends on the network access technology and the video format (e.g. HD or 4 K). The signal strength plays a significant role during handovers. The baseband processors collect the signal strength continuously and choose whether to switch between RATs (i.e. conduct a vertical handover for the same RAT or a horizontal handover if RATs change) or between cell antennas. Connectivity-wise, the smartphone user sees the signal strength as an overall health indicator of the network connection. Thus, a user may decide not to start a video call if the smartphone reports low signal strength, instead preferring to communicate via audio call only.

Data Consumption

Data consumption is a significant feature in the context of connectivity. The RAT limits the amount of data that can be transmitted, measured in seconds. Accordingly, the amount of data consumed is bound to the current network access technology. The data consumption depends on the type of services utilized by the smartphone user. Video applications consume a large amount of data, e.g. by downloading video, while a video calling application simultaneously generates and consumes a large amount of data by uploading and downloading a video. The overall data consumption also provides insight into the network traffic state. If the network encounters a large amount of traffic, this impacts the bandwidth available for use in a live video or other application by the user, and the user connectivity is affected. The amount of data downloaded and uploaded also indicates the user profile type, as some users consume less data than others. This may be due to the nature of their subscription to their operator (financial), the services used on their smartphones (behavior), and the quality of the link connecting them to the Internet (structural) over time [44].

User's Physical Mobility

User mobility is essential, as discussed previously. Indeed, connectivity and mobility are crucial to understanding participants' smartphone usage and connectivity changes. We explored participants' mobility per hour and the number of times each participant connected to the same tower or the same AP for multiple periods (days to weeks). A large number of unique identifiers (ID) is an indication of high mobility for a participant. One cell tower covers a few kilometers of land in a densely populated area (e.g. a 4G tower has a 16 km range), while a WiFi AP covers only a few meters (e.g. a WiFi ac reaches 12–35 m inside and up to 300 m outside).

Mobile Network Connectivity: Results

We analyzed results for the four features that quantify the connectivity level of an individual relying on the connection and usage of their smartphone network: the network access technology (section "Network Access Technology"), its signal strength (section "Signal Strength"), overall data consumption (section "Data Consumption"), and mobility (section "Users' Physical Mobility"). For each feature, we present the overall statistics (post-filtering) of the 110 participants organized by their respective collection period.

Network Access Technology

Table 23.8 presents the overall average of RAT distribution per measurement period. Figures 23.1, 23.2, and 23.3 illustrate the distribution of network access technology for P1, P2, and P3 participants, respectively. The figures clearly show the adoption of LTE (4G). In the P1 distribution, we observe a high presence of HSPA, while the P2 distribution suggests that some participants (particularly P2S98 and P2S64) were not connected (NOCO) for the majority of the study. Overall, we see lower access to the Internet in P2 than in P1 and P3. The most recent data demonstrate the rise of LTE and WiFi over the RAT. Furthermore, during P3 the participants had the most stable connection to the Internet (low NOCO), as presented in Table 23.8.

Figure 23.4 presents the overall average distribution over the three periods. We observe that LTE is more present than WiFi in P3.

The data imply that overall, on average for all periods, any connection to the Internet is present 93 ± 0.8% of the time (averaging 104,540 ± 64.36 min across all periods). This information is computed from the RAT distribution. Table 23.9 presents the distribution of the connectivity and the average minutes of connection for each period and reveals that P2 connectivity is lower than that of P1 and P3.

Table 23.8 Overall average RAT distribution (%) per data collection period

RAT/period [%]	P1	P2	P3
WiFi	52.1 ± 3.7	51.0 ± 3.2	47.7 ± 7.1
LTE	29.8 ± 4.1	28.7 ± 2.9	49.8 ± 0.5
HSPA+	3.1 ± 0.8	3.3 ± 1.2	0.8 ± 0.5
HSUPA	0.1 ± 0.1	0.0 ± 0	0.0 ± 0
HSDPA	2.2 ± 1.2	0.0 ± 0	0.0 ± 0
HSPA	3.9 ± 1.1	0.4 ± 0.1	0.1 ± 0.1
UMTS	3.1 ± 1	0.7 ± 0.3	0.3 ± 0.2
EDGE	2.0 ± 0.8	0.6 ± 0.2	0.2 ± 0.1
GPRS	0.0 ± 0	0.0 ± 0	0.0 ± 0
GSM	0.0 ± 0	0.0 ± 0	0.0 ± 0
UNKNOWN	2.6 ± 0.9	0.5 ± 0.3	0.3 ± 2
NOCO	1.0 ± 0.2	14.7 ± 2.4	0.7 ± 3
Download speed on cell network in Mbit/s Avg ± std.err	6.9 ± 3.3	6.4 ± 3	9.4 ± 4.6

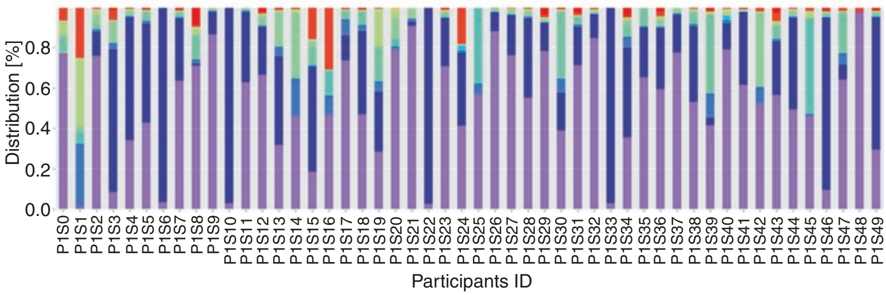


Fig. 23.1 RAT distribution of participants in P1 (N = 50)

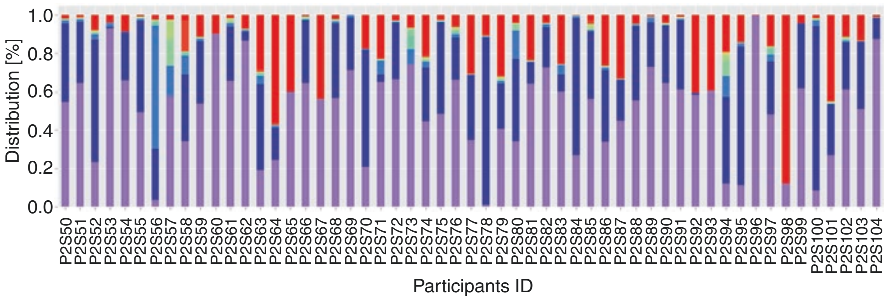


Fig. 23.2 RAT distribution of participants in P2 (N = 55)

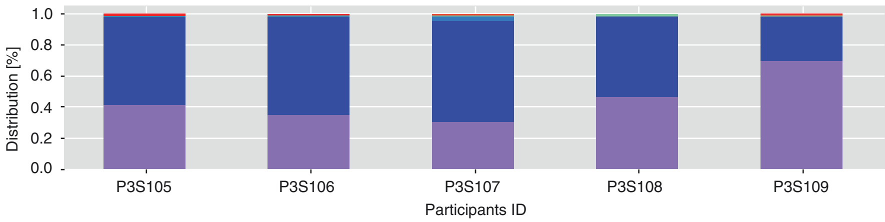


Fig. 23.3 RAT distribution of participants in P3 (N = 5)

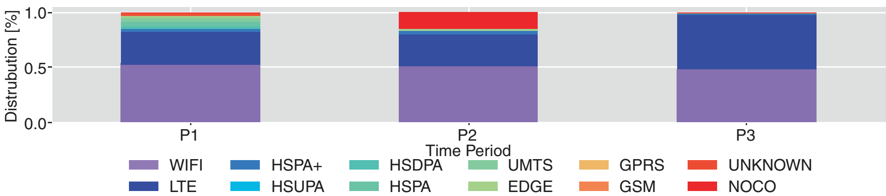


Fig. 23.4 Overall average RAT distribution over P1, P2, and P3

Table 23.9 Percentage of connectivity to internet distribution per data collection period

Connectivity (%) per period	P1	P2	P3
Mean	0.96	0.85	0.99
Std	0.06	0.18	0.00
Min	0.69	0.12	0.99
25%	0.97	0.77	0.99
50%	0.99	0.92	0.99
75%	0.99	0.97	0.99
Mean in Minutes/total time/in period ± std.err	233,162.51 ± 21,371	35,775.89 ± 2672	44,682.18 ± 2448

Signal Strength

The temporality of signal strength for each group is presented in Fig. 23.5. Signal strength increased with time for each group. P1 and P2 feature homogenous signal strength, in contrast to P3, which exhibits a higher signal strength at weekends and during mornings.

Figure 23.6 presents the overall signal strength distribution per period. The resampling process explains the high prevalence of the 0 bar.

Figure 23.7 presents the correlation between the signal quality and the connection type over all three periods. We note a high degree of correlation between WiFi

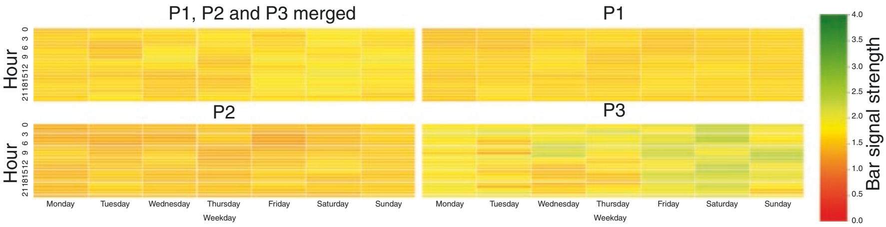


Fig. 23.5 Mean signal strength per data collection period

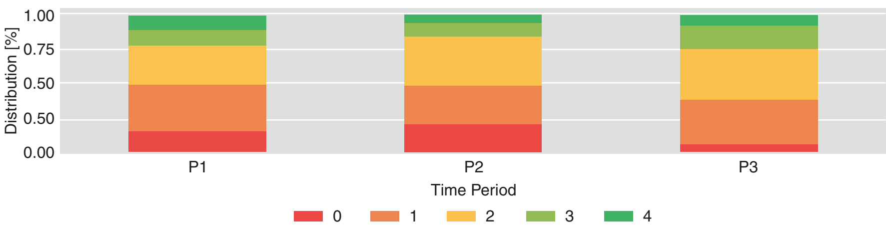


Fig. 23.6 Overall signal strength distribution per data collection period

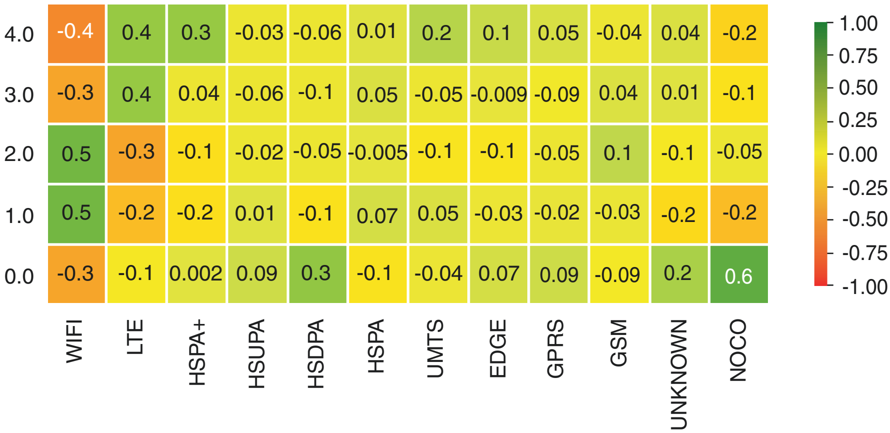


Fig. 23.7 Pearson Correlation Between Signal Strength and Network Access Technology Type

and signal strengths of 1 and 2 bars, while LTE network technology and signal strengths of 3 and 4 bars display a moderate correlation.

Data Consumption

During the analysis, we observed high data consumption by particular participants, as depicted in Fig. 23.8 with the cumulative distribution function (CDF) for monthly data usage and in Fig. 23.9 with the daily data usage for each participant (each data point on one of the lines corresponds to a participant). In both figures, each data point represents the average monthly data consumed by one study participant in terms of (1) rx (received, downlink) and (2) tx (transmitted, uplink), overall and for cell-based networking. The majority of the participants display similar data-consuming behavior, regarding both data receiving and transmitting. In both temporal modalities, the amount of data transmitted from the smartphone to the cellular network is lower than the amount of data received. The monthly and daily data usage follows the same pattern (Fig. 23.8), while we observed faster consumption in the daily data usage (Fig. 23.9), in both figures each sign represents a participant.

Figure 23.10 presents the min − max-normalized weekly mean data received from all participants over the three periods. A larger amount of downloaded data can be observed during the weekends compared to the rest of the week. Participants consumed more data during mornings and evenings, and downloaded more data on weekends. We observed clusters of spikes during afternoons and evenings. The P3 participants received fewer data during the weekend. As expected, a low volume of data was received by smartphones during the night.

Fig. 23.8 Monthly data usage CDF (all Periods)

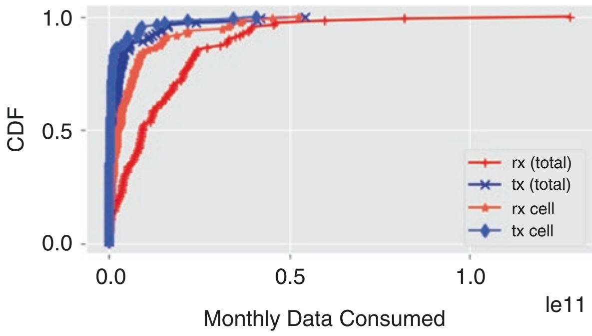
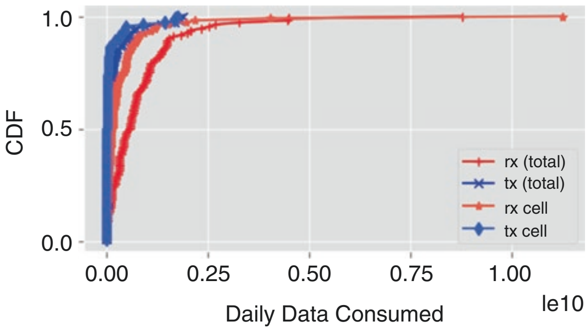


Fig. 23.9 Daily data usage CDF (all periods)



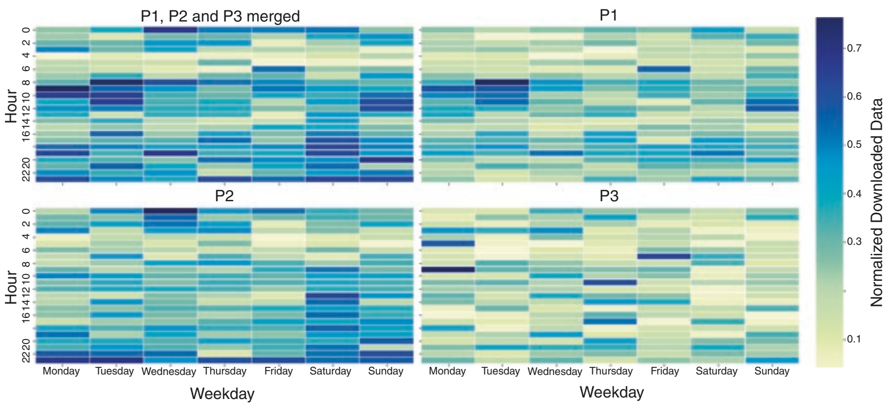


Fig. 23.10 Normalized weekly mean amount of data received per data collection per period

We found that participants in P2 consumed more data than the other cohorts, as shown in Fig. 23.11. P3 data consumption is less sparse, likely due to the number of participants in this cohort. In all three periods, we observed some outliers that consumed more data than other participants.

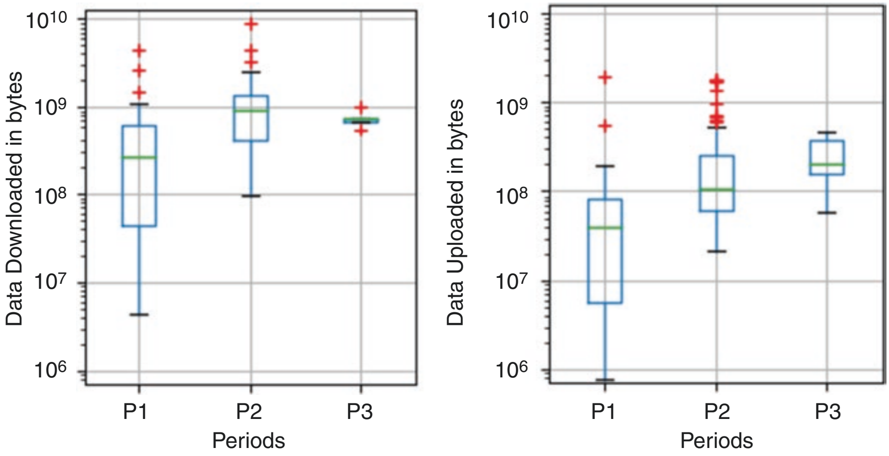


Fig. 23.11 Total downloaded and uploaded bytes per period normalized by number of data collection days

Users' Physical Mobility

We focused the analysis on the number of individual cells and AP IDs. The full dataset contains 59,602 unique cell IDs and AP IDs combined. It is important to note that the same Wi-Fi network can be accessed via different APs, in which case the ID is different, but the network is the same. This enables roaming between the different APs in the same domains. This type of configuration is often found in large networks, for example in companies, universities, and large houses. In such cases, a Wi-Fi repeater is installed to obtain better signal quality over the entire area. The repeater has the same Wi-Fi network name as the main AP, but it has a different ID. Like smartphones, these devices reconnect to another AP when they lose a connection, such as when the user is on the move.

The vertical handover process is seamless, and the device automatically reconnects to a Wi-Fi network that shares the same name as the previous network. In this case, the device already knows the security configuration to obtain a secure connection, namely a previously established authentication. Figure 23.12 shows the mean cumulative cell tower and Wi-Fi ID changes per hour and per day of the week, normalized from 0 to 1. In Fig. 23.12, we observe a lower number of unique IDs on Sundays for all periods. Other patterns are present; for instance, on Friday evenings participants were highly mobile, and the reverse is found during the night. P3 demonstrates lower mobility on Saturday evenings than P1 and P2. One possible explanation is the data collection time; P3 was recorded after the end of the first partial-lockdown in Switzerland during the COVID-19 pandemic. At this time, participants would have been less inclined to participate in external social gatherings on two consecutive nights.

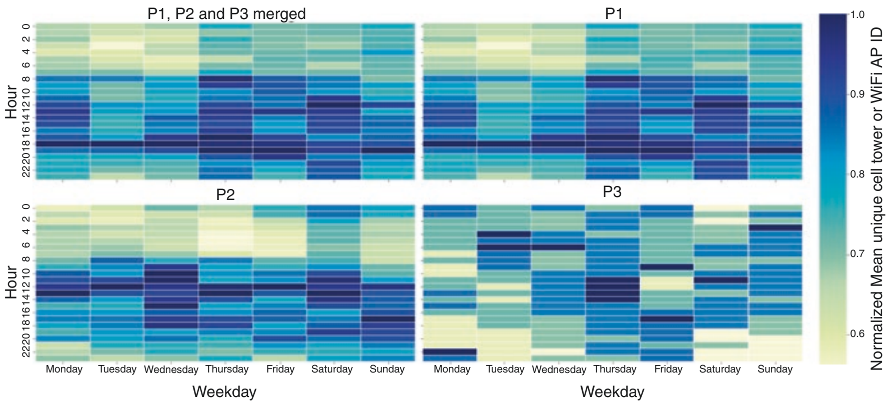


Fig. 23.12 Mean cumulative cell Tower and Wi-Fi AP ID Changes per Data Collection per Period

Discussion

The results confirm our hypothesis that network connectivity and consequently the mobile Internet is widely available in today's developed world. The results indicate that the participants' smartphones were connected to the Internet for 93% of their day (±0.8%) on average. Their devices were always either connected or searching for new network access via Wi-Fi APs and cellular towers. The quality of the connection was high overall, and we found a strong correlation between LTE and high signal strength. Furthermore, as data quantity is directly connected to the services used on the smartphone and the available network bandwidth, we observed multiple data consumption patterns that could be used to profile the users. Taken together, these findings provide important insights into the four features that impact users' connectivity and may influence an individual's decision-making and consequently their QoL. In this section, we discuss the results and their limitations before recommending other data sources for modeling environmental QoL via connected services.

Discussion of Overall Results

Over the data collection periods (2015–2020), the adoption of 4G (LTE) network access technology was close to complete in the Geneva area. The low presence of network access technologies other than LTE and Wi-Fi in P3 can be attributed to the continuous efforts of the mobile operators in updating network infrastructure (i.e., new antenna deployment), an update in performance of the smartphones' baseband processor (i.e., which leads to a faster handover), and the low mobility of the participants. A participant would have a higher number of connections if they were more mobile. Furthermore, contrary to the data in P1 and P2, data from P3 was acquired during a shorter period of time from a smaller sample size.

We found a strong prevalence of Wi-Fi usage during all three periods. As Wi-Fi is commonly used at home and at work, we made the assumption that Wi-Fi usage occurs mostly indoors, where participants are located. Furthermore, while Wi-Fi connection costs are not linked to the amount of data consumed, this is not the case for cell-based connections. Wi-Fi is generally provided by a broadband Internet connection. As noted in section "Network Access Technology", some participants use Wi-Fi less than others, possibly for cost and quality reasons. The cost of broadband is high in Switzerland, and it is cheaper to obtain an unlimited 4G connection than to have both a (Wi-Fi) broadband connection at home and a 4G subscription. The broadband connection quality also plays a role; if an area has a low population density, broadband operators will not invest in high-throughput infrastructures. As a result, using a smartphone's 4G connection to provide home Internet may become convenient and financially attractive.

Our results introduce an additional reflection with respect to the cellular and Wi-Fi connectivity, and especially the handover between the two. Autonomous handover between cell-based networks and Wi-Fi has not always been possible in smartphones. However, smartphone OSs have evolved and can now automatically switch between a Wi-Fi and a cell-based connection. In fact, the switching between the two types of connection is common in everyday smartphone usage. For example, after entering a home, a smartphone will automatically connect to the home's Wi-Fi router. A smartphone will switch to cell-based connectivity if the Wi-Fi connection is of low quality. This so-called *smart assist* feature is totally transparent to the user and does not require interaction with the smartphone. However, this process only operates in one direction (i.e., Wi-Fi to 4G); the smartphone does not subsequently test the Wi-Fi network to attempt to revert to the Internet's connection source. Given our results, we would recommend that the smart assist feature operate both ways.

Additionally, connection and disconnection events to a cell tower are important data for a network operator. Notably, operators ultimately use the data collected from their core network, particularly the number of smartphones connected to an antenna, to generate connectivity maps and understand how to improve their services. Indeed, the services can also be improved by the network operator by enabling better connection during times of increased demand for connectivity in a given area. Conversely, the network operator could also enable a low-power mode of their system during low data consumption hours, decreasing their standby energy consumption. As shown in section "Data Consumption", we found the same pattern as Walelgne et al. [45]: low data consumption during the night and higher consumption during the evening and early morning. These patterns reflect how people use their devices and connectivity. The observed higher throughput could originate from video consumption (leisure) or video conferencing with loved ones. This information can be used by a network operator to rent more bandwidth from its network provider, thus enabling a high-quality video conferencing experience at a specific time.

Study Limitations

This study has several limitations. The populations of participants in the three periods are not identical, so we are unable to comment on the evolution of the individual populations. Additionally, the two main OSs for smartphones are Android (Google) and iOS (Apple), but data was only collected from Android users in this study. As a result, information and insights about the population of iOS users is missing from this study. Additionally, the number of participants and the duration of P3 is lower than that of P1 and P2, so the generalization of the results between the cohorts is limited. We encountered another limitation during data logging due to the shortcomings of the OS de-prioritizing our logger. With the P1 dataset, we found that it was impossible to collect at least 50% of minute-based samples, even by sampling with the minute-based pulling method. Future studies shall be designed such that they address these limitations.

Quantified Self Movement

The Quantified Self (QS) movement brings together individuals from different backgrounds who wish to learn about themselves. The QS practitioners use tools, principles, and methods that are mostly enabled by smartphone applications and services and allow them to measure, analyze, and share their data [46]. The QS tools can include medical test results or well-being-oriented connected objects (e.g., fitness trackers, smartwatches), mobile applications, and web applications. Those sources of information can also contribute to collecting a high-dimensional connectivity dataset and data to quantify individuals' behaviors, health, and QoL [47]. Currently, the QS practitioners are mostly interested in their habits and health. They collect large amounts of data that they usually openly share on online platforms (e.g., quantifiedself.com, openhumans.org) for others to experiment with. In doing so, they expect to learn about themselves through their own analyses and through others'.

In the QS movement, smartphones are the main collection devices (c.f., Chap. 1). For instance, diary and reminder applications are often deployed to collect one's day-to-day emotions, mental states, social interactions, and other aspects of human life currently unquantifiable via autonomous, connected devices. Those devices and applications depend on mobile network connectivity to function. However, the collection of network connectivity by the followers of the QS movement is often neglected. At the same time, smartphone data loggers that collect smartphone user habits, such as mQoL-Log, are uncommon in QS. In the future, it will be important to explore the potential use of additional data sources in the QS movement such as smartphone connectivity levels and their influence on the daily life of the individuals. Knowledge and anecdotal data (i.e., a study with one participant) obtained by QS's followers could prompt further investigation by researchers into the links between mobile network connectivity, physical health, social iterations, individuals' overall decision-making, and QoL, for example.

QoL Technologies

The evolution of QoL technologies (QoLT), defined as technologies that enable assessment and assurance of life quality for individuals [48], is deeply linked to the development of individuals' connectivity. The possibility to improve one's life with QoLT would likely involve a component of communication to the Internet (e.g., a cloud) or edge network devices. The large amounts of data produced by personal wearable health sensors and smartphones, for example, would be processed for immediate use (in emergency situations) or for later use. The degree of QoS offered by QoLT would depend on the supported mobile network connectivity level. Therefore, the four features described in this chapter are important, as they are fundamental aspects that define the individual's connectivity. Without connectivity, there may be no QoLT. To elaborate on this point, we discuss QoL aspects defined according to the WHO and connectivity-dependent services.

The domain of physical health includes many important facets, including daily living activities. Some of these activities rely on indoor connectivity being provided in the home or at work, school, or other frequent locations. The activities may require a low-latency, high-throughput network connection to operate. For instance, smartphone applications can provide medication schedule reminders and notifications to a patient and their family. Energy, fatigue, and mobility are factors that can be quantified by smartphone and wearable data, and adequate real-time personalized care services can be provided to the individual, depending on their needs. The applications can also help a population with substance dependence issues; for example, some applications can put at-risk individuals in real-time communication with medical professionals. In the case of assisted living, connectivity can enable support services like remote healthcare and, in the future, robot care. Overall, many day-to-day physical health services provided to an individual in a given context can be supported by connectivity.

The psychological health domain of QoL may be influenced positively or negatively by smartphone applications. Connectivity to services through smartphone applications can contribute to improving this domain. Services that influence this field include entertainment (e.g., watching a video), which can influence feelings, and information services (e.g., reading news on social media), which can influence thinking processes.

In the social relationships domain, services enabled through an Internet connection can range from simple text-based messaging to smartphone-based video conferencing. More generally, opportunities for social relationships provided by connected services are extensive and are evolving. These services may range from interactive entertainment services (e.g., joint use of online games, which influences feelings) and social networks (i.e., communication and exchange of information, thus influencing the quality of the relationship). The sex industry understood this potential market and created multiple devices for remote sexual interaction through the Internet, providing intimacy for long-distance couples [49]. In the social relationships domain, the specific challenge is to ensure sufficient mobile network connectivity for both receivers to enable content exchange with sufficient user experience during the interaction.

The features of the environmental domain of QoL may be difficult to quantify, as it contains the most facets of any QoL domain and is influenced by contextual variables that may not yet be understood. For example, opportunities for leisure or education may involve the possession of interactive entertainment (and a joint use of devices such as smart TVs, for example, thus influencing feelings), the use of social networks, or the use of online education services (e.g., services for peer communication and the exchange of information). Because of the high interactivity of these examples of online leisure and education opportunities rely on connectivity to succeed. Overall, there are many services in the users' environments that may enable a better QoL and rely on mobile connectivity to be provided. However, the challenge is that a unified, well-understood model of these services and their connectivity does not exist yet.

In conclusion, QoLT may impact all the QoL domains in beneficial and detrimental manners, all depending on the implementation of the services it supports.

Conclusion

This chapter quantifies the mobile network connectivity of individuals in the Geneva area during three data collection periods between 2015 and 2020. Our results demonstrate that connectivity is ubiquitous in the day-to-day life of the participants of this study, as they could access their online services anytime and from any location. We also observed a time-based evolution of the participants' Internet connection throughout the day. Overall, our results suggest that connectivity in the same geographic location improves over time. The explored features (signal access technology, signal strength, data consumption, and users' physical mobility) offer some insights into the participants' connectivity.

We observed a high correlation between signal strength and several network access technologies. According to our data, on average, a better signal strength is available on LTE than on Wi-Fi. Furthermore, knowing the individual data consumption patterns (amount of data received and transmitted) permits the profiling of study participants. Users who consume more data during a short period (spike) may use services that other users may not access because of their low connectivity. Additionally, we considered the amount of data received and transmitted by the smartphones at different times of the day. Although we found peaks during the evenings for P1 and P2, P3 did not exhibit this pattern. It is possible that a large amount of data consumption was taking place on other devices for a better experience during the evening (e.g., watching YouTube videos on a television screen instead of a smartphone screen). In addition, we also observed less mobility on Sundays across all periods. We compared the overall mobility in all periods and noticed a lower mobility in P3, which was possibly due to the COVID-19 situation in Switzerland at the time of the study.

We discuss the results in the context of emerging QoLT, which, embedded in personal devices including wearables and smartphones, enable the collection of health information, which may support an individual's progress towards better health behaviors and, consequently, a better QoL. Overall, an increase in the use of QoLT may contribute to a better life. The range of services provided by QoLT rely on network connectivity, so future research work is needed to ensure that this connectivity matches the requirements of the technologies anywhere the user may be at any time.

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