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How Long and What For? Tracking a Nationally Representative Sample to Quantify Internet Use

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Abstract. Testing communication theories (e.g., on digital media use and effects) requires a valid empirical basis, yet especially for use time measures, retrospective self-reports may be biased. This study draws on a unique data set of 923 Swiss internet users who had their internet use tracked for at least 30 days on mobile and desktop devices (13.2 million time-stamped events) and took part in a survey covering person-level background variables. The analysis focuses on active use time overall and on the major services Google Search, YouTube, WhatsApp, Instagram, Facebook, and the online newspaper 20 Minuten. The results showed that the time people actually spend online was overestimated in self-reports. Regarding user shares for the major services, there were meaningful differences between age groups. These differences were less pronounced when it came to the time spent using these services. Internet users in all social groups spent the majority of their time online on a mobile device. Over the course of a day, the major services varied in their frequency of use: for example, messaging peaked before noon and in the late afternoon, whereas online news use was comparably constant at a lower level.

1 Introduction: Measuring Internet Use with Tracking Data

The way people use digital media and the internet has changed significantly in the past decade (Latzer et al., 2020). The internet is increasingly used across multiple devices, often on the go, and this use is very much integrated into everyday activities rather than being a discrete event with a clear beginning and end point. These usage habits have implications for measuring media use (for instance in terms of frequency or time), which has become more challenging as a consequence. This article provides a valid quantitative description of use time overall and of popular services across devices and social groups.

Whether we are interested in the prevalence of filter bubbles, want to know what the perils of being online for adolescents are, or care about internet users' privacy protection behaviors: addressing these questions and advancing media and communication theories requires solid empirical evidence on internet use, a foundational understanding of the scale of use in everyday life, in order to contextualize specific findings and to know where to look closer in future research. Such data has so far mainly been collected through people self-reporting their behavior in face-to-face, phone or web-based interviews. Recently, internet use tracking has emerged as a new option to gather such data. While there are unique challenges to logging people's internet use, it is a promising and complementary new measurement approach.

In addition to technological advances that have made gathering tracking data possible, the emergence of this new way of data collection was mainly due to biases in survey data, which is usually self-reported and retrospective. Although a recent meta-study attests self-reported data on media exposure a moderate reliability and a high stability (Scharkow, 2019), it is clear that answering questions like *"How much time do you spend online on an average day?"* is difficult and error-prone. When it comes to the use of specific services, it is likely that internet users find it even more challenging to recall exactly how many times they, for instance, scrolled through their Instagram feed and how much time they spent on the platform.

However, it is important to note that several studies have revealed various sources of biases or errors in tracking data as well. Jürgens et al. (2019), for instance, identified sampling, selection and response biases that are specific to tracking data and conclude that "tracking data should not by default be considered an unbiased source of 'true' media exposure" (p. 612). With the emergence of tracking data came several studies that compare self-reported (survey) with behavioral (tracked) data. Especially relevant in this context are not only comparisons between use times, but correlations with other relevant variables. For a sample of college students and MTurk workers, Jones-Jang et al. (2020) found that correlations between self-reported usage data and relevant outcomes were lower than between logged usage data and these outcomes, indicating that existing media use *effects* may often be underestimated rather than overestimated.

Theoretical questions of communication processes are increasingly addressed with sophisticated modeling techniques and cross-sectional regressions are no longer acceptable to support causal claims in many outlets. However, basic descriptive knowledge about the prevalence of an empirical phenomenon—such as who spends how much time on which digital platforms—is still scarce. The challenges in supplying this knowledge are often methodological, but also institutional because "simple" descriptions of media uses are not considered in many pertinent journals. This article addresses the following research question: *How much time do people actually spend online and using specific services? How does this use time differ between social groups (sex, age, education)?* The results are thus intended to contribute descriptive knowledge that is not just intuitively interesting but also necessary for subsequent theorizing of the causes and consequences of these observable patterns.

Given the existing body of literature, a combination of different data sources appears to be the most viable solution to circumvent methods-specific biases and provide a valid description of people's everyday internet use. Combining survey and tracking data is advantageous in many ways as it allows us to link behavioral data with self-reported, person-level background variables. Particularly given the research interest—describing internet use in different social groups—including self-reported demographic and socio-economic variables is vital (and they must be accurate). Such a combination of survey and tracking data has, for instance, been used to study echo-chambers in online news consumption (Cardenal et al., 2019). In existing big data research, such user characteristics are often inferred from user behavior such as clicking behavior or consumer purchasing data (e.g., for personalized advertisements). Studies that rely on tracking data for answering a plethora of different questions have other limitations, too. For instance, they tend to rely on convenience samples, are limited to very specific online environments (e.g., simulated news app to test effects of recommender systems on news exposure), and consider data from a single device or a whitelist of websites only (see e.g., Hannak et al., 2013; Loecherbach & Trilling, 2020; Möller et al., 2019).

2 Method

2.1 Data Collection

The data collection for this article consisted of two main parts: (1) All participants were already part of a mobile (*smartphone or tablet*) tracking panel (see p. 5 for a more detailed description of the sample). To gather tracking data for not only mobile but also desktop devices, the participants received installation instructions for a passive metering software for their *desktop or laptop* device at the start of the field phase. However, not all participants of the study used a desktop device or installed the passive metering software. Therefore, the proportion of mobile use time may be slightly overestimated compared to the general population. Between November 2018 and January 2019, we collected tracking data through the passive metering software on private mobile and (if the participants opted in) desktop or laptop devices. The collected variables were the URL of a visited webpage (desktop and mobile) or name of a used app (mobile only), duration and time of the visit, device, and operating system used. (2) At the end of this phase, the participants were advised to uninstall the passive metering software from their desktop or laptop devices and were invited to complete a survey questionnaire. The survey took 30 minutes on average and included questions on internet use, risk awareness online, and various internet-use related attitudes.

The participants received a small pecuniary incentive for their participation in the survey and tracking. All participants in the tracking and survey gave informed consent on their participation and the research design was approved by the authors' university's ethics review board.

2.2 Sample

An independent market and social research company recruited and sampled the participants from an existing internet panel. This panel is actively recruited, which is important in order to reduce the likelihood of a self-selection bias where people with lower privacy concerns would be more likely to select themselves into such a sample. The initial sample of 1'202 respondents is representative by age, sex, region, household size, and employment status for Swiss internet users aged 16 and over.

The data required preprocessing before analysis. At the level of tracked events (i.e., a site visit), we removed all events with 0 seconds of usage time ($N_{tracked\ events}$ = 233'675) because these reflect automatic redirects and were not part of the participants' actual internet usage; the passive metering software recorded any visited URL regardless of the time spent on it. At the level of participants, we excluded those participants ($N_{participants}$ = 51) who were tracked for fewer than the thirty days planned in the study design. Further, we excluded extreme outliers who reported more than 17 hours of internet usage per day for reasons of plausibility ($N_{participants}$ = 2). The resulting final sample ($N_{participants}$ = 923, $N_{tracked\ events}$ = 13'252'235) formed the basis for the reported results in this article.

2.3 Measures

The analyses in this article rely on a combination of the survey (self-reported use for the internet in total and major services, demographic and socioeconomic variables) and the tracking data (use time for the internet and major services).

Self-reported use. The respondents were asked to indicate whether they used the following services at least occasionally: Google Search, YouTube, WhatsApp, 20 Minuten (most popular free online newspaper in Switzerland), Facebook and Instagram.

Social background variables. Since the goal of this article is to compare internet usage in different social groups, the survey included various demographic and socioeconomic variables. In particular, the respondents were asked to report their sex as well as their age in years, which was recoded into four groups. They also reported their completed levels of educational attainment, which were recoded into three levels: individuals whose highest completed education level was the compulsory school were assigned the value *low* and those with tertiary qualifications (university degree or similar) were assigned the value *high*.

Use time: Internet total. The passive metering software logged the time the users spent on every website or app. We summed up these usage times for every participant and divided this sum by the number of days for which the respective participant's internet use was tracked (this varied between 30 and 120 days).

Use time: Major services. The measure for the use of major services was calculated by searching the tracking data for mentions of these apps and websites, and extracting these cases from the data set. Analogous to the measure for total internet use time, we summed up these usage times for every participant who reported using the respective service in the survey and divided this sum by the number of days for which the respective participant's internet use was tracked.

It is important to note that the tracking software measured *active use* of applications or websites, meaning the app or browser window was in the foreground. Therefore, our use data corresponds to the time that users spent on these respective apps or websites but does not reflect, for example, the time the participants were available to receive a message or a call on WhatsApp.

2.4 Data Analysis

Data analysis relied on descriptive statistics and particularly on mean score comparisons between different social groups in *R* (The script for the analysis and the detailed results are available at: https://osf.io/j5mhn/?view_only=4e2eee02f378420e86a1f1d8385c7b69).

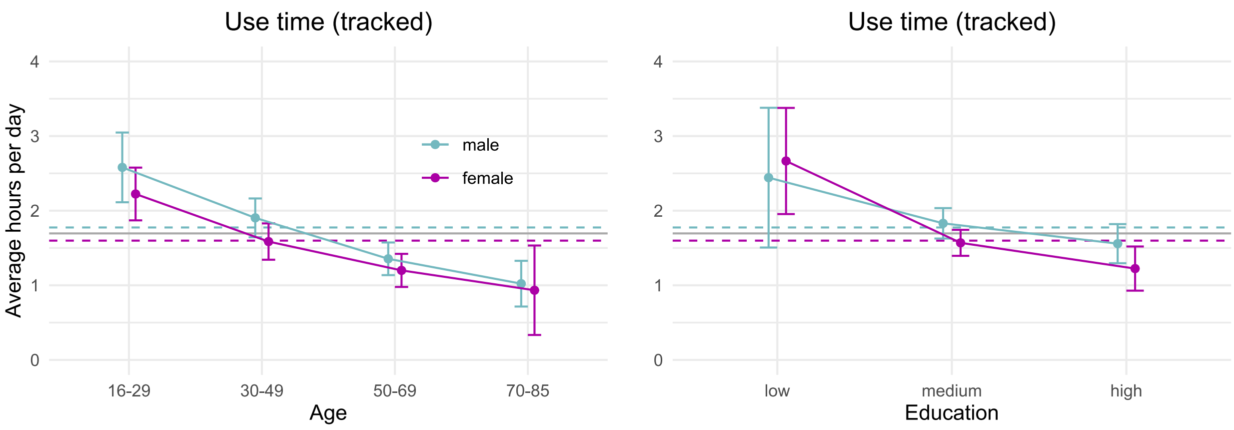
3 Results

The time Swiss internet users spend online everyday was measured both through the survey and tracking. The tracking data revealed that overall, Swiss internet users spent less than two hours on the internet every day. The self-reports were consistently overestimated in all age and educational groups and across both sexes. The mean time that internet users spent online was 1.70 hours based on the tracking data and 3.45 hours based on the survey data. These measures were weakly correlated: $r(933) = .24$, $p < .001$.

Figure 1 depicts differences in daily average tracked use time between different social groups.

Figure 1.

Total Daily Internet Use (Desktop and Mobile) by Sex, Age and Education



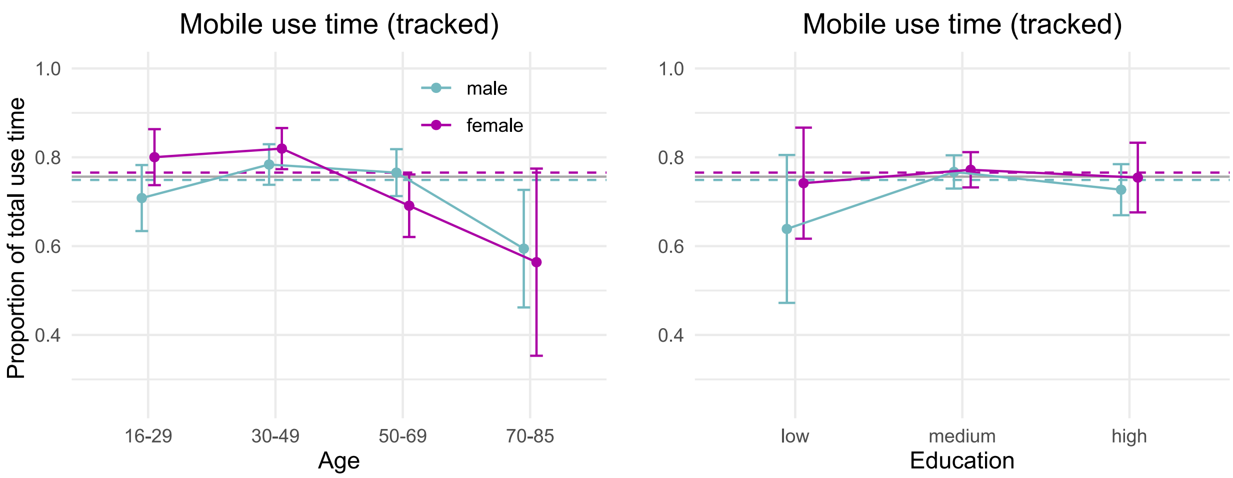
Note. Vertical bars represent 95% confidence intervals; Horizontal lines represent overall (solid) and group means (dashed). Y-axis indicates means on a continuous scale (hours per day). N = 923 internet users.

The results revealed that younger internet users and those with lower levels of educational attainment spent more time online every day. These differences were particularly pronounced for male members of the youngest age group, who spent 1 hour and 39 minutes more online on average compared to females aged 70 and over. While male internet users tended to be online longer everyday, these differences between the sexes were generally not significant.

The majority of this total internet use time was spent on mobile devices (M = 1.34 hours per day). The proportion of internet use time that was through mobile devices tended to be lower for older individuals: while females aged 16 to 29 spent 80% of their time online on a mobile device, this proportion was only at 56% for females aged 70 and over. There were no significant differences between education groups or between the sexes. Internet users across all age and education groups and across both sexes spent the majority of their time online on a mobile device.

Figure 2.

Mobile Use Time as a Proportion of Total Use Time by Sex, Age and Education



Note. Vertical bars represent 95% confidence intervals; Horizontal lines represent overall (solid) and group means (dashed). Y-axis indicates means on a continuous scale (hours per day). *N* = 923 internet users.

In addition to these global results on total internet use, this article specifically aims at empirically investigating the use of certain popular services. As the results in Table 1 reveal, virtually all Swiss internet users reported using WhatsApp and Google Search. A clear majority also used YouTube and Facebook, while 20 Minuten was used by half and Instagram was used by around a third. These six services accounted for more than a quarter (26.77%) of total internet use in terms of tracked events.

WhatsApp was the service that Swiss internet users spent the most time using on average (messages and calls), although the variance was also very high. There were also differences regarding the devices with which the internet users accessed the services. While WhatsApp, Instagram and the newspaper 20 Minuten were almost exclusively used through mobile devices (92–99% mobile accesses), the ratio between mobile and desktop accesses was more balanced for Facebook, Google Search and YouTube. The latter was the only service that was more commonly used on desktop devices.

Table 1.

Descriptive Overview: User Groups, Proportions of Mobile Accesses and Use Times

	User group	% mobile accesses	*M* use time (minutes per day)	*SD* use time (minutes per day)
WhatsApp	97.51 % (*N* = 900)	98.64% (*N* = 1'252'757)	13.23	34.53
Google Search	96.10% (*N* = 887)	51.62% (N = 474'614)	3.28	8.65
YouTube	87.87% (*N* = 811)	45.06% (*N* = 183'510)	11.91	32.55
Facebook	69.34% (*N* = 640)	60.81% (*N* = 353'720)	9.42	26.37
20 Minuten	51.44% (*N* = 475)	91.92% (*N* = 124'545)	3.46	10.17
Instagram	38.79% (*N* = 358)	93.37% (*N* = 219'499)	5.08	14.66

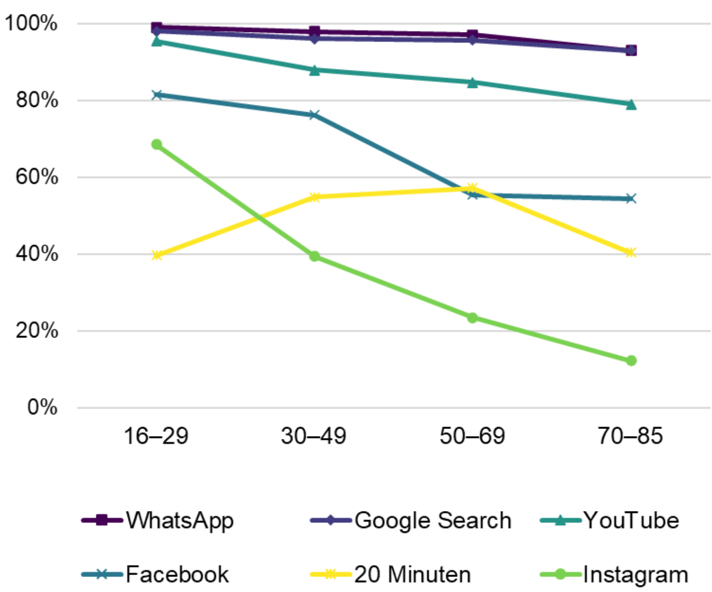
Note. User group depicts the share of internet users who reported using the service. % mobile accesses shows the share of tracked events for the respective service that were through mobile devices. The last two columns show the mean and standard deviation for the tracked time spent on these services.

When looking at how common using these services is in the Swiss internet user population, there were particularly significant differences across age groups (see Figure 3).While the use of WhatsApp and Google Search was almost uniformly distributed in the Swiss internet user population, there was a slight tendency for older internet users to use these services less. The same trend was found for YouTube and—even more pronounced—for Facebook and Instagram. 20 Minuten was the only service that was more widespread among older age groups.

Further, among those internet users who reported using a certain service, we investigated whether the time spent using these services differs between age and educational groups as well as between the sexes. Figure 4 shows how the daily time spent using Google Search varied between different social groups.

Figure 3.

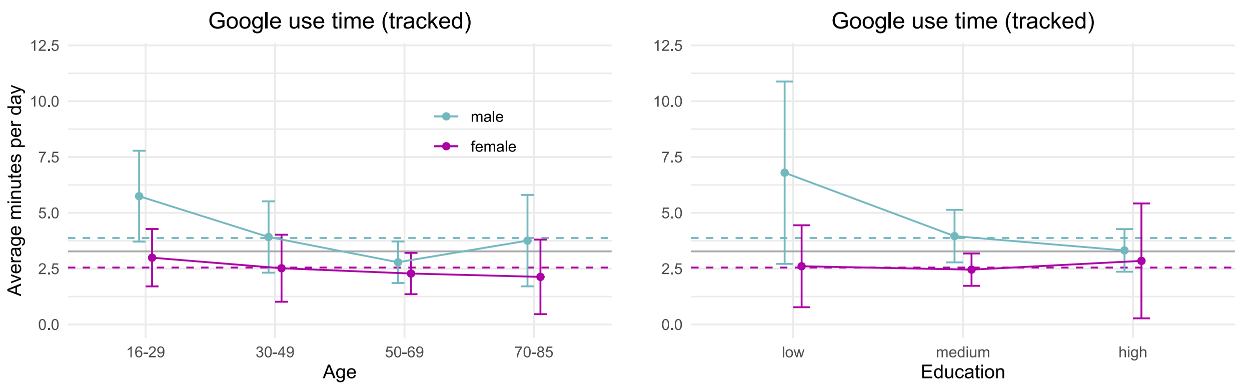
User Group of the Services by Age



Note. N = 923 internet users. The percentages depict the shares of the respondents who reported using a service in the survey.

Figure 4.

Daily Average Google Search Use by Sex, Age and Education



Note. Vertical bars represent 95% confidence intervals; Horizontal lines represent overall (solid) and group means (dashed). Y-axis indicates means on a continuous scale (minutes per day). N = 887 Google Search users.

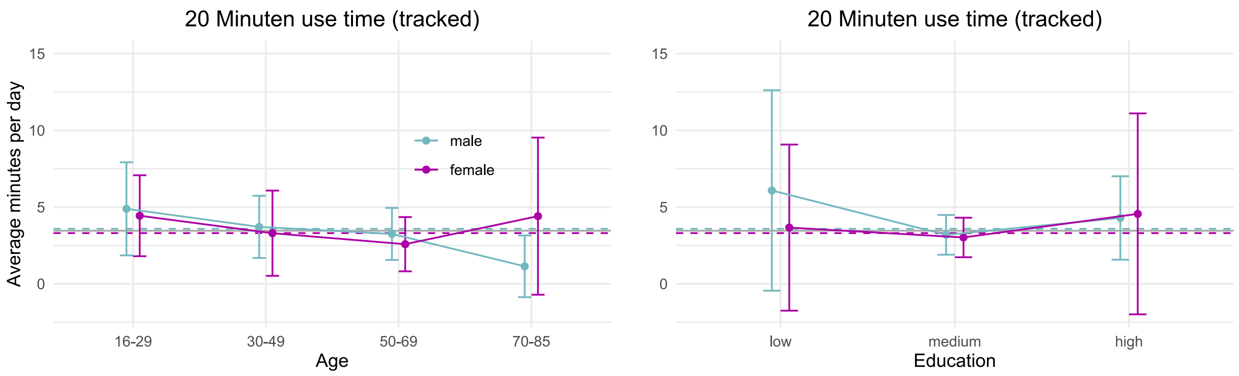
The relationship between age and time spent on Google Search was U-shaped, particularly for men: those aged between 50 and 69 spent less time on Google Search than the younger and older groups. Female internet users tended to spend less time on Google Search: while male internet users aged 16 to 29 spent 5.75 minutes per day on Google Search, this number was significantly lower at 2.13 minutes for females aged 50 to 69.

There were no significant differences between the educational groups regarding the time spent on Google Search. Male internet users with a low level of educational attainment had the highest mean Google Search use time.

Figure 5 reveals the results for the same comparisons for the online newspaper 20 Minuten. There were no significant differences between age and educational groups as well as across both sexes for the time spent using 20 Minuten.

Figure 5.

Daily Average 20 Minuten Use by Sex, Age and Education

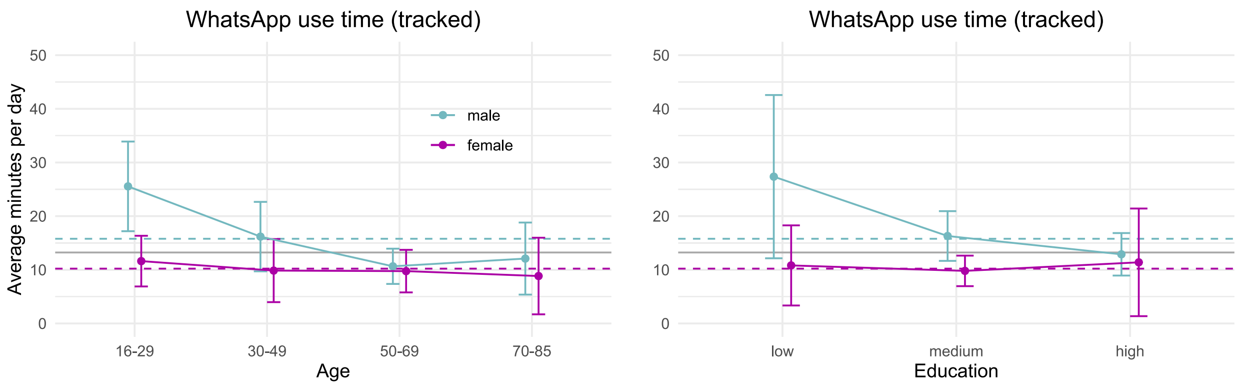


Note. Vertical bars represent 95% confidence intervals; Horizontal lines represent overall (solid) and group means (dashed). Y-axis indicates means on a continuous scale (minutes per day). *N* = 475 users of 20 Minuten.

In Figure 6, the differences in use time for WhatsApp are shown. Among female WhatsApp users, there was no difference in use time between age and educational groups. However, male WhatsApp users in the youngest age group (16–29) used WhatsApp significantly longer everyday than those aged between 50 and 69. Those aged between 16 and 29 were the only group with a significant sex difference: young male WhatsApp users spent a lot more time on the direct messaging service (M = 25.6, SD = 40.4) than their female peers (M = 11.6, SD = 24.3).

Figure 6.

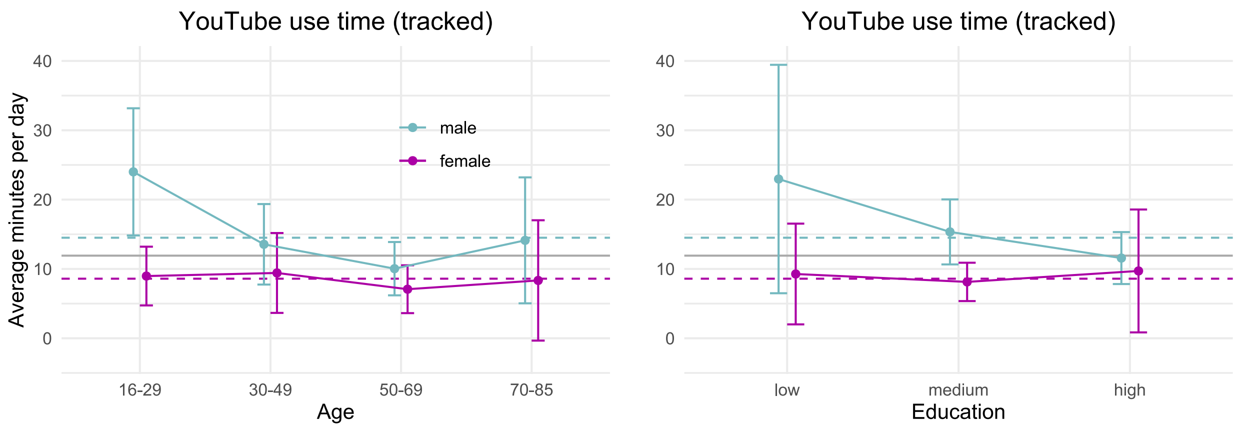
Daily Average WhatsApp Use by Sex, Age and Education



Note. Vertical bars represent 95% confidence intervals; Horizontal lines represent overall (solid) and group means (dashed). Y-axis indicates means on a continuous scale (minutes per day). *N* = 900 WhatsApp users.

Figure 7.

Daily Average YouTube Use by Sex, Age and Education

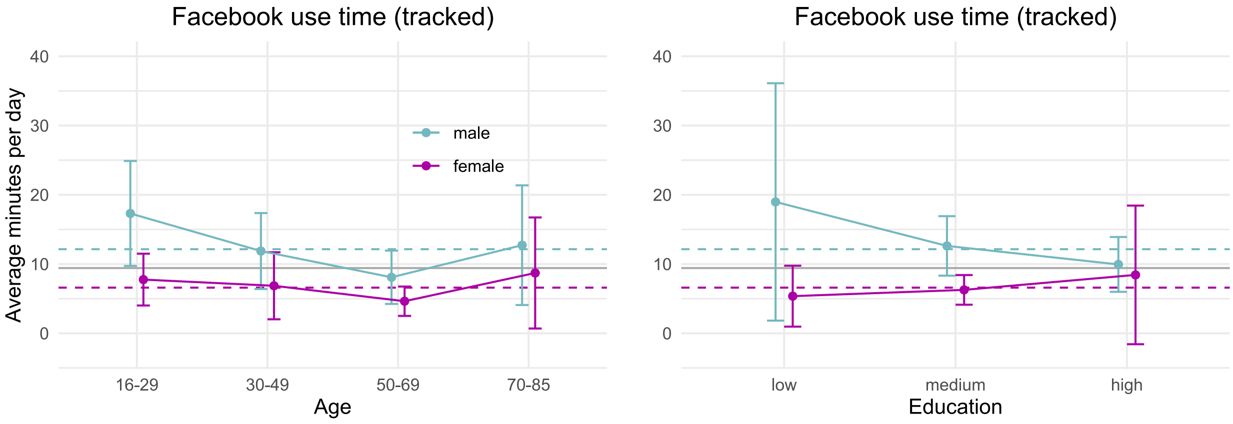


Note. Vertical bars represent 95% confidence intervals; Horizontal lines represent overall (solid) and group means (dashed). Y-axis indicates means on a continuous scale (minutes per day). *N* = 811 YouTube users.

For YouTube use time, Figure 7 shows the differences between social groups. Male internet users in the youngest age group or with low educational attainment were the groups that spent the most time on YouTube (24 and 23 minutes, respectively). Among those aged 16 to 29 was the only significant difference between the sexes where females spent significantly less time on YouTube. In general, time spent on YouTube decreased with age, although those aged 70 and over use YouTube longer everyday than those between 30 and 69. There were no significant differences between educational groups, but especially for men, time spent on YouTube tended to be higher for those with lower educational attainment.

Figure 8.

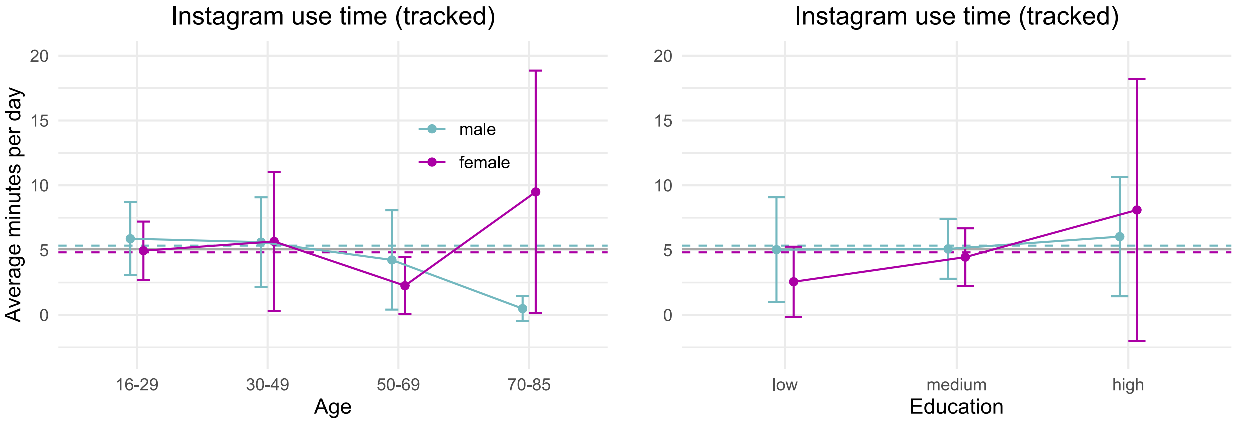
Daily Average Facebook Use by Sex, Age and Education



Note. Vertical bars represent 95% confidence intervals; Horizontal lines represent overall (solid) and group means (dashed). Y-axis indicates means on a continuous scale (minutes per day). *N* = 640 Facebook users.

Figure 9.

Daily Average Instagram Use by Sex, Age and Education



Note. Vertical bars represent 95% confidence intervals; Horizontal lines represent overall (solid) and group means (dashed). Y-axis indicates means on a continuous scale (minutes per day). *N* = 358 Instagram users.

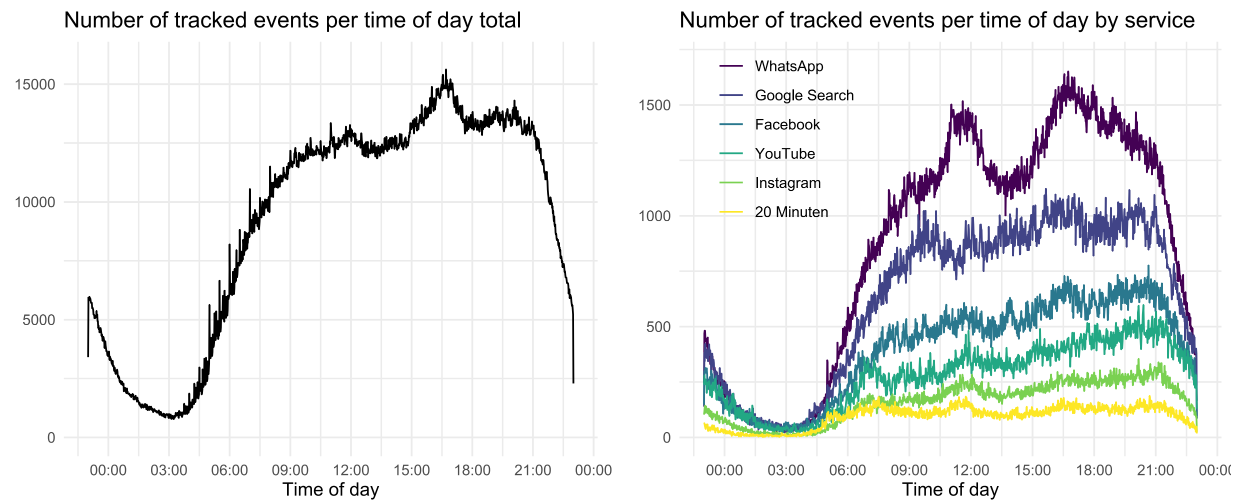
Figure 8 shows differences in use time for Facebook use. For the time spent using Facebook, there were no significant differences between age and educational groups or across the sexes. The time spent on Facebook tended to have a U-shaped relationship with age and male Facebook users tended to use the services longer every day.

Figure 9 shows the mean time spent using Instagram for different groups. Males and females did not systematically differ in the time they spent using Instagram. Younger internet users generally spent more time on Instagram everyday. Between educational groups, there were no significant differences. It must be noted that in the oldest age group, there were only 3 male and 4 female Instagram users in the sample. Therefore, the mean for this group should only be interpreted cautiously. For females with high levels of educational attainment, both the mean time spent using Instagram and the variation in time spent in this group were very high (M = 8.10, SD = 28.30).

Figure 10 depicts how many tracked events our sample contained across the course of a day. Regarding internet use in total, the amount of tracked events steadily increased from the early hours of the morning (about 6 am) and showed a clear peak between 4 and 5 pm. Thereafter, internet use started to decrease again. The daily usage pattern for the major services was similar in that there were less tracked events during the night and the use of these services started to increase at around 6 am in the morning.

Figure 10

Number of Tracked Use Events per Time of Day



Note. N = 923 internet users for the *left panel*; N = user groups of the respective services (see Table 1) for the *right panel*.

There were a few differences between the services we investigated. For WhatsApp, most uses occurred just before 12 pm and at 5 pm, with less activity on the app in the morning and during the afternoon. Internet users used Google Search, Facebook, YouTube and Instagram most heavily in the evening (around 9 pm), although there were also smaller peaks in the morning (e.g., at around 7 am for YouTube). The use of the online newspaper 20 Minuten was relatively uniformly distributed across the course of the day, except for smaller numbers of tracked events during the night.

4 Discussion and Conclusion

Relying on a combination of survey and tracking data, this article aimed at describing how much time internet users in different social groups spend online and using different services.

A major result of this article is that public perceptions of time spent online that are usually derived from self-reported data, particularly for younger people, are exaggerated: we find that on average, people spend less than two hours a day with an app or website on their screen, which is exactly half the time they self-reported spending on the internet. The stark differences between self-reported survey and tracked internet use data provided further indication for the importance of combining both methods for a valid empirical measurement of internet use and refinement of measurement strategies (it should not be assumed that tracking measures a ground truth and self-reports are always biased).

Moreover, our results indicate only small differences between age groups: while we did find differences in adoption rates of specific services, there were generally only small differences in use time between age groups among the users of a service.

There were a couple of results that may go against common intuitions. For instance, we found that in the youngest age group (16–29), male internet users spend more than double the time on WhatsApp as compared to female users. Also, the participants in all social groups spent the majority of their time online on a mobile device and, for instance, only one in ten accesses to the online newspaper 20 Minuten was through desktop devices. It remains an open question whether this mobile-to-desktop-ratio is different for other types of news outlets. However, the predominance of mobile over desktop internet use emphasizes the importance of tracking internet use on mobile devices including apps (previous studies mainly relied on desktop browser plug-ins). The results regarding internet use across the course of a day revealed that Swiss internet users start being online in the early hours of the morning. Internet use peaked in the later afternoon and decreased thereafter.

A major advantage of the tracking method in this study was that it gathered observational data in a natural internet use situation (media use *in situ*). Effects of the measurement on participants' behavior were likely small, because they did not see or feel the measurement during their everyday internet use. Such an approach allows a more accurate approximation of their *actual internet use*. There are, however, still a number of limitations to consider. For research ethical reasons, it was technically possible for participants to temporarily disable tracking at any time—however, we assume social desirability effects are negligible because the data reveal widespread use of typically sensitive activities such as pornographic video consumption (1.4% of all tracked events[1]).

Furthermore, there were respondents in the sample who reported using a service, but their tracking data did not include any tracked instances of that service. It is unclear whether this inconsistency can be attributed to the fact that the participants use these services only very rarely and did not happen to use them in the duration of the tracking data collection. Also, the tracking data was collected on the participants' private (mobile and desktop) devices. The data does not, however, allow us to distinguish between private and professional internet use. While internet use for professional purposes is, therefore, included in the data for those who use their private device for work, this is not the case for those who have separate devices for their work.

A few methodological conclusions for further studies relying on tracking data can be drawn from the empirical part of this article. Gathering and analyzing tracking-data is resource-intensive in many ways and entails specific challenges. Conducting a tracking study incurs *high cost*, particularly compared with collecting survey data. This is especially the case when the tracking data is collected over a long timespan, for a representative sample and for multiple devices—which is necessary to obtain an encompassing depiction of the participants' actual internet use. The main drivers of these costs are recruiting participants and building the necessary infrastructure for collecting and storing the data. Both the data collection and analysis processes tend to be more *complex* for tracking than for survey data including questions with closed answer categories. The tracking data that was collected for this article was significantly more messy than the survey data and required a thorough cleaning up process as well as profound understanding of the subject at hand. Despite carrying out this process meticulously, the data analysis for tracking data is probably more error-prone compared to survey data, which may be subject to more biases during the data collection process. It is clear, however, that especially considering these biases, it is extremely important to make the code used for preprocessing and analyzing tracking data openly available.

Taking these challenges and limitations into account, tracking data—especially in combination with self-reported survey data—provides a promising empirical basis for answering various questions about digital media use and consequences in the future, especially when considering that any empirical data can always only be a selective and incomplete depiction of reality.

[1] We calculated this figure by searching the tracking data for strings of the seven most popular pornographic video sites (see https://www.menshealth.com/sex-women/g22481925/most-popular-porn-sites/).

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