The smartphone as a tool for mobile communication research: Assessing mobile campaign perceptions and effects with experience sampling

Otto, Lukas P.; Kruikemeier, Sanne

Special Issue: Mobile Comm

new media & society
2023, Vol. 25(4) 795–815

Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/14614448231158651
journals.sagepub.com/home/nms

The smartphone as a tool for mobile communication research: Assessing mobile campaign perceptions and effects with experience sampling

Lukas P Otto
GESIS—Leibniz Institute for the Social Sciences, Germany

Sanne Kruikemeier
University of Amsterdam, The Netherlands

Abstract

Mobile communication differs from other forms of mediated communication in terms of connectedness, dynamics, omnipresence, and interactivity. Consequently, it can be difficult for scholars to investigate mobile communication using traditional research methods. The main goal of this article is to show how the mobile experience sampling method (MESM), in combination with data donations, can be useful for addressing the challenges of mobile communication research. We explicate the design using an experience-sampling study that was conducted on mobile campaigning during the Dutch 2021 national election. Using this case, we discuss how MESM can be extended and combined with other data sources, such as tracking data, GPS, and sensory data, to address the challenges of mobile communication effects research and facilitate future studies.

Keywords

Data donations, longitudinal methods, mobile communication, mobile experience sampling

Corresponding author:
Lukas P Otto, Computational Social Science Department, GESIS—Leibniz Institute for the Social Sciences, Unter Sachsenhausen 6-8, Cologne 50667, Germany.
Email: lukas.otto@gesis.org

Introduction

The smartphone has "invaded every sphere of our lives" (Ling, 2012: xi). But while smartphones are becoming an essential part of our communication toolkit (Ling, 2012; Schnauber-Stockmann and Karnowski, 2020), the omnipresence of mobile communication also poses new methodological challenges. Traditional surveys do not capture dynamic and short-lived mobile communication episodes and using "tracking" based on behavioral log data is technically difficult, if not impossible (Christner et al., 2021). Therefore, many research questions remain unanswered. However, while mobile communication is a challenging subject to investigate, the fact that mobile devices are ubiquitous provides opportunities for social scientists. The fact that we carry around mobile devices all the time might give a solution to the challenges of mobile communication research since it is easier to conduct mobile and in-situ surveys, collect passive sensor data, run field experiments because of the features of smartphones (Boase and Humphreys, 2018). Some researchers are even more optimistic and assert that we now have a "new methodological toolkit" for conducting empirical work (Schnauber-Stockmann and Karnowski, 2020: 145).

This article aims to describe the extent to which mobile methods can address some of the main challenges of mobile communication research. Mobile methods such as experience sampling involve "a naturalistic measurement approach in which human behavior is reported by an individual at multiple times over a period of days, weeks, or months" (Hedstrom and Irwin, 2017: 1). Thus, a more idiographic and dynamic method is perfectly suited to the characteristics of mobile communication and, therefore, provides a promising way forward. And while this method is certainly not new—it stems from the psychological measurement paradigm—it has attracted renewed attention as it is becoming an imperative tool to investigate mobile communication, especially in the current media environment.

We will first illustrate some of the core characteristics of mobile communication, such as dynamic, short-lived communication episodes, and demonstrate how they pose a challenge for traditional communication research methods. Such methods include retrospective self-report and experimental designs and computational methods that involve tracking digital behavioral data. Second, we will show how the mobile experience sampling method (MESM) might help researchers tackle the challenges of mobile communication research since it adapts to the characteristics of mobile communication. Memory errors can be decreased since surveys are delivered "in-situ"; dynamic, short-lived processes can be captured by the intensive longitudinal nature of many mobile designs; and data donations might overcome the challenge of proprietary apps and systems. We conclude by discussing the limitations of mobile designs and the possible extensions of MESM, such as mobile sensor data or data donations.

Characteristics of mobile communication and challenges for mobile communication research

These key characteristics of mobile communication provide unique challenges for scholars who conduct mobile communication research (Kuru et al., 2017). Mobile communication is characterized by (a) connectedness and an always-online, always-connected experience; (b) a traceable and highly personalized communication environment, and finally; and (c) synchronous and asynchronous interactivity, resulting in frequent but short communication episodes.

First, mobile communication creates a "social experience that is not bound by traditional spatial limitations" (Campbell, 2013: 104). People engage in mobile communication while moving from one location to another and engaging in public life. Due to its connectedness, compactness, and general affordability (Campbell, 2013), people can be "always online and always connected" (Vorderer et al., 2016).

To a large degree, the use of Internet-enabled applications (apps) is a unique and dominant feature of mobile communication, and these apps are predominantly designed to be used on a smartphone (e.g. personal messaging apps, such as WhatsApp, and social media apps, such as Instagram and TikTok). Moreover, social media platforms, such as Facebook, are most often used via mobile apps (Statista, 2021). However, this mobile ecosystem is generally very opaque, which means it is impossible for researchers to assess the ecosystem, characteristics, and context of communication in these apps (Razaghpanah et al., 2018). While GPS is used to track the location of individuals (locatability, see Schrock, 2015), other personal data are shared with many third parties. Such information may include email addresses, advertiser IDs, device IDs, and Facebook IDs (Brandtzaeg et al., 2019). These data can be used for analytical purposes and for targeting people with tailored information and ads (Grewal et al., 2016). Hence, the smartphone is becoming a highly personalized device that includes tailored apps and context-aware communication (Sarker et al., 2019).

Third, mobile communication, especially on social media, can involve more synchronous interactivity. When people receive information via their mobile phones, they can immediately respond. For instance, when an individual receives a text message via WhatsApp, they can directly start a conversation; when a story or picture is shared on social media, this can instantly result in likes or comments. This creates communication flows between network ties that have become increasingly synchronous (Kuru et al., 2017). However, such communication can also be asynchronous. While users can choose to respond immediately to a text message or a comment on a social media post or ad, they also can delay their response, resulting in asynchronous communication. This results in fast, short communication episodes and follows different dynamics than other forms of mediated communication (Naab et al., 2018). These key characteristics of mobile communication make it challenging to investigate. These challenges are linked to ways of measuring the *usage* of mobile communication (challenge I and challenge III), the *content* of mobile communication (challenge II and challenge III), and finally, the *effects* of mobile communication (challenge IV and challenge V).

Challenge I: mobile communication and retrospective self-reports

It might be a truism of communication research that measuring media exposure with retrospective self-report measures has become difficult in today's media environment (De Vreese and Neijens, 2016; Scharkow, 2016, 2019). The characteristics of mobile communication, especially the connectedness and short, frequent communication episodes, make it even more challenging to assess the quantity of mobile communication usage and usage patterns, sources, and communication repertoires.

The embeddedness of mobile devices in everyday life, as people access their smartphones at any time and from any place, makes it difficult for users to remember individual communication episodes. Moreover, smartphone usage is often incidental and might only last seconds, such as when users are reacting to notifications (Ellis, 2019). Thus, self-reported time spent on the smartphone may be biased when compared to other measures of media exposure, such as tracking methods (Johannes et al., 2020; Kobayashi and Boase, 2012; Verbeij et al., 2021), data donations (Ellis et al., 2019; Ohme et al., 2020), or repeated measures (Naab et al., 2018).

It is not only the quantity of mobile communication usage that is difficult for users to remember but also the different sources, apps, channels, and media environments. Thus, these factors are hard to assess. The always-online, always-connected nature of mobile communication and the hybrid media environment make it difficult, if not impossible, for recipients to identify individual sources and channels. In today's hybrid media landscape, platforms have become channels and sources of information, and, of course, recipients have become communicators (Dennis et al., 2016). Since mobile devices combine communication channels, mediums, and roles, asking detailed retrospective questions of users is more challenging than it was in years past. Since people access information about politics, health, interpersonal communication, entertainment, and educational content in short episodes on one device, it is challenging to distinguish and report individual sources of information and communication. Thus, the key characteristics of connectedness, location independence, and frequent-but-short communication episodes make the measurement of mobile communication usage even more challenging than measuring other forms of communication, such as traditional mediated communication.

Challenge II: personalized/targeted communication

Mobile users are increasingly tracked by various parties. Mobile apps collect, aggregate, use, and share personal data (such as location, account details, and other personal information). For instance, Brandtzaeg et al. (2019) examined how popular mobile applications (in their example, social media using the Android platform) share personal data with the first-domain and third-party trackers. They found that a majority (57%) of the apps in their study shared personal data. They noted that the actual rate of tracking is likely higher since the data are not easily accessible for some apps (e.g. Facebook). These personal data can be used and shared for advertisement purposes.

Moreover, the collection, aggregation, use, and sharing of personal data can be used to target small groups of potential mobile users by conveying personalized messages that may be tailored to their demographics, interests, personalities, and so on. Consequently, targeted mobile advertising is growing (Brandtzaeg et al., 2019; Schrock, 2015). Hence, mobile devices are now excellent tools for personalized communication such as online targeted advertising, political microtargeting, and data-driven campaigning, whether through social media apps on a smartphone or personal messages, emails, and notifications. Specifically, in the case of data-driven campaigning, segmentation, and personalization provide a challenge for traditional research methods and designs. Traditional campaign research operates on the assumption that campaigns deliver similar information and ads to a sizable group of recipients or voters (Chaffee and Metzger, 2001; Otto et al., 2022). However, traditional methods are limited when they are used to investigate the effects of multiple personalized campaign messages. Moreover, most experiments are tied to investigating either media selection *or* effects (Feldman et al., 2013) and thus do not fit the mobile communication flow (see challenge IV).

Challenge III: proprietary platforms and devices

From a technical perspective, the biggest challenge for the investigation of mobile communication material is the closed and proprietary structure of software, such as applications, on the mobile devices themselves.

Depending on the platform, it can be very difficult, and sometimes impossible, to obtain data (even for academic purposes), either on the content of communication (e.g. ads, search results, news feeds, messages) or on the communication behavior of users (comments, likes, shares, messages, exposure, usage; Christner et al., 2021). In an even greater challenge, scholars may face legal threats (e.g. the NYU Facebook ad observatory) when trying to gain access to platforms such as Facebook.

A possible solution for investigating digital communication on proprietary platforms is to use automated tracking tools that participants can install to capture the communication flows on a particular platform, such as Facebook (see Christner et al., 2021 for an overview). For some platforms, it is possible to scrape a vast amount of digital trace data (Menchen-Trevino, 2020; Stier et al., 2020). Tracking tools have many advantages and can solve many of the problems mentioned in this article—they make self-reports unnecessary and they provide detailed information on personalized and targeted messages, and they are able to capture dynamic and short-lived processes. However, while considered a "gold standard" in exposure research, tracking tools are not necessarily suitable for investigating *mobile* communication. First, most platforms, especially those that are most frequently used (e.g. Facebook or Google), are constantly updating their software to make it harder to gain access to the system and the data. The researcher is always dependent on tech companies to provide access.

Second, tracking and logging software can be limited when analyzing mobile communication tools such as social media apps, messengers, or video platforms. They primarily offer very general measures of screen time (Ellis et al., 2019; Ohme et al., 2020), only allow capture for mobile apps that are open or in the forefront (Johannes et al., 2020; Verbeij et al., 2021), or are limited to data about very specific activities, such as phone calls and short messages (Boase and Ling, 2013). Thus, measuring mobile communication *content* is "almost impossible" (Christner et al., 2021: 7), and researchers are stuck with relatively general information about app usage. This is mainly because the operating systems of many mobile devices add a second layer of security; mobile apps and systems are even more secured against tracking tools than the browser versions of those platforms. In other words, gaining access to social media data is already a significant effort, but collecting data from mobile devices might be even harder.[1]

This issue becomes crucial when considering that many social media platforms are only used on mobile devices. For example, the mobile-only share of Instagram is as much as 96%, and other platforms such as TikTok were not even developed outside of mobile applications and were for a long time not avail. Even for older social media networks such as Facebook, the desktop-only share is 1.5% (Statista, 2021). Thus, if a researcher is interested in studying communication on mobile social media apps, then browser-tracking methods are not suitable to capture these data.

Finally, even if there were technical solutions available for studying specific apps or systems, mobile communication is very diverse and not limited to one platform, medium, or channel. Therefore, even if researchers can gain access to *one* app, it is still impossible for them to collect data from messaging services, emails, news apps, video channels, or streaming providers. It poses a severe challenge for researchers to capture the detailed data necessary for answering a wide array of mobile communication research questions.

In short, this means that obtaining data from most smartphone apps is impossible through the use of logging data at the moment; meanwhile, most communication (for instance, on social media) takes place on mobile apps. Thus, if scholars are interested in social media communication or conversations taking place on most mobile apps, they cannot use tracking data as explained here, and they have to deal with large biases if they use traditional survey measures (as explained in challenge I).

Challenge IV: dynamic and short-lived processes in mobile communication

As outlined earlier, mobile communication is different from other forms of communication: In contrast to face-to-face communication or traditional mediated communication, it is characterized by frequent, intensive, and short communication episodes (Naab et al., 2018) that involve interactive, synchronous communication. Similar to the measurement challenges of mobile communication usage itself, it is also difficult to assess the *effects* of mobile communication since they are equally dynamic, short-lived, and context-dependent. Traditional designs, such as panel surveys and experiments, are not able to capture these processes. They rely on one or few measurement occasions with long time lags. Thus, they are not suitable for capturing communication dynamics, short-term patterns of mobile communication effects, and short-lived outcomes. Such phenomena include emotions or attentional processes (Otto et al., 2020) and episodic fluctuations of well-being (Johannes et al., 2020). In other words, the investigation of mobile communication *effects* needs to fit the frequent, short, and dynamic *usage* patterns of smartphones (see also challenge I).

As with the challenges above, tracking and logging tools could solve this issue and provide almost continuous, dynamic, fine-grained data. However, for most questions in communication research, digital trace data are insufficient and need to be combined with survey and self-report data (Stier et al., 2020). The particular problems of capturing digital trace data for mobile devices as described above (challenge III) apply not only to communication usage and content but also to communication behavior such as messaging, liking, sharing, and commenting.

Challenge V: minimal media effects and personal communication dynamics

While the era of "mass communication" was characterized by larger and more homogeneous media effects (Bennett and Iyengar, 2008; Chaffee and Metzger, 2001; Holbert et al., 2010), mobile communication is characterized by short communication episodes, "thin slices" of communication, and personalized media content. It is thus crucial to rethink the magnitude and pattern of media effects.

Researchers have concluded that the magnitude of mobile communication effects is often smaller than its "nonmobile" counterparts. Take, for example, the literature on learning through mobile devices versus on desktop computers. There is evidence that reading the news on a smartphone leads to less acquired knowledge than reading on a desktop computer or consuming news offline (Ohme, 2020). However, since recipients are most likely engaging with mobile news apps more often than traditional news media, it could be the case that those "minimal effects" add up and might even trump the effects of traditional news media. In other words, the research designs applied to mobile communication effects research need to fit the realities of the type of communication and the phenomena under study. That means if researchers are investigating a continuous stream and short episodes of communication usage and effects, then traditional experimental designs, panel surveys, and linkage analysis are not suitable, and studies need to employ more fine-grained, dynamic methods. Take mobile and potentially personalized campaign messages as an example: the effect of one message might be small and may not lead to changes in relatively stable variables like voting behavior. However, investigating (a) the constant stream of (targeted) campaign messages and (b) the immediate reactions to political ads might lead to a more nuanced picture of "minimal, but cumulating" effects.

Moreover, it is crucial to take into account and analyze complex and *individual* patterns of media effects. In other words, since usage patterns and communication content are personalized, it is necessary to think about the personal effects of media dynamics (Thomas et al., 2020; Valkenburg et al., 2021). For example, consider the effects of mobile political campaigns on citizens' interest in politics and the campaign. It might be the case that for some citizens, every political ad seen on a mobile phone contributes to their interest in the campaign or politics. In contrast, other citizens develop fatigue over the course of a campaign, and there is a tipping point at which they may even lose interest in the campaign. Additionally, for some individuals who might not ordinarily develop an interest in the campaigns, the dynamics change when they receive personalized messages. These individual communication patterns are very likely to occur when people are exposed to personalized and dynamic mobile communication; therefore, they cannot be captured through many traditional research designs. Additionally, if researchers simply "add up" the effects of each individual and do not take into account individual patterns, they might arrive at spurious conclusions and make false assumptions about communication effects (Thomas et al., 2020; Valkenburg et al., 2021).

Mobile devices as tools for mobile communication research

The challenges presented above can make it difficult for communication researchers to assess and analyze mobile communication. At the same time, mobile devices are powerful tools for researchers, and these devices allow for research designs that would have been hard or impossible to imagine in past decades.

There are many different ways to integrate mobile devices into the research process (Boase and Humphreys, 2018), but the *mobile experience sampling method* (MESM) is among the most commonly used approaches. It is sometimes also called ambulatory assessment or momentary ecological assessment. The idea is to measure the variable of interest multiple times per day via short mobile surveys. Triggers for these short surveys (the experience sampling form) can be signals and notifications (signal-based sampling) on the mobile device or specific events that automatically trigger the mobile survey (event-based sampling; Bayer et al., 2018; Johannes et al., 2020; Otto et al., 2022). Despite their introduction to communication research 25 years ago (Kubey et al., 1996), MESM designs are still not commonly used in communication research; Schnauber-Stockmann and Karnowski (2020) counted 31 studies to date in their review.[2]

While MESM designs alone are already well-suited to facing some of the challenges described above, such as mobile communication exposure and dynamics, it is a valuable approach to combine the intensive longitudinal data with other data sources such as tracking data or data donations (Beraldo et al., 2021). In our example, participants used the screenshot function of their mobile devices to provide the researcher with information on the content of a political ad that they received. The idea of MESM is to link recipients' reactions to the message with content analysis of these screenshots. This design, sometimes called *mobile intensive longitudinal linkage analysis* (Otto et al., 2022), is suitable for measuring mobile communication since it captures relevant media exposure much more accurately than retrospective self-report measures and diminishes memory errors and biased self-reports (Naab et al., 2018; Ohme et al., 2016; Verbeij et al., 2021). Also, it is adaptive to personalized and targeted communication since it captures media content on the individual level. Thus, it can also measure the effects of personalization and targeting. This design is independent of the security measures of social media platforms, app developers, or mobile operating systems since it uses simple solutions such as screenshots and intensive longitudinal surveys. Additionally, it can measure the dynamic, short-lived, episodic, and individual communication patterns that are typical of mobile communication. As we have argued above, MESM and data donations might be able to deal with some of the challenges of mobile communication research. Based on data from the Dutch elections in March 2021, we will show how such data is gathered, present methodological challenges and research questions, and determine which research questions could be answered based on this experimental design.

Experience sampling and data donations in the 2001 Dutch national election

For our study of MESM and mobile campaign communication, we created a set of methodological research questions that address participants' motivation and willingness to take part in such a study. Additionally, we created simple, substantive research questions that demonstrate how intensive longitudinal data can be used in dynamic communication environments such as political campaigns.

Example research questions: mobile ads and campaign interest

Election campaigns are especially suitable for showcasing intensive longitudinal methods since they represent dynamic periods in time (Thomas et al., 2021). In addition to persuading voters, campaigns should, from a normative point of view, also increase interest in the campaign. This goal is crucial for mobile social media campaigns that can be targeted at specific audiences and thus spark the interest of otherwise hard-to-research audiences. Online social media ads should also be designed to fit the targets' interests and therefore increase interest in campaigns and politics (Zuiderveen Borgesius et al., 2018).

The example research questions represent some of the challenges discussed above, especially challenges IV and V, which measure dynamic and individual processes, and challenge II, which relates to personalized and targeted communication. The questions also address challenge I, which relates to the usage of mobile communication—in our case, the use of mobile campaign ads (see Niederdeppe, 2014 for the challenges of measuring campaign exposure).

> RQ1: How are campaign interest and user evaluations of political ads related over time?

The ability to analyze causality is a strength of longitudinal design. Therefore, we also ask whether a user's campaign interest leads to a more positive evaluation of specific ads, whether a positive evaluation of the ads leads to higher interest in an election campaign, or whether "causality runs both ways" (Otto et al., 2018). Therefore, we attempt to determine the following:

> RQ2: Does campaign interest affect ad evaluations at a later point in time? Does ad evaluation affect campaign interest at a later point in time?

There may be more complex patterns at work in the longitudinal relationship between ad exposure and campaign interest. There could be, for example, a tipping point in the campaign where exposure and interest are increasing (hot phase of a campaign; Thomas et al., 2020) or a point where exposure to ads becomes annoying and people tire of the campaign communication. We therefore ask the following question:

> RQ3: Is there a uniform relationship between ad exposure and campaign interest, or does this relationship change during the campaign?

Methodological research questions

Since this article aims to illustrate the MESM design (with screenshot data donations) to mobile communication researchers, it is also necessary to address questions of data quality, the intrusiveness of the method, and participants' motivations. While there is some research on how to motivate participants for MESM studies (Bolger and Laurenceau, 2013; Fraley and Hudson, 2014; Napa Scollon et al., 2009), the combination of experience sampling and data donations makes the task more demanding for participants. Additionally, uploading screenshots introduces the following challenges: (a) a technical challenge since participants need to have the skills to take screenshots on their smartphones and upload them; (b) a self-selection challenge since interest in the topic could motivate participants to upload their data and be active, that is, politically interested citizens would upload more data; (c) a privacy challenge since participants will potentially upload personal data and need to trust that it will be used properly (Ohme et al., 2020). We, therefore, pose two additional research questions:

> RQ4: How does the motivation of participants develop over the course of an MESM study with data donations?
>
> RQ5: Do demographics (age, gender, education), motivation, interest in the campaign, and participants' privacy concerns predict their activity and their willingness to participate in the study?

Example study: mobile campaigns in the 2021 Dutch national election. This campaign provided a suitable example to showcase the characteristics and challenges of studying mobile communication in general. Like other forms of mobile communication, it is hard to assess mobile campaign exposure. The communication episodes can be short, incidental, and prone to memory errors in self-reports (Niederdeppe, 2014). Mobile campaign communication is hybrid, that is, spread over several apps and channels, such as ads on social media or news apps, personal messages, video platforms, and emails. Second, mobile campaigns are increasingly data-driven; they use digital trace data to target small groups of voters and personalize messages to appeal to them, which leads to the problems discussed above. Third, campaigners, political parties, and politicians themselves communicate through closed and proprietary systems, such as social media platforms or messenger apps. Finally, campaigns consist of highly dynamic communication periods that involve intensive general media usage (Thomas et al., 2020), important events such as political debates (Maier and Faas, 2011), and dynamic developments such as wins or losses in polls and increasing or decreasing levels of mobilization. In short, the challenges discussed above can be accurately represented based on the mobile communication that takes place during election campaigns.

We will showcase a mobile experience sampling study that utilized data donations during the Dutch 2021 national elections. The main focus of the study is to investigate the effects of personalized social media ads on users' emotions, political evaluations, level of interest, and attitudes but also on their voting intentions and mobilization.

Sample, procedure, and measures

In total, $N = 155$ (age: $M = 48.49$, $SD = 16.06$, 46% female) participants were invited to take part in the study. On the experience sampling form, they recorded every time they encountered political ads or campaigning material on their mobile devices (on social media and other platforms) starting 2 weeks prior to the 2021 Dutch national election. They were also asked to take a screenshot of the content they had just received and upload it together with the experience sampling form.

Additionally, participants filled out short mobile questionnaires every other day about current events in the campaign (debates, interviews, political/media events). Furthermore, they participated in a four-wave panel survey measuring their general political ideology, party identification, demographics, turnout, voting intention, and personality.

Whenever they encountered and uploaded a screenshot of the campaign material, participants also completed a short questionnaire that asked them to evaluate the message, their emotional reaction toward the message, and their opinion of the politician and/or party. More specifically, we asked participants to rate, on a scale from 1 to 7, the extent to which they found the ad "interesting," "informative," and "persuasive" (Cronbach's $\alpha = .94$, $M = 3.13$; $SD = 1.62$).

To learn more about the *motivation* and commitment of the participants, we asked them to indicate three times (on the first and the last day of the data collection period) the extent to which they found the study "boring" or "interesting" and whether they were "motivated to take part in the study" (Cronbach's $\alpha_1 = .71$; Cronbach's $\alpha_2 = .72$). We furthermore asked three times during the election campaign to rate their level of *interest* in the campaign on a scale from 1 to 7 ($M_1 = 3.98$, $SD_1 = 1.55$; $M_2 = 4.72$, $SD_2 = 1.37$; $M_3 = 4.77$, $SD_3 = 1.51$). To investigate whether participants' privacy concerns predicted their activity in the study, we asked them four questions regarding privacy. For example, "I am concerned that personal information (such as my online surfing and searching behavior, name, and location) is being misused by others" (Cronbach's $\alpha = .83$; $M = 3.8$; $SD = 1.5$).

Results

The participants uploaded, in total, $N = 2475$ ($M = 8.63$; $SD = 4.55$) ads. Since they were instructed not to actively look out for ads, but rather to upload an ad when they encountered it, we had no control over the number of measurement points. On average, the data indicate an upload every second day, and it is likely that some participants missed out on relevant messages because they were busy, forgot to take a screenshot, or neglected to upload the photo. However, by comparing the number of uploads to browser Facebook tracking data for the same period, the same participants revealed $M = 1.33$ ($SD = 0.64$) ad impressions per day. If we take the browser tracking data as a benchmark for the total exposure to political ads, we can conclude that the participants missed less than one ad per day. That means participants uploaded a significant sample of all the possible relevant situations or ads. However, we are currently unable to determine whether the uploaded ads represent a biased sample of the total ads (e.g. due to participants only uploading ads of the favorite party, only uploading bigger ads), but given this low

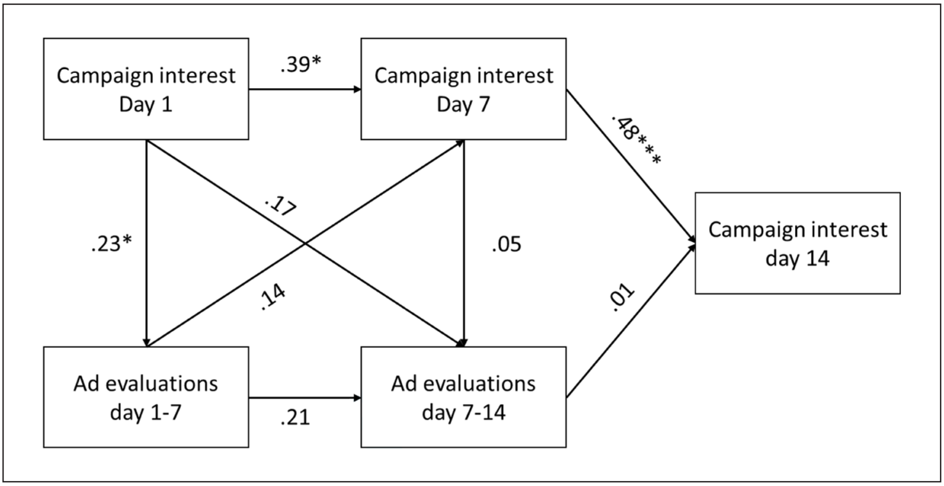

Figure 1. Longitudinal relationship between general campaign interest and immediate MESM evaluation of ads.
*$p < .05$; ***$p < .001$.

number of "missing ads," it was possible to build a representative and accurate sample of the total ad exposure.

To illustrate very simply how this intensive longitudinal data can be used, we show the relationship between participants' ad evaluation immediately after receiving an ad and their interest in the campaign. One might assume that a positive evaluation of the ads would affect interest in the campaign as a whole. However, it is also plausible to believe that interest in the campaign would predict the participants' evaluations of the ads. Interest in the election campaign rose significantly until campaigning day ($M_1 = 3.98$, $SD_1 = 1.55$; $M_2 = 4.72$, $SD_2 = 1.37$; $M_3 = 4.77$, $SD_3 = 1.51$; $p < .001$). Figure 1 shows the relationship between participants' evaluation of the ads as "interesting" and "persuasive" and their interest in the political campaign as a whole. These results are unique to the MESM data since it is the only design that can capture immediate reactions to mobile campaign ads and model the dynamic relationship with other variables. To answer the research questions posed above, we can see that only at the beginning of the campaign is there a significant relationship between campaign interest and participants' evaluation of the ads. Later in the campaign, this relationship fades.

As we assumed, the motivation of the participants dropped significantly during the 2 weeks of data collection, but even on the last day of the field phase, motivation was still over the scale mean ($M_1 = 5.51$, $SD_1 = 1.04$, $M_2 = 5.3$, $SD_2 = 0.88$, $p = .045$). Regression results reveal that the motivation of participants predicted the number of uploads ($\beta = .27$, $p = .035$), but neither interest in the campaign ($\beta = .01$, $p = .908$) nor any of the demographics (age: $\beta = .15$, $p = .114$; education: $\beta = -.178$, $p = .052$; gender (female): $\beta = -.021$, $p = .820$) predicted the number of uploaded screenshots. In addition, privacy concerns were not significantly related to participants' activity in the MESM study and their likelihood of actively uploading screenshots ($\beta = .02$, $p = .788$). Thus, there does not seem to be a bias in uploading behavior based on demographic variables or interest in politics and the campaign.

Discussion

Mobile experience sampling designs take the notion seriously that in mobile communication, "the only constant is change". The nature and characteristics of mobile communication—being always online and always connected, engaging in short communication episodes, dynamic communication processes, personalized communication, and proprietary systems—bring about challenges when studying the effects of mobile communication. However, scholars should also regard the mobile device as a research tool that potential participants carry around all the time (Ohme et al., 2016, 2020; Schnauber-Stockmann and Karnowski, 2020). In combination with other data sources, MESM designs are suitable for confronting the challenges of communication research when attempting to capture, analyze, model, and explain mobile communication.

First, mobile communication faces the challenge of measuring *media exposure*. This challenge is not only true for mobile communication but also for digital exposure in particular. However, research on mobile communication is especially prone to memory errors since it is often difficult for research participants to recall the length, content, and sources of the short communication episodes that are typical for mobile communication. MESM is suitable for overcoming this challenge since the measurement is closer to the moment of media exposure, which generally decreases self-report biases (Naab et al., 2018). Most of the time, researchers are less interested in mobile communication usage *in general*, but rather in specific behaviors such as texting, using social media, reading the news, or streaming videos. The event-based design demonstrated here is useful for measuring relevant communication usage—in the case of this study, exposure to political ads. It would be particularly difficult to answer the research questions in our example study regarding the effects of social media smartphone ads on citizens' interests in politics through any other design. It would be impractical to ask participants to remember how many ads they had seen on different social media platforms, how they would evaluate those ads, and more information.

The second challenge that we identified for mobile communication researchers is how to study personalized and tailored communication. This notion is not only important when studying the usage of social media applications and personalized ads but also the many apps that use tailored recommendations, agendas, and pricing. Since such apps make use of GPS data, sensory data, behavioral tracking, cookies, and much more, one could say that the smartphone is a personalized communication space. This, however, is not in line with traditional mediated communication paradigms in which a sizable part of the audience received similar media content. Since MESM is adjusted to the communication environment of an individual, it is an excellent fit for studying this fragmented and personalized media environment. The extension of MESM that we presented here (i.e. uploading personalized media content) makes it possible to access not only the effects of personalized communication but also the content. Take as an example the personalized and targeted messages used in election campaigns. By asking study participants to upload screenshots of those ads, we are now able to precisely analyze the personalized content of those ads and consider the individual's mobile campaign diet. Thus, MESM and data donations (i.e. mobile intensive longitudinal linkage analyses) are among the few designs that are able to investigate individual media diets.

While the challenges of digital communication research (De Vreese and Neijens, 2016; Niederdeppe, 2016; Valkenburg and Peter, 2013) can be partly solved by applying computational methods such as browser tracking and logging (in combination with automated content analysis), mobile devices and apps frequently block these methods, and researchers must rely heavily on the policies and goodwill of big tech companies. Furthermore, digital trace data are much more valuable when it is combined with self-reports (Stier et al., 2020). Thus, it seems beneficial to use a mobile method like MESM for mobile communication. This circumvents security problems and, at the same time, enables researchers to combine fine-grained self-reporting with other data sources (see below).

When characterizing mobile communication, the dynamic, interactive, and episodic nature of such communication is crucial. MESM designs are arguably suitable for capturing these short-term dynamics. We have demonstrated a very simplistic dynamic that examined participants' campaign interest and the evaluation of mobile ads to showcase the possibilities of MESM, but there are more sophisticated ways to analyze intensive longitudinal data. One direction for future research is to examine the within-person and between-person dynamics that are often overlooked in many models and theories of mobile communication (Hamaker and Wichers, 2017; Hamaker et al., 2018). Another research possibility is the study of reinforcing dynamics, in which two or more variables (e.g. communication usage and effects) are mutually reinforcing and might lead to spiral processes (Otto et al., 2020; Slater, 2007, 2015; Thomas et al., 2020, 2021). For example, does mobile phone usage in the classroom lead to distractions and low student motivation, or does low student motivation lead to higher usage of mobile devices in the classroom, or do both processes operate at the same time? MESM is particularly useful in disentangling these causalities and reinforcing dynamics. Recent studies on communication dynamics are beginning to examine *individual* communication dynamics. For example, the longitudinal relationship between mobile social media usage and self-esteem might be very different from individual to individual (Beyens et al., 2020; Valkenburg et al., 2021); ignoring these individual and short-term dynamics might lead to researchers drawing spurious conclusions about the relationship between variables (Thomas et al., 2020). This study has shown, based on the longitudinal relationship between campaign interest and campaign evaluations, how questions of reciprocity and causality can be addressed using intensive longitudinal methods. We demonstrated that participants' level of campaign interest and their evaluations of the campaign were only linked at the beginning of the campaign, but not toward the end—a result that is unique to the design we introduced here. There are several theoretical and empirical explanations for such a pattern. For example, campaign fatigue could be one reason why the evaluation and interest in the campaign do not reinforce each other over time. It could also be the case that participants in our study used campaign interest as a "proxy" for the evaluation of the campaign, while this variable played a less significant role toward the end. Further analysis is needed to demonstrate how party identification or different periods of the campaign might influence the dynamic relationship investigated here (Beyens et al., 2020; Thomas et al., 2020).

Extensions and additions to MESM

We already presented one way of not only capturing immediate reactions to media messages (in our case, political ads) but also the content and characteristics of mobile communication by asking participants to donate screenshots with relevant media content; of course, this method could also work for text messages, shopping cards, tweets, notifications, or news items. There is no other design that can capture immediate reactions (as in a media effects experiment) but at the same time capture longitudinal and dynamic processes (as in a panel survey). However, several other data sources might be useful additions to explain the mobile communication effects captured by MESM.

Mobile communication happens anywhere and anytime, but the location and time might be crucial and may influence communication usage and effects. Combining MESM with GPS data is, thus, a clear and valuable extension of the intensive longitudinal design (Doherty et al., 2014). It seems evident that the location does influence crucial concepts in mobile communication research, such as well-being—which is usually higher when people are on holidays, out in nature, or with friends (Müller et al., 2020).

Combining MESM with both GPS data and other sensor data (i.e. information that is captured through mobile device sensors such as cameras, microphones, etc.) collected by mobile devices provides a valuable extension to capture, enrich, and link MESM data with digital behavioral data, for instance, sleep quality or other health-related smartphone information. Sensor data might be a fruitful way to gather more passive, objective types of information on mobile communication—additionally, it may be applied to studies in other social science fields. There have been valuable links between sensor and smartphone use data (e.g. regarding smartphone usage and well-being; Marciano and Camerini, 2022; Marciano et al., 2022). While the use of sensor data and the combination of sensor data and self-reports are still relatively young, it offers one promising way to overcome some of the challenges described in this study and allows for the use of the smartphone as a tool for mobile communication research (Keusch and Conrad, 2021).

The combination of experience sampling and tracking data may offer a way forward when (a) aiming for a complete and general picture of a recipient's mobile communication environment and (b) describing detailed insights into the reactions and usage of mobile communication (Beraldo et al., 2021). As this study has demonstrated, browser tracking can be used as a benchmark for the quality of data obtained through MESM.

When compared with (screenshot) data donations and intensive longitudinal methods, the screenomics framework seems to provide a similar approach (Brinberg et al., 2021; Reeves et al., 2020). Within this design, the smartphone takes a screenshot every 5 seconds, which is then analyzed both automatically and manually to obtain a detailed picture of a user's smartphone behavior. Indeed, the design shares the idea of using smartphone screenshots to gain information about the content of mobile communication. Since the screenshots form a timeline of mobile communication, it is also able to address the challenge of dynamic and short communication episodes. However, it lacks the opportunity to ask users for reactions, attitudes, emotions, and thoughts: in essence, it neglects the *effects* of mobile communication. It can thus be regarded as a complementary tool if a detailed description of mobile communication content and behavior is required.

Limits of mobile-intensive longitudinal designs

The MESM and the extensions mentioned here come with several limitations. First, of course, MESM does not fully overcome the limitations of self-report; it is in no way objective and unbiased data. Screen tracking techniques might be more valuable in these instances; they are, however, less detailed than experience sampling measures of media usage. Thus, if the researcher is interested in general smartphone usage and not in specific content, apps, or behaviors, then screen time donations and logging data might be more useful (Ohme et al., 2020).

Second, depending on the research question and task, the MESM design relies heavily on the *commitment* of the participants. Since participants mostly select relevant communication situations and content themselves, relevant data points may be missed, and depending on the communication content, participants might be hesitant to upload relevant communication situations.

Third, the design is demanding for participants because they must monitor their mobile communication behavior and are possibly required to answer the same questions multiple times. In this study, the number of completed MESM forms and uploaded campaign ads depended on the participants' motivation to take part. Thus, participants' motivation and fatigue are crucial to data quality in MESM studies.

Moreover, MESM designs, since they are demanding, might suffer from two self-selection problems: first, taking part in such a study at all, and second, actively uploading material and completing the questionnaires. While there did not seem to be a self-selection problem in our study—participants who were not interested in the campaign and had high privacy concerns uploaded as many screenshots as the interested participants—some measures can be taken to minimize the number of dropouts and inactive participants. Of course, incentives play a crucial role, and there are sophisticated ways to incentivize active participation in MESM studies. Furthermore, contacting participants, reminding them of their tasks, and being available for questions always help to improve participant motivation and commitment (Napa Scollon et al., 2009). With respect to the participant's abilities, mobile surveys and screenshots do not demand high technical skills, especially in contrast to tracking tools and other forms of data donations (Christner et al., 2021; Ohme et al., 2020). On the side of the researcher, most of the experience sampling software is easy to learn and follows similar principles as ordinary survey software.

Third, MESM studies normally do not utilize huge sample sizes. Consequentially, a further limitation is that MESM studies usually do not allow for large and representative samples. If scholars are interested in certain between-person characteristics, they should be aware of the small sample sizes. However, despite sample sizes usually not exceeding 100 participants, studies show that the decisive factor for the power of intensive longitudinal studies is the number of measurement points rather than the number of participants (Bell et al., 2014).

Fourth, while the combination of MESM with screenshot data donations circumvents security measures, this "low-tech" solution also comes with some limitations. Some apps even prevent devices from taking screenshots; for instance, the streaming platform Netflix does not allow screenshots of their videos. Second, and maybe even more importantly, while MESM data can be used for audiovisual material, the combination with screenshot data donations is not easy to capture when it includes audio (e.g. phone calls, audio messages, podcasts) or video material. Thus, the extension of MESM with screenshots is limited to static media content.

Conclusion

Despite these limitations, we believe that experience sampling designs, especially in combination with screenshots or other data donations, can be a useful tool for confronting the challenges of mobile communication research. Since MESM designs use mobile devices as a measurement tool, they have a natural advantage when investigating mobile communication. As we have demonstrated, these methods are adaptive to the affordances of mobile communication and, thus, they are able to analyze mobile communication behavior in numerous facets and dynamics and on an individual level. First, MESM adapts to location independence since the measurement device—the smartphone—is similarly location independent. Second, MESM may adapt to the highly personalized mobile communication environment since it represents an individualistic, idiosyncratic approach to communication research (Conner et al., 2009; Valkenburg et al., 2021). Finally, MESM adapts to the short-lived communication flows and short communication episodes that are typical for interactive mobile communication, and thus, the "longitudinal design fits the phenomenon under study" (Slater, 2007: 286).

Combining intensive longitudinal methods with data donations, browser tracking, and other data sources enables scholars to make sound judgments about the mobile communication reality of citizens. Understanding individual mobile communication processes with innovative methods is, from our point of view, the way forward when aiming to understand the embeddedness of mobile communication in the daily lives of citizens. MESM methods will aid in researchers' understanding of the effects the usage of mobile devices might have on individuals and, in turn, on society in general.

Author's Note

Sanne Kruikemeier is now affiliated to Wageningen University & Research, The Netherlands.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: The research was part of the NORFACE Governance-funded project "Data-driven campaigns: intended and unintended consequences for democracy [DATADRIVEN]" (file number 462-19-030).

ORCID iDs

Lukas P Otto https://orcid.org/0000-0002-4374-6924
Sanne Kruikemeier https://orcid.org/0000-0002-8053-8200

Notes

1. Adding to this challenge, obtaining tracking data from the second largest group of users (i.e. iOS users) is impossible since the system does not, to date, allow phone logging software. Researchers must confront huge obstacles to capture data on devices that use iOS (Johannes et al., 2020; Nishiyama et al., 2020)
2. Including related designs, such as diary-style studies.

References

Bayer J, Ellison N, Schoenebeck S, et al. (2018) Facebook in context(s): measuring emotional responses across time and space. *New Media & Society* 20(3): 1047–1067.

Bell BA, Morgan GB, Schoeneberger JA, et al. (2014) How low can you go? *Methodology* 10(1): 1–11.

Bennett WL and Iyengar S (2008) A new era of minimal effects? The changing foundations of political communication. *Journal of Communication* 58(4): 707–731.

Beraldo D, Milan S, de Vos J, et al. (2021) Political advertising exposed: tracking Facebook ads in the 2021 Dutch elections. Available at: https://policyreview.info/articles/news/political-advertising-exposed-tracking-facebook-ads-2021-dutch-elections/1543 (accessed 12 March 2021).

Beyens I, Pouwels JL, van Driel II, et al. (2020) The effect of social media on well-being differs from adolescent to adolescent. *Scientific Reports* 10(1): 10763.

Boase J and Humphreys L (2018) Mobile methods: explorations, innovations, and reflections. *Mobile Media & Communication* 6(2): 153–162.

Boase J and Ling R (2013) Measuring mobile phone use: self-report versus log data. *Journal of Computer-Mediated Communication* 18(4): 508–519.

Bolger N and Laurenceau J-P (2013) *Intensive Longitudinal Methods: An Introduction to Diary and Experience Sampling Research*. New York: Guilford Press.

Brandtzaeg PB, Pultier A and Moen GM (2019) Losing control to data-hungry apps: a mixed-methods approach to mobile app privacy. *Social Science Computer Review* 37(4): 466–488.

Brinberg M, Ram N, Yang X, et al. (2021) The idiosyncrasies of everyday digital lives: using the Human Screenome Project to study user behavior on smartphones. *Computers in Human Behavior* 114: 106570.

Campbell SW (2013) Mobile media and communication: a new field, or just a new journal? *Mobile Media & Communication* 1(1): 8–13.

Chaffee SH and Metzger MJ (2001) The end of mass communication? *Mass Communication & Society* 4(4): 365–379.

Christner C, Urman A, Adam S, et al. (2021) Automated tracking approaches for studying online media use: a critical review and recommendations. *Communication Methods and Measures* 16(2): 79–95.

Conner TS, Tennen H, Fleeson W, et al. (2009) Experience sampling methods: a modern idiographic approach to personality research. *Social and Personality Psychology Compass* 3(3): 292–313.

De Vreese CH and Neijens P (2016) Measuring media exposure in a changing communications environment. *Communication Methods and Measures* 10(2–3): 69–80.

Dennis JW, Chadwick A and Smith AP (2016) Politics in the age of hybrid media: power, systems, and media logics. In: Bruns A, Enli G, Skogerbø E, et al. (eds) *The Routledge Companion to Social Media and Politics*. New York: Routledge, pp. 7–22.

Doherty ST, Lemieux CJ and Canally C (2014) Tracking human activity and well-being in natural environments using wearable sensors and experience sampling. *Social Science & Medicine* 106: 83–92.

Ellis DA (2019) Are smartphones really that bad? Improving the psychological measurement of technology-related behaviors. *Computers in Human Behavior* 97: 60–66.

Ellis DA, Davidson BI, Shaw H, et al. (2019) Do smartphone usage scales predict behavior? *International Journal of Human-Computer Studies* 130: 86–92.

Feldman L, Stroud NJ, Bimber B, et al. (2013) Assessing selective exposure in experiments: the implications of different methodological choices. *Communication Methods and Measures* 7(3–4): 172–194.

Fraley RC and Hudson NW (2014) *Review of Intensive Longitudinal Methods: An Introduction to Diary and Experience Sampling Research*. Abingdon: Taylor & Francis.

Grewal D, Bart Y, Spann M, et al. (2016) Mobile advertising: a framework and research agenda. *Journal of Interactive Marketing* 34: 3–14.

Hamaker EL and Wichers M (2017) No time like the present: discovering the hidden dynamics in intensive longitudinal data. *Current Directions in Psychological Science* 26(1): 10–15.

Hamaker EL, Asparouhov T, Brose A, et al. (2018) At the frontiers of modeling intensive longitudinal data: dynamic structural equation models for the affective measurements from the COGITO study. *Multivariate Behavioral Research* 53(6): 820–841.

Hedstrom A and Irwin M (2017) Mobile experience sampling method (MESM). In: Matthes J (ed.) *The International Encyclopedia of Communication Research Methods*. Hoboken, NJ: Wiley Online Library, pp. 1–13.

Holbert RL, Garrett RK and Gleason LS (2010) A new era of minimal effects? A response to Bennett and Iyengar. *Journal of Communication* 60(1): 15–34.

Johannes N, Meier A, Reinecke L, et al. (2020) The relationship between online vigilance and affective well-being in everyday life: combining smartphone logging with experience sampling. *Media Psychology* 24(5): 581–605.

Keusch F and Conrad FG (2021) Using smartphones to capture and combine self-reports and passively measured behavior in social research. *Journal of Survey Statistics and Methodology* 10: 863–885.

Kobayashi T and Boase J (2012) No such effect? The implications of measurement error in self-report measures of mobile communication use. *Communication Methods and Measures* 6(2): 126–143.

Kubey R, Larson R and Csikszentmihalyi M (1996) Experience sampling method applications to communication research questions. *Journal of Communication* 46(2): 99–120.

Kuru O, Bayer J, Pasek J, et al. (2017) Understanding and measuring mobile Facebook use: who, why, and how? *Mobile Media & Communication* 5(1): 102–120.

Ling R (2012) *Taken for Grantedness: The Embedding of Mobile Communication into Society*. Cambridge, MA: MIT Press.

Maier J and Faas T (2011) "Miniature campaigns" in comparison: the German televised debates, 2002–09. *German Politics* 20(1): 75–91.

Marciano L and Camerini A-L (2022) Duration, frequency, and time distortion: which is the best predictor of problematic smartphone use in adolescents? A trace data study. *PLoS ONE* 17(2): e0263815.

Marciano L, Driver CC, Schulz PJ, et al. (2022) Dynamics of adolescents' smartphone use and well-being are positive but ephemeral. *Scientific Reports* 12(1): 1316.

Menchen-Trevino E (2020) Digital trace data and social research. In: Welles BF and González-Bailón S (eds) *The Oxford Handbook of Networked Communication*. New York: Oxford University Press, pp. 520–538.

Müller SR, Peters H, Matz SC, et al. (2020) Investigating the relationships between mobility behaviours and indicators of subjective well–being using smartphone–based experience sampling and GPS tracking. *European Journal of Personality* 34(5): 714–732.

Naab TK, Karnowski V and Schlütz D (2018) Reporting mobile social media use: how survey and experience sampling measures differ. *Communication Methods and Measures* 13: 126–147.

Napa Scollon C, Prieto C-K and Diener E (2009) Experience sampling: promises and pitfalls, strength and weaknesses. In: Diener E (ed.) *Assessing Well-Being: The Collected Works of Ed Diener*. Dordrecht: Springer, pp. 157–180.

Niederdeppe J (2014) Conceptual, empirical, and practical issues in developing valid measures of public communication campaign exposure. *Communication Methods and Measures* 8(2): 138–161.

Niederdeppe J (2016) Meeting the challenge of measuring communication exposure in the digital age. *Communication Methods and Measures* 10(2–3): 170–172.

Nishiyama Y, Ferreira D, Eigen Y, et al. (2020) IOS crowd–sensing won't hurt a bit! AWARE framework and sustainable study guideline for iOS platform. In: Streitz N and Konomi S (eds) *Lecture Notes in Computer Science: Distributed, Ambient and Pervasive Interactions*. Cham: Springer, pp. 223–243.

Ohme J (2020) Mobile but not mobilized? Differential gains from mobile news consumption for citizens' political knowledge and campaign participation. *Digital Journalism* 8(1): 103–125.

Ohme J, Albaek E and de Vreese CH (2016) Exposure research going mobile: a Smartphone-based measurement of media exposure to political information in a convergent media environment. *Communication Methods and Measures* 10(2–3): 135–148.

Ohme J, Araujo T, de Vreese CH, et al. (2020) Mobile data donations: assessing self-report accuracy and sample biases with the iOS screen time function. *Mobile Media & Communication* 9(2): 293–313.

Otto LP, Thomas F and Maier M (2018) Everyday dynamics of media skepticism and credibility: an ambulatory assessment study. In: Otto K and Köhler A (eds) *Trust in Media and Journalism. Empirical Perspectives on Ethics, Norms, Impacts and Populism in Europe*. Wiesbaden: Springer, pp. 111–133.

Otto LP, Thomas F, Glogger I, et al. (2022) Linking media content and survey data in a dynamic and digital media environment—Mobile longitudinal linkage analysis. *Digital Journalism* 10(1): 200–215.

Otto LP, Thomas F, Maier M, et al. (2020) Only one moment in time? Investigating the dynamic relationship of emotions and attention toward political information with mobile experience sampling. *Communication Research* 47(8): 1131–1154.

Razaghpanah A, Nithyanand R, Vallina-Rodriguez N, et al. (2018) Apps, trackers, privacy, and regulators: a global study of the mobile tracking ecosystem. *The 25th Annual Networl and Distributed System Security Symposium (NDSS 2018)*.

Reeves B, Robinson T and Ram N (2020) Time for the human screenome project. *Nature* 577: 314–317.

Sarker IH, Kayes ASM and Watters P (2019) Effectiveness analysis of machine learning classification models for predicting personalized context-aware smartphone usage. *Journal of Big Data* 6(1): 57.

Scharkow M (2016) The accuracy of self-reported Internet use—A validation study using client log data. *Communication Methods and Measures* 10(1): 13–27.

Scharkow M (2019) The reliability and temporal stability of self-reported media exposure: a meta-analysis. *Communication Methods and Measures* 13: 198–211.

Schnauber-Stockmann A and Karnowski V (2020) Mobile devices as tools for media and communication research: a scoping review on collecting self-report data in repeated measurement designs. *Communication Methods and Measures* 14: 145–164.

Schrock AR (2015) Communicative affordances of mobile media: portability, availability, locatability, and multimediality. *International Journal of Communication* 9: 18.
Slater MD (2007) Reinforcing spirals: the mutual influence of media selectivity and media effects and their impact on individual behavior and social identity. *Communication Theory* 17(3): 281–303.
Slater MD (2015) Reinforcing spirals model: conceptualizing the relationship between media content exposure and the development and maintenance of attitudes. *Media Psychology* 18(3): 370–395.
Statista (2021) Facebook users reach by device 2021. Available at: https://www.statista.com/statistics/377808/distribution-of-facebook-users-by-device/ (accessed 4 October 2021).
Stier S, Breuer J, Siegers P, et al. (2020) Integrating survey data and digital trace data: key issues in developing an emerging field. *Social Science Computer Review* 38(5): 503–516.
Thomas F, Otto LP, Ottenstein C, et al. (2020) Measuring reciprocal dynamics between communication processes and effects in distinct growth sequences. *Communication Methods and Measures* 15(1): 17–42.
Thomas F, Shehata A, Otto LP, et al. (2021) How to capture reciprocal communication dynamics: comparing longitudinal statistical approaches in order to analyze within- and between-person effects. *Journal of Communication* 71: 187–219.
Valkenburg PM and Peter J (2013) Five challenges for the future of media-effects research. *International Journal of Communication* 7: 197–215.
Valkenburg PM, Beyens I, Pouwels JL, et al. (2021) Social media use and adolescents' self-esteem: heading for a person-specific media effects paradigm. *Journal of Communication* 71(1): 56–78.
Verbeij T, Pouwels JL, Beyens I, et al. (2021) The accuracy and validity of self-reported social media use measures among adolescents. PsyArXiv. DOI: 10.31234/osf.io/p4yb2.
Vorderer P, Krömer N and Schneider FM (2016) Permanently online—Permanently connected: explorations into university students' use of social media and mobile smart devices. *Computers in Human Behavior* 63: 694–703.
Zuiderveen Borgesius FJ, Moller J, Kruikemeier S, et al. (2018) Online political microtargeting: promises and threats for democracy. *Utrecht Law Review* 14: 82–82.

Author biographies

Lukas P Otto (PhD U of Koblenz-Landau) is a Researcher at GESIS – the Leibniz Institute for the Social Science, Computational Social Science Department. His research focuses on (online) political communication effects, media psychology, and (mobile) methods of communication research.

Sanne Kruikemeier (PhD, U of Amsterdam) is a Professor in Digital Media and Society at the Stategic Communication Group of Wageningen University & Research (WUR). Her research focuses on the consequences and implications of online communication for individuals and society.