Zooming in on Smartphone Habits:
Identifying Behavioral Indicators of Perceived Automaticity

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Abstract

Research suggests that a large portion of media use is driven by habit. Yet our ability to measure habitual processes directly remains limited, suggesting that more naturalistic methods are needed. Leveraging a deep mobile event log and experience sampling dataset of German Internet users (*N* = 889), we probe the situational dynamics of smartphone habits. We investigate how moment-to-moment smartphone behavior corresponds to the perception of automaticity, with implications for the measurement of habitual behavior more generally. Contrary to expectations, duration – rather than frequency – of smartphone behavior emerged as the more consistent predictor of situational habit perception at both within- and between-person levels. However, these links varied by the type of behavior, with sessions and episodes (but not glances) relating to perceived automaticity. Additionally, home screen and gateway app use were not associated with perceived automaticity. Our results generate new insights – and deep questions – into the nature of real-world media habits.

Keywords: smartphone use, temporal dynamics, habit, Mobile Experience Sampling Method, logging

For many people today, the smartphone is the first thing they reach for in the morning and the last thing they put down before going to sleep. Throughout the day, the phone is both physically and psychologically close. With just a swipe – or a well-practiced sequence of swipes – the device affords them the ability to chat, share, learn, record, relax, and, in countless other ways, live their 21st-century lives. This near-constant engagement spotlights how deeply integrated our phones are with our routines, often to the point that use becomes automatic (Schnauber-Stockmann & Naab, 2019b). In turn, prior research has underlined the heavily habit-driven nature of smartphone and mobile media use (LaRose, 2010; Oulasvirta et al., 2012; Schnauber-Stockmann & Naab, 2019b). That smartphone use often occurs without conscious thought echoes the powerful, though often overlooked and under-theorized, influence of *habit* on daily behavior. Given the diverse range of behaviors that take place on smartphones, understanding these cornerstone habits can provide valuable insights into media behavior more broadly. In this paper, we investigate the extent to which moment-to-moment smartphone behaviors align with the perception of habit, laying the foundation for research on the identification of media habits through digital traces.

Theoretical Perspectives on Media Habits

Habit represents a foundational perspective for understanding media behavior, and it has long been embedded in media and communication research. For example, Cantril and Allport (1935, p. 23) highlighted how radio, with its punctual broadcasts, created “time habits.” While the *Uses and Gratifications* paradigm emphasizes intentional media use to fulfill specific needs (Katz et al., 1973), Rubin (1984) found that much of media consumption is not actively driven by specific goals. This work suggests that media use often consists of more habitual and ritualized forms of media engagement. More recent work in this tradition thus often includes habit as a standard factor in understanding media engagement (Wohn &

Ahmadi, 2019). The longstanding importance of habit also extends to media effects. For example, drawing from the social construction of reality standpoint, Berger and Luckmann (1966) argued that habitual media behaviors reinforce cultural norms and societal value. Aligned with this, Hawkins and Pingree (1981) explored the role of TV watching habits and their influence on perceptions of social reality. Altogether, research on the role of habit helps to explain not just why we engage with media, but also *when*, and with what effects.

More recently, LaRose (2010) formalized habit as a theoretical perspective in communication and advanced the view that *media habits* act as key determinants of media behavior. He also argued that habit provides an alternative theoretical perspective to pathological models of media use, such as frameworks built on addiction and/or compulsion (LaRose et al., 2010). In doing so, LaRose (2010) integrated contemporary perspectives on habit theory from psychology into the communication literature. Accordingly, (media) habits are typically defined as automatic (i.e., minimally conscious) behaviors that are learned through experiencing rewards in specific contexts repeatedly over time (Wood & Rünger, 2016). More precisely, when a behavior is rewarded repeatedly in a given context, the brain gradually encodes an association between that context and the behavior itself (Amodio & Ratner, 2011; Wood, 2017). As this association strengthens, cues within that context alone can prompt habitual behavior directly with minimal conscious effort – even if the initial reward is removed (Orbell & Verplanken, 2015). Notably, habitual contexts can manifest as a wide variety of external environments (e.g., in public transport, while cooking, in an elevator) or internal states (e.g., anxiety) – and this diversity is only amplified when considering complex technologies and digital environments (Bayer & LaRose, 2018).

Over the last two decades, habit has been used as a theoretical lens across a range of communication research areas to explore the antecedents and consequences of repetitive engagement with media, with increasing attention to mobile and social media habits (Bayer et al., 2022). For example, Wohn and Ahmadi (2019) examined the predictors of mobile news snacking habits by analyzing the frequency and time spent on micro-news consumption, as well as the stability of contextual factors like time and locations. Habit has also been used to explore the consequences of media use, such as how email habits predict individuals' phishing susceptibility (Vishwanath, 2015), or how mobile checking habits influence adolescents' procrastination and well-being (Meier, 2022). Overall, previous research has typically sought to test the predictive role of habits compared to more intentional factors, as well as to counter more clinical models of media behavior that risk overpathologizing (Bayer & LaRose, 2018). In doing so, this body of work demonstrates that habitual processes shape the experiences and outcomes of a wide array of media behaviors.

Given that smartphones are used in a variety of situations for a variety of purposes throughout the day, the development of *mobile* media habits is not only common but also complex (Oulasvirta et al., 2012; Schnauber-Stockmann & Naab, 2019b). Unlike many other habitual behaviors, smartphone use is highly dynamic due to the wide range of variations in the contexts, cues, and rewards involved (Bayer & LaRose, 2018; LaRose, 2010). These cues can stem from the device itself such as notifications, or from internal states like feeling bored or inspired (Bayer et al., 2016). Additionally, cues can arise from particular physical contexts, like starting a car or waiting for a bus (Heitmayer & Lahlou, 2021), or from digital contexts like specific apps (Schnauber-Stockmann & Naab, 2019b). Mobile media habits may also reflect "general goal-related habits that are triggered by a variety of goals" (Naab & Schnauber, 2016; p. 131), and are thus not hinged to individual contexts (e.g., the living room). Altogether, the variable features, applications, and affordances of smartphones contribute to their capacity to amplify habit formation and activation in daily life.

Measuring Habits in Everyday Life

Although a wide variety of studies have shown that habit is a key predictor of media behavior (LaRose, 2010; Meier et al., 2023; Oulasvirta et al., 2012), measuring habit is surprisingly challenging. Media habit research has largely relied on self-report scales of habit strength or simple indices of how frequently a behavior has been performed (Peters et al., 2024). This approach poses a problem, as remembering how many times one has performed behaviors that are tightly integrated into daily life is difficult due to limitations in autobiographical memory (Jobe, 2003; Schwarz & Oyserman, 2001), leading to low accuracy of self-reported measures of mobile media use (Parry et al., 2021). This cognitive challenge is also exacerbated when a behavior is executed with minimal conscious thought because it involves less memory encoding (Mazar & Wood, 2018). As a result, self-reported and retrospective measures of habit strength indicate if a behavior is *perceived* as automatic rather than if the behavior was truly initiated or performed automatically (Hagger et al., 2015) – and people tend to overestimate the level of intentionality in their behavior (Mazar & Wood, 2018; Neal et al., 2012). In total, habits – by definition – occur with less conscious awareness than intentional behaviors, making them difficult to measure accurately via self-report.

Despite potential biases, self-report measures of habit remain crucial to empirical habit research. The perception of habit, regardless of its precise relationship to automatic cognition in the brain, may also play an important role in media effects. Indeed, a growing body of research has highlighted the importance of studying how people reflect on and make sense of their media use – whether or not it matches their objective behavior (L. N. Wolfers, 2024). Moreover, how people perceive their habits in the moment – or immediately after use – may differ significantly from their long-term reflections, creating gaps between immediate reactions and long-term evaluations of habit. Without measuring habit perception right after the behavior, studies fail to provide a clear picture of how habits operate in real-world contexts, leading to an oversimplified understanding of media use. Adopting more ecological approaches can thereby clarify how habit perception aligns with daily behavior, while also revealing gaps between theory, behavior, and perception.

While most empirical habit research has relied on cross-sectional survey or experimental methods, some studies have attempted to shine light on habit processes using more ecologically valid methods. Early diary studies asked participants to provide hourly reports of their habitual behaviors, along with other perceptions tied to those habits (Wood et al., 2002; Quinn et al., 2010). A variety of studies have also examined the rate and nature of habit formation using diary or intensive longitudinal designs (Gardner, 2015; Lally et al., 2010; Schnauber-Stockmann & Naab, 2019b; Stojanovic et al., 2020). More recently, an increasing number of studies have used the Experience Sampling Method (ESM; also Ecological Momentary Assessment or EMA) to understand habit processes in everyday life, such as the interplay with goal pursuit (Williamson & Wilkowski, 2022) and sleepiness (McLaurin et al., 2025). Overall, extant work provides insights into how habits are formed and facilitated, but leaves questions about whether and how real-world behavior shapes the *perception* of established (vs. new) habits.

Another ecologically valid way of measuring habits is through digital traces. A growing number of studies in communication are now using digital traces to measure the amount or nature of digital media use (Ohme et al., 2023; Parry & Toth, 2025). In doing so, many studies indirectly capture indicators of habitual behavior – i.e., the (disputed) frequency component of habit. Research centered on media habits has increasingly used designs that draw on digital traces (Anderson & Wood, 2021; Oulasvirta et al., 2012), with some studies attempting to capture more precise indicators of habit performance (Peters et al., 2024). Overall, measuring habits in the midst of daily life – whether via self-report or digital logs –

can help to counteract biases in cross-sectional studies, which can overestimate the role of intentional processes (Neal & Wood, 2009).

Linking Digital Behavior to *In Situ* Habit Perception

One of the key challenges in measuring automatic processes is determining how well established self-report measures of habits reflect their real-world performance . Addressing this core problem, here we focus our analyses on the relation between *moment-to-moment* digital behaviors and *in situ* habit perception. In the current study, we thus zoom in on the activation of established (i.e., previously formed) smartphone habits using naturalistic digital traces. Informed by habit theory, we suggest that digital trace data allow us to test whether the behaviors that *should* reflect perceptions of habit actually do. Specifically, we combine second-by-second mobile log data with self-reported habit perceptions collected using ESM.

Importantly, we measure self-reported habit at the situational level to capture it as closely as possible to the behavior itself. Habit research has tended to focus on the between-person level, overlooking situation-level processes (McLaurin et al., 2025; Schnauber-Stockmann, Bayer, et al., 2025) – including in media habit research especially (Bayer & LaRose, 2018). Our approach allows us to examine how digital logs reflect real-world habit perception in daily life and directly compare situation- and person-level variability. Recent research suggests that doing so is pivotal for understanding media effects (Schnauber-Stockmann, Scharkow, et al., 2025). By linking logged usage and *in situ* habit perception, we provide a test of how traditional dimensions of habit are (mis)aligned at the situational level. In other words, we aim to clarify whether – and which – objective patterns of use correspond to the subjective experience of habit.

However, smartphone usage can take many forms, each potentially reflecting different levels of habit strength. Here, we consider four key types of digital behaviors. First, we consider *glances*, which involve screen activation, optional interaction with applications on the lock screen (i.e., previewing a message or interacting with a media player), followed by screen deactivation. These short engagements with the device are associated with monitoring behavior and high reactivity to device cues, which reflects established habits (Oulasvirta et al., 2012; Reinecke et al., 2018). Second, we evaluate *sessions*, which start with activating the screen, followed by unlocking the device, potentially followed by one or more app uses, ending with locking the device (Zhu et al., 2018). Although sessions are not necessarily performed automatically (i.e., habitually) throughout, their initiation is likely to be more automatic (Bayer, Campbell, et al., 2016; Naab & Schnauber, 2016).

Third, we examine *app episodes*, which are discrete periods of engagement with specific apps within a session, before switching apps or ending the session. Apart from the session itself, each of the episodes within it can lead to the unconscious initiation of further episodes (Oulasvirta et al., 2012; Schnauber-Stockmann & Naab, 2019a). In addition to app episodes, we investigate the use of the *home screen* separately, which usually occurs between app use episodes. The home screen often serves phone navigation, idle time, or the search for and selection of the next app, and might tap into aspects of general smartphone habits that are distinct from specific app habits (Kasturiratna et al., 2025; Myers et al., 2022). These four types of behavior (i.e., glances, sessions, app episodes, and home screen uses) cover interaction with the device that involves screen activity[1]. While there are further levels of interaction (e.g., tapping banner notifications, previewing messages in the notification center), these four types capture the core contours of smartphone use.

Altogether, our study attempts to identify which digital behavior patterns align with the perception of habit – and thereby provide signals of real-world habitual processes. Past habit research has often measured habit cross-sectionally or over relatively extended time

[1] Use is possible while the screen is turned off or not viewed (e.g., listening to music, using voice commands).

periods (e.g., days, weeks), rather than in precise short-term windows in the real world. In this study, we zoom in on theorized indicators of habitual behavior across 30-minute windows. In doing so, we derive behavioral indicators within specific time frames, providing a more temporally precise approach to test the alignment between smartphone behavior and perception. That is, each behavioral indicator reflects usage within a predefined time block, corresponding to situational smartphone usage over time. In the following sections, we outline how different facets of digital behavior may underlie habit perception – specifically in the form of perceived automaticity.

Behavioral Predictors of Perceived Automaticity

Habit can be understood as a cue-contingent form of *automaticity*, or behavior lacking attention, awareness, control, and intention (Bayer, Campbell, et al., 2016; Orbell & Verplanken, 2015). Accordingly, the degree of automaticity can be seen as the most direct indicator of habit strength. Automaticity is often measured (indirectly) through perceived (self-reported) automaticity, or the amount an individual sees their own behavior as performed with minimal consciousness (Gardner, 2012; Gardner et al., 2024). Here, we seek to understand the predictors of perceived automaticity by drawing on four types of behavioral indicators derived from digital trace data: frequency, duration, and gateway apps.

Frequency – i.e., the amount a behavior has been performed – is a classic and common indicator of habit strength in empirical research (Aarts et al., 1998; Ouellette & Wood, 1998). Indeed, the most cited scale of habitual behavior (the *Self-Report Habit Index*; SRHI) includes frequency explicitly (Verplanken & Orbell, 2003). Frequency, or repeated performance, is necessary for behaviors to become habitual in the first place (i.e., habit formation; Lally et al., 2010). In recent decades, however, the role of frequency has been increasingly questioned and critiqued in habit research (Verplanken, 2006; Gardner, 2012) as well as media habit research specifically (LaRose, 2010; Bayer & Campbell, 2012). The core concern is that frequency measures generally conflate deliberate and automatic actions, undermining the assumption that habit is uniquely capturing automaticity.

Past perspectives thereby suggest that more frequent repetition helps habits to form (up to a point), but offer less clear guidance on the relationship between frequency and automaticity among *established* habits. Nonetheless, habitual behaviors are still generally assumed to occur more frequently, and empirical self-report datasets often reveal moderate (between-person) correlations between frequency and automaticity (Bayer et al., 2016; Gardner et al., 2024). In turn, contemporary perspectives on habit suggest that more frequent initiation of a given behavior should be associated with greater perceived habit strength (Gardner, 2012; Rebar et al., 2018). Thus, the number of smartphone actions enacted in a given period should be a predictor of perceived automaticity. The relationship between frequency and automaticity in habits is summarized in work by Meier et al. (2023 p. 2), which highlights that “while automaticity and frequency of [media] use are two distinct sides of media habits, they are conceptually and empirically linked.”

Each of the aforementioned behaviors may be related to habit perception in distinct ways. Frequent glances (e.g., brief screen activations to check notifications) may indicate cyclical habitual checks, suggesting a period of more automatic monitoring of one’s device. Notably, habitual behaviors are typically defined by automatic initiation, even if the subsequent actions may still be carried out consciously (Naab & Schnauber, 2016; Verplanken & Melkevik, 2008). Similar to a glance, then, a session can be perceived as habitual based on how it starts (e.g., unlocking the device instinctively), even if what follows is more deliberate. Moreover, sessions themselves may be perceived as more habitual if they capture scripts of different app episodes linked to each other sequentially. Just like glances, each episode within this sequence (i.e., each uninterrupted app use) can be triggered by content from the previous app, or cues from the device itself (e.g., a notification banner). Last, use of the home screen may spur subsequent episodes by acting as a launchpad for habitual apps, or may reflect habitual motor behaviors as individuals navigate their phones. Also, the home screen potentially shows counters on app icons that indicate updates (e.g., messages), which may trigger their use. Altogether, the frequency of glances, sessions, app episodes, and home screen use may all reflect habitual processes and therefore align with the perception of habit.

H1: Higher frequency of (a) glances, (b) sessions, (c) app episodes, and (d) home screen use will positively predict perceived automaticity.

Another fundamental indicator of smartphone use is duration. Duration has traditionally been used as an indicator for media use in general, and it is not typically considered a direct measure of habit. However, we argue that duration is an increasingly important dimension to account for in media habit research for several reasons. First, despite its flaws, "screen time" is the most commonly employed (and discussed) indicator of the amount of digital media usage (Fassi et al., 2024). Therefore, duration is an essential baseline comparison to test the distinctive role of habit-specific processes. Second, we raise the question of whether duration may indirectly capture habit processes. While it may not reflect the automatic initiation of behavior, longer durations could indicate sustained engagement with minimal conscious oversight, which could contribute to the perception of automaticity. Supporting this, Lee and LaRose (2007) found that longer durations of media use, such as gaming, were strongly correlated with perceived habit strength, indicating that time spent can serve as an indirect measure of media habits in some cases (Wohn & Ahmadi, 2019). Alternatively, duration may be negatively related to habit perception, as the conscious supervision may outweigh any automatic actions (particularly with longer session spans).

Given all the uncertainties regarding the specific ways in which duration may reflect habit perception, we pose the following research question:

RQ1: How does the duration of (a) glances, (b) sessions, (c) app episodes, and (d) home screen use relate to perceived automaticity?

Finally, we argue that the multi-layered structure of smartphone use demands investigation into the habitual processes that occur within sessions. In particular, the entry point to interaction with mobile media can serve as a gateway to automatic engagement, or what has been termed "gateway habits" (Oulasvirta et al., 2012; Schnauber-Stockmann & Naab, 2019a). Here, we propose that gateway habits can manifest as established doorways – i.e., apps that are frequently used to start sessions – in individuals' long-run smartphone usage. These stable entry patterns suggest that users' initial app choices become automatic over time, bypassing conscious decision-making (Schnauber-Stockmann & Naab, 2019b). Supporting this, Peng and Zhu (2020) found that users develop consistent routines for both starting and ending their phone sessions. In sum, repeatedly initiating sessions with specific apps may serve as an indicator of habitual behavior, or at least serve as a cognitive heuristic for self-perceived habit strength when users reflect on their recent behavior.

H2: Gateway app usage will positively predict perceived automaticity.

Method

We use a dataset collected as part of a project on mobile media use[2] among a panel of Internet users in Germany in 2023 (Toth et al., 2024). This dataset includes ESM data on the context, quantity, and nature of smartphone usage, Android event log data, as well as iOS data donations. Demographics and trait-level indicators of mobile media use were collected during the screening conducted by the panel provider and a baseline survey at the outset of

[2] The aim of this project was to investigate smartphone use in terms of quantity, gratifications, situations, habits and cognitive attachment.

the study. The procedures were approved by the ethics review board and the data collection was conducted in coordination with the data protection officer at Freie Universität Berlin.

Participants

Participants were invited to participate in a study on smartphone use over a two-week period between August and September 2023 by a panel provider in Germany (GAPFISH GmbH, n.d.). The recruitment process was designed to collect a sample that reflected the recent demographic distributions of age, gender, and education among adult German internet users aged 18-69. Additionally, efforts were made to achieve an equal distribution of Android and iOS users among the recruited participants. Due to unplanned over-recruitment of male Android users, the targeted distributions of gender and operating systems were not achieved. To account for this, all analyses (except for socio-demographic descriptives) were performed using weights corresponding to socio-demographic quotas of the German population at the time (*Best for Planning*, 2023).

In the present paper, we only analyze data collected from Android users to leverage the moment-by-moment Android event log data in all analyses. After eliminating problematic cases (e.g., duplicate baseline surveys, mis-matches between unique identifiers at different stages of the data collection), the initial sample consisted of n = 1,226 participants. Participants who a) failed an attention check in the baseline survey or b) completed fewer than 25 ESM surveys were excluded to ensure sufficient data to capture intra-individual variance (Arend & Schäfer, 2019). Additionally, participants using Android versions lower than 9.0 were removed, as these versions do not log events like device unlocking and locking, which are necessary for identifying usage sessions. After these procedures, the final sample included data from n = 889 Android users. Participants' mean age was 41.3 years (SD = 13.5), 26.8% were female, and the median of the highest level of education was Technical Baccalaureate. Table 1 presents descriptives of the sample demographic characteristics.

[Insert Table 1 about here]

Procedure

The ESM and Android event logging data were collected using a custom app developed for the larger project (Toth, 2023). During the study period, participants received seven notifications each day for seven days to complete a short 12-item survey between 08:00 and 22:00. To ensure a balanced distribution across the day, notifications were scheduled using a mix of random and interval-contingent signaling (van Berkel et al., 2019). The data collection period was divided into two-hour intervals (e.g., 08:00–10:00, 10:00–12:00, etc.) and within each interval, notification times were randomized. Additionally, notifications were restricted to appear at least 30 minutes after finishing the previous short survey. This prevented overlaps between response reference periods, as most items in the short surveys referred to behavior in the preceding 30 minutes in line with past work (e.g., Reinecke & Hofmann, 2016; Schnauber-Stockmann & Karnowski, 2020). Short surveys could only be completed until the end of the assigned interval. Otherwise, they expired and participants had to wait for the notification in the next interval to be able to complete a short survey. Participants were not informed about these restrictions and rules to prevent potential response biases.

The short survey, administered in German, comprised 12 items about the frequency, duration, nature, and context of participants' smartphone use. At the beginning of the short survey, participants were asked whether they had used their smartphone in the past 30 minutes and, if they had, they were asked to answer all subsequent questions in reference to those same 30 minutes. This ensured that participants were only asked to recall their behavior in the period immediately prior to the survey and thus limit retrospective biases. The starting and submission times for each survey were logged with timestamps. Participants were incentivized based on the number of short surveys completed (€15 – €45). Of the 43,561

ESM surveys theoretically possible across the final sample (889 participants; 49 short surveys), 31,381 complete surveys were included in the study (compliance rate: 72%). Each participant completed 35 surveys on average (*SD* = 5.5).

During the ESM period, the app regularly retrieved the Android Event Log data that are continuously stored on Android smartphones. Our app accessed the device event log which records detailed event-related information from the Android operating system at a low level, virtually eliminating the possibility of logging gaps. In our data, events were logged in 93% of all possible participant hours[3], which confirmed the high density, resolution, and completeness of the dataset throughout daily life. The data recorded in the event log details all events that take place on the device, including (but not limited to) actions such as unlocking or locking the device, screen interactivity, resuming or pausing activities/apps, and booting up or shutting down the device (*UsageEvents.Event*, 2024). Each event has a timestamp with millisecond accuracy and is associated with a package name that denotes the name of the application (e.g., *com.instagram.android*).

Measures

The descriptive statistics reported here were calculated considering the sample weights (see Participants section) and, unless indicated otherwise, refer to averages across 30-minute windows. Table 2 provides descriptives and correlations for all measures excluding control variables.

[Insert Table 2 about here]

Control variables

As control variables, we used age, gender, and education level, as well as the individual study day (1-7) and the short survey wave within the study day (1-7).

[3] The remainder is most likely accounted for by smartphones being turned off.

Perceived automaticity

Perceived habit strength is most commonly assessed with the *Self-Report Habit Index* (SRHI; Verplanken & Orbell, 2003) or its short version centered on automaticity, the *Self-Report Behavioural Automaticity Index* (Gardner, 2012; Verplanken & Orbell, 2003). Naab et al. (2019) found that two scale items correlated strongly with each other when assessing them using ESM (p. 12) and within a cross-sectional survey, both correlated strongly with the SRHI in general (p. 8). Given survey length considerations, we selected only one of these items, which aimed at unconscious initiation. Recent work has also demonstrated the feasibility of leveraging single-item measures of automaticity (Gardner et al., 2024; L. Wolfers & Baumgartner, 2025). Specifically, participants rated the statement "I began using my smartphone without thinking about it" in reference to the past 30 minutes on a 5-point Likert-type scale ranging from 0 (*not at all*) to 4 (*fully*), with 2 (neither nor) as the midpoint (M = 1.62, SD = 1.41).

Smartphone usage patterns

We used the Android event log data to extract and calculate metrics that describe patterns in participants' smartphone usage. The raw data included almost 70 million on-device events. Using an algorithm developed by Parry and Toth (2025), we extracted and labeled approximately 6.5 million instances of screen glances (activating the screen without unlocking the device), smartphone use sessions (locking to unlocking; Zhu et al., 2018), and app episodes (opening to closing an app) from these events.

As the ESM data were time-specific and the Android event logging data were associated with a timestamp, we could directly link them. This allowed us to create a corresponding 30-minute window of smartphone use for each completed short survey where applicable,[4] enabling the examination of different patterns of smartphone use leading up to

[4] Habit perception was only assessed when participants indicated smartphone use in the past 30 minutes. They did so in 19,666 out of 31,381 short surveys (62.7%). Smartphone use was actually logged in 18,353 out of these cases (93.3%).

each survey. Figure 1 provides a visual illustration of some of these 30-minute windows. The linkage resulted in a final dataset that contained 33,352 screen glances, 66,917 smartphone use sessions, 191,471 app episodes, and 136,598 home screen uses. Per participant, on average, the dataset included a mean of 36.2 screen glances (*SD* = 41.6), 74.4 smartphone use sessions (*SD* = 33), 216 app episodes (*SD* = 135), and 171 home screen uses (*SD* = 116). The resulting dataset was located at the short survey level, with the aggregated metrics of each type of smartphone use (glances, sessions, app episodes, home screen uses) associated with it. Consequently, all metrics were calculated for each 30-minute time window before a short survey, for each participant.

[Insert Figure 1 about here]

Frequency. The frequency of glances, sessions, and episodes were represented by the number of occurrences of each use type anytime during the 30-minute window. On average, each window contained 1.07 screen glances (*SD* = 3.45), 1.94 smartphone use sessions (*SD* = 1.77), 6.16 app episodes (*SD* = 7.5), and 4.57 home screen uses (*SD* = 6.01).

Duration. The duration of each use type was calculated as the sum of the duration of each occurrence during the full 30-minute window. In cases where the beginning of the 30-minute window fell within a glance, session, app episode, or home screen use, their duration was only counted from that point on. Of note, as this resulted in many artificial beginnings of use at the exact zero-mark, zero-mark logs were excluded from the calculation of frequency. On average, within each window, there were 33.19 seconds of glances (*SD* = 168.68), 494.90 seconds of smartphone use sessions (*SD* = 582.40), 466.35 seconds of app episodes (*SD* = 576.30), and 67.92 seconds of home screen use (*SD* = 172.89).

Gateway app usage. To measure gateway app usage, each app was ranked based on how many times it was used as a gateway app (i.e, appeared as first app in a session) at the person level,[5] with higher app ranks indicating more frequent gateway use. Apps that were never used as the first app in a session were not ranked (i.e., included). On the whole, participants averaged 28.22 gateway apps (SD = 12.64), as compared to 58.34 total apps (SD = 22.03). The number of gateway apps and total apps were correlated, $r = .69$, $p < .001$. We then quantified the extent that participants focused on their more established (i.e., highest ranked) gateway apps at the situational level. To account for individual differences in the number of gateway apps, the app ranks were normalized to make them comparable across participants (i.e., between 0 and 1, with 1 for the highest ranked app). Specifically, we calculated the average gateway rank of the apps that initiated sessions within each 30-minute window, quantifying the focus on more established gateways apps during that period ($M = .40$, $SD = .41$).

Analysis Approach

We used Linear Mixed Effects models with Maximum Likelihood estimation and random intercepts for each participant to account for the nested structure of our data (Level 1: 30-minute time frame/short survey; Level 2: participant). This allowed us to disentangle intra- and interindividual variance (Hox et al., 2017). In all models, we controlled for study day, survey wave, age, gender, and education level. All analyses were conducted using the R programming language (version 4.4.1), and we used the package *lme4* (Bates et al., 2015) for modeling. Significance was assessed using Satterthwaite's method (Luke, 2017) as implemented in the *lmerTest* package (Bates et al., 2015; Kuznetsova et al., 2017).

For H1, RQ1, and H2, all focal continuous predictors were included in the models in two ways: First, by centering within individuals and second, by centering the individual means between individuals[6] (Hox et al., 2017). This way, the situational and between-person

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[5] For this calculation, all available use data per person were considered (not only use data from identified 30-minute windows).

[6] For these calculations, all available log data in all 30-minute windows were used, regardless of whether the participant indicated in the corresponding short survey that they had used their smartphone.

influence of all predictors could be disentangled (Schnauber-Stockmann, Scharkow, et al., 2025). To avoid multicollinearity issues, separate models were estimated for glances, sessions, and app episodes when investigating H1 and RQ1.

Results

To understand the relationship between smartphone usage patterns and perceptions of behavioral automaticity (i.e., habit strength perception), we first tested whether the frequency and duration of smartphone use predicted habit perception. Table 3 presents all model results.

[Insert Table 3 about here]

In terms of *frequency* (H1), we found that glance frequency was not associated with automaticity within (β = -0.009, p = .096) nor between (β = -0.005, p = .860) participants. However, we found a negative effect of the session frequency within (β = -0.014, p = .009), but not between (β = -0.016, p = .547) participants. App episode frequency also had a negative effect on automaticity within (β = -0.014, p = .015), but a positive effect between (β = 0.067, p = .014) participants. Lastly, the effect of home screen use frequency on automaticity was not statistically significant within (β = 0.008, p = .170) nor between (β = 0.048, p = .057) participants.

In terms of *duration* (RQ1), we found that glance duration was not related to automaticity within (β = -0.004, p = .493), nor between (β = 0.047, p = .079) participants. Session duration had a positive effect at both levels (within: β = 0.024, p < .001; between: β = 0.092, p < .001). For app episode duration, we observed a positive effect within participants (β = 0.037, p < .001), but no significant effect between participants (β = 0.050, p = .067). The duration of home screen use neither had an effect within (β = -0.010, p = .090), nor between (β = 0.008, p = .766) participants.

Last, we investigated the effects of gateway app usage on automaticity (H2). The results showed that a higher degree of gateway app usage predicted automaticity neither within (β = -0.001, p = .818), nor between (β = -0.009, p = .719) participants. All model results are included in Table 4. Figure 2 visualizes all key model coefficients for H1, RQ1, and H2.

[Insert Table 4 about here]

[Insert Figure 2 about here]

Discussion

Untangling how smartphone habits operate outside of the lab is particularly hard for a simple reason: real-world media behavior is complex. People use their phones for many different purposes, in many different situations, and in short bursts that can appear almost random at the ground level (e.g., Toth et al., 2024). In this study, we investigated the dynamics of situational smartphone use to explore the relationship between behavior and the perception of habit. Adopting a mixed-methods design that linked mobile sensing and experience sampling, we were able to capture real-time digital activities alongside self-reported automaticity. In doing so, we uncovered how specific metrics of smartphone use – i.e., the frequency, duration, and gateway apps – relate to momentary habit perception. To disentangle the habit mechanisms even further, we separately considered the core components of smartphone use: glances, sessions, app episodes, and home screen use. Below, we underline the theoretical implications for the study of media habits, as well as the methodological implications for the broader study of habitual behavior.

Prior habit research has treated frequency as a defining facet of habit (e.g., Verplanken & Orbell, 2003), particularly during habit formation. Frequency and automaticity also tend to be highly correlated when measured side-by-side (e.g., Gardner et al., 2024). We thus expected that the frequency of glances, sessions, app episodes, and home screen use would be positively related to elevated automaticity (H1). The results showed that, contrary to expectations, the situational frequency of sessions and app episodes was negatively related to perceived automaticity within persons. This means that unlocking the smartphone and launching apps more often than one usually does was associated with *lower* perceived automaticity. The inverse relationship suggests that using one's phone more often in a short timeframe (i.e., 30 minutes) does not inherently reflect more (perceived) habitual use. Rather, it may be that more bursts of activity than usual are an indicator of situations necessitating deliberate use (e.g., navigating a new city). Such situations may require specific, goal-oriented behavior rather than well-rehearsed scripts. Interestingly, we also did not find effects for glances and home screen use. This was striking, as such checking navigating behaviors have been assumed to be – and in some cases found to be (Oulasvirta et al., 2012; Bayer et al., 2016) – the most automatic part of smartphone use.

At the same time, we found a positive relationship between app episode frequency and perceived automaticity between persons. In line with H1, this suggests that people who launch apps more frequently tend to perceive their smartphone use as more habitual. This finding conforms more with general assumptions of habit research, perhaps by zooming back out to the person (vs. situation) level where long-run behavior better matches high-level perception. However, this effect did not hold for glances, sessions, or home screen use, suggesting that the perception of automaticity may be driven more by the number of discrete app behaviors (vs. general checking or phone navigating).

In parallel to frequency, we examined the relationship between duration and habit perception (RQ1). Although duration is less clearly tied to habit theory (vs. frequency), it is a central indicator (also known as *screen time*) of smartphone use across disciplines. Interestingly, the results showed that the duration of sessions and app episodes – but, again, not glances or home screen use – was positively related to habit perception at the situational level (within persons). In other words, we found convergent evidence that having the smartphone unlocked and apps used for longer than usual was linked to higher perceived automaticity. This indicates that more engaging use sessions are viewed as more habitual, raising intriguing questions about the (mis)alignment between objective behavior and subjective perception. Notably, our models revealed that the duration of sessions was positively associated with habit perception at the person level (between persons) as well.

The positive relationship between duration and habit perception strengthens the findings of a few cross-sectional studies on media habits (Lee & LaRose, 2007; Wohn & Ahmadi, 2019). While habits are triggered by specific cues, media habits such as smartphone checking are likely to be triggered by various *goals* that cross situational boundaries (see Naab & Schnauber, 2016) due to their versatility and mobility. As such, using the smartphone for longer likely involves multiple goals that may transition into one another within sessions, and even within app episodes, which increases the chances to trigger habits. Moreover, longer phone sessions inherently involve more habitual processes given the many motor habits (e.g., tapping, scrolling) needed to navigate a mobile interface (Bayer et al., 2022). These micro-habits are not typically in the crosshairs of communication researchers (and may be below the awareness of users), but still reflect automatic cognition. In this sense, longer sessions are embedded with more habits. Whether they are more habitual *proportionally*, however, is more questionable.

Alternatively, longer sessions may indicate more immersive engagement (e.g., losing track of time watching videos or playing games), and it is possible that participants perceived their duration in terms of habit. Users may associate long engagement with the smartphone with a lack of control (e.g., Hagger et al., 2015; LaRose, 2015), which they then explain with a lack of consciousness when reflecting on how they started to use the device. Hence, even if immersion does not align with theoretical perspectives on habit, individuals may *interpret* their behavior in this way. This syncs with the cross-sectional survey studies by Bayer et al. (2016), wherein texting automaticity and immersion were positively related to one another.

The feeling of time lost that accompanies immersion (e.g., Chen et al., 2024) may thus be more relevant to habit perception than previously acknowledged. More generally, our study highlights the role of time spent as a driver for the *perception* of habit – aligning with one recent study which found the duration of phone use is more predictive of self-reported "problematic" use than frequency (Marciano & Camerini, 2022).

Finally, we tested whether gateway app use was associated with amplified habit perception (H2). This hypothesis paralleled the first hypothesis, but directed a more targeted scope toward established gateway apps (i.e., the apps that participants started sessions with the most across the study period). More focus on top gateway apps was not associated with habit perception, however, undermining the notion that gateway apps are perceived as distinctively habitual on a situational basis. Notably, no relationship was observed either within or between persons. Nonetheless, it is instructive to consider the implications for the gateway concept, along with the assumptions of our analysis. In theory, launching sessions with more established gateway apps than usual (i.e., within persons) could trigger more habits within the same session, since they act as a well-rehearsed "hub" for subsequent habit sequences. For instance, a conversation in a top messaging app that initiated a session might trigger the use of a top web browser app to look up something. However, just like general app frequency was negatively related to habit within persons, using top gateway apps to start sessions more frequently than usual may not increase the perception of automaticity. Also striking was the lack of relationship between the overall focus on top gateway apps and perceived automaticity (i.e., between persons). In other words, the people who exhibited more repetitive patterns of starting sessions on average did not view their phone use as more automatic.

Of note, the first app used in a session often coincides with the last app used in the session before, as unlocking the device inherently re-launches it (unless the device was locked from the home screen). Although session initiation (i.e., checking) is typically assumed to be more automatic (Bayer et al., 2016), more conscious behavior could take precedence as a session progresses (LaRose, 2010, p. 197; Naab & Schnauber, 2016, p. 130). In this sense it is also possible that the last app used in a session is actually the *least* habit-driven. In sum, the various complexities tied to gateway apps (and their subsequent action sequences) may have canceled each other out, or perhaps these micro-behaviors simply do not register in subjective habit perceptions.

Altogether, our analyses unveiled a number of novel links between logged behavior and self-reported automaticity, offering a closer look at the inner workings of real-time smartphone habits. Whereas we expected positive relationships between the frequency of smartphone behavior (and gateway app use especially) and habit perception, instead we encountered a more complicated story. Further, we identified duration as an unexpectedly consistent (positive) predictor of habit perception. These findings generate new challenges to the assumptions of habit theory, and underscore the need to distinguish habit behavior and perception in future research. In the process, our study has the potential to inform the measurement of media behavior in other areas of communication research. Our work reinforces calls for disentangling situation- and person-based influences on media behavior (Schnauber-Stockmann, Scharkow, et al., 2025). Indeed, in some cases, the within- and between-person effects went in opposite directions, illustrating how past work (including habit studies) may have conflated different factors.

More broadly, our study highlights the promise, and challenge, of measuring real-world habits and detecting habitual *processes* directly. We sought to assess whether digital traces of smartphone activity can reveal these habit processes (or at least habit perceptions) driving everyday media use. Clearly, the fine-grained relationship between smartphone use and habit cannot be deconstructed using self-report measures alone, nor can it be disentangled in cross-sectional study designs (whether via logs or self-reports). Our design aimed to address limitations in past research by measuring both objective behavioral indicators and subjective habitual perceptions at the ground level. Nonetheless, the existential challenge for habit researchers remains: are “objective” or “subjective” indicators more valid proxies for habitual processes? Indeed, self-report measures often fail to capture the full complexity of habit. For instance, Gardner (2015) argues that traditional habit measures do not effectively differentiate between automatic initiation and execution. The distinction between initiation (i.e., beginning to perform the behavior) and execution (i.e., performing the behavior) is especially critical for smartphone use, where many micro-behaviors are performed in sequence, leading to patterns that can be quite complex (Phillips & Mullan, 2023; Rebar et al., 2018). In a similar vein, our mixed findings pertaining to frequency duplicate calls for disaggregating within- and between-person processes in habit research specifically, as prior work has overly focused on between-person differences (Gardner, 2015).

Limitations and future directions

While our findings provide valuable insights into smartphone habits, several limitations merit acknowledgment. First, while the Android event log data provided highly precise records of smartphone activities and avoided the perceptual biases often seen in self-reports (Parry et al., 2021), there remains the possibility of logging errors. For example, in our raw data, a small number of participants exhibited extended gaps in logging or very long usage sessions. Whether these were the result of natural behaviors (phone battery dying, prolonged usage sessions, etc.) or technical issues is unclear. During data extraction, unnaturally long use sessions were removed (see Parry & Toth, 2025, for a description of this procedure). While such irregularities primarily occurred outside of the ESM period, there remains the possibility that some logging errors persist.

Second, the potential effects of compliance and reactivity warrant acknowledgement. Despite the randomization of the short surveys within the measurement intervals, short survey expiration, and a relatively high compliance rate, participants may have delayed completing the surveys until it was convenient for them, potentially introducing biases into the ESM responses. While participants were not explicitly informed about the exact scheduling mechanism, they may still have noticed that they were not always required to complete the short survey immediately after being notified. In addition to potential biases introduced by repeated assessment using ESM (Eisele et al., 2023), the awareness of being observed may have led participants to alter their smartphone use (e.g., Toth & Trifonova, 2021). Future research should further explore how logging awareness impacts behavior, as this has implications for all sensing studies.

Last, as is common in mobile sensing research, our study involved self-selected participants (limited to Android users due to methodological constraints on iPhones), who may be more tech-savvy or less concerned about their privacy than the general population, potentially limiting the generalizability of our findings.

Conclusion

Smartphone habits have been tightly woven into everyday life for many years, yet communication researchers are just beginning to zoom in to see them in high resolution. Whereas the measurement of media habits in the past was commonly based on aggregate retrospective self-reports, our design set out to capture both digital and perceptual signals of habit at the situational level. Our study thereby represents one step forward in the exploration of real-world habit processes. Our findings surfaced a number of unexpected takeaways – and raised a number of deep questions – related to our understanding of habitual behaviors. In particular, results highlighted the overlooked role of duration in predicting real-time habit perception. By contrast, the critical habit facet of frequency exhibited a complex connection to perceived automaticity, with divergent relationships seen for within- vs. between person indicators. Overall, our study underlines the value of a situational lens for advancing the measurement of (media) habit processes. By identifying the digital patterns that best reflected automaticity, we laid the groundwork for a more precise measurement of real-world habits, and habit perceptions. In this way, our study illustrates the overlooked value of both habitual and situational processes for researchers in communication and beyond.

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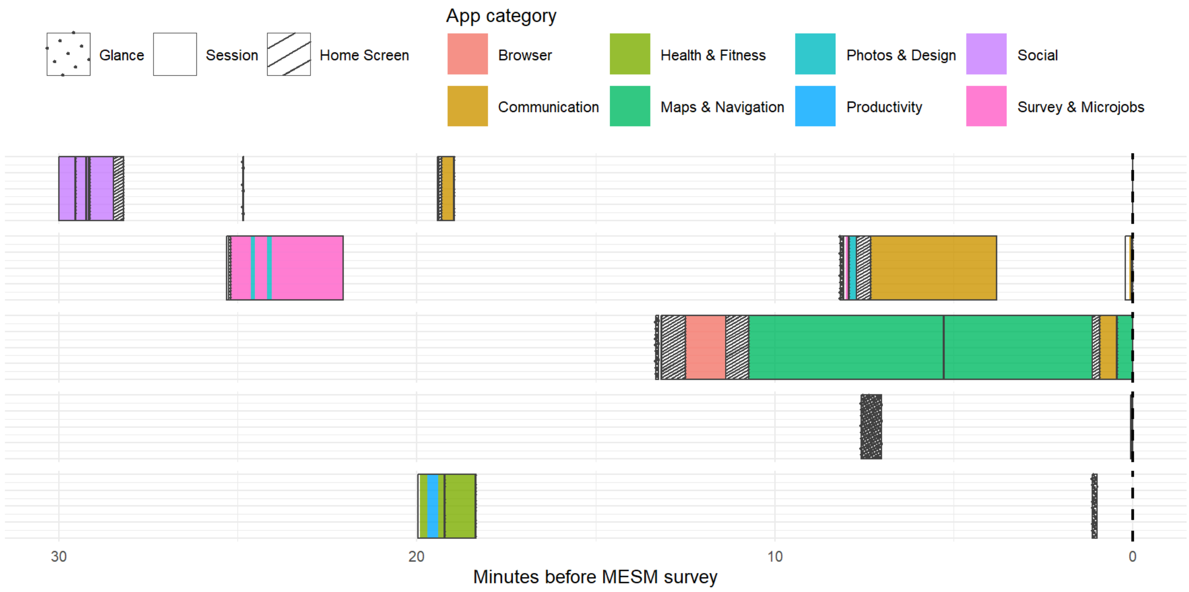
Figure 1

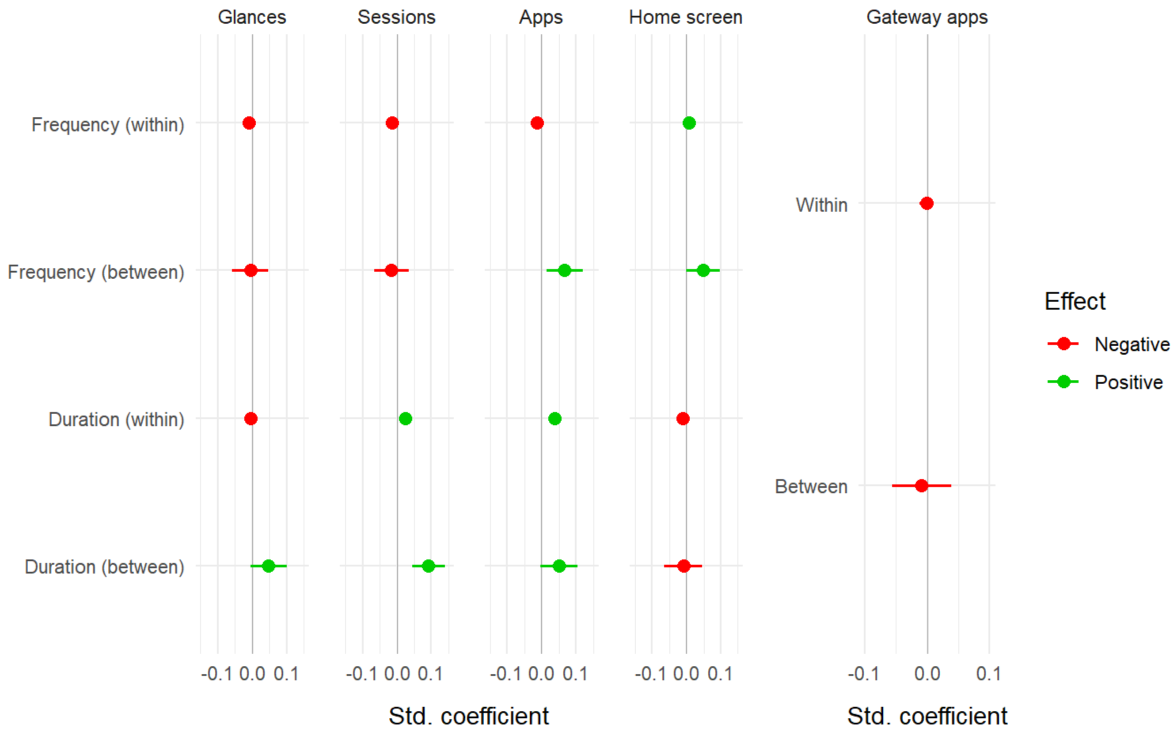
Sample of smartphone use within 30 minutes before a short survey was launched.



Note. The x-axis depicts the number of minutes before the ESM survey. This means that use at the 30-minute mark took place at the beginning of the time window the short survey referred to. The dashed line at the 0-minute mark represents the moment the short survey was accessed.

Figure 2

Overview of results for H1, RQ1, and H2



Note. All effects reflect standardized coefficients. Control variables are omitted.

Tables

Table 1: Sample statistics

Variable	n	%
Gender		
female	238	26.8
male	648	72.9
diverse	3	0.3
Age		
18-30	228	25.6
31-40	233	26.2
41-50	174	19.6
51-60	156	17.5
61-69	98	11.0
Education		
No school diploma (yet)	2	0.2
Secondary modern school (without completed professional training)	50	5.6
Secondary modern school (with completed professional training)	140	15.7
Secondary school	229	25.8
Technical baccalaureate	41	4.6
Baccalaureate	172	19.3
Polytechnic university	72	8.1
University	174	19.6
Doctorate	9	1.0

Table 2: Descriptive statistics, within- and between-person correlations of habit perception and digital log behaviors

	Descriptive		Correlations										
Variable	**M**	**SD**	**1.**	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**	**9.**	**10.**	**ICC**
1. Perceived automaticity	1.62	1.41	-	.10*	-.01	.14*	.17*	.22*	.17*	.13*	.03	.06	.48
Glances													
2. Frequency	1.07	3.45	-.03*	-	.68*	.30*	-.05	.17*	-.08*	.13*	-.13*	.14*	.10
3. Duration (sec)	33.19	168.68	-.02*	.62*	-	.13*	-.05	.07*	-.07*	.03	-.05	.10*	.44
Sessions													
4. Frequency	1.94	1.77	-.02*	.23*	.12*	-	.10*	.60*	.05	.52*	-.00	.41*	.24
5. Duration (sec)	494.90	582.40	.03*	-.12*	-.10*	.13*	-	.59*	.92*	.41*	.43*	.18*	.15
Apps													
6. Frequency	6.16	7.50	.01	.03*	-.01	.46*	.58*	-	.56*	.73*	.27*	.34*	.26
7. Duration (sec)	466.35	576.30	.04*	-.15*	-.12*	.03*	.88*	.56*	-	.34*	.28*	.21*	.19
Home screen													
8. Frequency	4.57	6.01	.02*	.05*	.01	.49*	.51*	.83*	.46*	-	.56*	-.11*	.32
9. Duration (sec)	67.92	172.89	.01	.01	.00	.31*	.40*	.43*	.25*	.57*	-	-.34*	.29
Gateway apps													
10. Rank	.40	.41	.00	.04*	.01*	.23*	.24*	.24*	.18*	.14*	.06*	-	.28

Note. * = p < .05, ICC = Intraclass correlation coefficient. For habit perception n = 18,354 and for all other variables n = 29,253. Within-person correlations depicted below, between-person correlations above the diagonal. Descriptives and correlations are based on aggregations for each 30-minute window. For duration, the descriptives represent average total seconds.

Table 3: Results for H1 (frequency) and RQ1 (duration)

	Glances	Sessions	Apps	Home screen
Parameter	***β*** **[95% CI]**	***β*** **[95% CI]**	***β*** **[95% CI]**	***β*** **[95% CI]**
Fixed (main)				
Intercept	-0.05* [-0.10, 0.00]	-0.04 [-0.10, 0.01]	-0.04 [-0.09, 0.01]	-0.05 [-0.10, 0.00]
Frequency (within)	-0.01 [-0.02, 0.00]	-0.01* [-0.02, 0.00]	-0.01* [-0.03, 0.00]	0.01 [0.00, 0.02]
Frequency (between)	0.00 [-0.06, 0.05]	-0.02 [-0.07, 0.04]	0.07* [0.01, 0.12]	0.05 [0.00, 0.10]
Duration (within)	0.00 [-0.01, 0.01]	0.02* [0.01, 0.04]	0.04* [0.03, 0.05]	-0.01 [-0.02, 0.00]
Duration (between)	0.05 [-0.01, 0.10]	0.09* [0.04, 0.14]	0.05 [0.00, 0.10]	-0.01 [-0.06, 0.05]
Fixed (covariates)				
Day	-0.01 [-0.02, 0.00]	-0.01 [-0.02, 0.00]	-0.01 [-0.02, 0.00]	-0.01 [-0.02, 0.00]
Survey index	0.02* [0.01, 0.03]	0.01* [0.00, 0.03]	0.01* [0.00, 0.02]	0.02* [0.01, 0.03]
Age	-0.19* [-0.24, -0.14]	-0.18* [-0.23, -0.13]	-0.15* [-0.21, -0.10]	-0.17* [-0.22, -0.12]
Gender	-0.02 [-0.07, 0.03]	-0.04 [-0.09, 0.01]	-0.03 [-0.08, 0.02]	-0.02 [-0.07, 0.03]
Education	-0.05* [-0.09, 0.00]	-0.05* [-0.09, 0.00]	-0.05* [-0.09, 0.00]	-0.05* [-0.09, -0.01]
Random				
Intercept	0.65 -	0.65 -	0.65 -	0.65 -
Residual	0.73 -	0.73 -	0.73 -	0.73 -

Note. * = p < .05, b = Standardized coefficient, CI = Confidence interval

Table 4: Results for H2 (gateway apps)

Parameter	***β***	**95% CI**
Fixed (main)		
Intercept	-0.05*	[-0.10, 0.00]
Rank (within)	0.00	[-0.01, 0.01]
Rank (between)	-0.01	[-0.06, 0.04]
Fixed (covariates)		
Day	-0.01	[-0.02, 0.00]
Survey index	0.02*	[0.01, 0.03]
Age	-0.19*	[-0.24, -0.14]
Gender	-0.02	[-0.07, 0.03]
Education	-0.05*	[-0.10, -0.01]
Random		
Intercept	0.65	-
Residual	0.73	-

Note. * = p < .05, b = Standardized coefficient, CI = Confidence interval