The Loop and Reasons to Break It: Investigating Infinite Scrolling Behaviour in Social Media Applications and Reasons to Stop

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Today's social media (SM) platforms are toolkits consisting of features with different use cases, some strongly related to habitual and regretful use. Especially Infinite Scrolling (IS) has been reported to make users feel like they are being caught in a loop, regretfully elongating SM sessions. We investigated and defined this loop while unveiling the processes that make users break it. Based on a one-week-long field study (N=46), we unfolded and categorized general reasons for leaving social media and related those to IS. In light of our findings, we argue that SM interventions should not only focus on the app but incorporate the user's context, as most reasons to break SM sessions were not related to the app but the user's general context. Our findings and prior work also indicate the coexistence of multiple loops, which we define as inner (intra-session) loops surrounded by an outer (habitual) loop.

CCS Concepts: • **Human-centered computing** → **Field studies**; **Smartphones**; **Empirical studies in ubiquitous and mobile computing**.

Additional Key Words and Phrases: infinite scrolling, endless scrolling, the loop, regretful use, social media

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1 INTRODUCTION

Social media platforms should not be regarded as a singular tool but as a toolkit of features with different use cases and affordances [45]. Among others, there are one-on-one (i.e., directed

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communication: one person communicates with one other person) and non-targeted interactions (e.g., broadcasting such as posts) with other users[11]. Besides such active participation, there is also passive use of the platforms in which users are consuming content but not interacting with its creator [11]. Passive usage can be divided into social browsing and social searching. Wise et al. [50] define social searing as the act "of looking for specific information about offline acquaintances with the goal of knowing them better " [50, p. 556], social browsing is the "less particular act of "surfing" general information about both friends and strangers " [50, p. 556]. Scrolling through the news feed would, therefore, fall into the category of social browsing, where we gather information about different topics presented to us by the social media platform. Such passive usage was found to induce, for example, feelings of loneliness [10, 33], lower life satisfaction [27], higher levels of regret [8], and social anxiety [44].

A user interface element, which is integrated in almost all major social media platforms is the feature of Infinite Scrolling (IS, also known as Endless or Continuous Scrolling). In the beginning, it was said to break "a number of expectations for users and causes quite a bit of confusion" [17, p. 96]. Nevertheless, over time it became a standard feature of social media. It was even implemented in news outlets like the LA Times and Fox News [51] and many other webpage/app categories. In IS, replacing the classical pagination approach, the user now triggers the dynamical loading of additional content by scrolling down the page instead of clicking-through content pages. The newly loaded content is then added to the bottom of the page, leading to a seemingly endless stream of information.

Recently, IS was criticized. In a survey on SM usage, 25% of participants stated that they regretted spending too much time on Facebook's IS "news feed " [35]. Further study found that IS in general lead to the highest amounts of retrospective regret [8]. Participants in other studies noted that a common reason for an unwillingly elongated social media session was "endless scrolling" through their social feeds [37]. They named this feeling for being "caught in a loop " [14]. In addition to these scientific findings, IS inventor Aza Raskin[1] started raising attention to his invention on multiple occasions. He condemned the technique in the Netflix documentary "The social dilemma"[2] and denoted it as "not [...] best for the user or humanity"[3] on his Twitter account.

In our work, we investigated IS for a better understanding of its effects on social media users. In line with the definition of different session types by Banovic et al. [2], we explored how IS is part of and potentially dominating what they call (1) short review sessions (sessions <= 1min) and (2) engage sessions (sessions > 1min). As related work [14, 37] also hints at IS being a defining part of longer sessions and creating "the loop", we also look at (3) long sessions (10 minutes and up). Besides the composition of SM sessions, we also investigated the influence of IS on the users' feelings. We also collected reasons for leaving SM sessions, thereby exploring the users' context at the moment of leaving as a potential field from which interventions can be deducted.

In light of these questions, we conducted a week-long in-the-wild experience sampling method study with N=46 participants. For this, we developed an application running in the background of participants' smartphones to monitor the usage behavior of five of the most-used SM applications, implementing IS on their home screens (Facebook, Instagram, TikTok, Reddit, and Twitter). In questionnaires triggered in response to leaving SM sessions, participants answered questions about their recent social media sessions. In this manner, we recorded the opening and closing time of 6605 single app sessions on which we recorded 1064 triggered questionnaires.

[1]https://www.thetimes.co.uk/article/i-m-so-sorry-says-inventor-of-endless-online-scrolling-9lrv59mdk, Accessed: 11 NOVEMBER 2022
[2]https://www.netflix.com/de-en/title/81254224; Accessed: 11 NOVEMBER 2022
[3]https://twitter.com/aza/status/1138268959982022656, Accessed: 11 NOVEMBER 2022

Analyzing and systematically categorizing the recorded breakout reasons allowed us to identify three categories for breaking out of a SM session: the real world, the device itself, and Internal, user-related reasons. As static interventions "decline in effectiveness over time as users begin to ignore them" [26], Cho et al. [8] argue that feedback needs to be low-level and account for intra-app usage context. However, in light of our findings, we argue to extend Cho et al. [8] assumption. Besides the intra-app context, we also found contextual, external reasons to leave SM sessions that go beyond what is happening inside the application. We, therefore, propose utilizing the found reasons for leaving "the loop" as interventions to shorten potentially regretful SM sessions and give practical examples of how such interventions could look. Further, based on our findings and prior work, we argue that IS does not facilitate one but two inter-weaved loops, which can entrap the user. First, IS features can facilitate habitual, repeated use, creating an outer loop of repeatedly opening SM to utilize IS features. Second, the same IS features can then escalate these sessions catching the user in an intra-sessional, inner loop leading to elongated regretful use. While there is an interplay between the inner and outer loop, IS features can also, detached from the outer loop, trigger a feature tour. Here, they can high-jack other sessions that began through other activities inside the same application, becoming a part of almost all long sessions.

Contribution Statement:
With our work, we make the following contributions to the scientific community:

- The uncovering and categorization of reasons leading to a break-out of IS and social media sessions in general and quantifying their relative appearance. Researchers and Developers can build on this knowledge to develop new interventions tackling regretful SM use from new angles.
- A structured analysis of IS features, focusing on the proportion they take in short, medium, and long sessions and their influence on valence. We argue for the existence of an inner and outer IS loop, and contribute to a better understanding of the impacts of IS on SM users.

2 RELATED WORK

In the following, we introduce the main topics our work is built on: interventions against regretful smartphone usage, IS, and "the Loop".

2.1 Interventions

Lanette et al. [29] report "that nearly 90% of parents and teens use language of addiction/obsession, distancing/defensiveness, and/or concern/shame when responding to the open-ended survey and interview questions about their relationship with their phones " [29, p.18]. While users perceive their repetitive, habitual phone usage as an annoyance rather than an addiction [40], multiple self-regulatory interventions have been developed to cut down usage time and frequency of applications [15, 22–25]. These interventions typically build on a single, static feature that tries to persuade users to behave in a way deemed as desirable [26] by restricting usage or notifying them about undesirable behavior.

Hiniker et al. [15] and Kim et al. [22] block unwanted interactions for a fixed period, restricting users from unwanted activities to assist them in achieving their goals. In another work, they limit the overall daily usage time [23]. Such restrictive, time-based interventions have lately found their way into smartphone operating systems like Android[4] or iOS[5]. Users can perceive their usage times on an app-base and set boundaries for their usage. Expanding on this idea, related work has also

[4]https://www.android.com/digital-wellbeing/, Accessed: 28 DECEMBER 2022
[5]https://support.apple.com/en-us/HT208982, Accessed: 28 DECEMBER 2022

explored variations of restriction-based interventions by incorporating social traits. Ko et al. [25] utilized social support in a group setting by sharing information about a user's wished limiting behavior. In later work [24], they approached implemented social interventions by synchronously restricting all members of a group at the same time.

All these interventions perceive applications as single entities and, therefore, restrict them as a whole. This might not be the best approach, as especially today's social media applications serve multiple purposes [45]. A single application could, for example, include features used in leisure time, while others are needed in a work context. In a study on habitual use by Tran et al. [46], participants stated that they were not frustrated with habitual use as such. While frustrated about their lack of self-control, some activities during regretful sessions can be meaningful to them as they deliver, e.g., social or informational rewards. Cho et al. [8] argue that different usage patterns are connected to different features, making some more regrettable than others (e.g., subscription-based compared to suggestion-based features). Therefore, interventions not including feedback on intra-app usage context could be too high-level and improved by incorporating it.

While breaking down the intra-app context might allow more detailed interventions targeting certain features, Kovacs et al. [26] showed that static interventions decline in effectiveness with users beginning to ignore them over time. In turn, rotating between different kinds of interventions (e.g., Informing the user, removing rewards, or setting time limits) helped users gain control of their online habits. They argue that we, therefore, have to gain an understanding of users' mental models to reduce attrition with interventions.

To better understand this mental model and build a comprehensive picture of the user's phone usage, one part is to understand what leads users to finally break out of SM sessions, which could be reasoned by more than what is happening on the smartphone itself. In semi-structured interviews, Tran et al. [46] identified three main reasons for leaving an application when compulsory using it: Old content, the users' surroundings, and realizing how much time has passed. In a laboratory setting, Nontasil and Payne [39] unveiled that we do not judge the Valence of a social media session by its length but by the content consumed. They did not find a connection between the posts and why they ended the session.

Based on these findings, we argue that building a comprehensive picture of why participants conclude their SM usage can aid in developing interventions tailored to nuanced app-usage contexts that not only incorporate intra-app events but the user as a whole. We take the first step towards this goal by exploring the reasons for leaving an application and painting this comprehensive picture in a real-world setting.

2.2 Infinite Scrolling and The Loop

Interventions are reasonably applicable to activities that lack sufficient meaning, leading to regret. Kahneman and Tversky [21] defines regret as the emotion experienced when comparing reality with what might or should have happened instead. One feature of SM applications that is frequently associated with regret is IS [8, 14, 35].

In the context of social media application, Mildner and Savino [35] found that after entertainment features (with 34%), the news feed (with 24%) took second place on features the users regretted spending too much time on. In their study on application usage, Heitmayer and Lahlou [14] found that participants' interaction with Facebook, Instagram, and the phone's web browser was longer than, e.g., in chat or email applications. They argue that this could be due to the implemented IS. In the context of regret, Cho et al. [8] took a deeper look at different social media features. Here, they report that participants regretted habitual checking patterns, which Lukoff et al. [31] connected to having lower levels of meaning to users. While participants mainly regretted using features implementing IS on habitual use, they also reported going on a 'feature tour'. Here, they detracted from the original task and wandered around different features within one app after completing their main entry goal. Here, again IS features were linked with regret, triggering participants to stay longer and "fall down the rabbit hole of regret " [8, p. 19]. Participants in other studies also stated that they felt as though they were caught in a loop [14]. Trying to examine the relationship between biological rhythms and technology-mediated social interactions, Murnane et al. [38] report that social media kept them awake longer than they planned to be. They stated "endless scrolling" through their social feeds as a common reason.

Harris [13] argues that IS functions as a gambling machine. Like pulling the lever of a slot machine, scrolling down the feed can result in perceiving content we enjoy and feel rewarded by or do not. Nontasil and Payne [39] argue that this non-predictable pattern of reward can be considered partial reinforcement, which is often seen in the context of compulsive use. Partial reinforcement refers to the phenomenon that behavior we learn is more robust to extinction when we are not rewarded for every response but only for a few [16]. Lewis [30], for example, found that when gambling, participants that only won in 60% of trials played longer than those winning in every trial. Furthermore, it was shown that the rate of reinforcement also correlates with addictive behaviour [18]. Jenkins and Stanley Jr [19] argue that partial reinforcement could work due to delaying the effects of satiation, prolonging the training phases.

With our work, we contribute to understanding IS scrolling features. Firstly, while Nontasil and Payne [39] have unveiled that we do not judge the Valence of a scrolling session by its length, they did not find a connection between the posts and the reason to end the session. As people get stuck in a loop but do not "quit their sessions because their enjoyment had diminished " [39, p. 6], we still lack comprehensive knowledge on how they finally break out of those loops. Secondly, we want to define "the loop" further by examining how IS is distributed over different session types. In this turn, identify whether habitual scrolling-only sessions exclusively happen in short sessions while scrolling in longer sessions results from mixed activity "feature tours". Lastly, we add to the knowledge of why we scroll even though regretting it later. In a study by Nontasil and Payne [39], participants deemed scrolling to be an overall positive experience. We, therefore, explored how IS features influence our feelings compared to other activities inside SM.

3 STUDY

To (1) paint a comprehensive picture of reasons leading to the termination of sessions (called *Breakout-Reasons*), (2) connect those reasons to IS features, and (3) further define "the [IS] Loop" and (4) how IS makes us feel, we conducted an in the wild study using the mixed-context experience sampling method. We recorded log data of participants' social media usage on their smartphones and subjective data collected through questionnaires triggered by social media closing events. Prior studies in the field of social media already established the experience sampling method (ESM) as a tool for insights into social media usage [4, 28, 41, 48].

These ESM studies mostly utilize a classical approach [20] asking the participants to fill out questionnaires on pre-defined times [4, 41, 47, 48] or randomly triggered within certain time frames [28]. Kross et al. [28], for example, triggered surveys five times per day, between 10 am and midnight, within a 168-Minute window defined by the first message. Instead of reacting to recorded screen times at certain pre-defined times or in daily retrospect, we decided to utilize an event-triggered approach. Triggering questionnaires in reaction to actual SM usage produced more detailed and accurate data on past behavior than self-reported retrospect estimates [36]. For example, Cho et al. [8], Bayer et al. [3], and Chang et al. [7] used similar approaches in their studies. This means that a questionnaire is triggered at the end of a SM session that is connected to this specific SM session.

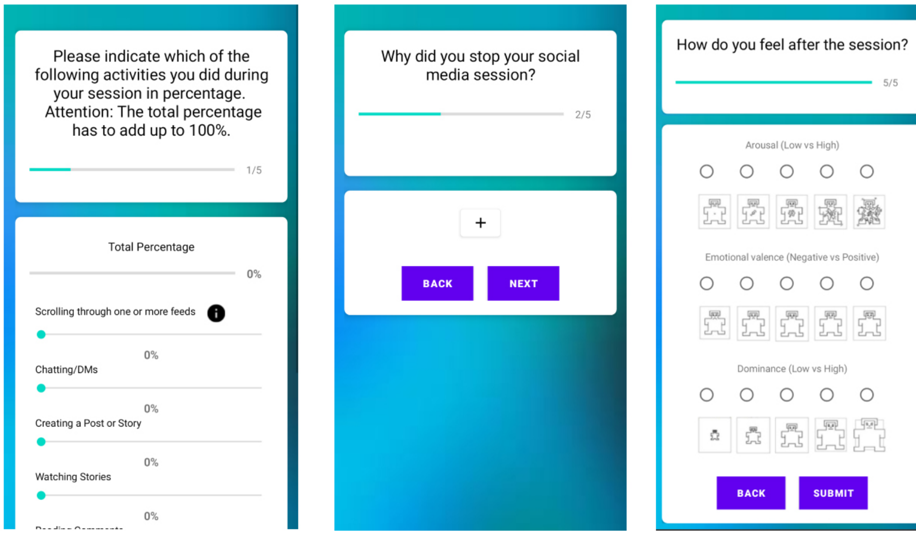

Fig. 1. Screenshots from the session questionnaires triggered by our application. On the left, the participants had to indicate the share of time different activities inside their session took. In the middle, participants had to indicate the reason they broke out of their session. Here, pressing the '+' button led to a dialogue that allowed to add a new reason. That reason was then selectable. On the right, participants were asked to indicate their feelings after the session.

As we wanted to produce a more diverse picture on *newsfeed* and *infinite scrolling*, we captured usage of 6 of the ten SM networks most used in the US in 2020[6]. These included Facebook, Instagram, Twitter, Reddit, and TikTok while excluding Yelp, LinkedIn, Youtube, Pinterest, and Snapchat as they do not employ IS on the landing page (Snapchat, Yelp) or are not considered as social media primarily (YouTube, LinkedIn, Pinterest). All included applications led the user directly to a news feed implementing IS. In addition, multiple applications also implemented *infinite scrolling* in their search feature (TikTok, Instagram) and their marketing/store feature (Facebook, Instagram).

To the best of our knowledge, neither Android nor iOS natively provides functionality that enables reacting to app closing events. Therefore, we developed our Android application for the study.

3.1 Apparatus

As a tool for the study, we developed a native Android application that runs as a service in the background. To notice opening and closing events, we developed a listener service that reacted to changes in Android's internal logging system implemented through the UsageStatsManager[7]. Here, the Android operating system logs all applications' foreground times, which applications can then query. By frequently querying the times (all 5 seconds) for all monitored applications, we were able to detect the opening and closing events when they happened. This means that we could detect that an application left the foreground and, therefore, a closing event within 5 seconds of its appearance. With a three-hour cool down (to not annoy the participants, see paragraph below), we used the closing events to trigger a notification for the participant. Opening this notification

[6]https://www.statista.com/forecasts/997135/social-network-usage-by-brand-in-the-us, ACCESSED: 15 JULY 2022
[7]https://developer.android.com/reference/android/app/usage/UsageStatsManager; Accessed: 04 AUGUST 2022

triggered a questionnaire. This procedure led to a possible notification every three hours. After filling out the questionnaire, the application closed its foreground appearance and continued to run in the background. After the study ended, we terminated the listener service and asked the participants to uninstall the application.

From a study conducted by Möller et al. [36], we know that triggering questionnaires at a high frequency is annoying to participants and, in turn, leads to an increased number of dropouts. Therefore, we decided to restrict the number of triggered questionnaires by introducing a three-hour cool down after each triggered questionnaire. Assuming that the average person sleeps 8 hours a day, this would lead to a maximum of 5 questionnaires a day which is in line with the four to six time-triggered questionnaires in conventional experience sampling method studies [4, 28, 41, 48]. From related work [2] as well as a small trial run of our study, we knew that users and, therefore, potential participants most likely experienced a multitude of smaller habitual sessions. As we were also interested in how IS is present in longer sessions and revealing *Breakout-Reasons* for them, we decided to also trigger questionnaires on every session over 10 minutes This helped to build a database on such longer sessions that avoided overfitting in the analysis as we used linear mixed models, which are sensitive when using small sample sizes [34]. Overall this means that with the closing of an SM app, a questionnaire was triggered if (1) the last questionnaire was triggered more than 3 hours ago or (2) the SM session was longer than 10 min. Also, participants could skip answering a questionnaire if they could not answer them in their context.

3.2 Measurements

In the following, we describe the measurements we took during our one-week-long study.

3.2.1 Initial Questions. In an initial questionnaire, we queried demographic data (age, gender) and data related to social media usage. In single-item questions, participants were asked to state how much they agreed with certain statements, from 1 (strongly agree) to 5 (strongly disagree). These statements were: "I often spend more time on social media than I intended to.", "I often feel like scrolling through posts without reaching the end." and "I often feel stuck on unnecessary posts for a long time."

3.2.2 Experience Sampling Method Questionnaire. During the one-week-long experience sampling method phase, we collected objective data in the form of timings. This data allowed us to calculate the *Time* a session took. Here, *Time* is defined as the time between the start and end of a *Session* and, therefore, its actual length. We use these timings to categorize the subjective measurements we gathered through questionnaires by *Session Length Category*. In line with the definition by Banovic et al. [2], we divided sessions into short *Session Length Category* (<1 minute) and engage sessions (>=1). As we were especially interested in longer sessions, we defined sessions longer than 10 min as *Long Session* sessions. Which lead to engage sessions into *Medium Session* (1 to 9 minutes) and *Long Session* (> 10min).

As privacy measures inside the Android operating system did not allow monitoring the session further than opening and closing timings, we let participants map what they did inside the session. On sliders from 1 to 100% (as depicted in Figure 1), they were able to indicate how much of the overall time the respective feature and, therefore, *Activity* took. Overall, sliders could not be moved past an accumulated 100%, mapping the whole session. Examining the applications individually, coding features, and discussing, four of the authors arrived at the identification of the six main features of the apps surveilled in the study: "Scrolling through one or more feeds" (*IS-percentage*), "Chatting/DMs" (*chat-percentage*), "Creating a Post or Story" (*posting-percentage*), "Watching Stories" (*watch-stories-percentage*), "Reading Comments" (*com.-read-percentage*), "Writing Comments" (*com.-write-percentage*). We also added an "Other" (*other-percentage*) category to account for possible missed functionalities. When participants declared this option as non-zero, the participant was asked to specify their actions that fell into the category of "Other". To specify that IS feeds were meant by "Scrolling through one or more feeds", we added an info text in the app that highlighted the names (e.g., News Feed, Reels Feed, Search Feed) for feeds with IS capabilities inside monitored applications. In the following, we will analyze the recorded *Proportion* as a percentual value and the identified *Main Activity* for each session. The *Main Activity* is defined as the activity with the biggest share of the respective session.

Additional to mapping the sessions, the participants' emotional states as assessment of *Affective Response* in the form of the self-assessment-manikin scale (SAM) was employed. It was introduced by Bradley and Lang [5] as an "inexpensive, easy method for quickly assessing reports of affective response in many contexts" [5, p. 49] and became a go-to method of assessing a participant's emotional state. In single-item scales, on scales from 1 to 5, the SAM questionnaire measures the participants *Arousal* (Low to High), *Valence* (Negative to Positive), and perceptions of *Dominance* (Low to High).

We also asked participants to state why they ended their session (*Breakout-Reason*) in a free text field. To shorten the required time for finishing the questionnaire, answers from previous questionnaires were added as quick-select options. Therefore, instead of repeatedly writing each *Breakout-Reason*, the participants were able to select from one of the previously given answers directly. During the prior trial run, the participants required approx. 5-15 seconds to finish the questionnaire.

3.3 Participants

In two batches, we recruited our participants via Prolific[8]. We only addressed US citizens to avoid confounding variables such as culture [42]. Of 205 participants recruited through Prolific, 143 registered for the one-week-long study by downloading our application. Of those, we excluded 92 as they did not finish the study. Following the Prolific guidelines on attention checks[9]), we included attention checks with a probability of 25% in each session questionnaire. Analyzing those, we further excluded *Questionnaire* participants for missing more than one attention check. This led to 46 included participants (26 in the first batch, 20 in the second batch). As both batches received the same study treatment, we will not report them individually but as the total amount of participants in the same study. The included participants (23 identifying as female and 23 as male, 0 non-binary) were aged 20 to 73 (M = 33.74, SD = 12.98). Participants only partaking in our pre-registration study received £0.99, while participants partaking in the whole study were compensated with a further £7 for their effort.

3.4 Procedure

We structured the study into four parts. After starting with our registration study and accepting the consent form, we presented the participants with the parts in the following order.

3.4.1 *Registration and Downloading the App.*

After access through Prolific, we explained the purpose of our planned study to the participants. They then answered questions about their current smartphone and their willingness to participate in our main study, taking place over the cause of seven days. As our application ran on Android Smartphones only, only participants stating that they owned an Android Smartphone with the operating system version 6.0 or higher were allowed to proceed. Participants willing to partake in our longitudinal study were then instructed to download

[8]https://www.prolific.co/, Accessed: 24 JANUARY 2022

[9]https://researcher-help.prolific.co/hc/en-gb/articles/360009223553-Using-attentionchecks-as-a-measure-of-data-quality, Accessed: 24 JANUARY 2022

our application from the Android App Store. We hosted it there to simplify the registration with our study.

3.4.2 Initial Questionnaire. After installing our application, we again explained to them that we would monitor their social media usage and, from time to time, ask them questions about it. After consenting and giving the application the rights to push notifications and access the UsageStatsManager, they were asked to fill out initial questions about their social media usage (see subsection 3.2).

3.4.3 Week-Long Experience Sampling Method Questionnaires. After finishing the initial questionnaire, a week-long surveillance period started as described in subsection 3.1. Questionnaires were triggered in reaction to the end of a *Session*, with a cool down time of 3 hours, except for sessions longer than 10 minutes. During the week, participants could see a notification confirming that the application was still running. They were instructed to restart the application if the notification disappeared. After the seven-day period ended, a final form was triggered, questioning them about occurrences and errors in the application. Afterward, we thanked them for their participation and asked them to uninstall the application. Participants were then compensated for their efforts.

3.5 Data Preparation

We registered 6605 sessions over these 46 participants and the cause of 7 days. 1183 of those have triggered session questionnaires. Of those 1183, we excluded 4 for failing attention checks. Further, we analyzed the time between a questionnaire being triggered and the participants beginning to answer it. We removed 115 extreme outliers [9] (Q3 + 3 * IQR), leading to the exclusion of questionnaires that participants answered over ≈24 min after the *Session* ended. This procedure resulted in 1064 answered questionnaires taken into account for the analysis.

4 RESULTS

In the following, the results of our study are reported, starting with *Breakout-Reasons*. To statistically analyze our data, we (with one exception in analyzing the connection between *Time* and *Overall Sessions*) used Linear mixed models as a robust way to take advantage of the full dataset and to account for the non-independence of observations within participants. For this reason, each of the models included participants as a random effect. All other variables were modeled as fixed effects. We ran the models in R (version 4.2.2) using RStudio (version 2022.07.2+576), estimating through restricted maximum likelihood (REML) estimation within the lme4 package. We updated all packages to the newest versions before executing the analysis in November 2022. To avoid extensive repetition, in the following, talking about fitted linear mixed models always implies participants were being used as random effects in those models. Further, *Overall Sessions* refers to all the data collected in the background, therefore, including both sessions that did and did not trigger questionnaires. *Questionnaire*, in turn, refers to the sessions that triggered a questionnaire and were successfully filled out.

4.1 Breakout Reasons: Categorization

In the 1064 recorded questionnaires, 278 unique *Breakout-Reasons* were stated. To analyze those reasons, we used the thematic coding approach following the guidelines presented by Robson and McCartan [43] as, for example, Haas et al. [12] have done in their research. In the first step, two of the authors familiarized themselves with the data collected in the study. After that, they iterated over around 40% of the data, gathering similar *Breakout-Reasons*, which were then labeled. Afterward, the labels were ordered and categorized to generate an initial codebook. With this codebook, the remaining 60% of the data was individually coded by the two authors. The remainder

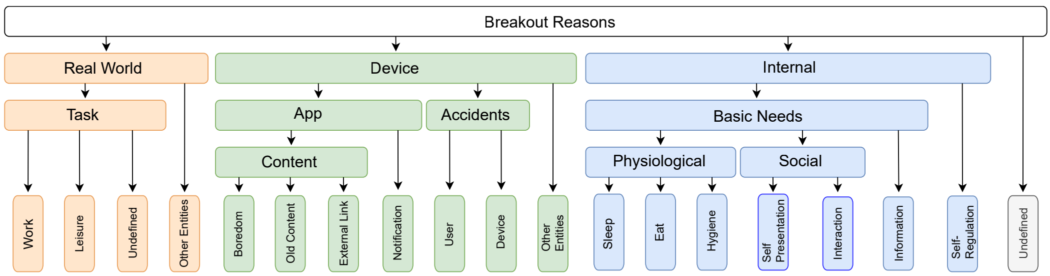

Fig. 2. The codebook resulting from the thematic coding. Four main reasons for breaking out of a session can be defined: Real-world, Device, Internal and Undefined Reasons. Section 4.1 describes the categories and their subcategories in detail.

of unclear or un-coded data was discussed by three authors, which led to a revised and extended codebook. The authors then re-iterated the dataset, re-coding it with the new codebook. The process was repeated for the second batch, taking the prior codebook as a base. The final version of the codebook is shown in Figure 2.

We arrived at three main categories encapsulating the reasons to conclude a social media session. These can be anchored in the *Real World*, the *Device* itself, or the users *Internal* workings. Participants also repeatedly stated that they switched applications without naming a specific reason, leading to a fourth *Undefined* (or switching applications) category. The following discusses the categories and their sub-categories in more detail, underlying them with example statements from the participants, fitting the category.

4.1.1 Real World Related Factors. The first category encapsulates all reasons anchored in the *Real World*. This category relates to "Competing Demands", which is one of the three main reasons (along with Recycled Content, The 30-Minute Ick Factor) Tran et al. [46] discovered in the context of ending habitual smartphone sessions. They describe it as "being pulled back into the real world by other demands" [46, p.6]. While finding related reasons, we discovered that those could further be divided into two sub-categories. Firstly, the reason for being pulled back can be *Other Entities* in the user's surrounding demanding attention. This entity can, for example, be a baby (e.g., "had to change baby's diaper"), a dog (e.g., "my dog wants to be let outside"), or a conversation with another person (e.g., "I got distracted by a conversation"). Secondly, the real-world distraction could be the starting or continuation of a real-world *Task*. This task could either be *Work-Related* (e.g., "leaving for work", "Work Break Ended"), *Leisure Time* activities (e.g., "go shopping", "watching a movie"), or an *Undefined Activity* (e.g., "got busy", "had other things to do").

4.1.2 Device-Related Factors. Tran et al.'s [46] second main reason for stopping habitual use is related to the devices themselves. More specifically, the app and the recycling of content that has already been seen before. While we also encountered this reason, we found many other device- and application-related *Breakout-Reasons*. These reasons can emerge in the application used, through others that call or send messages, or through accidents happening in interaction with the device. Such *accidents* can either be triggered by the *user* (e.g., "accidentally closed out") or by the *Device* itself (e.g., "app crashed"). As in the real world, *Other Entities* like friends or family can demand the user's attention through the device by messaging or calling the user (e.g., "phone call", "Got A Message"), making them leave their social media session. Additional to others, the content of the *app* can be a trigger for leaving the application. Here, we can identify three main reasons. First, the content itself can no longer hold up to being entertaining, showing nothing interesting to the user, creating *Boredom* (e.g., "bored", "Nothing interesting"). Second, in accordance with Tran et al. [46], the app fails to present novelty to the user showing only *Old Content* (e.g., "nothing new to look at", "read through all new posts"). Last, the app offers links that redirect the user to another application through an *External Link* (e.g., "followed a link to an other site"). In addition to a dynamic reason resulting from the usage of the application itself, the user can also enter the app through a *notification* to just check its content. Therefore, one reason to leave is to complete the task associated with the notification (e.g., "only had to check notifications").

4.1.3 Internal Factors. As described above, breaking out can be triggered by the real world or the device. Additionally, we found that the reasons can originate from the user themselves. These reasons can be grouped into arising physical and social basic needs [32] or accounted for self-regulation. We call those *Internal* factors.

While using the application, a user can notice an urge to satisfy a basic human need. On the one hand, these can be physiological needs to *Eat* (e.g., "to go make food", "Getting a snack"), *Sleep* (e.g., "falling asleep", "need to sleep"), and the need for *Hygiene* (e.g., "shower", "need to shower"). On the other, social needs like *Self Presentation* (e.g., "I'm done posting for today") or *Interaction* with other individuals (e.g., "to message a friend", "wanted to have a conversation with someone"). Also, this can be driven by the need for new information, which can happen in two ways. First, getting into the application to find *Information* and leaving after it is done (e.g., "I'm searching for something specific", "I didn't find what I was looking for"). Secondly, leaving the application after the urge for new information rose up (e.g., "wanted to look up something", "checking the weather on another app").

Apart from basic needs, the user can conclude that they do not want to continue their session through a personal internal decision (e.g., " felt I seen enough", "I was done"). Tran et al.'s [46] third main reason, the "30-Minute Ick Factor", for leaving habitual sessions fall into this category. Here, they state that many "participants described a recurring sense of disgust after spending time habitually checking their phone" [46, p.6], which led to a conclusion of the current session. In accordance with Bandura [1], we call this *Self-Regulation*, as participants self-monitoring their behavior [1] and set it in relation to personal standards, decided to conclude their session. In contrast to the device-related factors, self-regulation is an intrinsic motivation to break the session and not motivated through extrinsic factors such as "old content"

4.1.4 Undefined Factors/Switching Applications. While we were able to categorize the reasons mentioned above, participants repeatedly - in the context of switching to another app - did not further specify their reason for doing so. As it is possible to find a multitude of possible explanations for each of these switches and no unambiguous assignment can be made, we categorized the reasons for these switches as *Undefined Reason / Switching App* (e.g., "I switched apps", "use another app").

4.2 Breakout Reasons: Statistics

In the following, we will discuss the statistics regarding the *Breakout-Reasons*. We divided sessions by *Session Length Category*. First, we will go over the proportion of the occurrence of overall breakouts. Second, we will relate the breakouts to the prior happening amount of IS.

4.2.1 Breakout Reasons General. The general reasons for breaking out of a SM session are displayed in Figure 3. Here, the *Breakout-Reasons* are ordered by the percentage of occurrence during the study. It can be observed that *Boring Content* and *Self-Regulation* are major factors for leaving in each *Session Length Category*. In short sessions, the *Interaction* and *Notifications* are in the top five. These are less prominent in *Medium Session* and *Long Session*. In turn, *Undefined Task* takes the lead in *Medium Session* and *Long Session* sessions.

Short/Review				
Reason		(n)	Valence	(SD)
Content Boring	12.98%	(37)	2.43	(1.21)
Self Regulation	11.93%	(34)	2.79	(1.01)
Interaction	11.23%	(32)	4.31	(0.90)
Switching App	10.53%	(30)	3.17	(0.83)
Notification	8.42%	(24)	3.46	(0.83)
Undefined Task	8.42%	(24)	2.83	(0.96)
Information	7.37%	(21)	2.14	(1.15)
Task Leasure	7.02%	(20)	2.65	(0.99)
Content Old	5.61%	(16)	2.81	(0.83)
Task Work	3.51%	(10)	2.90	(0.88)
Device Other E.	2.81%	(8)	2.50	(1.31)
Sleep	2.81%	(8)	3.88	(0.83)
Ext. Link	2.11%	(6)	2.50	(0.84)
Accident User	1.40%	(4)	2.00	(1.15)
Needs Eat	1.40%	(4)	2.75	(1.71)
Real Other	1.40%	(4)	3.00	(1.63)
Accident Device	0.70%	(2)	2.00	(1.41)
Self Presentation	0.35%	(1)	5.00	-

Medium				
Reason		(n)	Valence	(SD)
Undefined Task	16.94%	(63)	2.84	(0.85)
Content Boring	16.67%	(62)	3.00	(1.12)
Self Regulation	14.78%	(55)	2.84	(1.07)
Information	8.87%	(33)	3.00	(1.15)
Switching App	6.45%	(24)	3.21	(0.88)
Content Old	6.18%	(23)	3.26	(0.75)
Sleep	5.38%	(20)	2.85	(0.93)
Task Leasure	4.84%	(18)	2.89	(1.28)
Task Work	4.03%	(15)	2.60	(0.99)
Real Other	3.49%	(13)	3.38	(0.77)
Device Other E.	2.96%	(11)	3.45	(0.93)
Interaction	2.69%	(10)	3.60	(1.17)
Notification	2.15%	(8)	3.00	(0.76)
Needs Eat	1.88%	(7)	2.71	(0.49)
Ext. Link	1.34%	(5)	2.80	(1.10)
Needs Self Pr.	0.81%	(3)	4.00	(1.00)
Accident Device	0.27%	(1)	5.00	-
Accident User	0.27%	(1)	3.00	-

Long				
Reason		(n)	Valence	(SD)
Undefined Task	20.15%	(82)	3.04	(0.76)
Content Boring	12.78%	(52)	2.98	(1.23)
Self Regulation	12.53%	(51)	3.92	(1.25)
Switching App	11.06%	(45)	3.40	(0.75)
Sleep	9.09%	(37)	3.08	(0.64)
Interaction	6.39%	(26)	3.92	(1.06)
Information	5.65%	(23)	4.22	(0.74)
Task Work	5.65%	(23)	3.26	(1.01)
Real Other	3.44%	(14)	3.43	(0.94)
Content Old	3.19%	(13)	3.00	(1.08)
Task Leasure	2.95%	(12)	3.25	(0.45)
Device Other E.	2.46%	(10)	3.00	(1.05)
Needs Eat	2.46%	(10)	3.90	(0.74)
Accident User	0.98%	(4)	3.50	(0.58)
Accident Device	0.74%	(3)	4.67	(0.58)
External Link	0.25%	(1)	5.00	-
Hygene	0.25%	(1)	1.00	-

Internal External
Device Related Unknown

Fig. 3. Statistics for *Breakout-Reasons* grouped by *Session Length Category*. The tables show *Breakout-Reasons* for *Review Session*, *Medium Session*, and *Long Session* ordered by which proportion of the overall breakouts they caused. The *Breakout-Reason* are color-coded by their belonging to a main category from our coding (see Section 4.1).

4.2.2 Breakout Reasons related to IS. We now relate the reasons for breaking out of a SM session to the number of IS that happened previously. This can be seen in Figure 4. Here, the *Breakout-Reasons* are ordered by the Median (Mdn) of *Proportion* of IS features that were related to the respective sessions. Here, it can be observed that the Median (Mdn) of *Proportion* was highest when participants left because of a *Undefined Tasks* they had to start or get back to. Also, when leaving because of old and boring content, the prior sessions had a high amount of IS. The sessions that were left because the participant just wanted to check a notification, in turn, showed the lowest amounts of IS in *Review Session*.

4.3 Objective Measurements: All Recorded Sessions

During the study, data for 6605 sessions were collected. We fitted a linear model (estimated using OLS) to predict *Time* within the *Overall Sessions* and each participant's overall *Session Amount*. A significant regression equation was found (R^2 = 0.009, F(1, 6603) = 65.33, p < .001) with the model's intercept, corresponding to, is at 282.45 (t(6603) = 27.91, p < .001). Here we found a statistically significant and negative effect (beta = -0.23, t(6603) = -8.08, p < .001). **The recorded *Time* therefore decreased by 0.23 seconds with each session reported during the study.** The low R^2 value indicates that the amount of *Overall Sessions* only has a small influence on *Time*.

4.4 Differences in Applications: *Valence* and *Time*

From the SAM questionnaire, we only extracted the values for valence as our main objective, which is an indicator for positive or negative feelings [6]. Hence, we fitted two further linear mixed models to predict *Time* and *Valence* with *Application* (Ref: *TikTok*) (see Table 1). *Valence* was measured through *Questionnaires*, while *Time* is an objective measurement on *Overall Sessions*. We found significant negative effects of *Facebook*, *Instagram*, *Reddit*, and *Twitter* in *Time*. **This means that *TikTok* sessions are significantly longer than those of the other applications.** We also report

Short/Review				
Reason	Mdn	M	SD	n
Task Undefined	100	87.625	(21.46)	24
Switching Apps	100	78.1	(36.66)	30
Content Old	97.5	86.9375	(25.56)	16
Content Boring	97	67.0811	(41.21)	37
Information	91	63.6667	(43.28)	21
Self Regulation	90	68.1176	(39.56)	34
Eat	75	62.5	(47.87)	4
Sleep	72	56.5	(46.16)	8
Task Work	71	63.1	(39.09)	10
Task Leasure	65	53.4	(47.27)	20
Accident Device	50	50	(70.71)	2
Real Other E.	50	50	(57.74)	4
Accident User	0	25	(50.00)	4
External Link	0	16.6667	(40.82)	6
Device Other E.	0	20.625	(39.32)	8
Interaction	0	4.09375	(18.34)	32
Self Presentation	0	0	-	1
Notification	0	31.75	(40.85)	24

Medium				
Reason	Mdn	M	SD	n
Accident Device	100	100	-	1
Accident User	100	100	-	1
Content Old	100	91.86	(13.76)	23
Real Other E.	100	79.9231	(36.74)	13
Self Regulation	100	81.2364	(33.83)	55
Task Undefined	100	81.619	(28.67)	63
Sleep	95	79.9	(25.30)	20
Task Work	90	70.7333	(35.16)	15
Switching Apps	89	65.75	(42.45)	24
Device Other E.	85	71.3636	(39.07)	11
Eat	80	81.4286	(19.73)	7
Content Boring	70	62.871	(33.32)	62
Notification	55.5	47.625	(42.96)	8
Task Leasure	40	46.5556	(44.01)	18
Information	23	40.0909	(42.81)	33
External Link	12	24	(32.23)	5
Interaction	0	21.1	(36.71)	10
Self Presentation	0	3.33333	(5.77)	3

Long				
Reason	Mdn	M	SD	n
Accident Device	100	100	(0.00)	3
Content Old	100	77.2308	(40.87)	13
Interaction	100	91.1538	(27.00)	26
Task Leasure	100	83.6667	(29.58)	12
Task Undefined	100	89.0488	(21.80)	82
Switching Apps	100	76.0889	(32.74)	45
Sleep	99	82.7568	(23.09)	37
Accident User	83	69	(40.22)	4
Task Work	75	70.2174	(31.96)	23
Real Other E.	72.5	69.9286	(29.13)	14
Content Boring	68.5	66.8077	(26.97)	52
Eat	66.5	54.6	(27.52)	10
Self Regulation	63	52.6667	(44.32)	51
Device Other E.	58	53.3	(32.67)	10
External Link	41	41	-	1
Hygene	30	30	-	1
Information	27	33.6957	(35.28)	23

Internal External
Device Related Unknown

Fig. 4. Statistics for *Breakout-Reasons* grouped by *Session Length Category*. The tables depict the median and mean proportion of IS for the sessions belonging to the breakout reasons. The *Breakout-Reason* are color-coded by their belonging to a main category from our coding (see Section 4.1).

Table 1. Linear Mixed Models Predicting *Time* and *Valence*

	Dependent variables:	
(Ref: *TikTok*)	*Time*	*Valence*
(Intercept)	696.78***	3.54***
	(26.92)	(0.13)
Facebook	−480.91***	−0.41***
	(20.49)	(0.09)
Instagram	−529.96***	−0.23**
	(19.66)	(0.09)
Reddit	−493.58***	−0.99***
	(33.45)	(0.14)
Twitter	−579.05***	−1.08***
	(24.49)	(0.11)
Observations	6605	1064
R^2*conditional*	0.21	0.50
R^2*marginal*	0.14	0.12
Note:	*p<0.05; **p<0.01; ***p<0.001	

significant negative effects of all four apps on *Valence*. **This means that participants reported a higher level of *Valence* after using *TikTok* compared to *Facebook*, *Reddit*, and *Twitter*.**

4.5 Amounts of Scrolling per Session Length

	(n)	Only Scrolling	Some Scrolling	Some Amount of Scrolling or Story
Short/Review	285	40.35%	65.96%	71.93%
Medium	372	45.70%	85.48%	89.52%
Long	407	45.21%	89.43%	96.81%

Fig. 5. Statistics of session occurrences divided by *Only Scrolling*, *Some Amount of Scrolling*, and *Some Amount of Scrolling or Story*

Of the 1064 analyzed questionnaires, only 194 (22.30%) did non contain any *infinite scrolling*. When also including *Watching Stories* only 132 (14.16%) did not include any. Figure 5 divides the amounts by *Session Length Category* and depicts the portions of sessions that only consisted of IS (*Only Scrolling*), contains some IS (*Some Amount of Scrolling*), or contained IS or *Watching Stories* (*Some Amount of Scrolling or Story*).

Next, by fitting further linear mixed models, we predicted *Valence* with *Only Scrolling* (R^2 = 0.37, marginal R^2 = 0.03, Intercept at 3.23 [t(1060) = 30.83, p < .001]) and *Some Amount of Scrolling* (R^2 = 0.37, marginal R^2 = 0.01, Intercept at 3.46 [t(1060) = 26.22, p < .001]). Within the first model, *Only Scrolling* (Ref: No) is statistically significant and negative (beta = -0.40, t(1060) = -6.09, p < .001). Within the second, *Some Amount of Scrolling* (Ref: No) is statistically significant and negative (beta = -0.34, t(1060) = -3.99, p < .001). As we executed multiple tests on the same data, we used Bonferroni-adjusted alpha levels. **The findings suggest that participants reported significantly higher levels of *Valence* on sessions that were not only composed of scrolling activity. It was also shown for those that did not contain any kind of scrolling compared to sessions that implemented scrolling.** Again, the low R^2 marginal indicates that interpersonal differences have a higher influence on *Valence* than the composition of a session.

4.6 Differences in the activity composition per *Session Length Category*

To analyze how the *Proportion* of *Activity* varied between the different levels of *Session Length Category*, we fitted six additional linear mixed models to predict each of the six *Actions* with length. These models can be seen in Table 2. **The main findings are that *Review Session* had a significantly lower amount of *IS-percentage* compared to *Medium Session* and *Long Session*. In turn, *chat-percentage* takes a higher amount in *Review Session* sessions and less the longer the session gets. The *watch-stories-percentage* were significantly longer in *Long Session* compared to *Review Session*.** Although, particularly low marginal R^2 values indicate that the significant differences are mainly explainable by interpersonal differences described in our random variable.

4.7 Main Activities

We fitted a linear mixed model to predict *Valence* with *Main Activity*. The model's total explanatory power is substantial (conditional R2 = 0.42), and the part related to the fixed effects alone (marginal R2) is 0.05. The model's intercept, corresponding to IS, is at 3.00 (t(1056) = 27.33, p < .001). Within this model, the effects of *Posting* (beta = 0.59, t(1056) = 2.15, p = .032) and *Watching Stories* (beta = 0.92, t(1056) = 7.60, p < .001) are statistically significant and positive. **This means that, overall, participants reported higher levels of *Valence* after sessions that mainly consisted of *Posting* or *Watching Stories* compared to those that mainly centered around *infinite scrolling*.**

Table 2. Linear Mixed Model Predicting *Proportion* by *Session Length Category*

	Actions in Percent of Sessions:					
	Scrolling	Story	Chatting	Posting	W. Comments	R. Comments
(Intercept)	59.31^{***}	6.04^{*}	15.49^{***}	0.96	11.22^{***}	1.03^{**}
	(4.20)	(2.45)	(2.62)	(0.62)	(2.95)	(0.34)
Medium Session	8.80^{***}	0.45	-8.18^{***}	0.89	2.55	−0.58
	(2.60)	(1.60)	(1.60)	(0.68)	(1.45)	(0.37)
Long Session	11.72^{***}	4.70^{**}	-13.03^{***}	−0.74	2.85	−0.39
	(2.67)	(1.64)	(1.64)	(0.69)	(1.49)	(0.37)
Observations	1064	1064	1064	1064	1064	1064
R^2	0.39	0.35	0.41	0.07	0.52	0.07
Marginal R^2	0.01	0.04	0.01	0.01	0.002	0.002
Note:						*p<0.05; **p<0.01; ***p<0.001

5 DISCUSSION

In this study, we investigated two main topics. First, the reasons to break out of social media sessions, with a particular focus on scrolling sessions. Second, which share IS activities take in regard to sessions of different lengths. In the following, we discuss the findings of our study.

5.1 Breakout Reasons

Today, interventions primarily focus on the applications they try to limit [8], but the context in which usage happens is more complex. Here, we found that many *Breakout-Reasons* were not directly connected to the application itself (see Figure 3).

In prior work, Tran et al. [46] found that repetitive content was the main reason for leading users to leave habitual sessions. In turn, we found that accumulated old and boring content only made up 18.59% (review sessions) to 22.85% of leaving rate when looking at our recorded SM sessions (see Figure 3). Here, old content was actually less prevalent, while boring content made up more than double the leaving rate.

Analogous to what Tran et al. [46] found for habitual use, the real world (or as they call it, "Competing Demands") was a main factor for leaving applications in our study, too. We were able to further refine these *Breakout-Reasons* into sub-categories of reasons related to Other Entities and Tasks. While participants also reported Work- and Leisure-Time related *Breakout-Reasons*, being busy with an Undefined Task was one of the major reasons to leave a *Medium Session* (16.94%) or *Long Session* (20.15%). This implies that users might postpone the continuation or beginning of a task by having medium and long sessions. Although Tran et al. [46] found that users often chose to terminate their sessions upon realizing the extent of time they had spent, it is important to note that this was just one of the reasons tied to user behavior. While self-regulation made up a major part of *Review Session* (11.23%), *Medium Session* (14.78%), and *Long Session* (12.53%), we found that the urge to fulfill basic needs also led to breaking out of sessions. These might be needs postponed by the sessions (e.g., going to sleep [8, 38]) or arise during it (e.g., getting hungry). In turn, the reason for leaving the application can be connected to the basic need that made them into it. For example, users might present themselves by creating a post or interacting with others on the platform and subsequently leave the session as their need is fulfilled. Cho et al. [8] found that such interaction with others is accompanied by feeling socially rewarded and was a part of SM sessions that participants in their study did not regret. We found that fulfilling such social interaction needs was in the top three reasons for leaving *Review Session.* At the same time, it was a less prominent *Breakout-Reason* for *Medium Session* and *Long Session.*

5.1.1 Implications: Practical Application of Breakout Reasons in Interventions. Having a broader understanding of the reasons to leave a SM session, these can now be utilized to develop interventions that can help users break out of their SM sessions, counteracting emerging low valence sessions.

As Cho et al. [8] found that a feature-level summary of smartphone usage helped users to identify an actionable plan, employing contextual factors could further increase the long-term chances of this plan. As mentioned above, we found that participants left because they felt the urge to satisfy basic needs (e.g., sleep). These basic needs might come to mind during the session or be delayed. For example, not being able to stop watching videos before going to bed [8]. Contextual interventions could, therefore, remind the user of these needs. It remains under-evaluated whether such interventions (e.g., "depending on your alarm clock, you only have six more hours to sleep) are more efficient than application-related interventions. These contextual factors open up a wide array of potential for user-related observation. For example, the necessity to fulfill basic needs (e.g., hunger, sleep) could be determined via the front-facing camera. However, this is subject to data privacy challenges.

We also found that while we discovered statistical differences for the fixed factors accounted for a smaller amount than the individual differences between participants. This further highlights that SM users are influenced in differing ways suggesting that not only the user's context and current state but the learning about the user's general being could influence its effectiveness.

In addition to contextual and user-tailored interventions, interventions could try to anticipate a user's reason for starting a SM session. The initial plan for an SM session might be to e.g. just check a notification and leave afterward. In turn, concluding the task that leads to starting a SM session is, therefore, the subsequent reason to leave the session. In this context, we found that being done checking notifications made up 8.42% of the *Review Session* sessions and 4.1% of the *Medium Session* sessions' reasons to leave. For the *Long Session* sessions, none of the participants mentioned a checked notification as a reason for leaving the session. The need to check notifications and leaving directly afterward also led to low values of IS in *Review Session* (Mdn = 0.0) and bigger but still comparably low IS *Proportion* (Mdn = 55.5) in *Medium Session.* Similar trends can be seen for the *Breakout-Reason* Interaction; therefore, the (just fulfilled) wish for interacting with another person. Following this, contextual interventions could consider how the user entered the application or infer with which intention they came by analyzing their behavior in the beginning. If the user enters the application through a notification or texts a person, their main goal for coming may be already satisfied. When then falling into a "feature tour" by beginning IS, they could therefore be quickly reminded of why they came in the first place, making them think about if they want to pursue their SM session that is now potentially becoming regretful.

Summarized, looking at the found *Breakout-Reasons*, researchers - and companies alike - can now utilize them as a base for potential context-sensitive interventions that could prevent users from regretful SM use and work towards a more healthy relationship to SM.

5.2 "The Loop" and Habitual Use

Currently, there is an unclear nomenclature about habitual use and "the loop". We argue that being in the loop can refer to using the application longer than intended [14] but that the feeling of being caught in a loop also incorporates a habitual part, an outer loop, that leads users to get into the (inner) loop repeatedly. This leads to the loop being manifested in two ways, the habitual outer loop as well as the inner intra-sessional loop. In the following, we will discuss our findings regarding these loops.

5.2.1 The Intra-Sessional Loop. Like the self-filling bowl by Wansink et al. [49], where participants ate more soup when the bowl filled itself unknowingly, IS is also suspected of leading to longer sessions [14, 37]. We found that the number of sessions that only included scrolling did only slightly differ between *Review Session* (47.37%), *Medium Session* (56.35%), and *Long Session* (51.38%) circling the 50% mark (see Figure 5). However, when not looking at IS separate activity but part of a social media session, we can see that longer sessions (*Medium Session* and *Long Session*) mostly (≈90%) contain some scrolling (see Figure 5). These findings indicate that combining with another feature ("feature tour") leads to longer sessions. We also found a significant rise in scrolling *Proportion* when sessions become longer (see Table 2).

Therefore, our data indicate that scrolling as a sole purpose is not directly related to session length. This is in line with the findings of Cho et al. [8] and suggests that users can not or do not want to use the applications for a sole purpose (e.g., chatting, posting) but become quickly intrigued by the Infinite Scrolling mechanism. Furthermore, we found a tendency that the longer the session gets, the more likely it is that IS becomes part of it. In line with this, we found that sessions that ended because the user finished the initial task (e.g., looking at a notification or the need for interaction) appeared more often in shorter sessions than in longer sessions. This leads to suspect that those did not fall into the feature tour and therefore did not start getting into the loop.

In line with previous work by Nontasil and Payne [39], we found that participants generally reported slightly positive valence after sessions mainly consisting of IS. We nevertheless found higher levels of reported valence when posting or watching stories was the main activity. We argue that this might be because we are less prone to regret subscription-based content (happening in stories) compared to suggestion-based content (as in many IS feeds) [8]. Sessions that did not contain any scrolling at all also led to higher levels of valence. In contrast, mixed activity sessions led to higher values of reported valence than sessions that included only scrolling.

Therefore, we infer that being caught in the (inner) loop might not only happen because users come for the sole purpose of scrolling but as a consequence of getting lured into a feature tour. Getting into the loop this way also made the participants report higher levels of valence, making it potentially more compelling.

5.2.2 The Outer Loop - Habitual Use. We found that participants who were able to identify with the feeling of being stuck in the loop had indeed not longer but shorter sessions and that participants coming to SM more often had significantly shorter sessions.

Cho et al. [8] found that participants of their study regretted the newsfeeds and stories in habitual sessions. We found that 40.35% of the *Review Session* happening in our study were composed of only interacting with IS features. Additionally, we found that breaking out because of old and boring content happened when scrolling had medians near 100%. Combining this with findings by Tran et al. [46], stating that old content was one of the main reasons for breaking out of habitual sessions, we believe these might be short, habitual sessions. We also found that they left such scrolling-dominated short sessions because they were busy with other tasks, suggesting that they postponed or interrupted tasks to insert a short scrolling session.

Combining these findings, we argue that while users can be caught in an intra-sessional loop, participants can also get caught in a loop of habitually using IS features looking for new information and interesting content. Opening SM and scrolling through the newsfeed can either end in the user finding engaging (new) content or in them leaving again as they were unable to satisfy their need for information.

As Nontasil and Payne [39] argue, the variation between interesting and non-interesting content within a session can be regarded as a partial reinforcement mechanism. We argue that this mechanism might also happen in between short habitual IS sessions. Thereby, it reinforces the pattern of repeatedly coming to watch for new content, creating the outer loop. Depending on the success of finding new information, such outer loop-triggered sessions can get users caught in the inner, inter-sessional loop.

5.2.3 The Interweaving of Inner and Outer Loop. We argue that such an interweaving of the inner and outer loop can be promoted by certain features. While technically not infinite, stories implement a similar scrolling mechanism as connected IS features. As they are only available 24 hours, participants must come at least once a day to avoid missing out on them. They are establishing a habitual checking of stories, the outer loop. Concerning the inner loop, we found that stories made up significantly bigger parts of *Long Session* than *Review Session*. We might see one explanation in what participants in Cho et al. [8]'s they interviewed about stories stated. They said that once they began to watch stories, they flipped through them to the end. This creates the inner loop, but here, not the infinite supply makes the loop effective but the temporary nature of the content. Also, knowing there is a time-intensive but reachable goal (of seeing all stories) might lead to longer sessions. This, in turn, means that in certain situations, infinite supply might be an argument for not staying longer but leaving earlier.

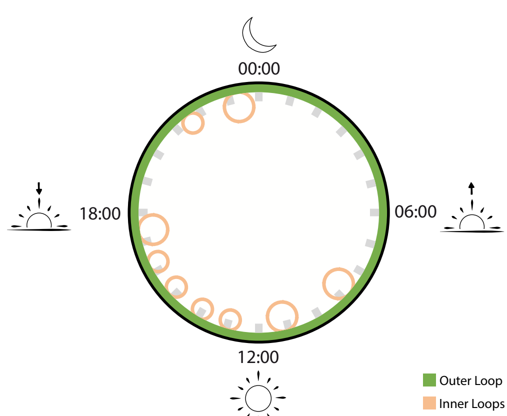

Fig. 6. Depiction of the Outer Loop in addition to multiple Inner Loops happening throughout the day.

In summary, we argue that IS features facilitate habitual, repeated use, creating an outer loop of repeatedly opening SM to utilize IS features. IS features can then escalate these sessions - as well as other sessions that began through other activities inside the same application - catching the user in an intra-sessional inner loop. We, therefore, argue that IS does not facilitate one but two inter-weaved loops, which can entrap the user. Illustrating this, Figure 6 contains a depiction of outer and inner loops during a day and how those might occur.

5.3 TikTok And The Evolution Of Scrolling

Our study found that TikTok sessions with an average time of ≈ 11.5 min and significantly longer than the sessions of all other apps. They exceeded Facebook sessions by 474.83 sec (≈ 8 min), being the second-longest. Compared to other applications, TikTok employs a relatively novel video-based approach to being a social media platform. Instead of utilizing static content (text or pictures), the platform and, therefore, the IS features are based on videos[10]. Cho et al. [8] found that watching videos in the newsfeed on Facebook leads to more regret, and participants reported losing track of time. However, while they found that suggested posts led to higher levels of regret than subscription-based posts, we found that participants reported higher levels of Valence in TikTok (whose main feature is a suggestion-based reel feed) compared to more following-centered applications Reddit, Twitter, and Instagram.

We argue that this might indicate that TikTok's concept of IS through video content instead of mixed, text, or picture-based content might lead to longer sessions. While video content is more engaging, the recommendation algorithms of TikTok might also result in more personalized content than its opponent SM platforms. Another reason for TikTok's higher valence scores might be its purpose to entertain, while Facebook and Instagram are also social tools to connect with friends. Video-based IS could, therefore, be one (or even the one) reason for users spending more time on the platform while feeling more positive afterward. While Instagram started as picture centered platform, it leveraged this effect and adapted its feed to contain more video content[11] and implemented a TikTok-like Reels feed. Such a feed was also implemented by Facebook [12]. Focusing more on video content might account for finding a smaller difference in Valence between TikTok and Instagram.

Our findings, combined with the trend that advertisement-financed SM applications implement video-based IS feeds, leads to the assumption that these might pull users in stronger, spending more time in the loop and even feeling better afterward. Thereby extending the inner loop and creating a bigger incentive to start an outer loop.

5.4 Limitations and Future Work

Due to technical limitations, we only implemented an Android application to monitor participants and, therefore, limited the participant pool.

We avoided presenting the questionnaire after **every** social media interaction to prevent participants from becoming annoyed by our app. However, this prohibited us from getting a full picture of all social media interactions, especially the shorter ones.

Finally, while we found that contextual factors are relevant for the *Breakout-Reasons*, due to the setup of the study with high external validity, we could not get a clear picture of the participants' external factors (living arrangements, daily schedules, etc.). Future work should consider these when implementing context-related intervention mechanisms.

As we did not make explicit distinctions between different types of content in our study, our assumptions are somewhat limited in scope. It is possible that the type of content, whether it is video, picture-based, or text-based, could have an impact on the outcomes of our user study. Additionally, the algorithms that dictate content recommendations also play a significant role in the performance of social media platforms. Unfortunately, these algorithms are kept secret by the companies that develop them, preventing us from drawing any meaningful conclusions beyond this point. Therefore, future work should further investigate this by explicitly comparing picture, text, mixed, and solely video-based feeds in the domains of time consumption and consequential influences on the user's feelings As the concrete interactions inside an application do influence these feelings, tracking app-internal interactions would gain more insides to distinguish between.

[10] https://apps.apple.com/us/app/tiktok/id835599320; Accessed: 12 February 2022
[11] https://www.forbes.com/sites/forbescommunicationscouncil/2021/08/30/how-to-adapt-to-instagrams-focus-on-video/; Accessed: 12 FEBRUARY 2022
[12] https://about.fb.com/news/2021/09/launching-reels-on-facebook-us/#:~:text=%20on%20Facebook%20can%20consist,or%20share%20it%20with%20friends, Accessed: 14 FEBRUARY 2022

While the objective of this research was to investigate IS behavior, future work should also look into users' behaviors for non-IS applications such as YouTube or Snapchat.

6 CONCLUSION

Overall, this work presented the findings of an in-the-wild study with N=46 participants studying social media behavior with a focus on Infinite Scrolling. By implementing an Android application capable of running in the background of the participants, we were able to determine *Breakout-Reasons* by triggering a questionnaire after longer sessions and after sessions every three hours. Our findings imply that the real world, the device, and the inner workings of the user can be responsible for breaking out SM sessions. Hereby, we defined finer sub-categories, which we argue can be utilized to develop concepts for context-sensitive interventions against regretful, elongated SM use. With our findings, we also define "the [IS] loop" and find that IS can especially be combined with other SM features to lead to longer sessions, creating an intra-sessional inner loop. However, IS can also promote habitual reoccurring use of features implementing it, creating a habitual outer loop. We, therefore, identify that IS do not facilitate one but two interwoven loops that catch its users.

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