Scrolling in the Deep: Analysing Contextual Influences on Intervention Effectiveness during Infinite Scrolling on Social Media

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Abstract

Infinite scrolling on social media platforms is designed to encourage prolonged engagement, leading users to spend more time than desired, which can provoke negative emotions. Interventions to mitigate infinite scrolling have shown initial success, yet users become desensitized due to the lack of contextual relevance. Understanding how contextual factors influence intervention effectiveness remains underexplored. We conducted a 7-day user study (N=72) investigating how these contextual factors affect users' *reactance* and *responsiveness* to interventions during infinite scrolling. Our study revealed an interplay, with contextual factors such as being at home, sleepiness, and valence playing significant roles in the intervention's effectiveness. Low valence coupled with being at home slows down the *responsiveness* to interventions, and sleepiness lowers *reactance* towards interventions, increasing user acceptance of the intervention. Overall, our work contributes to a deeper understanding of user responses toward interventions and paves the way for developing more effective interventions during infinite scrolling.

CCS Concepts

• **General and reference** → *Surveys and overviews*; • **Human-centered computing** → *HCI design and evaluation methods*; **Scenario-based design**; **Empirical studies in HCI**.

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Keywords

infinite scrolling, digital interventions, context-aware, field study, longitudinal study

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1 Introduction

In the era of social media (SoMe), platforms such as TikTok and Instagram changed how we consume digital content by employing interaction mechanisms such as infinite scrolling. This mechanism, where content endlessly loads as users swipe or scroll, can lead to prolonged screen time [56], leading users to a feeling of being caught in a loop of unconscious and habitual use [79] and post-usage regret [14]. It is, therefore, classified as an attention-capturing dark pattern [62] designed to manipulate users into actions contrary to their interests [31]. Infinite scrolling is particularly prevalent in SoMe, as this mechanism is designed to capture users' attention and increase engagement with the presented content. The interaction design of TikTok is a prominent example of infinite scrolling, which was recently suspected of violating the Digital Services Act by the European Commission [24], as the design of TikTok's system "*[...] may stimulate behavioral addictions and/or create so-called 'rabbit hole effects'*" [25]. In support of this, Mildner and Savino [56] highlighted that 25% of their participants expressed regret over the excessive duration spent infinitely scrolling through Facebook's newsfeed. This interaction is categorized as a passive form of interaction [28] and is therefore often perceived as lacking in meaningfulness, reducing users' sense of control [50] and their affective well-being [102]. Despite users' awareness of the issue and their intentions to limit digital media consumption [41] (e.g., with the aid of digital well-being applications for Android [2] and iOS [3]), users often encounter resistance to reminders and self-imposed limitations [33]. This resistance often stems from a deficiency in self-control regarding digital media consumption [18]. Hence, there have been several attempts to develop interventions to reduce SoMe usage driven by dark patterns such as infinite scrolling (e.g., time limits [33], mindful intention prompts [94], vibrations [66], or lockout task interventions [40]). However, these refer to SoMe usage as an isolated interaction without considering the users' context during usage. For instance, whether the user is at work or relaxing during leisure time, their emotional state (e.g., stressed or content) or their social situation (e.g., alone, with friends, or in a public setting) might affect how they respond to interventions. In fact, evidence hints that the context plays a crucial role in how users respond to interventions [21, 70].

Nevertheless, while the influence of context in behavior change [21, 55, 70] and mobile phone interactions [1, 5] has been well studied, these findings are often based on active interactions with mobile devices (e.g., typing performance [1]). Meske and Potthoff [54] have highlighted the importance of optimal timing for digital nudges, and Purohit and Holzer [74] advocated for context-aware intervention timings to enhance user receptivity and foster healthier digital habits. However, these approaches do not fully address passive interaction like infinite scrolling, where users are prone to normative dissociation, meaning that "[...] users' volition is not accessible to them, which may prevent them from disengaging" [7, p. 11]. Infinite scrolling can place users in a "trance-like" state driven by the need to pass time [50], resulting in an absorption that is difficult to break effectively through interventions. Thus, the contextual influence on interventions for infinite scrolling is likely to be different, as users may not respond in the same way as they would in more active phone interactions.

Recognizing the research gap in context-aware interventions in infinite scrolling, we explored how contextual factors influence intervention effectiveness during scrolling. To assess effectiveness, we defined it based on two dimensions: *responsiveness* and *reactance*. We measured users' *responsiveness* as the objective effect of an intervention, defined as the duration it took for users to stop infinite scrolling after an intervention occurred. However, while some interventions objectively reduce SoMe usage, they could elicit subjective negative reactions, causing participants to revert to their initial habits, as stated by Okeke et al. [65]. Thus, subjective evaluations of the effects of these interventions also have to be taken into account [59]. Therefore, we also measured the *reactance* toward the intervention. *Reactance* within the HCI context is adopted from Ehrenbrink [23], who defined it as the resistance individuals feel when their freedom of choice is perceived to be under threat. This resistance is rooted in psychological models [20], implying that "*messages [interventions] designed with the objective of behavior change must necessarily (implicitly or explicitly) limit an audience's freedom*" [76, p. 67]. Thus, an intervention during infinite scrolling may also be perceived as threatening the individual's freedom to continue scrolling, thus creating *reactance*. Hence, we defined the following research question:

> **How does the user's context influence the *reactance* and *responsiveness* towards interventions during infinite scrolling?**

We conducted a longitudinal field study with N=72 participants over 7 days who installed *InfiniteScape*, a native Android application that tracks users' infinite scrolling behavior. Once prolonged ($> 15min$) infinite scrolling was detected, participants were shown an intervention overlay stating that it is time to take a break from scrolling. Participants were then prompted with a questionnaire asking for their current context, including their valence, social situation, current activity, location (being at home or not), multitasking behavior, and level of sleepiness, as well as their *reactance* toward the intervention.

Our findings suggest an interplay between multiple contextual factors. Hence, different contextual elements are closely linked and influence each other. We found that users tend to accept interventions more when they are tired, possibly due to an awareness of the negative impacts of bedtime procrastination. However, this awareness does not translate into action, as users did not disengage from scrolling after an intervention. In addition, the familiar and comfortable environment of their home may not provide enough distraction from negative emotions, leading users to ignore interventions and continue scrolling. Further, multitasking, particularly during moments of these negative emotions, emerged as a factor that encouraged users to stop scrolling sooner. This suggests that additional activities can serve as an effective distraction from infinite scrolling and coping with negative emotions.

Contribution Statement [106]

Empirical study that tells us about people. Through our longitudinal, 7-days-long study (N=72), we provide empirical evidence that the effectiveness of interventions during infinite scrolling is contextually influenced. Our analysis revealed that multiple interconnected contextual factors, such as location, sleepiness, and valence, significantly influence users' *responsiveness* and *reactance* to these interventions.

2 Related Work

This section outlines proposed digital interventions designed to mitigate SoMe overuse, highlighting the potential benefits of reduced phone usage for individuals' digital well-being. Further, we discuss previous research that investigated the contextual influence on behavior change, including smartphone usage. Problematic smartphone use has been widely researched [6, 45, 69, 86, 97, 102], with two main perspectives defining it. Firstly, research has examined whether users show addictive behaviors towards their phones [47]. This approach focuses on the patterns and frequency of phone usage that resemble addictive characteristics. Secondly, it considers whether specific designs or usage patterns are problematic [56, 57]. Hence, there have been several attempts in academia to develop interventions to reduce SoMe or smartphone usage, which we briefly describe.

2.1 Interventions for Limiting Social Media Use

There are two main types of interventions [49, 73]: external and internal. On the one hand, internal interventions involve making changes inside the application itself. For example, removing the newsfeed of SoMe applications [73]. On the other hand, external interventions do not change the functionality of an application but intervene on a higher phone level, meaning they affect the overall smartphone system rather than individual apps. Within these external interventions, four distinct features exist [61], varying in level of severeness. Firstly, phone timers merely provide users with data regarding their smartphone usage, aiding in awareness and potential habit alteration [33]. Secondly, persuasive interventions involve sending reminders and notifications to users, prompting them to reconsider their smartphone habits and fostering a more conscious phone usage [72, 75]. Thirdly, take-a-break prompts remind users to take breaks from smartphone usage, for instance, to engage in other more meaningful activities [93]. Here, design frictions such as breathing exercises are mainly used to limit SoMe use [32]. Finally, phone blockers increase the difficulty of phone use, benefiting individuals who experience difficulty with self-regulation [40].

There remains a notable research gap in interventions tailored to the user's specific context. Yet, many researchers emphasize the need for interventions that are not one-size-fits-all but adaptable to each user's unique circumstances and environment [67, 74, 79–81, 90]. This approach recognizes that the impact and effectiveness of interventions can be enhanced when tailored to the users' context, considering the unique behaviors, needs, and challenges users face daily [99]. Therefore the next section discusses contextual influences on behavior change and smartphone usage.

2.2 Contextual Influence on Digital Behavior Change

In behavior change, context plays a significant role [38, 74, 96]. Ding et al. [21] emphasized the crucial role of time and location when it comes to setting reminders to change behavior. They argue that using time and location effectively can make reminders more helpful and less bothersome as "*[...] context information plays a very important role in increasing the effectiveness and reducing the annoyingness of reminders*" [21, p. 7]. Further, Pinder et al. [70] points out that various factors, such as one's location, the time of day, current mood, and even physiological states like hunger, can affect how people react toward digital behavior change interventions. This highlights the importance of delivering interventions in the right context to be effective [74]. Orzikulova et al. [68] demonstrated this in their field study, showing that just-in-time interventions resulted in significantly lower smartphone overuse than static interventions. Additionally, Akpinar et al. [1] asserted that context shapes user interactions with their devices, identifying environment, mobility, social interaction, multitasking, and distractions as key factors. While these studies underscore the importance of context on digital behavior change, much of this research centers on general smartphone interactions without distinguishing specific interaction types or states of engagement. In the context of infinite scrolling, however, the user's sense of control [50] may diminish, leading to normative dissociation [7] and reduced affective well-being compared to active interaction, such as direct exchanges with others [102]. In this state, users are more habitual and may respond differently to interventions than in other smartphone interactions.

Rixen et al. [79] specifically explored why users might disengage from SoMe with infinite scrolling, finding that users often express regret for time spent using SoMe to cope with negative emotions or procrastinate. They highlight the potential benefits of interventions that react to the users' context, which is defined as device-specific, real-world related, and internal context. Purohit and Holzer [74] demanded similar by proposing a model to determine the best timing for digital nudges, categorizing context into five areas: location, social setting, internal state, current situation, and individual behavior patterns. However, their model is in contrast to Monge Roffarello and de Russis [61]. They allowed users to add contextual conditions such as location to their personalized interventions. However, only a few users used this feature. Therefore, they imply that "*[...] users consider their behaviors problematic independently of their contextual situation*" [61, p. 11].

Although previous research suggested that contextual interventions can increase the effectiveness of digital interventions, there is a lack of evidence. Thus, our study investigated this claim. Therefore, in the next section, we identified contextual factors from related work to examine their influences on intervention effectiveness.

3 Contextual Factors for the User Study

Recognizing the wide range of possible contextual influences, we used existing research to identify six key factors most likely to influence the effectiveness of interventions during infinite scrolling. These factors were investigated in the subsequent user study. We assumed that the following contextual factors are closely linked and influence each other, as hinted by Purohit and Holzer [74]. Hence, **we refrained from formulating specific hypotheses** but rather explored how they influence the effectiveness of interventions during infinite scrolling.

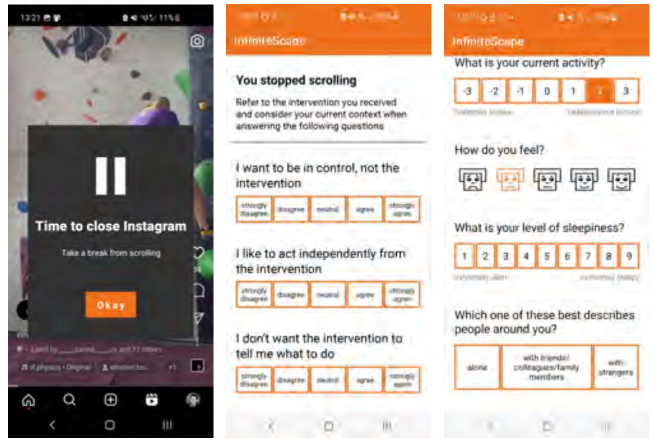
Current Activity. Rixen et al. [79] hinted that SoMe sessions are shorter when the declared breakout reason is due to work activity compared to leisure activity. Therefore, we assume that the current activity (work or leisure activity) influences the effectiveness of interventions during infinite scrolling.

Social Situation. When people are in social situations, like sitting in a coffee shop surrounded by strangers or having a meal with friends, using the phone is often perceived as impolite [26, 58]. Studies show that checking the phone during social situations can interrupt conversations and reduce people's connectedness and empathy to each other [51, 60, 71]. However, when people are eating alone, they tend to use their phones more, usually for fun or to pass the time [104]. As social norms create pressure not to use the phone during social gatherings, we assume that this is an important factor in influencing users' *reactance* and *responsiveness* towards an intervention.

At Home. Hintze et al. [34] found that mobile phone session durations were twice as long when users were at home compared to other locations. This difference in usage patterns could be influenced by the absence of social norms around phone use in private spaces like the home, potentially affecting how users respond to interventions in these environments.

Multitasking. Akpinar et al. [1] found that multitasking during phone use leads to more typing errors as users are distracted. Although typing is not directly related to infinite scrolling, we believe that when users are multitasking—like eating, cooking, or watching TV—an intervention during infinite scrolling could redirect their focus back to the main activity. This shift in attention could potentially affect the intervention's effectiveness.

Valence and Sleepiness. Rixen et al. [79] found "*[...] that participants reported significantly higher levels of valence on sessions that were not only composed of scrolling activity*" [79, p. 15]. Valence refers to the positive or negative emotions that individuals experience [27, 100]. This suggests that infinite scrolling has a negative impact on users' valence. Additionally, Diefenbach and Borrmann [19] noted that people often turn to their smartphones as a way to cope with negative emotions. This raises the possibility that the emotional impact of infinite scrolling might influence how users respond to interventions. Further, Yang et al. [107] found that excessive smartphone usage is significantly related to poor sleep quality, also influencing daytime sleepiness [63]. In particular, "*longer average screentimes during bedtime and the sleeping period were associated with poor sleep quality*"[15, p. 2]. We, therefore, assume that sleepiness might be related to the effectiveness of an intervention during infinite scrolling.



(a) Intervention **(b) Questionnaire pt. 1** **(c) Questionnaire pt. 2**

Figure 1: InfiniteScape. Including the intervention overlay and the questionnaire making for the participants' *reactance* and current context. The questionnaire is only partly visible (see subsection 4.3 for more details)

4 User Study

To investigate how contextual factors influence users' *responsiveness* and *reactance* towards interventions during infinite scrolling, we conducted a 7-day-long field study with N=72 participants. For the user study, we selected six of the most used SoMe applications in the United States in 2023 [92], which were also investigated in related work [79]. These applications are Facebook, Instagram, X (former Twitter), Reddit, TikTok, and YouTube (specifically their Shorts feature).

4.1 Apparatus

To answer our research question, we developed *InfiniteScape*, a native Android application that monitors users' infinite scrolling behaviors across the six SoMe platforms. To achieve this, we implemented Android's Accessibility Service,[1], which enables access to the content variable of each application's window tree. This setup allowed *InfiniteScape* to detect the active tab or section within each SoMe app and determine whether the user was engaged in infinite scrolling. Our monitoring focused solely on infinite scrolling, deliberately excluding other interactions such as direct messaging or content creation within these platforms. For instance, if a user switched from the "Reels" tab in Instagram to direct messaging, the content variable would update from "Reels" to "Messages," which *InfiniteScape* interpreted as an interruption in infinite scrolling. A similar logic was applied across other SoMe platforms; for example, navigating outside of YouTube's Shorts section within YouTube would also be interpreted as an interruption in scrolling. Closing the application while engaged in infinite scrolling was likewise logged as an interruption of continuous infinite scrolling. This approach ensured that only continuous scrolling sessions, without any interruptions, were categorized as infinite scrolling.

Upon detecting uninterrupted, continuous infinite scrolling for 15 minutes, an intervention overlay (see Figure 1a) appears on the smartphone's screen, modeled after the screen-time reminders from TikTok[2] and Instagram[3]. The 15-minute latency to start the intervention after scrolling was informed by Terzimehić and Aragon-Hahner [93]. They found that after approximately 10–20 minutes, most participants stated negative feelings toward smartphone usage. Further, Rixen et al. [79] reported that in sessions exceeding 10 minutes, infinite scrolling was the predominant activity during SoMe sessions. Thus, the intervention overlay always appears when users scroll continuously for 15 minutes without interruption. Users could remove this intervention by tapping "okay". This allowed users to continue infinite scrolling. If users ultimately stopped infinite scrolling after dismissing the intervention—such as by closing the application or switching to a non-infinite-scrolling activity inside the same app—they were shown a questionnaire. This questionnaire captured their current context (see subsection 4.3) and assessed the *reactance* they experienced towards the intervention. Additionally, we measured the time between the intervention overlay occurred until the users eventually stopped infinite scrolling, defining this duration as the *responsiveness* towards the intervention. We also logged the time of day (hh:mm:ss) of the intervention.

This real-time feedback collection uses the Experience Sampling Method (ESM), which has been validated by existing research (e.g., [9, 43, 79]). Unlike traditional ESM implementations that trigger questionnaires at pre-determined (periodic) times [9, 43, 78, 103],

[1]https://developer.android.com/reference/android/accessibilityservice/AccessibilityService, accessed: March 11, 2024

[2]https://support.tiktok.com/en/account-and-privacy/account-information/screen-time, accessed: March 11, 2024

[3]https://help.instagram.com/2049425491975359/?cms_platform=android-app&helpref=platform_switcher, accessed: March 11, 2024

our method triggers questionnaires when participants stop infinite scrolling. This event-based approach received higher response rates than the traditional, periodic approach [98]. However, this method also has its limitations, as it only captures the participant's context at the moment they decide to stop scrolling. Hence, we missed data from those who continued scrolling, as the questionnaire would not be triggered. Despite this, we chose event-based ESM because of its effective usage in other SoMe studies (e.g., [8, 11, 13, 79]).

4.2 Procedure

Prior to participating in the longitudinal 7-day study, participants were guided through a short registration survey. Here, they were provided with an in-depth explanation of the study's objectives and procedure to explore contextual influences towards interventions during infinite scrolling. We pre-screened participants from the United States via Prolific. Further, we excluded participants from the study who did not own an Android phone with version 10 or higher as the required permissions were optimized for these versions, and more than 85% of American Android users had version 10 or higher during the study period [91]. Further, only participants who expressed regret during infinite scrolling ("*Do you ever regret scrolling too much on social media apps?*") were invited to take part in the 7-day study by downloading the application. This decision aligns with Self-Determination Theory [83], which emphasizes that intrinsic motivation, driven by autonomy and alignment with personal values, is essential for behavior change. Regret signals participants' recognition of excessive scrolling as problematic, thus fostering a willingness to engage in interventions. In contrast, those without regret may lack intrinsic drive, reducing the study's ability to evaluate intervention effectiveness. Regardless of whether they downloaded the application, participants in the registration study were compensated 0.19£ for their median effort of 1:40 minutes.

Those participants who proceeded with the longitudinal study received an instructional video detailing the *InfiniteScape* application's download and installation process. Due to the use of Android's Accessibility Service for detecting infinite scrolling, the application could not be hosted on the Google Play Store [30]. Thus, an anonymized repository was available for the download of the *.apk* file. This was accessible either via a QR code for desktop-based registrants or a direct download link for mobile participants. Upon installing *InfiniteScape*, participants were shown the terms-of-consent form, which they were encouraged to read carefully before agreeing to participate. Both the study and consent form received approval from the university's Ethics Committee, ensuring that all privacy protocols and ethical standards, such as anonymization of the data, were upheld. After the form, the application guided them to grant the necessary permissions. Finally, the application prompted participants to enter their age and specify the gender with which they most closely identify (male, female, non-binary, prefer not to answer). After the demographic survey, the application started its service, indicated by a continuously displayed icon in the phone's top bar—a standard requirement for Android foreground services.[4]. This icon was present during the entire duration of the study. Given its constant presence, we expect participants to become habituated to it, minimizing any influence on their natural scrolling behavior.

During the 7-day user study, the participant's infinite scrolling behavior was tracked, intervening with an overlay after 15 minutes of continuous scrolling. After the participants stopped infinite scrolling by closing the application, they were provided with a questionnaire asking them about their perceived *reactance* and current context. For each completed questionnaire, participants were compensated with a bonus payment of 0.5£. This results in an average bonus payment of 5.20£ per participant who completed the study. After the 7-day study, the application notified participants that the study had finished and that they could delete the application.

4.3 Questionnaire Design

This section outlines the specific questions used to measure the dependent variables and contextual factors collected during the study. Recognizing the importance of participant engagement and the potential for survey fatigue, we predominantly utilized concise, single-item measures. Although single-item measures can produce measurement error [17], their use is well-established and validated in the field of SoMe research, offering a balance between data quality and respondent burden [8, 9, 11, 79]. Nonetheless, to mitigate potential measurement errors and maintain data integrity, we incorporated random attention checks within the questionnaire. A detailed list of the concrete items used during the user study can be found in Appendix B.

Dependent Variables. According to Rains [76], interventions aiming for behavior change reduce user's sense of control [48]. Hence, we assume this is also true for interventions during infinite scrolling. Thus, intervening can create *reactance* towards the intervention. This phenomenon in HCI is defined by Ehrenbrink [23], who refers to *reactance* as the resistance individuals feel when their freedom of choice is perceived to be under threat. Hence, increased *reactance* can reduce the effectiveness of the intervention by affecting the user's acceptance of the guidance or constraints imposed. Consequently, we used *reactance* as our first dependent variable, as suggested by Meinhardt et al. [53]. We measured *reactance* using the subscale Threat of the Reactance Scale for Human-Computer Interaction (RSHCI) [23]. This subscale included five question items that were rated on a five-point Likert scale ranging from 1="strongly disagree" to 5="strongly agree." For each observation, we calculated the *reactance* score by averaging across these five items. Additionally, we used *responsiveness* towards an intervention, defined as the time span in seconds from displaying the intervention and the moment when participants eventually stopped infinite scrolling.

Contextual Factors. The specific questionaires that we used for surveying the contextual factors (see section 3) are described in the following:

- For the **Current Activity**, we used the interval scale proposed by Samdahl [85], which extends from (-3),"definitely leisure", to (+3), "definitely not leisure" context.
- For assessing the **Social Situation**, we employed a question inspired by Akpinar et al. [1], who defined social context during smartphone usage as "Which one of these best describes people

[4]https://developer.android.com/develop/background-work/services/foreground-services, accessed: November 13, 2024

around you?". We gave three possible responses: alone, with acquaintances (friends, family, colleagues), or with strangers.

- To assess whether participants were **At Home**, they were asked, "Are you currently at home?" and were given a yes or no answer.
- We added the contextual factor of **Multitasking** by asking, "Did you do anything else besides being on [App Name]?". This question could be answered either with yes or no.
- To define the internal context, we asked for the participants' **Valence** using the self-assessment Manikin scale (SAM) [10] as already employed by Rixen et al. [79]. The scale contains five images of manikin. However, we only used the dimension for valence. Further, we simplified the scale by only using the faces of the images used in the SAM, as this is the only part changing for valence in the SAM.
- To measure **Sleepiness**, we used the Karolinska Sleepiness Scale (KSS) [87] ranging from 1="extremely alert" to 9="extremely sleepy".

4.4 Participants

We recruited participants over approximately one month to recruit a total of 460 participants who completed the registration phase of the study. As mentioned above, participants who did not experience regret during infinite scrolling were excluded from the user study, resulting in 316 eligible participants. A total of N=160 participants successfully downloaded *InfiniteScape* and enrolled in the longitudinal study. The participants who refrained from downloading the application mentioned reasons such as privacy concerns, difficulties with the download process, or the perceived burden of a 7-day commitment to the study. In addition, we believe this drop-out range can largely be attributed to the low initial effort required for registration. This may have led participants to claim the initial reward without full commitment to completing the longitudinal study. While the drop-out rate may appear substantial, it is consistent with Rixen et al. [79], who reported comparable rates. To ensure consistent exposure duration for each participant, we excluded data from 88 participants who did not complete the full 7-days during the study. This resulted in a final sample size of N=72 participants, with a mean age of $MD = 35.50$, $SD = 10.01$ years (33 male, 29 female, 10 non-binary, 0 prefer not to answer). These participants provided a total of 946 data points, which were used in our subsequent analysis.

4.5 Results

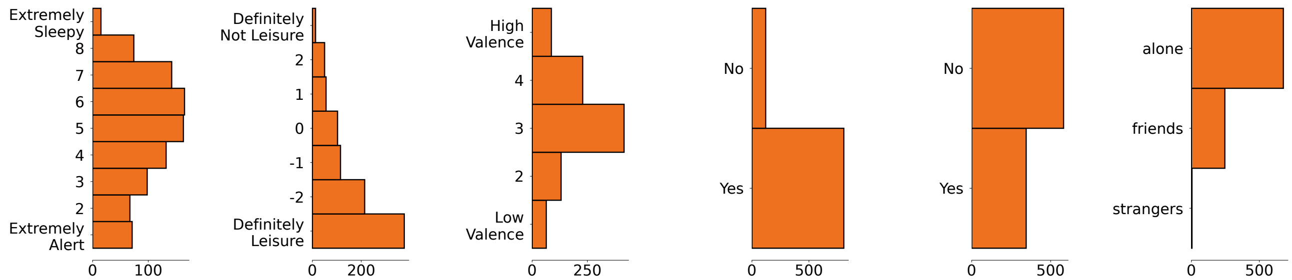
To address our research question of how context affects users' *reactance* and *responsiveness* towards interventions during infinite scrolling, we fitted linear mixed models (LMM) for each dependent variable to explore the main effects and interactions. This enabled us to include a random intercept for each participant, as the models account for the correlation between repeated measures of *reactance* and *responsiveness* within the same participant.

We used R version 4.3.1 and RStudio version 2023.12.1 with up-to-date packages as of September 2024 for analysis and Python version 3.10.4 for plotting.

4.5.1 Data Pre-Processing. Initially, we removed 11 data points of participants who failed the attention checks. We then used the z-score method to identify and remove outliers in the dependent variables, setting the threshold at a z-score of 3. Thus, data points that were not within three standard deviations of the mean are considered statistically rare and were removed from the data set. Accordingly, 8 data points were removed as they exceeded the z-score threshold for *responsiveness*. Looking at these data points, the time to stop infinite scrolling after the intervention exceeds 3 hours. Hence, we assume that there were technical issues during these sessions. After preprocessing, 927 data points from 72 participants (with an average of 12.88 (SD=13.02) data points per participant) remained for subsequent analysis (see Appendix A for detailed frequency of data points per participant). Subsequently, we evaluated the distribution of our dependent variables using the Shapiro-Wilk test [88]. The results indicated that both *reactance* ($W = 0.95$, $p < 0.001$) and *responsiveness* ($W = 0.48$, $p < 0.001$) are not normally distributed. Despite this non-normality, according to Arnau et al. [4], deviations from normality have only minimal impact on the standard errors of estimation methods for longitudinal studies. Consequently, we assessed skewness and found that while *reactance* was nearly symmetric (-0.36), *responsiveness* was strongly right-skewed (3.62). To correct this and gain more robust estimates, as suggested by Draper and Smith [22], we applied a logarithmic transformation to reduce the skewness of *responsiveness* to 0.782. After this correction, the Shapiro-Wilk test showed $W = 0.88$, $p < 0.001$, indicating an improvement toward a normal distribution.

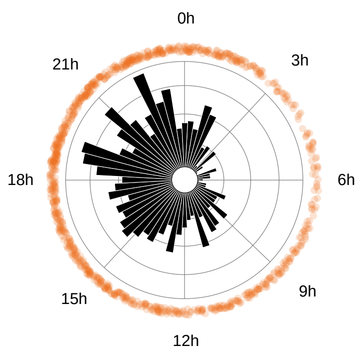
4.5.2 Descriptive Data. The descriptive data indicate that the overall level of *reactance* was rated as medium on a range from 1 to 5, with a mean of 3.55 (SD=1.03). In terms of *responsiveness*, the duration users continued infinite scrolling after an intervention varied widely, from 0 seconds to 67 minutes and 20 seconds. On average, users stopped scrolling after 3 minutes and 31 seconds (SD=8 minutes and 21 seconds). The interventions of the six SoMe applications were distributed as follows: TikTok was the most used at 40.30%, followed by Reddit (26.48%), Facebook (13.49%), Instagram (11.13%), X (5.56%), and YouTube Shorts (3.03%). The distribution of the contextual factors is depicted in Figure 2. Further details regarding the contextual factors are summarized in Appendix C. The majority of interventions occurred late afternoon and evening (see Figure 3a), with a peak between 18h and 23h (40.99% of the data points). During the night (between 0h and 6h), a minimal of interventions occurred (14.78%), suggesting minimal engagement in infinite scrolling during these hours.

4.5.3 Linear Mixed Models. For our analysis, we fitted two LMMs for each of our independent variables (see Table 1): *reactance* and *responsiveness*. For Models 1 and 3, we investigated the main effects, employing the formula: *Reactance*/*Responsiveness* ∼ At Home + Current Activity + Sleepiness + Valence + Side Activity + Social Situation. Conversely, Models 2 and 4 examined interaction effects, using the formula: *Reactance*/*Responsiveness* ∼ At Home * Current Activity * Sleepiness * Valence * Multitasking * Social Situation. In all models, participants were included as a random effect, denoted as ∼ 1 | ProlificID. To control for the increased risk of Type I errors due to multiple comparisons and the exploratory nature of this study, we adjusted the alpha level using the Bonferroni correction to $\alpha = 0.025$, ensuring that the results are robust against the possibility of finding false positives.

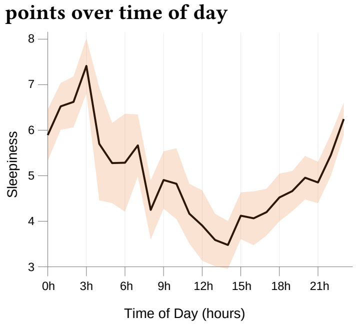


(a) Sleepiness [87] **(b) Current Act. [85]** **(c) Valence [10]** **(d) At Home** **(e) Multitasking** **(f) Social Situation**

Figure 2: Distribution of the investigated contextual factors during infinite scrolling interventions



(a) Distribution of intervention data points over time of day



(b) Relation between sleepiness [87] and time of day in hours with 95% CI

Figure 3: Distribution of the interventions over time of day and the relation between sleepiness and time of day

In Models 1 and 3, which focused on the main effects, one significant main effect was found. In Models 2 and 4, which assessed interaction effects, four significant main effects were also observed. Notably, while the main effects for Models 1 and 3 are valid for interpretation, the main effects in Models 2 and 4 should not be interpreted due to the presence of interaction effects as noted by the guidelines from Nelder [64]. This is due to the relationship between independent and dependent variables being altered, making it inappropriate to interpret main effects in isolation [101]. Thus, in Table 1, these main effects in Models 2 and 4 are grayed out, and only their interaction effects are considered for the subsequent interpretation. Detailed results for all four models (two for each independent variable) are presented in Table 1.

Although the time of intervention could also potentially influence how users respond to an intervention, we refrained from including this factor in the LMMs. The rationale behind this exclusion is that the periodic nature of daytime does not fit well with the linear analysis used in LMMs. Furthermore, individuals' daily schedules vary widely (e.g., a shift worker might wake up at 1 am compared to a student waking up at 9 am), making it difficult to generalize the effect of daytime on participants' reactions toward interventions. Instead, we argue that sleepiness is a more appropriate variable. As shown in Figure 3b, sleepiness increases during the night and decreases during the day. This pattern not only represents the individual physiological rhythms common to all participants but also serves as a linear factor for our models.

4.5.4 Main Effects. This section will report the significant main effect for *reactance* and *responsiveness* depicted in Figure 4. We found that sleepiness negatively affects *reactance* ($t(917) = -3.40$, $p < .001$). This indicates that users experience less *reactance* towards an intervention as they become more sleepy. However, our analysis did not reveal a significant main effect of sleepiness on users' *responsiveness* to interventions. Additionally, we found no other significant main effects impacting user's *reactance* or *responsiveness*. However, we found multiple interaction effects on our dependent variables.

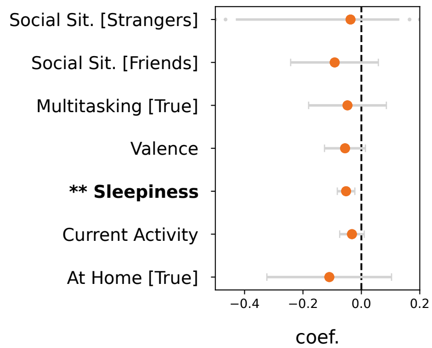
4.5.5 Interaction Effects. We found no significant interaction effects on *reactance*. However, for the dependent variable *responsiveness*, we found a negative interaction effect between Valence × Social Situation [Strangers] ($t(857) = -2.51$, $p = 0.012$), which was significant; see Figure 5a. This indicates that while being alone, the *responsiveness* to the intervention is almost unaffected, while it strongly increases with increasing valence when participants are in a social situation with strangers. However, one should note that no data points were obtained for low valence (1 and 2) and high valence(5).

Table 1: Linear Mixed Models predicting *reactance* and *responsiveness*. Coefficient (Standard Error)

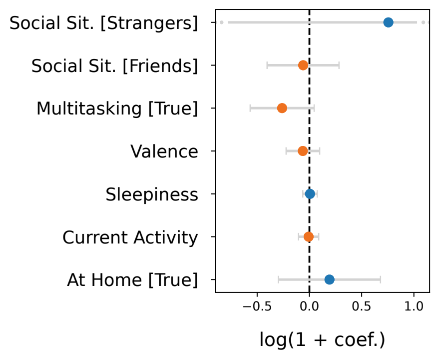
	Dependent variable:			
	Reactance		Responsiveness	
	Model 1	Model 2	Model 3	Model 4
Main Effects				
Social Sit. [Strangers] (Ref. alone)	−0.04 (0.40)	8.76 (15.90)	0.76 (0.93)	93.39* (36.99)
Social Sit. [Friends] (Ref. alone)	−0.09 (0.08)	40.46 (26.73)	−0.06 (0.18)	74.43 (61.99)
Multitasking [True]	−0.05 (0.07)	3.56 (4.58)	−0.26 (0.16)	24.36* (10.64)
Valence	−0.06 (0.04)	0.76 (1.10)	−0.06 (0.08)	7.11* (2.56)
Sleepiness	**−0.05**** (0.02)	0.40 (0.96)	0.01 (0.04)	2.70 (2.22)
Current Activity	−0.03 (0.02)	1.77 (1.66)	−0.01 (0.05)	−6.86 (3.88)
At Home [True]	−0.11 (0.11)	2.77 (4.13)	0.19 (0.25)	30.76** (9.63)
2-way Interaction Effects				
Valence x Social Sit. [Strangers]		−2.58 (3.54)		**−20.69*** (8.23)
Sleepiness x Social Situation [Strangers]		0.16 (0.92)		**−5.14*** (2.13)
Current Activity x Social Sit. [Strangers]		0.84 (0.43)		0.16 (0.99)
Valence x Multitasking [True]		−0.90 (1.26)		**−7.27*** (2.93)
At Home [True] x Multitasking [True]		−3.27 (4.70)		**−29.21**** (10.94)
At Home [True] x Valence		−0.78 (1.12)		**−8.25**** (2.61)
At Home [True] x Current Activity		−1.80 (1.69)		8.53 (3.93)
3-way Interaction Effect				
At Home [True] x Valence x Multitasking [True]		0.87 (1.29)		**8.33*** (3.00)
AIC	2271.9	2308.1	3816.1	3957.9
BIC	2320.2	2646.3	3864.4	4196.1
log − likelihood	-1126	-1084	-1898.1	-1858.9
deviance	2251.9	2168.1	3796.1	3717.9
R^2 *conditional*	0.42	0.41	0.34	0.36
R^2 *marginal*	0.02	0.02	0.0072	0.07
Significance Codes:	*p<0.025; **p<0.005; ***p<0.0005			

There is another significant negative interaction effect for Valence × Multitasking [True] (t(857) = -2.48, p = 0.013); see Figure 5c. Hence, while having a side activity besides infinite scrolling, the *responsiveness* increases with increasing valence. However, when participants have no side activity, the effect reverses, and the *responsiveness* decreases with increasing valence.

Another significant negative interaction effect was identified between being at home and valence (t(857) = -3.17, p = 0.002), as detailed in Figure 5e. This finding suggests that when participants are at home, their *responsiveness* moderately decreases as valence increases. In contrast, when participants are not at home, there is a notable increase in *responsiveness* corresponding with an increase in valence. Further, the interaction between Sleepiness × Social Situation [Strangers] is statistically significant and negative (t(857) = -2.41, p = 0.016); see Figure 5b. This interaction indicates that when alone, an increase in sleepiness leads to a moderate increase in *responsiveness* to interventions. However, when in the presence of strangers, an increase in sleepiness results in a much stronger decrease in *responsiveness.* It is important to note that during instances of extreme sleepiness while being with strangers, the intervention did not occur. There was an interaction between being At Home [True] × Multitasking [True], which is significantly negative (t(857) = -2.67, p = 0.008; see Figure 5d). This result suggests that when users are at home, engaging in a side activity alongside infinite



(a) Main effects for *reactance*



(b) Main effects for *responsiveness*

Figure 4: Coefficients of the main effects for *reactance* and *responsiveness*. As the *responsiveness* was logarithmically transformed, the coefficients must be considered as log(1+ coef.). Blue dots indicate a positive coefficient, orange dots negative ones.

scrolling does not impact their *responsiveness* much. In contrast, when users are not at home, multitasking alongside scrolling has a pronounced negative effect on their *responsiveness*.

Lastly, we found a significant positive three-way interaction between At Home [True] x Valence x Multitasking [True] (t(857) = 2.77, p = 0.006).

4.5.6 Model Comparison. To identify whether interaction effects or main effects are better to explain the influences of the context factors, we conducted likelihood-ratio tests to compare the models, including main effects (n = 10 parameters), with the models including interaction effects (n= 70 parameters). On the one hand, for *reactance*, the main effects model (Model 1) yielded an AIC of 2271.9 and log-likelihood of -1126, while the interaction effects model (Model 2) produced an AIC of 2308.1 and a log-likelihood of -1084. Comparing the two models indicated a significant improvement in fit with the inclusion of interactions ($\chi^2(60)$ = 83.848, p = .023). Hence, despite the increased complexity of the interaction model, the significant p-value suggests that the interactions between contextual factors provide an improvement in explaining the contextual influences for *reactance*. On the other hand, for the *responsiveness*, the model with main effects (Model 3) produced an AIC of 3816.1 and a log-likelihood of -1898.1. In contrast, the interaction effects model (Model 4) resulted in an AIC of 3857.9 and a log-likelihood of -1858.9. The likelihood ratio test indicated a $\chi^2(60)$ = 78.265, p = .057. Thus, although the interaction model showed a lower deviance (3717.9) compared to the main effects model (3796.1), suggesting a better fit to the data, the increase in model complexity and the p-value slightly above the alpha level of .05 suggest that the improvement in fit may not justify the additional complexity introduced by the interaction terms.

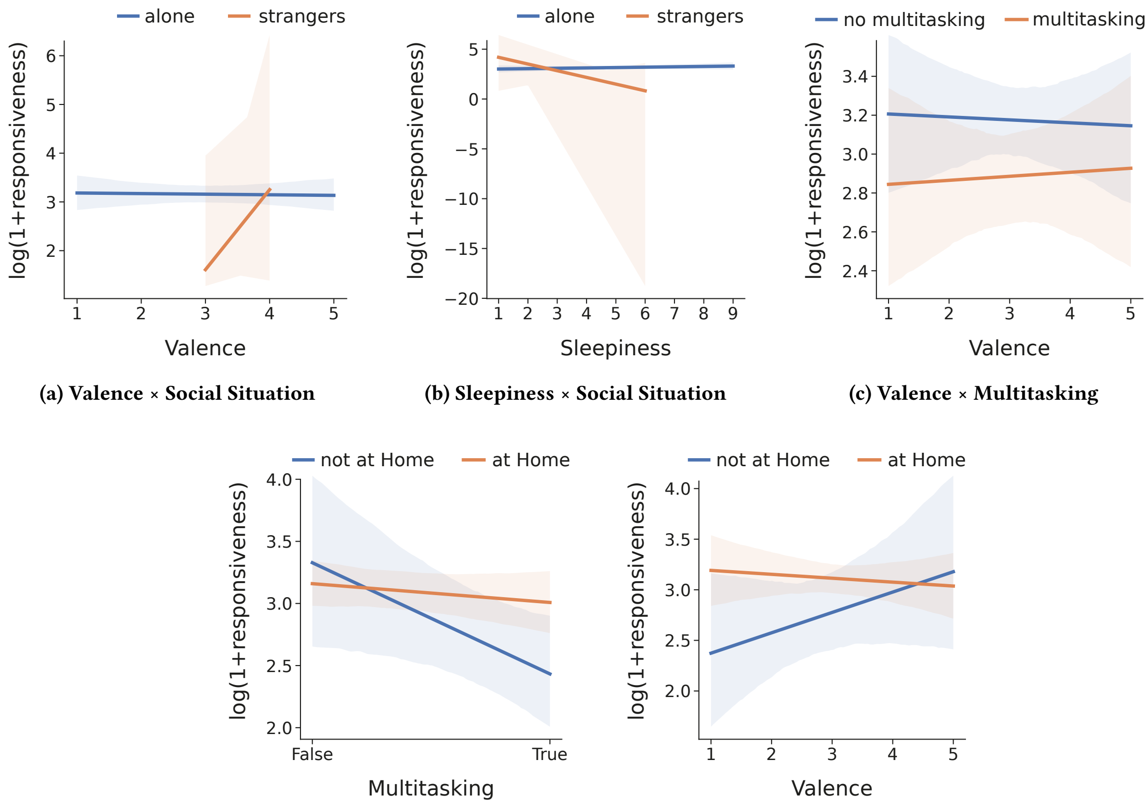
5 Discussion

This work explored how contextual factors influence users' *reactance* and *responsiveness* towards an intervention during infinite scrolling on SoMe. We conducted a longitudinal user study for 7 days with N=72 participants, who installed our self-developed *InfiniteScape*, a native Android application tracking their infinite scrolling behavior. Upon detecting continuous scrolling (e.g., in Instagram or TikTok) for more than 15 minutes, participants were prompted with an intervention overlay nudging them to stop scrolling. We gave participants the option to dismiss this intervention and continue scrolling. Once they stopped infinite scrolling, such as by closing the SoMe application, we asked participants about their *reactance* to the intervention and their current context, including valence, social situation, current activity, being at home or not, multitasking behavior, and level of sleepiness. These six contextual factors were based on previous research [74, 79]. Additionally, we recorded the time span between the intervention and when participants stopped scrolling to measure their *responsiveness*. In this section, we will explore the implications of our findings, discuss how the identified contextual factors play a role in user behavior, and offer practical implications for designing context-aware interventions during infinite scrolling on SoMe.

5.1 Contextual Influences

Our analysis revealed only one significant main effect, while five significant interaction effects between the contextual factors were found. However, when comparing models (see subsubsection 4.5.6), the addition of interaction effects showed only slight improvements over the models that considered main effects alone. In particular, the model for *reactance* improved significantly with interaction effects, but the enhancement for the *responsiveness* model was not statistically significant (p = .057). This observation implies that the interaction effects should be interpreted with caution. However, Jameson [37] suggests the importance of incorporating multiple contextual factors to assess the user's context accurately. This indicates that context cannot be considered individually. The interplay of these factors points to a complex network of interrelated contextual influences, each intricately connected to and affecting the others. This complexity highlights the need to view context as an integrated system, with various components interacting to impact interventions' effectiveness during infinite scrolling.

5.1.1 Bedtime Procrastination. We observed a main effect that increased sleepiness led to a decrease in *reactance* towards interventions during infinite scrolling. This implies that **people more**



(a) Valence × Social Situation

(b) Sleepiness × Social Situation

(c) Valence × Multitasking

(d) At Home × Multitasking

(e) At Home × Valence

Figure 5: Interaction effects of *responsiveness* with 95% CI

likely accept interventions when tired. Supporting this, Christensen et al. [15] found that phone usage at bedtime is linked to poor sleep quality, which might be an issue users are aware of, thus reducing their *reactance* towards interventions. Interestingly, our results did not show that sleepiness led to a faster response to the intervention. Instead, being alone–in a private context–actually increased the time users spent on infinite scrolling after the intervention. In contrast, being surrounded by strangers reduced this time. However, we did not record any data for situations where users were extremely sleepy and in the company of strangers. Therefore, we assume that high sleepiness levels are more likely in private contexts, such as in bed. The increased *responsiveness* when alone, coupled with the reduced *reactance* due to sleepiness, suggests that users recognize the adverse effects of poor sleep quality and, therefore, accept the intervention when in bed. However, they do not necessarily react to it by stopping their scrolling behavior. We attribute this contradicting behavior to bedtime procrastination, a tendency to delay going to sleep in favor of more engaging activities such as watching TV [42]. Related to smartphone usage, it has been noted that "*individuals with smartphone addiction are inclined to postpone their bedtime*" [29, p. 1]. We infer that while people may be **aware of the negative effects of bedtime procrastination** and thus more receptive to interventions, they **still find it challenging to disengage** from infinite scrolling when tired. This suggests an internal conflict between awareness of habits and the difficulty in altering them, particularly in the context of infinite scrolling at bedtime.

5.1.2 *Infinite Scrolling as Coping Strategy for Negative Emotions.*

Smartphone usage has been found to be a coping mechanism for negative emotions [19]. In particular, the consumption of SoMe is often used as a way to procrastinate on undesirable tasks [77], providing a short-term mood boost [89]. However, this temporary relief often leads to negative feelings such as guilt or regret [14, 35]. However, we could not find any main effect on *reactance* or *responsiveness* with regard to the participant's valence. Instead, the interaction with valence, being at home, and multitasking revealed more nuanced insights. Particularly, the decision to stop infinite scrolling after the intervention was influenced not only by the users' valence but also by whether they are at home and if they perform an activity alongside infinite scrolling. Our findings show that when users are at home, their response time to an intervention remains relatively long, regardless of other factors like multitasking (see Figure 5d) or their valence (see Figure 5e). In this context, **being at home seems to act as a stabilizing factor**, reducing the influence of other variables on responsiveness.

In detail, we found that high valance does not alter *responsiveness* to interventions when users are at home or elsewhere. In contrast, low valence tends to slow down the response time to interventions when users are at home (see Figure 5e). This suggests that **the familiar environment** of beginning at home may **not provide enough distractions from negative emotions**, leading users to ignore interventions and continue scrolling. Conversely, when users are in different settings, external stimuli offer more distractions from their negative emotions, resulting in a faster reaction to stop infinite scrolling after an intervention, as shown by the interaction effect between multitasking and being at home (see Figure 5d). This observation aligns with the interaction effect between valence and multitasking (see Figure 5e). When users are engaged in **multitasking during moments of negative emotions**, they tend to **disengage in infinite scrolling faster** compared to when their focus is solely on scrolling. This effect can be explained by the Multiple Resource Theory [105], which posits that interference between tasks increases when they compete for the same cognitive resources, such as modality or type of attention (e.g., focal vs. ambient). When multitasking, activities that draw from overlapping resource pools increase cognitive demand. In this context, multitasking alongside infinite scrolling likely increases interference, compelling users to free cognitive capacity by responding to the intervention faster. Hence, performing a peripheral activity while infinite scrolling may demand sufficient shared resources to nudge users toward disengaging from infinite scrolling when prompted by an intervention.

5.2 Does Context Truly Matter?

Although we found multiple significant effects for certain contextual factors, the overall influence of context on the intervention's effectiveness appears limited. For instance, while some factors, such as sleepiness, were found to impact intervention effectiveness significantly, other contextual factors, like the current activity (whether the participant was engaged in leisure or working activities), did not occur in any significant main or interaction effects. This raises the question of the true importance of context in designing effective interventions for infinite scrolling. Interestingly, prior research offers mixed insights into this question. The user study by Monge Roffarello and de Russis [61] found that participants rarely used the personalization feature of interventions, suggesting that they did not perceive their context to be crucial in interventing their smartphone use. However, this contrasts with several studies that emphasize the importance of context in behavior change. For example, research argues that timely, context-aware interventions are more effective because they align with the user's immediate environment, mood, or task [21, 70]. Similarly, Purohit and Holzer [74] highlights the need for interventions to be aware of location, time, and social settings to optimize behavior change, particularly in digital well-being. This disparity between our findings and existing research suggests that the role of context may be more nuanced than previously understood. It is possible that some contexts, such as sleepiness, directly influence the user's valence. In contrast, other contextual factors, like current activity, may not have had a strong enough or immediate impact to show significant effects in this study. Another possibility is that the design of the intervention itself plays a role in how much context matters. For example, more immersive or intrusive interventions could override the need for context awareness by being effective regardless of those factors. Additionally, device-specific contexts, such as whether users scroll over old or new content in their feed, might affect intervention effectiveness [79]. Despite this, our study provides statistical evidence that certain contextual factors—such as sleepiness, valence, being at home or not, and multitasking—significantly influence interventions' effectiveness.

5.3 Practical Implications for Designing Context-Aware Interventions

Although previous work indicated that digital interventions should be context-aware, they lacked empirical investigation. The findings of our study emphasize the nuanced and interconnected influences of contextual factors in shaping the effectiveness of interventions during infinite scrolling. This highlights the need for context-aware interventions that consider being at home, social situations, valance, multitasking, and sleepiness as the main factors of an integrated system. For example, the reduced *reactance* observed during increased sleepiness suggests an opportunity for bedtime interventions to increase acceptance of it. Interventions such as promoting calming activities such as mindfulness prompts [95] or journal writing [84] might subtly encourage disengagement during bedtime. However, the lack of effect on *responsiveness* suggests that a multi-step approach may be necessary, with gradual intensification of interventions during bedtime, which could help elicit faster responses without initially overwhelming the user. Building on the recommendations of Ruiz et al. [82], integrating design friction interventions during infinite scrolling could be effective. Their study showed that requiring users to rate each post before accessing the next increased frustration and effectively reduced engagement. Adapting this approach to bedtime procrastination by progressively increasing interaction friction could strike a balance by maintaining low *responsiveness* at the beginning and gradually provoking faster *responsiveness* as the intervention intensifies.

We further found that being at home acts as a stabilizing factor, diminishing the impact of other variables like valence or multitasking on *responsiveness* to interventions. When users are not at home, their response time varies depending on their valence or whether they are multitasking. However, when users are at home, their response time remains consistently high. This emphasizes the need to focus on tailoring interventions specifically for when users are at home, e.g. by synchronizing with smart home devices. While we could not find significant effects on *reactance* associated with being at home, we suggest using more severe interventions when users are at home compared to interventions when they are elsewhere to enhance *responsiveness*. Terzimehić and Aragon-Hahner [93] found that users often wished they had engaged in more meaningful activities, such as physical exercise or social interaction, instead of regretful smartphone use. Hence, interventions could build on this insight by promoting outdoor activities that align with these preferences, such as suggesting nearby parks, fitness classes, or social meetups. A similar approach was already taken by Consolvo et al. [16] by setting goals to encourage physical activities. By leveraging these insights, SoMe platforms can move beyond one-size-fits-all approaches to foster meaningful, sustainable changes in infinite scrolling behavior, aligning with their promise of reducing excessive screen time.

5.4 Detecting Contextual Factors

For the practical implications discussed earlier to be effective, it is crucial to detect the users' context while they engage in infinite scrolling. While detecting the users' location using GPS data to determine if they are at home or elsewhere is relatively straightforward, identifying other contextual factors presents a greater challenge. Factors such as the user's current activity, valence, social situation, or whether they are multitasking require more sophisticated approaches for detection. However, recent advancements in sensing technology, particularly in machine learning, have significantly improved our ability to detect specific aspects of the users' context. For instance, Liang et al. [46] demonstrated the use of smartphone recordings to detect face-to-face conversations, providing valuable information about the user's social situation. Further, Mandi et al. [52] developed a framework capable of assessing a user's valence and arousal through facial image analysis using a smartphone camera. In addition, the detection of sleepiness [36] and multitasking [39] has primarily been explored within the context of driving, utilizing eye-tracking technology. Transferring these methods to the domain of smartphone usage, particularly in the context of infinite scrolling, could offer novel ways to tailor context-aware interventions more effectively. While these technologies can provide valuable context data, they also raise privacy concerns. Thus, any implementation of context-aware interventions must prioritize user privacy and ensure that such technology respects individual boundaries and maintains ethical data handling.

While those contextual factors could be detected with current and future technology, our study required using Android's Accessibility Service to monitor infinite scrolling behavior. However, apps utilizing this service face restrictions on the Google Play Store, as they are not permitted for non-accessible purposes [30]. This presents a challenge for the practical application of apps capable of tracking infinite scrolling and intervening in such behavior. Nonetheless, ensuring user privacy while effectively tracking digital behaviors is crucial. Future developments in this area must balance the technical capabilities for tracking infinite scrolling with privacy standards and marketplace regulations to make these tools available to a broader user base.

5.5 Limitations and Future Work

Looking ahead, future research should extend this research by investigating various interventions to determine the most effective ones for specific contexts. While our study employed a simple pop-up intervention adopted from current state-of-the-art interventions in SoMe applications (see subsection 4.1), it is plausible that alternative types of interventions may perform better or worse depending on the context.

In reflecting on the limitations of our study, it is important to acknowledge certain aspects that could influence the interpretation of our findings. First, our participant pool was limited to Android users, which inherently excludes a substantial number of smartphone users, particularly those using iOS devices. This restriction potentially limits the diversity of our study sample and may impact the applicability of our findings across different technological platforms. Further, our study's 7-day duration may not capture the full scope of longer-term effects of contextual influences on infinite scrolling. While there are longer-term studies on general smartphone overuse (e.g., approximately 13 weeks [32]), future research should examine the extended impacts specifically related to infinite scrolling behavior. Additionally, our approach to assessing participants' current context after the intervention relied on self-reporting, not objective detection [36, 46, 52]. While our work gave first insights into the complexity of contextual influences, future work should take those objective detection approaches to investigate whether context detection matches the outcomes of our study. Another limitation is that, due to the event-based ESM, only contextual information was collected from participants, who eventually stopped infinite scrolling after the intervention occured. Therefore, we are missing data from those who continued scrolling and, therefore, ignored the interventions and did not answer the questionnaire. In this study, interventions were triggered after 15 minutes of continuous infinite scrolling. While a baseline condition, in which no intervention would be triggered, could have provided further insights into contextual factors on participants' unaffected reasons for stopping infinitive scrolling (such as already hinted by Rixen et al. [79]), it was not included in the current study due to the primary focus on contextual factors on intervention effectiveness. Further, we only included participants who expressed regret during infinite scrolling, ensuring intrinsic motivation to engage with interventions, as supported by Self-Determination Theory [83]. However, individuals who unconsciously scroll without regret may require different interventions, such as increasing awareness or breaking habits through external triggers. Future work should address this group to broaden intervention applicability.

Our study examined specific contextual factors identified in prior research [1, 34, 74, 79, 104], but these represent only a subset of potential influences on user behavior. Future research could expand on this by exploring a broader range of contextual elements. This expansion could reveal additional layers of complexity in user behavior on interventions during infinite scrolling. Besides contextual factors, Vanden Abeele [99] hints that the content consumed during infinite scrolling might also influence reactions towards an intervention (e.g., engaging content might cause higher *reactance* than boring content). Hence, future work should look into the influence of the consumed content, e.g., via screenshots [12, 68].

Concerning statistical power, our approach shows the inherent challenges in estimating power for LMMs [44]. Proper power analysis requires simulations based on data from prior studies, which may introduce variability in the estimated power depending on the prior study's sample. This lack of precise power calculation means that we cannot fully assess the risk of Type II errors - missing true effects due to insufficient sample size. As a result, there may be significant effects that we have not detected. Nevertheless, the fact that significant interactions were found is already an indication of sufficient power. Nevertheless, the low R^2 marginal values (see Table 1) in the LMMs indicate that the variance in user responses explained by our models is subtle. This suggests that individual differences between users may have a more pronounced impact than the specific contextual factors identified. This insight is interesting for future research because it highlights the importance of personalization in intervention design, recognizing that individual user characteristics may play a key role in determining intervention effectiveness.

6 Conclusion

This paper explored the impact of contextual factors on the effectiveness of interventions during infinite scrolling on SoMe, defined by the *reactance* and *responsiveness* towards the intervention. To achieve this, we developed *InfiniteScape*, designed to monitor users' infinite scrolling behaviors and present an overlay intervention after 15 minutes of continuous activity. Once participants stopped scrolling, a follow-up questionnaire captured their *reactance* toward the intervention and their prevailing contextual factors. Furthermore, the duration between the intervention and the moment participants stopped scrolling was recorded as their *responsiveness*.

Our study spanned 7 days and involved N=72 participants who installed *InfiniteScape*. The findings reveal that multiple contextual factors are interlinked, showing that they should not be considered in isolation. In particular, we found interaction effects on the *responsiveness* for the users' valence with their social situation, whether they are at home or elsewhere, and whether they were multitasking while scrolling. Specifically, low valence combined with being at home tended to slow users' *responsiveness* to interventions, whereas multitasking during low valence resulted in users responding to the intervention more quickly. Further, we observed a main effect indicating that increased sleepiness reduces users' *reactance* towards interventions, suggesting that users are more likely to accept an intervention when they feel tired. These findings underscore the complexity of intervention effectiveness and emphasize the need to design context-aware strategies to mitigate excessive infinite scrolling on SoMe platforms. Examining how these different contextual aspects interact together within an overall system is important.

Our research contributes to our understanding of how contextual factors impact the effectiveness of digital interventions and provides evidence to support the development of more effective, context-aware interventions to address infinite scrolling.

Open Science

The source code of the native Android application *InfiniteScape*, and the RScript for analysis are available under the following link: https://github.com/luca-maxim/scrollingInTheDeep.
The study data are provided in an anonymized format. Hence, to ensure privacy, we replaced each participant's Prolific ID with a unique sequential Participant ID.

Acknowledgments

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A Frequency of Data Points per Participant

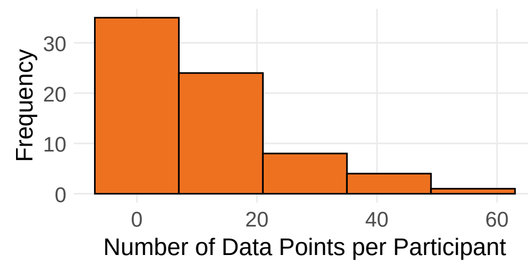

Figure 6: This plot shows the frequency of how many data points were provided per participant (M=12.88**, SD**=13.02**)**

B Question Items Used in the User Study

Table 2: Question items used in the user study

Measurement	Question Item	Answer Items	Reference
Reactance (Threat subscale)	I want to be in control, not my phone. I like to act independently from my phone. I don't want my phone to tell me what to do. I don't let my phone impose its will on me. I alone determine what to do, not my phone.	5-point Likert scale from "strongly disagree", to "strongly agree"	[23]
Current Activity	What is your current activity?	7-point Likert scale from (-3), "definitely leisure", to (+3), "definitely not leisure"	[85]
Valence	How do you feel?	five images of manikin showing different valence levels	[10]
Sleepiness	What is your level of sleepiness?	9-point Likert scale from (1), "extremely alert", to (9), "extremely sleepy"	[87]
Social Situation	Which one of these best describes people around you?	"alone", "with friends/ colleagues/ family members", "with strangers"	[1]
Multitasking	Did you do anything else besides being on [app name]?	"yes", "no"	–
At Home	Are you currently at home?	"yes", "no"	–

C Descriptive Data of the User Study

Table 3: Table of the descriptive data of the user study

Contextual Factor	**min**	**max**	**mean**	**SD**	**median**	**distribution**
Sleepiness	1	9	4.91	2.05	5	
Current Activity	-3	3	-1.59	1.60	-2	
Valence	1	5	3.16	1.01	3	
At Home						True (86.95%), False (13.05%)
Multitasking						True (37.22%), False (62.78%)
Social Situation						alone (73.03%), friends (26.54%), strangers (0.43%)
Dependent Variables						
Responsiveness	0s	67m 20s	3m 31s	8m 21s	8s	
– log.-trans.	*0*	*8.30*	*3.07*	*2.14*	*2.20*	
Reactance	1	5	3.55	1.03	3.80	
App Distribution						
TikTok (40.30%), Reddit (26.48%), Facebook (13.49%), Instagram (11.13%), X (5.56%), YouTube Shorts (3.03%)						