Stop Fiddling With Your Phone and Go Offline: People Experiencing High Information Overload Have Sparse Online Sessions

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Abstract

People suffer from information overload while using digital devices, yet little is known about the interaction of the overload experiences and everyday web behavior. We conducted a large-scale longitudinal observational study (N=277) over seven months. The study combines over 13M passively observed web traces from desktop computers and mobile devices with four waves of surveys measuring the experienced information overload. Our results demonstrate that repetitive, short-duration use of devices (i.e., high sparseness) in online sessions differentiate highly overloaded individuals from others with a large effect. Furthermore, mobile web duration and session sparseness predict increase in the overload. Overall, our results highlight that the web usage duration, the temporal patterns of usage, and the choice of a device are associated with information overload. By highlighting session sparseness as an actionable behavioral signal, our results inform the development of digital wellbeing tools that nudge users toward healthier interaction patterns and reduce overload.

CCS Concepts

• **Human-centered computing → Empirical studies in HCI**; **Empirical studies in ubiquitous and mobile computing**.

Keywords

information overload, web browsing, app usage, mobile device, longitudinal study, digital traces, digital wellbeing

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1 Introduction

A large proportion of contemporary lives is spent online through web browsers and mobile applications [16]. Web browsing is the most common activity people do on their computers with browsing consuming around 63% of computer use time, and websites related to social media, work, and entertainment forming the majority of browsing activities [21]. At the same time, users spend more time on their smartphones engaging with mobile apps in various ways, such as to communicate with other users, play games, and read news [13], and web browsers and apps show similar revisitation patterns [39]. Thus, both web browsing and app usage constitute an integral part of life. However, users also engage in several unwanted behavioral traits: smartphones are overused [55] or used out of habit [74], and many activities are experienced as meaningless [60]. Moreover, people often feel overloaded by the interaction with web browsers [17, 63] or when using the social media [53, 69, 103].

Information overload is a phenomenon where people feel that the information processing demands exceed their available processing capacities [30]. Many studies have investigated qualitatively [17, 86] or with cross-sectional surveys [53, 85, 103] how and in what contexts users feel overloaded when using computers. These contexts have a wide range, including email [23] and mobile phone use [85], multichannel communication [62], personal information management [2], web browsing [17, 63], and social media use [53, 103]. However, few quantitative studies exist which relate information overload experienced by people to their online behaviors in everyday life. Studying user online behaviors in-situ would allow more accurate estimates of how much time people spend online, at what time they use the devices, and what activities they engage on their devices, especially as the use habits can be complex [79]. Moreover, this would allow discovering patterns of use in which people suffering from information overload are engaging in as well as detecting and mitigating the overload. In addition, longitudinal studies of information overload would improve our knowledge on how information overload is experienced in life.

A recent meta-analysis found that experienced information overload is associated with decreased well-being and poorer performance [30]. Furthermore, several studies have investigated how web activities reflect users' well-being with mixed results [43, 61, 66, 68, 100] indicating that the issues are complex; thus, there is a need for more nuanced accounts on interaction between digital well-being and online behaviors. Specifically to information overload, to our knowledge, no studies have investigated how online behavior is associated with information overload in everyday contexts, and literature lacks longitudinal studies of information overload in general [30] with only a few existing studies [69, 97]. A better understanding of association between web behavior and information overload has two implications. First, the gained knowledge informs designers, policy makers, and the public on the possible causes of information overload and suggests behavioral change targets to mitigate information overload through interventions and designs. Second, the gained knowledge aids users to reflect on their habits that drive information overload and then provide means to adjust these habits for achieving healthier interaction with the web.

To address these research gaps, we seek to answer the following research questions:

RQ1 How are web browsing behaviors associated with information overload in everyday life contexts?
RQ2 What changes in web browsing behaviors are associated with information overload?
RQ3 Can we identify user profiles which differentiate highly overloaded and non-overloaded users based on their web browsing behaviors?

To answer these questions, we conducted a seven-month observational study in which we tracked web browsers and mobile apps, and collected responses from a series of surveys sent to participants in two-week waves over a three-month period. Based on the tracked web events from devices, we operationalized *browsing behaviors* as the durations of web page and app views, on-and-off patterns of web pages and apps (which we call session sparseness), and entropy of domains and apps in a single session. We examined these behaviors on different devices and in different times of the day to determine the patterns associated with high information overload, which was measured using self-reports in the surveys. The combined data of surveys from 277 individuals and 13,801,079 logged events was analyzed using statistical and cluster analysis methods to explore how the subjective overload experiences interact with the objective behavior.

In this paper, we show that the temporal aspects of everyday web behavior predict overload better than the content aspects. Our results indicate that repetitive, short-duration usage, which we call session sparseness, differentiates highly overloaded people from non-overloaded ones. Furthermore, while the general duration of web use on mobile devices predicts overload, the time spent on desktop in general or on specific activities on either device do not. We find that individuals experience similar levels of information overload from one week to another and that there are large differences between individuals. Our results contribute to a nuanced view of how information overload and web behaviors interact in time. Although individuals experience high information overload connected to their web browsing behaviors, our results highlight that users do not generally change their behavior, indicating that both information overload and web behaviors are likely embedded in everyday habits.

The major contributions of this paper are as follows:

- We identify high average session sparseness, which refers to repetitive, short duration usage as a behavioral pattern, which predicts information overload and differentiates highly overloaded individuals from non-overloaded individuals. We define session sparseness as the relative inactivity in-between consecutive web events prior to the longer inactive time.
- We explore the association of web use duration with information overload and reveal that the web time spent on mobile devices predicts overload, while web duration on desktop does not. Furthermore, the specific activities demonstrate no association on overload.
- By contrast, we investigate how the level of information overload impacts web behavior and show that higher overload predicts 1) decrease in desktop use duration and 2) session sparseness on the day following an information overload measurement. However, in a larger time window, there are no differences.
- We explore further details about sparse sessions and identify the mutual occurrences of session sparseness, messaging related activities, mobile device use, and short web event duration.

Our study contributes to the growing HCI literature on digital well-being by connecting the subjective measures of overload to the objective measures of web behavior. The results inform both the theory of information overload in technology use as well as practical HCI. For the theory, our results support the idea that use duration (i.e., quantity of information received) is associated with the experience of information overload [30], while highlighting that the view might be overly simplistic. Instead, the way people process information [82], such as repetitive, short duration usage, might be more important to the overload. In practice, existing digital well-being tools to control one's online duration often focus on limiting the total use time on distracting app or blocking it [12, 80]. In addition, both the Android [5] and iOS [6] platforms include digital well-being features for monitoring screen time and limiting specified app use times. Furthermore, most tools are designed for single-device use although people regularly use multiple devices [71], such as smartphones and desktops. Our results indicate the association of online duration and information overload is rather weak on mobile devices and non-existent on desktops, thus questioning the effectiveness of focusing on total-duration limitations. Instead, we discuss how the highly overloaded individuals could be helped the most by incorporating suitable features to the platforms that could mitigate short-duration usage by monitoring and blocking session sparseness.

2 Related work

Both web behaviors and information overload have been studied widely in recent years. In this section, we review HCI research on web browsing and app usage, and literature on information overload. Furthermore, we discuss how web behaviors are linked to overload.

2.1 Web behavior

Recent studies have found that web browsing is proportionally the most common activity that users perform on their computers [21, 99]. On average, users spend around 2.6 hours on their computers daily of which 1.7 hours is spent on browsing the web [21]. A majority of the web browsing consists of work, social media, or entertainment-related activities. Long-term trends indicate that users increasingly browse on smartphones [96].

On mobile devices, the app use events are typically very short, and users engage with messaging apps during the day and with games at night [13]. However, unlike desktops, mobile devices are pervasive and are argued to form checking habits [74]. Habitual use, in turn, is experienced to be more meaningless than instrumental use [60]. Habits are automatic behaviors formed through repeated responses to the similar cues in the past [51]. Smartphone use habits can take complex forms in which contextual cues (e.g., time of use, location, notifications) and app-related factors (e.g., certain apps triggering use of other apps) drive the device use [79]. Moreover, the social expectation of constant connection [3] and fear of missing out [77] steer towards multitasking.

On both devices, larger use patterns are often conceptualized as sessions. In web browsing studies, activities occurring together before at least 10–30 minutes of inactivity form a session [11, 21, 34]. Mobile device users are proposed to engage in micro-usage of activities for less than 15 seconds [26], while at the same time, tasks can extend over many sessions [64]. Breaking large tasks into micro-tasks has been shown to decrease mental workload during the task but leads to longer overall time [19]. The notion of a session can refer to a sequence of browsing events that have a common objective for which time-based session categorization is often inaccurate [94]. In our study, we use session as a temporal notion of a series of web events that occur close by but are separated by longer inactivity.

The parallels between web browsing use and app use derive from many apps and web pages hosting the exact same services, such as Meta and Google products being available as apps and through the web. Many apps also allow access to the web pages within the app [91]. Studies have found that smartphone app use is very similar to web browsing on a desktop with similar revisitation patterns, reflecting the services accessed instead of the technology used [39]. Thus, the app use and web browsing should be seen as a partially merged activity.

2.2 Information overload

Information overload refers to the experience that the information processing required by a task exceeds the cognitive processing capacities of a person [30]. People experience information overload in many technology-related contexts, such as web browsing [17, 63], social media use [28, 53, 103], file management [88, 98], mobile phones [85], multichannel communication [62], email [23], and personal information management [2]. Furthermore, people commonly receive an overload of notifications from systems [36] which increases negative affects [8]. The diversity of technology contexts further highlights the ubiquity of information overload in everyday life.

Although information overload is studied widely, there are no commonly agreed models of its mechanisms. According to the theoretical model by Graf and Antoni [30], information overload occurs when information quantity or quality causes cognitive overload on individual, thus resulting in information overload that in turn results in behavioral (e.g., information avoidance and performance-related) and experience (e.g., well-being) outcomes. Cognitive overload is further mediated by factors such as gender, age, occupation, and the information technology used. Rutkowski and Saunders [82] propose that the mechanism for mediating the amount of information and information overload is based on individual chunking abilities, which determine how effectively a person can process the information. Furthermore, overload has both cognitive outcomes, such as increased mistakes and leaving the task unfinished, and emotional outcomes, such as stress and anxiety.

Moreover, information overload has many significant negative consequences. A recent meta-analysis [30] found that information overload correlates negatively with well-being and performance. Although negative consequences of information overload are widely accepted, possible interventions for its mitigation is an active topic of research with mixed strength of evidence in their support [7].

2.3 Linking web behavior to overload

While it is widely accepted that people often feel overloaded when interacting with technologies, it is not obvious what type of behavior would result in or indicate information overload. Studies analyzing digital traces to investigate behavioral or psychological characteristics have made several findings: Smartphone use has an associated overuse risk group with longer duration spent on the phone as well as more morning and evening use [55], and browsing negative content results in a cycle of worse mood and reduced well-being, and more negative content browsing [43]. In contrast, other studies have found that adolescents’ smartphone-use frequency and duration predict the increase in well-being [66], or did not find association with the phone use duration and well-being, while suggesting that night-time use is associated with negative well-being [42]. At the same time, several studies have concluded that there is a lack of evidence or minor effect for association between well-being and internet adoption [101] or online gaming time [100]. These studies highlight the many ways in which analyzing web activities can inform about users’ psychological states.

Based on cognitive approaches to information overload (e.g., [30]), which view information overload mainly as an issue regarding human information processing limits, indicate that the expected link between information overload and web behavior is related to the quantity of information received in the online activities. It has been suggested that human information processing functions at an approximate rate of ten bits per second [106]. Consequently, the active web time could be treated as an approximation of information quantity, and a longer duration should approximate more information and result in higher information overload. Furthermore, the cognitive load theory [92] implies that cognition can be overloaded by three different mechanism: Intrinsic cognitive load occurs when the task at hand requires complex information processing; Extrinsic cognitive load occurs when the way information is presented requires additional processing; Germane cognitive load occurs when new schemas are constructed.

In addition, multitasking or task switching has been associated with information overload [82]. A focus on similar categories might indicate the focus on an object-driven task, while many categories, use of multiple devices, or on-and-off usage patterns can indicate multitasking, which burdens the cognition through attention residue and keeping many active task goals in memory [56]. Task switching in online activities could be associated to switching between different web pages or apps with different functionality, such as an entertainment app and email. This would result in higher entropy of the different pages or apps. On the other hand, task switching could also manifest in on-and-off switching of the web pages or apps, as this implies that the user is switching between online and offline activities. This would result in less active duration within the sessions, or sparseness of the sessions.

Furthermore, different activities can burden the user to different extents. For example, reading and responding to email [23, 67] and numerous notifications on mobile devices [73] can overwhelm users; entertainment consumption is associated with meaninglessness [60] and increases in information overload [69]; users reduce their responses to messages on social media, email, and other social platforms when overloaded [31, 32, 38, 46, 78]; instant messaging overwhelm users when they need to keep track of the conversations distributed across different applications [62]; using short-form video apps for taking a break in between tasks degrades prospective memory [20]; and complicated information searches can get cluttered [63]. Thus, in addition to the general use duration, different types of content can have different impact on information overload.

Prior research has investigated many contexts in which information overload occur. Nevertheless, the relationship between subjective experiences of information overload and web behaviors remains underexplored. Our work contributes to the current research by investigating this relationship through a longitudinal empirical study combining surveys and tracking data from desktop and mobile devices. Understanding interactions of overload experiences and behavior offers possibilities for better identification and countering the negative consequences of information overload when they emerge.

3 Method

We conducted a longitudinal study combining a collection of activity-logging from user devices [52] and a panel design of surveys [35] in four waves. Similar designs have been used in several studies investigating the relationship between digital behavior and user experiences (e.g., [10, 40, 75, 100]). In the this section, we report the methodology of our study.

3.1 Study ethics

The university research ethics committee evaluated and accepted the study plan. The study participants gave their informed consent to participate in the study with the possibility to retract their consent at any point during or after the study. The participants were pseudonymized in the data collection phase to protect their privacy. Moreover, the company redacted any identifying information, such as user IDs and passwords, before sharing the data. The company that recruited the participants followed GDPR regulations.

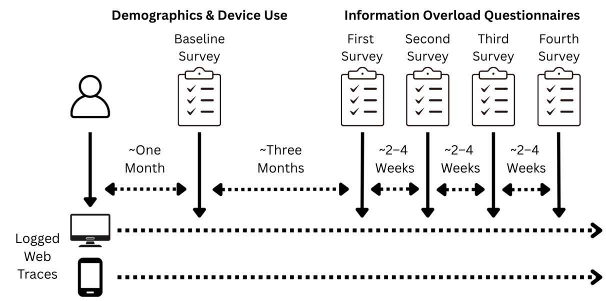


Figure 1: General outline of the data collection procedure.

3.2 General outline

The data collection consisted of two interlinked parts: 1) web traces data collected from the participants who had agreed to be tracked, and 2) a series of surveys sent to the participants whose devices were tracked. Figure 1 illustrates the study procedure. The passive device tracking lasted for seven months (from beginning of June until the end of December 2023) during which participants were invited to answer voluntary surveys on different topics. In the beginning, all participants were invited to answer a baseline survey including questions on demographic characteristics, and web and device usage. The surveys used to gain information on participants' information overload experiences were first sent out approximately four months after the beginning of the device tracking and three months after the baseline survey.

3.3 Participants

The participants were recruited via a GDPR-compliant European panel company, which maintains a panel of individuals who have opted-in to install a web tracker software on their desktop or mobile devices. Participants were compensated 1—3€ per month depending on how many devices were tracked, and an extra compensation based on the company's usual rate (6€/hour) for filling out each survey. The median fill-out times for the four surveys ranged between 3.5 to 5.0 minutes.

The participants were German residents and represented diverse gender, age, and professions. Table 1 presents the demographic features of study participants after the pre-processing steps reported below. Prior work has shown that the panel's demographic distribution matches to a great extent the demographic distribution of adult population in Germany in terms of gender and age [10] and captures the most visited websites in Germany [47].

3.4 Survey Materials

3.4.1 Information overload questionnaire. Information overload was measured using items from technology overload inventory [41] with slight adjustments to measure participants' overload experiences related to their web browsing, as is commonly done with the items [53, 85, 104]. The German translations of the items from

Table 1: Demographic characteristics of study participants after the pre-processing steps (N=277)

Gender	
Female	154 (55.6%)
Male	123 (44.4%)
Age	
18–24	7 (2.5%)
25–34	26 (9.4%)
35–44	51 (18.4%)
45–54	67 (24.2%)
55–64	97 (35.0%)
65+	29 (10.5%)
Education	
Secondary School	182 (65.7%)
Some College Studies	19 (6.9%)
Bachelor's Degree	49 (17.7%)
Master's Degree	25 (9.0%)
Doctoral Degree	2 (0.7%)
Profession	
Academic/Technical	27 (9.7%)
Crafts/Mechanic	31 (11.2%)
Managerial	7 (2.5%)
Office	71 (25.6%)
Sales	17 (6.1%)
Services	44 (15.9%)
Worker/Agriculture	21 (7.6%)
Other	59 (21.3%)

a study by Saunders et al. [85] were used. Items used in the survey can be found from Table 4.

3.4.2 Other measures. Other variables used in the surveys consisted of questions on how much participants' life situation and web browsing have changed recently, for what type of activities do they usually use a web browser, and how much of their web browsing is work-related and personal-related tasks. In addition, the last survey asked the participants about the changes in their behavior due to the ongoing end-of-the-year holiday season.

3.4.3 Quality. The quality of the data was ensured in several steps. Validated and translated survey items were used. The survey was iteratively proofed by five native German speakers to ensure the quality of the translated questions and items. The survey included from one to two attention check questions depending on the length of each survey, and all of the survey responses were evaluated to detect anomalously fast responses (i.e., less than a minute to fill the survey). No fails to attention checks or anomalous responses were found, which indicates good quality.

3.5 Procedures

During the recruiting phase, participants were given an information sheet and a privacy notice, which described the data collection, storage, and processing practices of the study. After recruitment, the data collection occurred in two concurrent procedures for surveys and web traces.

3.5.1 Web traces procedure. Tracking software was installed on participants' devices where it ran in the background throughout the study period. The data collected from the devices consisted of a user identifier, Uniform Resource Locator (URL) for the active tab on the web browser or the app name in the foreground for mobile devices, time stamp of the event, and the active time spent on each web page or app. We refer to the single instances of web page or app views as *events*, duration of the page or app view as *active time* or *active duration*, and the varying combinations of page and app views commonly as online *activities* or browsing behavior.

The full web traces dataset was 1,056 individuals and 40,972,142 events tracked from desktop computers, and 958 individuals and 15,817,612 events tracked on mobile devices.

3.5.2 Survey procedure. The four questionnaires for measuring information overload were distributed at two-week intervals. In the first phase, participants who agreed to install the tracker software on their devices were invited to take part in a baseline survey. People who submitted an answer to the baseline survey were invited to answer to the first survey, and people who answered to the first survey were invited to the remaining three surveys. In total, 1121 individuals responded to the first survey, 954 to the second, 815 to the third, and 924 to the fourth.

Each survey was open for responses for two weeks, and the median response intervals ranged from 26 to 33 days per survey pair with minimum at 14 and maximum at 42.

In the beginning of each survey, the participants gave their consent to participate in the study. After this, the participants were presented with questions in the same order and the items in a random order. In all questions, participants were advised to think about their web browsing in relation to the items presented to them.

3.6 Data analysis

Figure 2 illustrates the general outline of the data analysis pipeline. The data analysis procedure consisted of pre-processing the web traces data, computing key variables from both traces and survey data, and predictive modeling. Next, we report on the procedure.

3.6.1 Inclusion and exclusion of data. Figure 3 illustrates the exclusion steps in data pre-processing. First, the web traces data was filtered to match the participants who had submitted at least one survey. In total, this included 1120 individuals, of which 802 individuals were tracked on desktop devices and 728 on mobile devices. One participant was excluded due to not having data from any tracked device. From the desktop data 216,610 events and from mobile data 327 events were excluded since they lasted zero seconds (e.g., automatic pop-ups). To filter out professional survey takers and retain panelists with more organic web use, participants who spent more than 20% of their device use time filling surveys were excluded, resulting in exclusion of 234 individuals.

Moreover, there were individuals who reported in the baseline survey that they 1) had other people using the devices that were tracked or 2) used other devices in addition to tracked devices. We included only those 288 individuals who were the sole users of the tracked devices and did not use any other devices besides the tracked ones, because their web behavior would more accurately

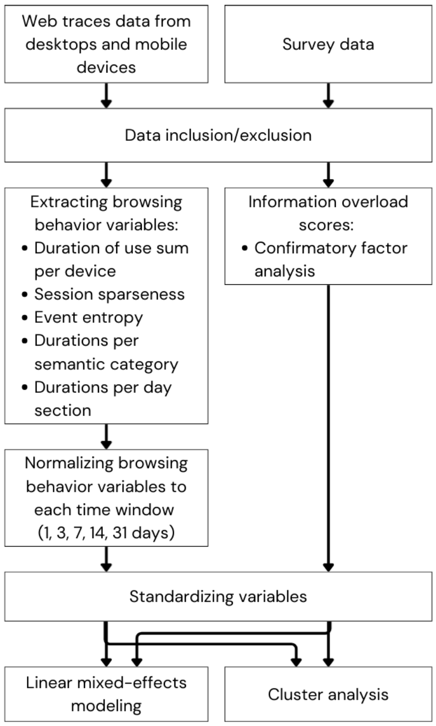


Figure 2: Data pipeline visualized. Data from tracked devices and surveys were pre-processed separately, and combined in linear mixed-effects modeling and cluster analysis.

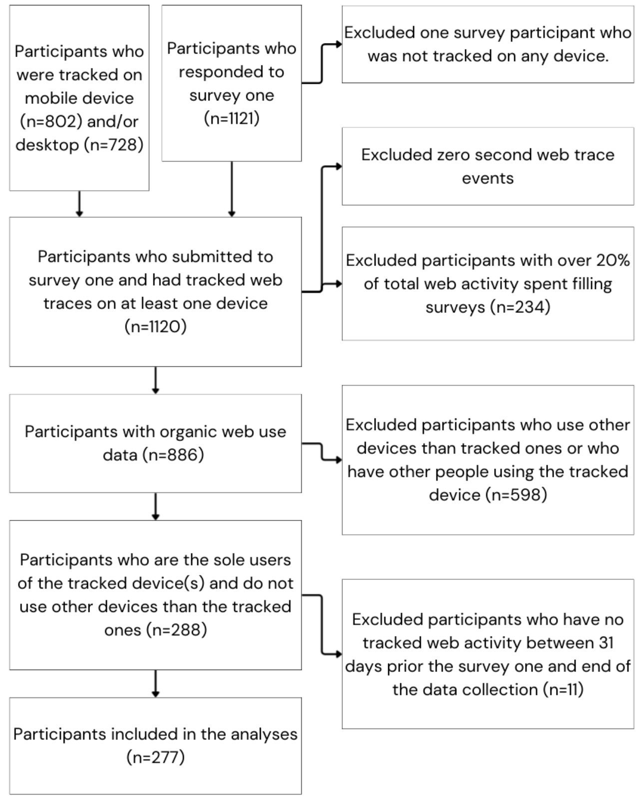


Figure 3: Outline of inclusion and exclusion choices of participants in pre-processing. The exclusion was primarily based on the web traces data. Participants were excluded due to data representing mostly survey response activities, participants having other devices besides tracked ones or other people using the devices, and having no data during the study period, thus compromising the meaningful prediction of information overload based on the web activity behavior.

represent their full behavior. Finally, eleven individuals were excluded because they had no tracked activities during 31 days prior or after the first survey. The resulting dataset consisted of 277 individuals and 13,801,079 events during the study period of 214 days. From the 277 individuals, 70 were tracked only on mobile, 54 only on desktop, and 153 were tracked on both devices. No participant was excluded based on survey data.

We chose not to exclude any tracked events based on event duration, since we had no external criteria for threshold when an extremely long event would represent extreme behavior and when participant inactivity, such as participant falling asleep with their device open. Excluding events based on duration would risk ignoring extreme behaviors, which could be important for identifying information overload. Events longer than two hours accounted for 0.03% of total events, and events longer than 8 hours occurred 247 times (0.002% of events) making them extremely rare. Events longer than 8 hours were associated with 39 unique participants and occurred on both desktop and mobile devices on various URLs and apps. We analyze web activities in more detail in Section 4.1.1.

3.6.2 Semantic categories. The web pages and apps were divided into thirteen semantic categories based on their primary function. The semantic categories were used in grouping the web events to gain finer-grained knowledge about the content of online activities. These were applied in extracting variables from the traces data, as described below.

The categories were derived from a combination of categorizations by app stores and web domain directories, and by visiting the domain or the app. For the platform domains, such as Google, the categorization was based on subdomains, such as Gmail and Google Docs. Table 2 presents the categories and examples. Due to the large amount of data, not all events could be categorized. For the dataset used in this paper, 83.3% of events were categorized.

3.6.3 Extracting variables from web traces data. We extracted two kinds of variables from the traces data: web and app view durations and session metrics. Durations were computed by aggregating event durations over given time windows, which refer to a fixed number of days between a survey and a web event. Figure 4 gives a summary of the variables and how they were applied in the analyses.

The traces data was aggregated over different time windows to compare how the association of browsing behaviors and information overload compare depending on how many days of web traces data were included. For example, a 31-day time window included data from 31 days prior the survey response and survey day. To

Category	Instances
Adult	xvideos.com, xhamster.com
Entertainment	Spotify, twitch.tv, Youtube
Gambling	kicktipp.de, lotty.de
Games	State of Survival, mylittlefarmies.de, chess.com
Health	tk.de, MyTherapy, menshealth.de
Messaging	WhatsApp, Telegram, discord.com
News	bild.de, n-tv Nachrichten
Other	Calculator, paypal.com, My Files, wikipedia.org
Search	Google Search, bing.com
Shopping	Amazon Shopping, ebay.de, mydealz.de, Lidl Plus
Social Media	instagram.com, Snapchat, twitter.com
Survey	ebesucher.de, Google Opinion Rewards, surveyd.bilendi.com
Work Related	Google Calendar, outlook.live.com, Google Drive, mail.yahoo.com

Table 2: Semantic categories of the domains, subdomains, and apps. Examples are illustrative selections from the top ten most visited subdomains and apps in each category.

avoid overlaps between consecutive time windows, the maximum length was set to the time period between two consecutive survey responses for each individual. If a participant had missed a survey, the time window was computed to the most common fill-out date in the survey wave. For this reason, 31-day time windows varied in lengths between participants. Each time window was normalized by dividing the sum of durations with the time window length to make them comparable between participants. For finer-grained analyses, the data was first grouped based on the time of day when the event occurred (i.e., time of the day duration) or the semantic category of the app or the web page (i.e., category duration).

To summarize how much task or context switching occurs in a session, we computed two metrics: *session sparseness* and *event entropy*. These metrics quantify how much online versus offline time occurs in a session, and how much different and unexpected online events occur in a session. A session was defined as continuous web use that was preceded and followed by at least 20 minutes of inactive time, following conventions from the literature [11, 21, 34].

We propose *sparseness* as a simple metric to understand temporal density of web activities. We define sparseness as a proportion of inactivity within a session relative to the session duration. Intuitively, sparseness captures how much on-and-off switching occurs before a longer period of inactivity marked by the session end. For example, if a user spends one minute online reading news, then five minutes offline, and finally four minutes online shopping before an hour long break, the total active time amounts to five minutes in ten-minute session. The proportion of activity is thus $\frac{5}{10}$. However, if a user spends ten minutes online doing various activities, such as reading news or shopping, without breaks followed by an hour long break, the proportion of activity is thus $\frac{10}{10}$. In a one-device use, the theoretical maximum of activity proportion is thus 1, so we get the notion of sparseness (i.e., proportion of inactivity) by subtracting the proportion of activity from one. Formally, sparseness S is computed as

$$S = 1 - \frac{\sum_i^k d_i}{T_{max} - T_{min}}, \tag{1}$$

where the duration of each event d_i from event durations $d_1, .., d_k$ in a session are aggregated and divided by session duration, i.e., the difference in the session end time T_{max} and start time T_{min}. In contexts where the user is using only one device at a time, sparseness ranges from 0 to 1, where zero indicates a session with no inactivity in-between activities, and values close to 1 indicate a session with only short start and end events. In situation where the user uses two devices in parallel, sparseness ranges from 1 to -1, which indicates full activity consecutively with two devices (See Section 4.5 for illustrations).

Another metric we use for summarizing web usage patterns is *event entropy*. Based on the formula of Shannon entropy [89], event entropy refers to the randomness of events (i.e., web domain and app uses) which occur in the session. Intuitively, event entropy quantifies how focused the session is on domains or apps. Higher event entropy indicates lower focus on specific tasks since there are more switches to other domains or apps. Event entropy E of events e_i from session events $e_1, ..., e_k$ is computed as follows:

$$E = -\sum_i^k p(e_i) log_2 p(e_i). \tag{2}$$

3.6.4 Computing information overload scores. To quantify how strongly individuals experienced information overload, information overload scores were computed from survey responses using confirmatory factor analysis (CFA). CFA estimates a latent variable (i.e., information overload score) based on the observed variables (i.e., numerical survey responses). As longitudinal responses from an individual correlate in time due to them being responses from same individual, accounting for correlating residuals and establishing longitudinal measurement invariance is important [45]. This ensures that the information overload scores between the surveys are comparable in a meaningful way. The CFA model was defined as a strict invariance model, which assumes that the latent variables are measured similarly and with similar precision across the surveys [45]. More technically, this means that the latent factor intercepts, factor loadings, and error variances and covariances are fixed to be equal between measurements. The model was then fit to the survey data using a maximum likelihood estimator with Satorra-Bentler corrections because the variables were non-normally distributed, and after examining that the model had an acceptable fit, the latent variable scores were computed for each participant for each survey they responded. The model was implemented using R package lavaan [81] (version 0.6-12). Guided by recommendations of Kline [45], we considered following global fit statistics together with local fit tests acceptable: the chi-square test $p > .05$, root mean square error of approximation ($RMSEA$) $\leq .05$ with 90% CI below .10, comparative fit index (CFI) $\geq .95$, and standardized root mean squared residual ($SRMR$) $\leq .08$.

3.6.5 Linear mixed-effects modeling. We employed linear mixed-effects modeling (LMM) to model the interaction of information overload scores and the duration and session variables extracted from web traces data. LMM is a flexible method that allows modeling linear relationships from repeated measures, and it can handle imbalances of data due to missing data from some individuals [27], which we had since some participants missed one or more surveys. LMM is also robust against many distributional assumptions, such as skewness or heteroskedasticity [87].

Linear mixed-effects models were implemented using R packages lme4 [9] (version 1.1.37) and lmerTest [49] (version 3.1.3). Reported confidence intervals (CI) are profile likelihood confidence intervals [9]. P-values are not adjusted since the scope of the research is exploratory, and we wanted to avoid Type II errors [25]. For our analyses, information overload and web traces variables were standardized.

3.6.6 Cluster analysis. Cluster analysis was used to identify user profiles based on their web traces data and information overload scores. The K-means clustering algorithm [33] was chosen because it has been shown to be an effective yet simple clustering algorithm to investigate participant clusters in HCI [18, 83, 105]. K-means was implemented in the R package stats (version 4.5.1) and used 100 random starts.

3.6.7 Between-cluster comparison. The differences in features between the clusters were tested using Welch's analysis of variance (ANOVA) and pairwise comparisons with Games-Howell test, which has suitable balance of Type I error control and statistical power [84] and by default applies p-value adjustment. These are alternatives for the common ANOVA and Tukey's test that are better suited for cases where unequal group variances occur [24, 54]. For Welch's ANOVA and Games-Howell test, implementations from R packages stats (version 4.5.1), rstatix (version 0.7.2), and effectsize (version 1.0.1) were applied.

4 Results

We analyzed the interaction of browsing behaviors and information overload using two complementary methods: linear mixed-effects modeling and cluster analysis. The results show that high average session sparseness, that is, repetitive short-duration use of devices differentiates highly-overloaded individuals from non-overloaded individuals. Furthermore, mobile use duration, especially in the morning, predicts overload, while desktop use does not. When examining use durations based on the semantic category of the activity, such as news or shopping, no duration predicts overload.

The results proceed in five sections. First, we present general trends in the browsing behaviors and information overload through the seven-month study period. Second, we explore how web use durations and session metrics are associated with information overload. Third, we investigate how, in turn, information overload and pre-survey browsing behaviors predict behavior on post-survey days. Fourth, through cluster analysis, we explore user profiles based on browsing behaviors and information overload. Fifth, we further explore what sparse online sessions are like.

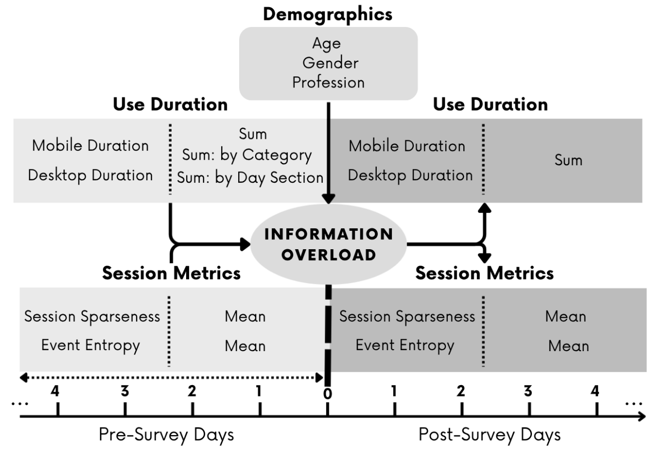


Figure 4: Analysis schema illustrated. Use duration and session metrics are aggregated over different length time windows of 1 to 31 days prior each survey. Aggregated duration values are computed separately for mobile devices and desktops, and all variables are standardized around grand mean. These variables are used for predicting information overload. Furthermore, information overload is used for predicting use durations and session metrics for post-survey days. Demographic variables are used as control variables.

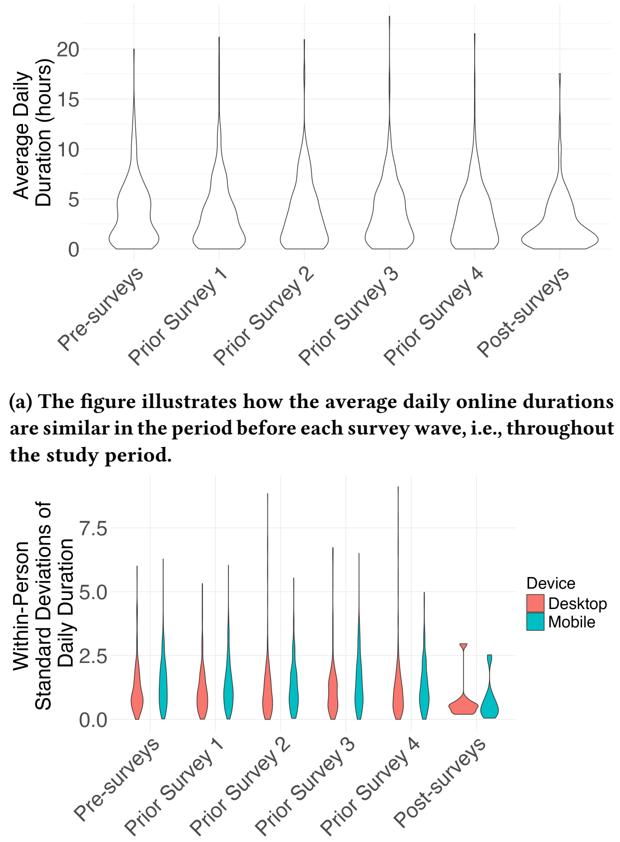
4.1 How the participants use devices and experience overload?

4.1.1 People spend many hours online, and mostly on their mobile devices. Table 3 presents the summary statistics of web traces for the entire seven-month period. The participants were active online users who spent a large proportion of their days immersed in online activities mostly using their mobile devices. On average, participants spent around 3.5 hours online daily, from which 2.3 hours utilized mobile and 1.3 hours desktop devices. Most of the tracked activities were app-related with around 2 hours daily, and 1.5 hours was spent browsing the web. On average, daily web browsing consisted of 177 page views on 3.6 unique domains and 59 unique web pages. Desktop use duration had a high correlation with web metrics ($r = .52 - .98, p < .001$) but statistically non-significant correlation with mobile use duration ($r = -.13, p > .05$) and app usage metrics. In contrast, mobile use duration correlated highly with app use metrics ($r = .63 - .98, p < .001$), but it had near zero and non-significant correlations with web use metrics, except for the number of unique domains ($r = .19, p < .05$). The distributions of average daily online durations and day-to-day variation of active duration remained similar throughout the study period, as illustrated in Figure 5. See Appendix A.2 for more correlations.

Table 3 also reports the session level summaries. On average, the participants online duration consisted of 6.2 sessions daily with an average length of 51.0 minutes each. The mean number of different categories of web pages or apps per session was 3.0 and consisted on average of 44.9 continuous page or app views. Figure 8 illustrates session sparseness and event entropy densities. Most sessions have sparseness and entropy near zero, which implies that the activities

Table 3: Summary statistics of the online behavior traces (N=277). Total use is the aggregate for each participant from the 214 days of data collection. Daily average is computed by dividing the total use by the number of days for each participant. Concurrent desktop and mobile use were computed by aggregating the use durations from events, where end time on one device overlapped with the start time of the next event on another device. Recurrence rate was based on Tauscher and Greenberg [93]. Session metrics represent averages per participant sessions except the number of sessions, which is the number of sessions averaged over the number of days.

	Daily mean (SD)	Total mean (SD)
Online Durations (h)		
Total Online Duration	3.53 (3.12)	754.97 (666.62)
Mobile Duration	2.27 (2.55)	270 (459.42)
Desktop Duration	1.26 (2.15)	484.97 (545.86)
Concurrent Desktop Use	0.12 (0.87)	25.96 (186)
Concurrent Mobile Use	0.15 (0.61)	31.37 (129.88)
Web Browser Usage		
Total Web Page Views	176.8 (272.52)	37835.1 (58320.13)
Web Use Duration (h)	1.52 (2.21)	324.33 (473.16)
Unique Domains	3.59 (3.49)	768.14 (747.68)
Unique Web Pages	59.44 (79.69)	12719.15 (17052.64)
Average Page View (sec)		48.41 (57.47)
Mobile Application Usage		
Total App Views	56.02 (69.78)	11988.29 (14932.26)
App Use Duration (h)	2.01 (2.36)	430.65 (505.98)
Unique Apps	0.32 (0.34)	67.48 (72.49)
Average App View (sec)		169.57 (252.74)
Recurrence of Use (%)		
URL Recurrence Rate		59.93 (13.26)
App Recurrence Rate		96.9 (12.25)
Day-to-Day Variance		
Within-person Standard Deviation of Duration		1.85 (1.20)
Session Metrics		
Number of Sessions	6.19 (3.68)	
Session Duration (min)		50.95 (35.93)
Session Sparseness		0.25 (0.11)
Event Entropy		1.48 (0.62)
Number of Categories		2.95 (1.17)
Unique Domains/Apps		6.69 (4.87)
Number of Views		44.92 (56.11)



(a) The figure illustrates how the average daily online durations are similar in the period before each survey wave, i.e., throughout the study period.

(b) Within-subject standard deviations of daily online durations. The day-to-day variances of online durations are not large for most participants. Few individuals have very large variance in their day-to-day behavior.

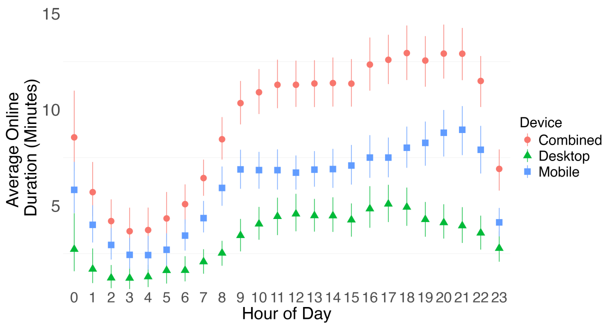
Figure 5: Average online durations and day-to-day within-subject standard deviation of online durations segmented based on the survey waves.

revolve around a single domain or app and include little on-and-off switching or simultaneous dual-device use.

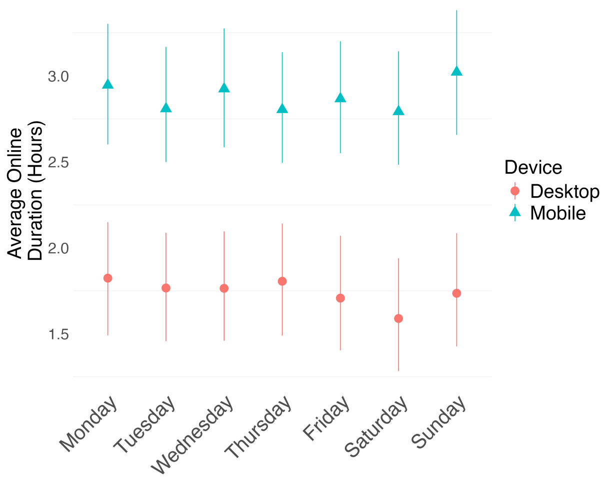
The web activities followed a daily rhythm of increasing use from the morning until afternoon with most active hours taking place at the late evening, as illustrated in Figure 6a. The usage drops steeply for the night where the most variance between online durations occur. The participants were the least active during the night time. Mobile use included longer durations through the day than desktop use. A similar pattern is visible from device use across different days of the week in Figure 6b where there are clear differences between devices in use duration, while little changes through the week.

Figure 7 illustrates the main patterns in semantic categories of the web activities. Differences between devices demonstrate that large proportions of mobile use is spent on games, messaging, and social media, while desktop use is more diverse across categories. The largest proportions of desktop use occurs in surveys, work-related activities, and entertainment. Entertainment and games account for an increasing proportion during the night hours, while messaging on the mobile devices increases during the morning and afternoon. Social media use takes up a significant proportion of the active duration throughout the day on mobile devices and during the period of morning to evening on desktops.

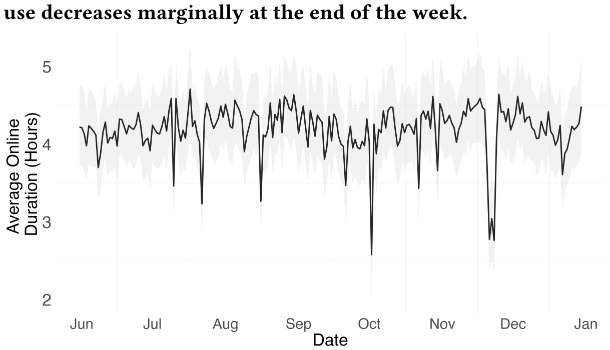
4.1.2 Information overload correlates in time, but varies between people. Information overload scores (IO) were computed from the



(a) Average online durations per hour of the day. The users are on average most active during the day, especially the late evening. Mobile use is consistently larger throughout the day and peaks faster than desktop use. Mobile use also increases after regular working hours, while desktop use starts to decrease.

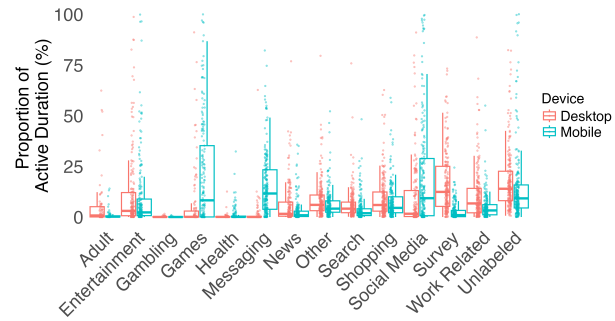


(b) Average online durations by day of the week. Mobile use is consistently larger than desktop use on every day of the week. There are no major differences between the days, but desktop use decreases marginally at the end of the week.

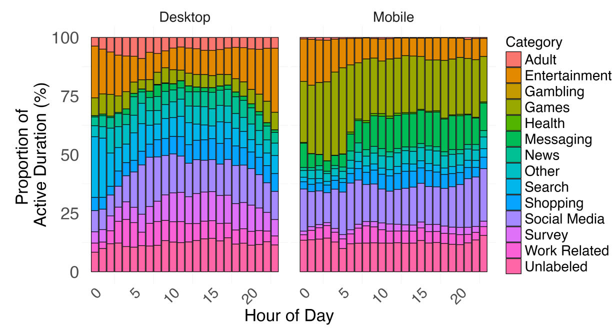


(c) Average daily use durations across the study period. The average daily use duration fluctuates, but remains constantly around four hours a day. The largest drop in average duration corresponds to German Unity Day, a national holiday.

Figure 6: Temporal patterns in use durations.



(a) Proportion of participants' online duration on each device. Large proportions of mobile active time are spent on games, social media, and messaging. Desktop use is more evenly distributed, with survey and work-related categories having the largest proportions. Many individuals dedicate over 75% of their device use time on entertainment, games, or social media.

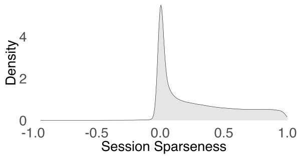


(b) Proportions of durations across different web page and app categories by hour of the day. Usage differs between devices and between hours of the day. Entertainment consumption increases proportionally after midnight on both devices and in the evening on desktop. Games comprise a large proportion of mobile use throughout the day with an increase in the midnight hours. Social media use is consistently notable throughout the day on mobile devices, while the desktop use mostly occurs during morning to evening hours. Messaging occupies a notable proportion of mobile duration between morning and evening hours, but it is almost non-existent on desktops.

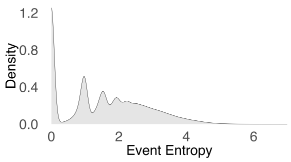
Figure 7: Active durations on mobile and desktop devices by categories of the web pages and apps.

survey responses reported in Table 4 using confirmatory factor analysis. The model was fitted using the complete cases (N=579). The model had a good fit ($\chi^2 = 141.018$, $p = 0.009$, $df = 104$, $CFI = 0.992$, $RMSEA = 0.030[0.016, 0.042]$, $SRMR = 0.028$) and Cronbach's alphas indicated acceptable internal consistency in each wave ($\alpha_{1-4} = 0.88 - 0.91$). The fitted model was used for computing the IO scores for all values where data was available.

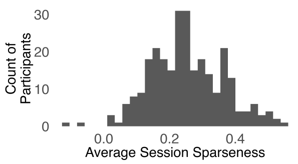
Table 4 reports the information overload scores for the participants used in analyses of this paper, and Figure 9 illustrates the distributions. The IO scores were positively skewed indicating low overload for most participants. In each wave, the range was from approximately -2 to 4, where smaller values indicate less overload.



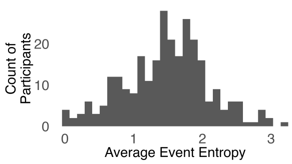
(a) Density distribution of session sparseness metric. Most sessions have sparseness near zero indicating little on-and-off switching within a session. Negative values indicating simultaneous use of two devices are very rare.



(b) Density distribution of event entropy metric. Most sessions have near zero entropy indicating that they revolve around one domain or app. Sessions with a large number of different domains and apps are rare.



(c) Distribution of average session sparseness for each participant. On average, the session sparseness range from zero to a half suggesting that many participants have some inactive time in their sessions usually.



(d) Distribution of average session event entropy for each participant. On average, the event entropies are distributed around 1.48 indicating that on average a session contains several apps or domains.

Figure 8: Distributions of session metrics.

The scores showed high within-person correlation with the wave-to-wave correlations ranging from 0.73 to 0.86 ($p < .001$) with an increase in each wave.

4.1.3 Self-reported device use and life changes. In addition to information overload, participants were asked about the use of tracked devices and their recent life changes. These variables supplement and largely agree with the information gained from tracking the web activities directly from the participants' devices. Most participant did not report major life changes during the study period, used the tracked devices for personal information searches and entertainment and rarely for work, and perceived that their web browsing on the tracked devices reflected their usual web browsing behavior well. Appendix A.3 reports the detailed summaries.

4.2 How web behavior is associated with information overload?

The interaction of information overload and web behaviors was explored with linear mixed-effects models (LMM). The following sections report LMM analyses that used web traces data grouped differently to answer different questions: 1) Baseline model used session metrics and web use durations on desktop and mobile to answer how browsing behaviors in general predict information overload; 2) Diurnal model used web durations aggregated over different day sections to answer how browsing at different times of the day predicts information overload; 3) Category model used web durations aggregated over different semantic categories of the web pages and apps to answer how the time spent on different contents predict information overload. Each LMM included information overload (*IO*) scores from the surveys as the dependent variable and the browsing behavior variables together with the survey number (*Time*) to indicate passing of time during the study as the independent variables. Since participants had differing levels of overload and each participant is likely to have a different developmental trajectory for their overload depending on their overall life situation, both random intercepts and random slopes were used in the models. In all models, *Age*, *Profession*, and *Gender* were included as control variables.

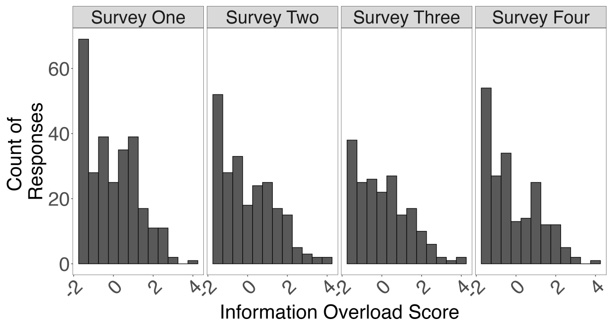
As there were no similar studies that could inform us how the association of browsing behaviors and information overload changes when the online activities are further apart from the survey, comparison was needed. We compared how using online activity data with different time windows (i.e., how many days of data prior each survey is aggregated) changes the association. To do this, a series of LMMs was fitted with different time-windowed data. Next sections report the main findings, and additional details are reported in Supplementary materials.

4.2.1 Mobile usage duration and session sparseness predict overload. We fitted LMMs with data from different time windows to establish a baseline on how browsing behaviors are associated with information overload. The models applied information overload score as the dependent variable and aggregated web durations on both devices (i.e., *Mobile Duration* and *Desktop Duration*) together with the mean *Session Sparseness* and *Event Entropy* as independent variables. Table 5 reports the short version of results with the focus on comparing the strength of association in different time windows.

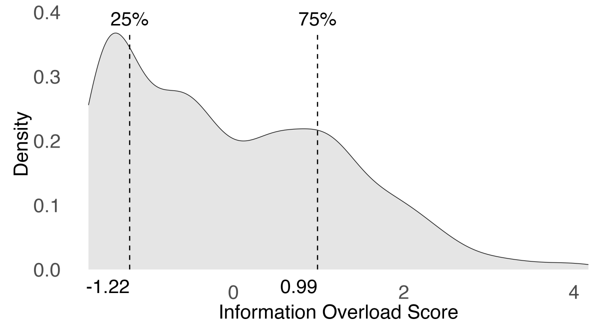
Figure 10 illustrates improvements in model fits when shorter time windows were used. Models with time windows of one or three days had best overall fits. In both models, *Mobile Duration* ($\beta = 0.09 - 0.10, p < .01$) predicted information overload together with *Session Sparseness* ($\beta = 0.07 - 0.08, p < .01$), while *Desktop Duration* ($\beta = 0.01 - 0.04, p = .270 - .796$) and *Event Entropy* ($\beta = 0.02, p = .556 - .625$) had confidence intervals overlapping zero. Furthermore, the small, negative slope of *Time* ($\beta = -0.03 - -0.04, p < .05$) indicates that IO scores decrease slowly through the study period. From the control variables, profession has a significant association with the information overload. People in academic and technical professions ($\beta = 0.57, p < .05$) as well as managers ($\beta = 0.89, p < .05$) have much higher levels of information overload than people in reference professions of crafts and mechanics. However, none of the other professions have statistically significant differences.

Random effects reported in Table 5 indicate that the means of participants' information overload largely differ, as the standard deviation of the random intercepts is 0.88, while the within-participant standard deviation of the data around their individual trajectories is 0.40. The standard deviation of the slopes of overload in time is minor with value 0.12, indicating that the growth rates differ only by a small magnitude between individuals. Moreover, the correlation between the slope and the intercept is weak with value -0.07, indicating that the magnitude of change in overload has a small negative relationship with the average level of overload.

Comparison of both fixed and random effects between the models fitted on different short time-windowed data suggests that the differences are marginal. We considered a model fitted with three



(a) Distributions of information overload scores in each survey. In each survey, non-overloaded individuals are more represented, while highly overloaded are a minority.



(b) Distribution density of pooled information overload scores from all surveys. Dotted lines represent lower and highest 25% of the scores. The top quartile ranges from around 1.0 to 4.0.

Figure 9: Information overload score distributions based on the surveys.

Table 4: Means and standard deviations of information overload items used in the surveys. Participants were presented with a question "Please think about the situations in which you use your web browser. Please indicate to what extent you agree or disagree with the following statements." The items were used to compute information overload scores using CFA. The overload scores are transformed to a standard normal distribution and range from around -1.7 to around 4.1. On group level, the means and deviations remain unchanged through the study, while the range of overload values in each survey is large. High values represent high experienced overload. See Appendix A.4 for the German translations used in the surveys.

Item	Survey One (N=1121)	Survey Two (N=954)	Survey Three (N=815)	Survey Four (N=805)
	Mean (SD)			
I am often distracted by the excessive amount of information I receive through my web browser.	2.92 (1.64)	2.85 (1.66)	2.96 (1.68)	2.82 (1.66)
I feel overwhelmed by the amount of information delivered through my web browser on a daily basis.	2.62 (1.61)	2.52 (1.57)	2.58 (1.62)	2.44 (1.55)
I am concerned that the amount of information that I receive through my web browser prevents me from processing the most important pieces of information.	2.95 (1.67)	2.86 (1.63)	2.96 (1.67)	2.76 (1.63)
I often feel pressured to deal with everything delivered by my web browser.	2.63 (1.60)	2.5 (1.60)	2.62 (1.64)	2.45 (1.58)
Scale: 1 'strongly disagree' – 7 'strongly agree'				
Information overload scores (N=277)				
Mean (SD)	-0.04 (1.22)	0.03 (1.33)	0.06 (1.30)	-0.15 (1.28)
Min-max	[-1.67, 4.01]	[-1.65, 4.09]	[-1.63, 4.17]	[-1.70, 4.03]
Missing Participants	0 %	19 %	31 %	28 %

days as the best model, since it is the best compromise between model fit and insensitivity to the randomness of the day when a participant answered a survey unlike the model with data from only one day. Using this data, the overall model explained variance is 84% with fixed effects explaining 9% of the variance in information overload scores.

4.2.2 Morning mobile web duration predicts overload. Next, an LMM with desktop and mobile durations grouped based on the time of the day were fit to the data in different time windows. These models investigated how the duration of use in different times of days is associated with information overload. The day sections were grouped to morning (6:00 to 11:59), afternoon (12:00 to 17:59), evening (18:00 to 23:59), and night (0:00 to 05:59).

Table 6 reports the model results for the 3-day time window. Morning mobile device duration consistently predicts overload with coefficients ranging from 0.09 to 0.14 depending on the time window, as Figure 11 illustrates. Usage on desktop or mobile use during any other time of the day did not predict overload with coefficients close to the zero, although with longer time windows of 14 and 30 days night time mobile use showed patterns of increase.

4.2.3 Time spent on a specific category of a web page or app does not predict information overload. To investigate how the contents of web activities impact the overload prediction, an LMM with desktop and mobile durations grouped according to thirteen semantic categories were fit. In all time windows, all the duration variables had near-zero coefficients and absolute values ranging from 0.00 to 0.05 with confidence intervals overlapping zero. Few exceptions

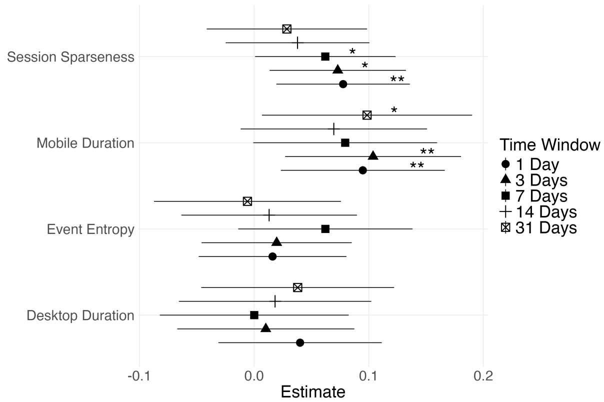


Figure 10: Regression coefficients with confidence intervals of the baseline model in different time windows. In shorter time windows (1-day and 3-day), mobile use duration predicts overload, similar to session sparseness. Association with overload and event entropy and desktop duration are statistically non-significant.

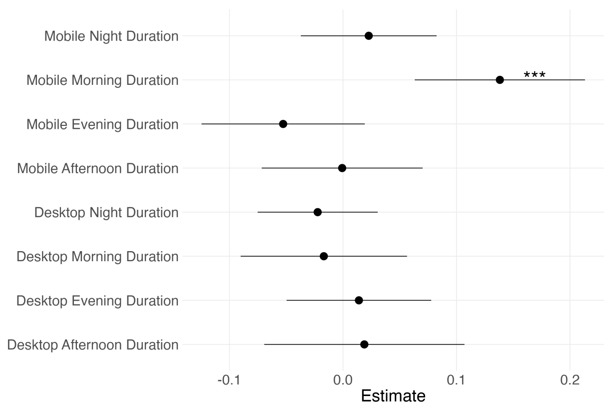


Figure 11: Regression coefficients with confidence intervals of the diurnal model for a 3-day time window. Mobile use duration in the morning predicts information overload, while usage in the other times do not show significant results.

were significant, such as shopping on the desktop ($\beta = 0.06$ in a 7-day time window) or health related mobile use ($\beta = 0.06$ in a 14-day time window), but as these were individual cases, the overall patterns indicate null results for the categories durations.

4.3 Overload predicts decrease in desktop use and spareness, but not in mobile use and event entropy

Next, we focused on how an information overload level would predict changes in web behavior for the days following each survey. We fitted LMM models with online duration on each device for the post-survey days as the dependent variable and information overload, pre-survey online duration, and the survey time as the independent variables. Four sets of models corresponding to the data from the durations on both devices and for session metrics were examined in different time windows. Models using duration data for 14-days and models using session metrics for 31-days time windows resulted in singular fit, and these were discarded.

Table 5: Comparison of fixed and random effects of the baseline model in different time windows. The model with a 3-day time window was chosen as the best model. In short time windows, increases in mobile usage and session sparseness predict overload. Managers and academic and technical professionals have higher overload than people in other professions. Random effects indicate that most differences occurred between individuals rather than within-individuals. The overall model explains around 84-85% of the variance, from which fixed effects explain 9%.

Fixed Effects					
Time Window	Term	β	SE	CI	p
1-day	Intercept	0.59	0.47	[-0.35-1.52]	0.216
	Time	-0.04	0.02	[-0.08-0.00]	0.028
	Desktop Duration	0.04	0.04	[-0.03-0.11]	0.270
	Mobile Duration	0.09	0.04	[0.02-0.17]	0.009
	Sessions Sparseness	0.08	0.03	[0.02-0.14]	0.009
	Event Entropy	0.02	0.03	[-0.05-0.08]	0.625
3-day	Intercept	0.59	0.47	[-0.34-1.51]	0.212
	Time	-0.04	0.02	[-0.07-0.00]	0.028
	Desktop Duration	0.01	0.04	[-0.07-0.09]	0.796
	Mobile Duration	0.10	0.04	[0.03-0.18]	0.008
	Sessions Sparseness	0.07	0.03	[0.01-0.13]	0.016
	Event Entropy	0.02	0.03	[-0.05-0.09]	0.556
	Gender	-0.13	0.12	[-0.37-0.10]	0.267
	Age: 25–34	-0.72	0.47	[-1.64-0.20]	0.125
	Age: 35–44	-0.73	0.45	[-1.61-0.15]	0.103
	Age: 45–54	-0.72	0.45	[-1.61-0.16]	0.107
	Age: 55–64	-0.86	0.44	[-1.72-0.01]	0.052
	Age: 65+	-0.59	0.47	[-1.51-0.33]	0.205
	Profession: Academic /Technical	0.57	0.25	[0.07-1.06]	0.024
	Profession: Managerial	0.89	0.42	[0.06-1.72]	0.036
	Profession: Office	0.28	0.21	[-0.13-0.69]	0.179
	Profession: Other	0.20	0.22	[-0.23-0.63]	0.364
	Profession: Sales	0.35	0.30	[-0.24-0.94]	0.244
	Profession: Services	-0.07	0.23	[-0.52-0.38]	0.761
	Profession: Worker/Agriculture	0.38	0.27	[-0.14-0.90]	0.152
7-day	Intercept	0.67	0.47	[-0.25-1.59]	0.153
	Time	-0.03	0.02	[-0.06-0.00]	0.045
	Desktop Duration	0.00	0.04	[-0.08-0.08]	0.999
	Mobile Duration	0.08	0.04	[0.00-0.16]	0.052
	Sessions Sparseness	0.06	0.03	[0.00-0.12]	0.047
	Event Entropy	0.06	0.04	[-0.01-0.14]	0.109
14-day	Intercept	0.67	0.43	[-0.18-1.53]	0.123
	Time	-0.03	0.02	[-0.06-0.00]	0.042
	Desktop Duration	0.02	0.04	[-0.07-0.10]	0.670
	Mobile Duration	0.07	0.04	[-0.01-0.15]	0.094
	Sessions Sparseness	0.04	0.03	[-0.02-0.10]	0.236
	Event Entropy	0.01	0.04	[-0.06-0.09]	0.738
31-day	Intercept	0.48	0.41	[-0.34-1.29]	0.249
	Time	-0.03	0.02	[-0.06-0.00]	0.057
	Desktop Duration	0.04	0.04	[-0.05-0.12]	0.376
	Mobile Duration	0.10	0.05	[0.01-0.19]	0.035
	Sessions Sparseness	0.03	0.04	[-0.04-0.10]	0.423
	Event Entropy	-0.01	0.04	[-0.09-0.08]	0.888
Random Effects					
		τ_{SD}	σ	$R^2_{Marg/Cond}$	ICC
1-day	Random Intercept ($\tau_{0,0}$)	0.88			
	Slope: Time ($\tau_{1,1}$)	0.14	0.40	0.09 / 0.85	0.83
	Corr: Intercept x Slope ($\rho_{0,1}$)	-0.06			
3-day	Random Intercept ($\tau_{0,0}$)	0.88			
	Slope: Time ($\tau_{1,1}$)	0.12	0.40	0.09 / 0.84	0.83
	Corr: Intercept x Slope ($\rho_{0,1}$)	-0.07			

Table 6: Fixed and random effects table for a diurnal model for a 3-day time window. Mobile use in the morning predicts information overload, while mobile use in evening, night, or afternoon or desktop use do not. Random effects indicate that most of the variance is between individuals rather than within-individuals. There is a small negative correlation between the slope and the intercept indicating that higher overload have smaller slopes.

Fixed Effects

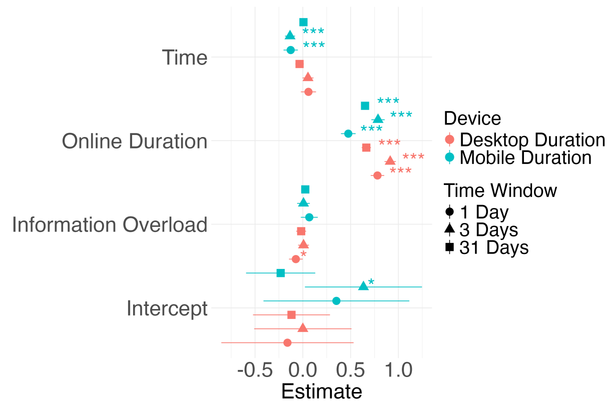
Time Window	Term	β	SE	CI	p
3-day	Intercept	0.45	0.40	[-0.34-1.24]	0.267
	Time	-0.03	0.01	[-0.06-0.00]	0.058
	Desktop Afternoon	0.02	0.04	[-0.07-0.11]	0.676
	Desktop Evening	0.01	0.03	[-0.05-0.08]	0.666
	Desktop Morning	-0.02	0.04	[-0.09-0.06]	0.651
	Desktop Afternoon	-0.00	0.04	[-0.07-0.07]	0.983
	Mobile Evening	-0.05	0.04	[-0.12-0.02]	0.150
	Mobile Morning	0.14	0.04	[0.06-0.21]	<0.001
	Mobile Night	0.02	0.03	[-0.04-0.08]	0.457
	Desktop Night	-0.02	0.03	[-0.08-0.03]	0.407
	Gender	-0.14	0.12	[-0.37-0.09]	0.220
	Age: 25–34	-0.55	0.40	[-1.33-0.24]	0.174
	Age: 35–44	-0.48	0.38	[-1.23-0.26]	0.203
	Age: 45–54	-0.54	0.38	[-1.28-0.20]	0.153
	Age: 55–64	-0.71	0.37	[-1.43-0.02]	0.056
	Age: 65+	-0.47	0.40	[-1.25-0.31]	0.235
	Profession: Academic /Technical	0.50	0.24	[0.03-0.97]	0.037
	Profession: Managerial	0.68	0.38	[-0.07-1.44]	0.074
	Profession: Office	0.29	0.20	[-0.10-0.68]	0.149
	Profession: Other	0.12	0.21	[-0.28-0.53]	0.550
	Profession: Sales	0.26	0.27	[-0.28-0.80]	0.350
	Profession: Services	-0.06	0.22	[-0.49-0.36]	0.770
	Profession: Worker/Agriculture	0.34	0.26	[-0.16-0.84]	0.184

Random Effects

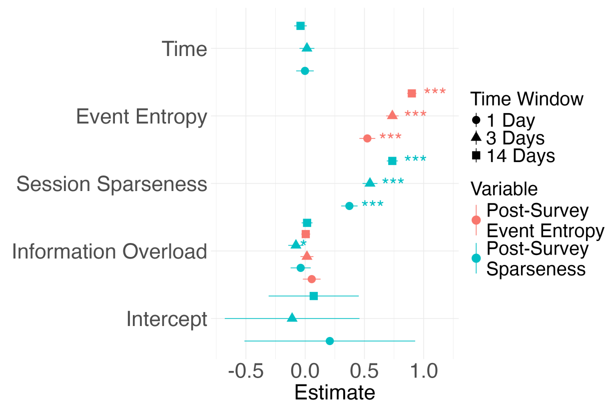
		τ_{SD}	σ	$R^2_{Marg/Cond}$	ICC
3-day	Random Intercept ($\tau_{0,0}$)	0.86	0.42	0.07 / 0.82	0.81
	Slope: Time ($\tau_{1,1}$)	0.11			
	Corr: Intercept x Slope ($\rho_{0,1}$)	-0.11			

Figure 12a illustrates how overload predicts mobile and desktop use durations: The models indicate that prior web durations predict well post-days durations with high coefficients ($\beta = 0.65 - 0.91, p < .001$), except for mobile duration for the following day of the survey ($\beta = 0.48, p < .001$), which is less correlated with the pre-survey day. For the information overload, higher overload predicts decrease in desktop durations for the first day following the surveys ($\beta = -0.07, p < .05$). For the same day, mobile durations coefficient confidence interval overlaps with zero ($\beta = 0.07, p = .134$). However, the general mean duration for mobile use duration is higher on post-survey days. In a wider time window both set to near zero.

Figure 12b illustrates how information overload predicts decrease in sparseness for the following three days ($\beta = -0.08, p < .05$). Results for the overload predicting event entropy are null ($\beta = 0.02, p = .586$). Both sparseness ($\beta = 0.37 - 0.74, p < .001$) and event entropy ($\beta = 0.52 - 0.90, p < .001$) are predicted well from pre-survey values with increasing correlation, but as the random effects indicate that the between-individual variance approaches zero in wider time windows, the results imply that in wider time windows average session sparseness and event entropy are near the population means.



(a) Regression coefficients with CI of the model where information overload and pre-survey online durations predict post-survey online durations. Duration coefficients on both devices are high in general. Information overload coefficient is negative for the desktop for a 1-day window but non-significant for mobile devices and close to zero for both in other time windows.



(b) Regression coefficients with CI of the model where information overload, pre-survey sparseness and event entropy predict post-survey sparseness and event entropy. For a 1-day window, sparseness is negative and event entropy is near zero. Both variables have high coefficients for the autoregressive relationships.

Figure 12: Coefficients of analyses predicting post-survey online behaviors.

4.4 What differentiates high overloaded individuals from others?

We were interested if there would be behavioral characteristics that differentiate highly overloaded individuals from the non-overloaded individuals. To investigate the issue, the participants' web traces and their information overload scores were clustered based on similarity. Similar profiles could offer insights into how information overload and the web behavior relate to each other.

4.4.1 Cluster analysis identifies highly overloaded users based on their average behavior. K-means cluster analysis was implemented to identify similar user profiles. As the initial analysis, we chose to use a 3-day time window since the LMM analyses indicated that to be a good compromise between maximizing the amount of data and the predictive value. Since the K-means algorithm cannot operate with missing values, only complete cases were used (N=101).

As there are no baseline estimates for the appropriate number of clusters (k), different values were explored. The criteria for successful clustering were that 1) the clusters differ in their mean information overload levels, and 2) each cluster has more than 10% of the total individuals to avoid overfitting. Using the elbow method, 3–5 clusters were determined as promising candidates. The analysis was run on 3–7 cluster numbers, from which 5–7 clusters resulted in single-individual clusters emerging indicating overfit. Furthermore, analyses with 2–3 clusters indicated no differences in overload between the clusters. Thus, the only successful model included four clusters, which are referred to as clusters C1-C4 in the following sections. The analyses were re-run with the extended time window of 7 days and session metrics computed with the threshold of 30 minutes (as this is another cut-off threshold in literature [48, 58]) to evaluate the consistency of the cluster analysis, and the results were similar in the re-runs.

4.4.2 High overloaded users have sparse sessions. Table 7 reports on the browsing behavior variable averages across the clusters. To test whether the information overload and web behavior levels would differ among the clusters, the variables were analyzed using Welch's ANOVA. The clusters had significant differences between the key variables with large effect sizes.

Figure 13 illustrates the differences between the clusters based on Games-Howell pairwise post-hoc tests. Tests indicate that cluster C2 had a significantly higher level of overload than the others. When comparing these *highly overloaded individuals* to others on behavior variables, the only variable that was significantly different from less overloaded clusters was session sparseness for which highly overloaded individuals had high levels as well. Highly overloaded individuals have 1.5 times higher average session sparseness than the next highest clusters, and their average information overload is over one standard deviation higher than the next highest cluster. This indicates that the highly overloaded individuals differ from others by large effect. Compared to other clusters, highly overloaded individuals had the second-highest average mobile use duration and the third-highest total use duration, desktop use duration and event entropy. See Appendix A.5 for detailed pairwise comparisons.

The remaining three clusters (C1, C3, C4) did not have statistically significant differences in overload levels, but they demonstrate other differences between the average-to-low overloaded individuals. The clusters with the second and third highest mean overloads (C1, C3) have similar levels of overload and sparseness, but they differ in that they have the highest (C3) and lowest (C4) total online duration across devices. Since individuals in C4 also have the lowest event entropy among all clusters, they could be characterized as *passive users*. Individuals in C3 could be characterized as *heavy mobile users*, and individuals in C1 as *active desktop users*.

Table 8 presents the cluster average of the average total online duration percentage by categories for each individual. Although heavy mobile users (C3) have the highest total duration, they spend most of their time on games, while the highest overloaded individuals (C2) spend it on messaging. Passive users (C4) have the least total duration, they have similar level overload as the heavy mobile

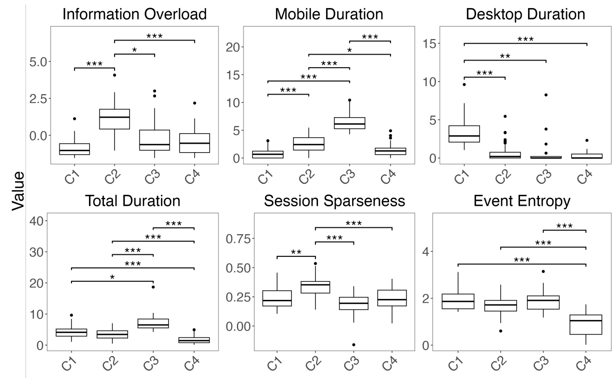


Figure 13: Average variables by clusters. *Highly overloaded people* (C2) have the highest session sparseness. Highly overloaded people use mostly mobile devices, but they are only the second heaviest mobile users, and the third heaviest combined use duration. The lowest overloaded people (C1) mostly use a desktop and have the lowest average mobile web duration. Heavy mobile users (C3) spend the most time on mobiles and in total duration, while having also the lowest session sparseness. Passive users (C4) spend the least time online and when they do, it is mostly on a mobile device. Passive users also have the most focused sessions, as their average event entropy is the lowest. Durations are expressed in hours.

users and spend large proportion of their time on games and social media. Desktop users (C1) have the lowest overload and spend their time mostly on goal-centered categories, such as surveys, shopping, and news, while also using a large proportion of time to social media and the least proportion among the clusters on messaging.

Figure 14 illustrates the proportions of age groups and professions between the clusters. These figures are merely descriptive since there were not enough individuals in each group for statistical analyses. However, the figures demonstrate a pattern where the highly overloaded cluster (C2) has the youngest participants, while the least overloaded cluster (C1) has the oldest individuals. Similarly, C2 includes mostly individuals that could be characterized as knowledge workers, while C1 has the largest proportion of crafts and mechanics professionals.

4.5 What characterizes sparse sessions?

The analyses using LMM and clustering both indicated that session sparseness is an important variable to characterize overloaded users. Next, we explore the features that characterize sparse sessions.

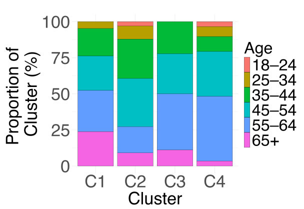
Sparseness ranges in the data from -0.93 (very dense sessions with two devices) to 0.99 (very sparse sessions) with a mean at 0.29. While session sparseness is a continuum, the sessions were classified into three for study purposes: high-sparse sessions having more than half (values > 0.5) and average sparseness sessions having less than half of the session duration inactive ($0 <$ values ≤ 0.5), and multitasking sessions having more active duration than the session duration indicating use of two devices concurrently (values < 0). Figure 15 illustrates the main differences in temporal aspects of web activities captured by the session sparseness.

Table 7: Means and standard deviations of variables in each cluster (C1-C4) from K-means analysis (N=101). Cluster C2 has the highest information overload level, while other clusters have lower but mutually similar levels. C2 also has the highest session sparseness, and it is the second most active mobile user. Welch's ANOVA results of cluster comparison indicate statistically significant ($p < .001$) differences among clusters for each variable. Effect sizes (ω^2) suggest large effects for all variables.

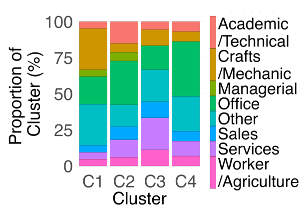
Cluster	C1 (n=29)	C2 (n=33)	C3 (n=18)	C4 (n=21)	ANOVA	ω^2
Information Overload	-0.82 (0.68)	1.13 (1.17)	-0.12 (1.42)	-0.37 (0.94)	$F(3.00, 47.99) = 19.69^{***}$	0.52
Total Duration	4.31 (2.20)	3.32 (1.64)	7.32 (3.33)	1.81 (1.31)	$F(3.00, 43.58) = 20.26^{***}$	0.55
Desktop Duration	3.50 (2.17)	0.80 (1.30)	0.82 (2.09)	0.29 (0.52)	$F(3.00, 39.57) = 15.16^{***}$	0.49
Mobile Duration	0.81 (0.99)	2.52 (1.66)	6.47 (1.78)	1.51 (1.25)	$F(3.00, 48.27) = 49.15^{***}$	0.73
Session Sparseness	0.23 (0.09)	0.34 (0.09)	0.18 (0.12)	0.23 (0.10)	$F(3.00, 47.08) = 11.82^{***}$	0.39
Event Entropy	1.97 (0.50)	1.68 (0.43)	1.90 (0.50)	0.90 (0.52)	$F(3.00, 47.37) = 23.37^{***}$	0.57

Table 8: Average percentages of web durations per category. Social media is among the highest categories in each cluster. Gaming and messaging are also common. The highest three for each cluster are bolded.

Category	C1	C2	C3	C4
Adult (%)	0.8	0.6	0.9	0.1
Entertainment (%)	8.3	**10.5**	4.5	6.5
Gambling (%)	0.0	0.0	0.1	0.1
Games (%)	8.2	9.2	**32.0**	**16.9**
Health (%)	0.2	2.0	0.1	0.2
Messaging (%)	3.7	**15.0**	**10.6**	8.0
News (%)	10.5	3.5	1.8	2.7
Other (%)	5.9	8.3	3.9	**8.7**
Search (%)	5.5	4.5	2.5	5.7
Shopping (%)	**10.7**	9.6	6.4	6.5
Social Media (%)	**13.5**	**13.9**	**16.9**	**19.3**
Survey (%)	**11.4**	6.7	3.6	5.6
Work Related (%)	8.0	6.1	5.0	4.0



(a) Proportions of age groups in clusters. The cluster of highly overloaded individuals (C2) has the highest proportion of individuals under 45 years old. The least overloaded cluster (C1) has the highest proportion of individuals aged 55 or older.



(b) Proportions of professions in clusters. The highly overloaded cluster (C2) has the most of academic, technical, and manager professionals. The least overloaded cluster (C1) has the most of mechanic and crafts professionals.

Figure 14: Demographic differences between clusters.

4.5.1 Sparse sessions include mostly messaging on mobile devices. Table 9 reports the average session sparseness based on the most common category in the session. Sessions where messaging is the most common event category have the highest sparseness with the mean of 0.36, while sessions of mostly adult (0.14) and games (0.18) content are the least sparse on average. Welch's ANOVA indicates statistically significant differences between the mean sparseness of sessions based on the session most common category ($F(12, 1451.2) = 466.7, p < .001$). Exploring the categories that are prominent in sparse sessions, Games-Howell post-hoc test suggest that sparseness of messaging sessions are statistically significant ($p < .001$) and higher than all the other sessions, except for gambling ($p = 0.07$), which only has 61 instances. In contrast, games and adult sessions are lower in sparseness with statistically significant difference to all other session types ($p = .003$ for games-adult, $p < .001$ for others), except for gambling ($p = 1.0$). Search, shopping, health, and work-related categories are also on average among the high sparseness sessions. Together the results indicate that there are connections between sparseness and the category of the activity, but the relationship is complex, as many categories are near equally present in sessions, such as work-related or social media, which is visually clear in Figure 16.

Table 9: Average session sparseness based on the most common category in a session. The highest and lowest are bolded.

Category	Average Sparseness (SD)
Adult	**0.14** (0.35)
Entertainment	0.27 (0.29)
Gambling	0.20 (0.25)
Games	0.18 (0.25)
Health	0.29 (0.36)
Messaging	**0.36** (0.35)
News	0.24 (0.26)
Other	0.33 (0.32)
Search	0.29 (0.29)
Shopping	0.28 (0.28)
Social Media	0.24 (0.28)
Survey	0.23 (0.23)
Work Related	0.30 (0.31)

Mobile use indicates higher session sparseness, which is illustrated in Figure 17b. Based on the most common device used, mobile sessions have higher average sparseness of 0.30 than the desktop, which have an average of 0.24. For sessions where both devices are equally common, the average is even higher with the value of 0.41, although these sessions were rare. Welch's ANOVA indicates that the differences are statistically significant ($F(2, 769.35) = 799.48, , p < .001$) with all pairwise differences significant ($p < .001$) based on the Games-Howell test.

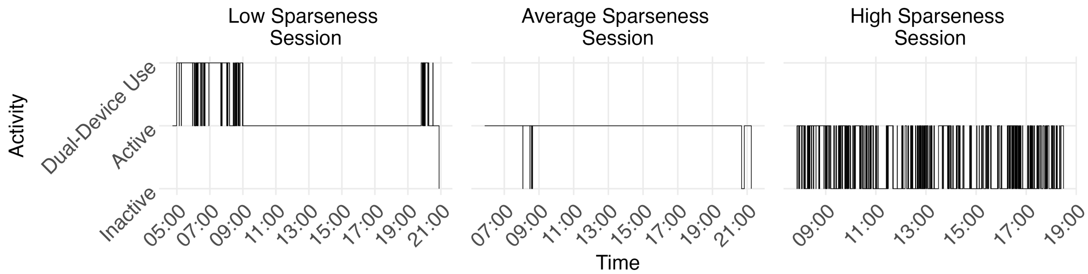


Figure 15: Visualized sessions with different levels of sparseness: low (value -0.2), average (value 0.01), and high (value 0.53). Continuous lines in low and average sessions indicate continuous activity with peaks to either inactivity (average) or dual-device use (low). In a high session, the short periods of activity and inactivity follow each other. From categorized sessions, around 26% were high sparseness sessions, around 52% were average sparseness sessions, and around 22% were negative sparseness sessions.

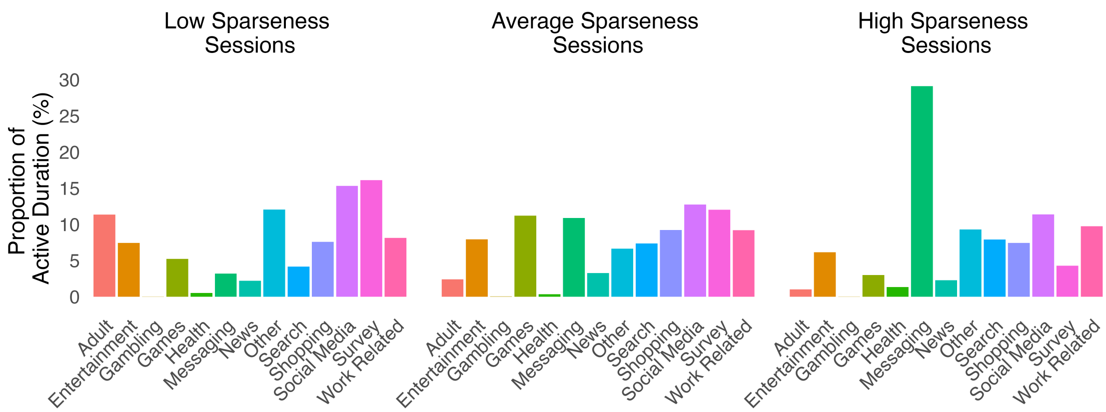
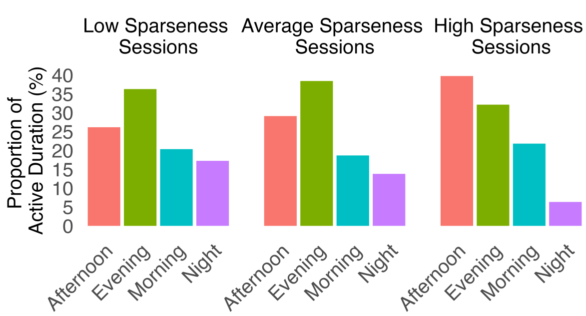
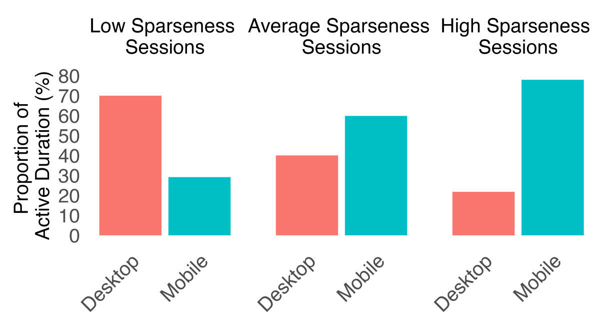


Figure 16: Proportions of active durations based on categories in each sparseness category. Messaging is the most common category in a majority of the high sparseness sessions. The proportions of mostly messaging based sessions is drastically lower in average or negative sessions, which include a more diverse set of categories. Figures include around 93% of the sessions in each category. Sessions that had multiple equally represented categories are excluded.



(a) Distributions of day sections based on sparseness. Most high-sparseness sessions occur in the afternoon or evening, while average and low sparse session occur mostly in the evening.



(b) Distributions of device use based on sparseness. High-sparseness sessions occur most commonly on mobile devices, while negative-sparseness sessions occur commonly on desktop.

Figure 17: Distributions of proportions of active web durations in differently sparse sessions grouped by the time of day and devices used.

4.5.2 Sparse sessions consist of short and isolated events. Sparseness correlates negatively with the mean event duration ($r = -0.16, p < .001$), indicating that higher sparseness sessions consist of short web page or app views on average. Furthermore, sparseness correlates positively with the number of categories in a session ($r = 0.11, p < .001$) and event entropy ($r = 0.15, p < .001$). These indicate that higher sparseness sessions have on average more different events that occur rarely, and they have wider distribution in their categories. Together, the three correlations suggest that sparse sessions can be characterized as fragmented web behavior.

4.6 Limitations

The study applied best research practices to ensure reliable results. We discuss the limitations below.

First, the data was collected in an observational study, which means that while our data represents naturalistic everyday web behavior, we cannot establish a causal relationship between the user behavior and their overload experiences as manipulation studies might do. Future studies could implement manipulated experiments in-between the extended periods of naturalistic observations to gain more detailed knowledge on the causal processes.

Second, we excluded participants who explicitly reported that they regularly use other devices than the ones tracked to gain more control over the analyses, but it is possible that some of the participants use devices not tracked or reported, which could result in our analyses underestimating the effects of online duration. Furthermore, an observer effect [83] could have impacted the types of activities users engage in.

Third, we surveyed participants overload experiences using a widely employed survey construct with modifications that specifically asked about overload in relation to web browsing, as is commonly done with these items. However, asking to reflect on experiences concerning a specific device in contrast to more general overload experiences might have resulted in more variance in how people interpret these items. Since no other studies have previously compared the survey responses with objective behavior, we cannot estimate how precisely people reflect on their overloaded experiences to the named device in contrast to their more general overload experiences.

5 Discussion

This paper presents the results of an observational study where we tracked everyday web behaviors on mobile and desktop devices for seven months and measured information overload with a series of surveys from 277 participants. Based on two complementary analysis approaches, linear mixed-effects modeling and cluster analysis, we conclude that information overload is associated with certain browsing behaviors, users do not show lasting changes in their behavior when overloaded, and user types differ based on their overload and web behaviors.

The main results show that 1) One user type differs from others in terms of information overload and average session sparseness with large effects. These highly overloaded individuals use mobile devices more than average but are not the heaviest users in terms of duration. In contrast, the heaviest users have much lower information overload and the lowest average session sparseness; 2) In general, mobile use duration and session sparseness predict information overload, while desktop use duration does not; 3) The overload's association with mobile use is even stronger when considering morning use, and other times of day did not show similar effect; 4) Surprisingly, the duration of use based on the categories of web page or app, such as news or social media, did not show consistent relationship with information overload; 5) Both device use durations and information overload correlated highly in time, which suggests that these represent habits users engage in their everyday lives. In general, the results imply that temporal patterns of use are more important for information overload than the time spent on specific activities and these patterns might be driven by technology design.

Next, we discuss the findings in detail. We first elaborate what our results show about the information overload in everyday web use. Thereafter, we discuss how our results inform interventions and designs on mitigating information overload.

5.1 Characterizing information overload in everyday web behavior

The results suggest that people's information overload levels are rather stable over time, with past information overload predicting the future overload levels well. One possibility is that this reflects the overall life context, or information environment, where individual habits, information needs, and information demands are embedded. However, there were large differences between individuals and a majority of the people were not overloaded during the study period: 75% of the information overload scores were within the lowest 2.5 units, while 25% extended to highest 3 units. This indicates that highly overloaded individuals are rare, but the problem is persistent to them. Future studies could use higher density measures of information overload, such as the experience sampling method, to detect more details about contextual changes.

From the browsing behaviors, session sparseness was the most strongly associated variable with information overload. High average sparseness differentiated highly-overloaded individuals from others with a large effect (see more on effect sizes, e.g., [50]). As defined, sparseness refers to the proportion of inactivity within a session relative to the session duration. The explorations of sparse session demonstrated that one way to characterize highly sparse sessions is repetitive, short-duration web behavior: Sparse sessions are 'sparse', they have 'holes' in the activity or discontinuances. Although the correlations between sparseness and event entropy, the number of categories in a session, and average event duration were small, together they suggest that sparse sessions are fragmented: increase in sparseness indicates more rarely occurring events, such as single views of pages, shorter page or app views before termination, and events that span a wider range of categories instead of focusing on a single one, as focused web use would assume. Prior research has associated fragmented visual attention in web browsing to short page views [76].

Session sparseness likely reflects task switching behavior, where negative sparseness reflects intense, dual-device multitasking while high sparseness reflects on-off-device task switching. This can explain why session sparseness is connected to information overload. In cognitive terms, sparseness could explain information overload through increase in cognitive load presented by multitasking [102]: on-and-off switching from app or page takes resources from the task-relevant information processing and requires more effort for the integration of the information from different sources.

A possible interpretation of the results is that messaging app design drives behavior leading to information overload. We observed that high session sparseness occurred mostly on mobile devices and with messaging and social media activities. However, messaging or social media durations did not predict information overload. This suggests that the messaging activity itself is not associated with overload but rather the temporal characteristics of session sparseness closely associated to messaging. The on-and-off behavioral pattern implied by sparse sessions could reflect habits driven by smartphone design [74], browser design [59], social usage [95], or the nature of messaging services in general (see [39]). Alternatively, this behavioral pattern could be influenced by the use of social media apps with notifications, which has been associated with self-reported problems in focus, more mistakes in tasks, and stress [90]. Prior research shows that the majority of very short mobile usage is attributed to be notification initiated, while user initiated micro-usage is most commonly associated with social applications [26], and people often self-interrupt themselves from the tasks they are engaging in [22] and engage in meaningless smartphone use to escape negative emotions [60]. Information overload in everyday web use could be caused by the habitual use of devices to respond to external (e.g., notifications, messaging application design) and internal (e.g., self-interruptions, escapism) cues. Future studies could explore what other factors contribute to information overload, such as personality, device settings, and boredom.

Another important finding shows that mobile use duration is associated with information overload, however, the interaction is complex: while there was a small linear relationship between mobile use and information overload, the highly overloaded individuals were only the second heaviest mobile users. This partially supports the theoretical notion that an increase in information quantity would predict an increase in information overload [30]. However, since the same pattern was not identified in desktop use, this raises a question whether quantity-based models of information overload are valid. Instead, focus on how people process information in relation to information overload looks more promising [82]. However, controlling the flow of information in naturalistic setting is extremely difficult, since people are embedded in sources of information in their everyday lives. While we aimed to control this relationship by excluding individuals who reported to have other devices in use, it is possible that the participants were exposed to other sources of digital content during the study. Thus, our results could be seen as lower-bound of the association, since it is likely that people receive more information than we estimated with the tracking. In addition, we did not measure cognitive abilities, such as working memory, which have been shown to affect speed in web browsing [99], app use [29], and other computer tasks [57]. Furthermore, cognitive differences, such as ADHD or dyslexia, could also moderate the interaction of browsing behaviors and overload, which we did not measure. Additionally, it is noteworthy that the effect sizes of mobile use durations are comparable to other observational studies investigating psychological constructs through device use (see [43, 66]).

Information overload seems to reflect recent device use, but the device use in general seems to be embedded in everyday life habits. The relationship between information overload and mobile use duration was the strongest when evaluating one to three most recent days and again when evaluating a whole month. This suggests that people likely evaluate very recent experiences with their technology when inquired with surveys. Furthermore, since the morning mobile use was associated with information overload, this implies that the overload and device use are embedded in the everyday life habits. Prior research also suggests that smartphone over-users are active in the morning [55] and messaging applications are often activated the first thing in the morning [13]. We also found that although there were small negative changes in desktop use and session sparseness in days following the surveys, which were associated with information overload, people did not change their behaviors by large even when they were overloaded. This contradicts with prior findings that assign app use discontinuance intentions to overloaded people [14, 65]. Based on our results, the information overload does not manifest in discontinued use although there might be intentions, which we did not measure.

Finally, the results suggest that a larger context in life situation is important to information overload: from control variables, profession indicated large differences in overload levels. Prior research has identified differing information management practices between professions where academics have more permeable work-non-work message checking boundaries [15], which could account for the differences in information overload. However, since the behavioral variables increase overload even when control variables are included, it suggests they have a separate effect on overload. Age also showed clear patterns in both LMM and cluster analysis where younger individuals had higher overload, and the highest overloaded cluster included highest proportion of younger people among clusters. However, results on age were not statistically significant; thus, they need to be further examined in future studies (see also [85]). These findings deserve further studies since it has been shown that with age people experience less stressful events and are less reactive to it affectively [1] and that there are different digital use patterns between younger and older people with younger people using more social and communication apps [4]. In addition to demographic traits, the stability of information overload levels could reflect differences in sensitivity to stress and information contents, different meanings and interpretations given to a person's information behavior, or other psychological states, such as general stress or depression. These offer important and hopefully fruitful directions for future research on information overload.

5.2 Practical implications – Mitigating overload through reshaping habits

Several practical implications emerged from our analyses: 1) Well-being applications that track use duration can support mitigation of information overload. However, the effect of limiting use duration is likely limited; 2) Session sparseness has the greatest promise to inform about presence of information overload and as a path for mitigating it; 3) Individuals do not change their online behaviors even when experiencing overload. Thus, interventions targeted to habit changes and larger contexts of a life situation are needed to counter information overload. We discuss these implications next.

Our results inform digital well-being design by showing that information overload interacts with the web use duration, but the effect is small on mobile devices and near zero on desktops. Technology overuse remains an open challenge for HCI, and many available technologies for digital wellbeing support make simplistic assumptions about the connection between well-being and device use or apply ineffective intervention techniques [80]. Currently, many self-control applications utilize increased awareness, goal-advancement, or block user decided distracting apps [12] of which many focus on tracking the total time. Based on our study, the focus on screen time has likely a limited effect since highly overloaded individuals were not the heaviest mobile device users although their use time was higher than the overall average. Thus, a more nuanced account of user behavior is needed to reduce information overload.

Our results suggest that the most promising path for helping the highly overloaded individuals would be to focus on the session sparseness. The cluster analysis shows that although the differences of average session sparseness of highly overloaded individuals are smaller in absolute sense than those for other user types, the information overload differences are large. This means that even a small difference in average sparseness can indicate a large difference in information overload. Thus, digital well-being applications could incorporate average session sparseness as a metric to monitor users' information overload level. When the average session sparseness starts to deviate from the common average, the system could inform the user that their behavior indicates overload. Roffarello and De Russis [79] have applied similar approach to notify user about detected meaningless use habits.

Since our results imply that the information overload levels persist on a week-to-week basis, sparseness could be used to nudge users into changing their habits. Prior research has proposed that instead of focusing on screen-time limiting, people should be supported in new habit formation [70]. Through monitoring sessions where high sparseness occurs, it would be possible to automatically identify events that are associated with high sparseness and, in turn, inform the user, or apply a lockout task or a behavioral nudge to discourage the use of the application [44, 72]. If we assume that sparseness causes information overload (e.g., through task-switching induced cognitive load), then the cluster analysis results suggest that reduction of session sparseness would successfully reduce information overload. Thus, in addition to identifying information overload, sparseness could be used for steering away from behaviors that account for the overload. Together with opportunities to educate users on unhealthy habits to support reflection and self-determined behavioral change (see [71]), this seems as a promising path to mitigate overload in everyday web use.

In addition to habitual use, sparseness could imply that users are task switching or responding to notifications. Notably, since messaging was the most prominent activity among high sparse sessions, this indicates that notifications could be muted or postponed and released in larger batches to allow for longer non-online duration. Prior research has shown that the best time for notifications are at the task boundaries [36]. Thus, notification designs should avoid interrupting offline tasks as well as online ones, since it increases annoyance and the time to return on task [37], which could incrementally add to the total online duration.

To counter task-switching-related sparseness, designs should not encourage short and frequent engagement with the web page or the app but instead favor focused sessions with longer between-session durations. Instead of monitoring the total use duration of an app or web browser, the digital well-being tools could monitor and restrict the number of sessions the user has and nudge the user to complete the tasks in fewer sessions. In addition, the sessions could be restricted to certain pre-selected themes to emphasize the focus on a certain task instead of task switching. For example, allowing for a few messaging sessions throughout the day without a time limit instead limiting the total time used on a messaging app would naturally nudge the user to maintain clearer boundaries on messaging time and other activities.

Finally, our finding that people experience stable levels of information overload from one week to another indicates that the larger context of life and personality should be considered in interventions to information overload. Solely focusing on online activities is likely to be ineffective in countering information overload, as the profession was a major factor in experienced overload. Work design, work-life balance, and web activities should be considered together to make large differences in information overload.

Our results contribute to HCI research on digital well-being by deepening our understanding of the user habits, which are associated with information overload in an everyday multi-device context. The results presented in this paper suggest that the temporal aspects of use are the most promising path for practical interventions and design implications targeting to reduce information overload. Interventions and designs that nudge users towards fewer, more focused use sessions, while reducing the overall web duration at the same time, might lessen overload.

6 Conclusions

People experience information overload in their everyday lives when interacting with information technology. This study investigated how web behaviors on desktop and mobile devices are associated with self-reported information overload. The results suggest that high average session sparseness (i.e., repetitive, short-duration use) differentiates highly overloaded individuals from non-overloaded ones with a large effect. Furthermore, the time spent on mobile devices predicts information overload, while time spent on desktop does not. Furthermore, time spent browsing specific contents, such as social media or news, did not predict information overload. In general our results suggest that temporal aspects of use are important for information overload.

The results contribute to both theory and practice of HCI. For theory, the results suggest that simplistic models where information quantity results in information overload might need to be upgraded with more nuanced notions of how people process information. For practice, our results inform digital well-being designs by suggesting that average session sparseness could be a useful metric for detecting and mitigating information overload. As the results suggest, designs and interventions for countering information overload could target reducing the repetitive use of devices and support longer, focused sessions.

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A Additional details about the study materials and analyses

A.1 Linear mixed-effects modeling details

Detailed results of all linear-mixed effects models reported in the Results section are included as Supplementary Material.

A.2 Web behavior variable correlations

Table 10 reports the correlations of variables from the web traces data.

Table 10: Correlations of the web behavior variables.

	1	2	3	4	5	6	7	8	9
Combined Duration (1)									
Desktop Duration (2)	0.58***								
Mobile Duration (3)	0.73***	-0.13							
Total Web Page Views (4)	0.50***	0.76***	-0.02						
Web use Duration (5)	0.65***	0.98***	-0.02	0.80***					
Unique Domains (6)	0.51***	0.52***	0.19*	0.76***	0.59***				
Unique Pages (7)	0.46***	0.72***	-0.04	0.93***	0.75***	0.80***			
Total App Views (8)	0.45***	-0.17.	0.69***	-0.06	-0.10	0.25**	-0.07		
App Use Duration (9)	0.71***	-0.14	0.98***	-0.08	-0.07	0.12	-0.09	0.68***	
Unique Apps (10)	0.41***	-0.15	0.63***	-0.03	-0.08	0.23**	-0.02	0.59***	0.62***

A.3 Additional questions in the surveys

In addition to information overload, participants were asked about their device use and life changes in the surveys. Table 11 reports that most participants reported that they often use the tracked devices for personal information searches and entertainment, but only a minority reported using the devices for work. Furthermore, most participants perceived that their web browsing on the tracked devices reflected their usual web browsing behavior well. These patterns largely align with the observations that most participants on average did not have large changes in their tracked web activities (see Figure 5) and that entertainment categories constitute a large proportion of the active duration on devices (see Figure 7). Most participants did not report to have experienced major life changes during the study as illustrated in Figure 18. In the last survey, participants were asked about the changes in their device use due to the end-of-the-year holiday season. Most participants did not report changes as reported in Table 12.

Table 11: Questions on the use of tracked devices and general life situation from surveys (N=277). Throughout the study period, changes in life situations were rare, and participants perceived that their web activities near survey periods reflected their usual activities. The participants commonly used their tracked devices for information searching and entertainment, but only a minority used them actively for their work.

	Survey One	Survey Two	Survey Three	Survey Four
"Have there been any changes in your life situation in the last month that have had an impact on your browsing behavior?"	17 (6.1%)	10 (3.6%)	15 (5.4%)	6 (2.2%)
	Number of 'Yes' answers.			
"How different are your usual activities from the activities you performed online last month?"	3.87 (1.08)	4.03 (1.03)	3.95 (1.09)	4.10 (1.01)
	Scale: 1 'very different' – 5 'very similar'			
"How often do you use these devices for work?"	2.07 (1.48)	1.88 (1.36)	1.92 (1.46)	1.95 (1.39)
"How often do you use these devices for personal information searches?"	3.95 (1.09)	4.16 (1.01)	4.17 (0.91)	4.07 (1.04)
"How often do you use these devices for entertainment?"	3.79 (1.19)	3.96 (1.12)	3.86 (1.11)	3.8 (1.17)
	Scale: 1 'very rarely' – 5 'very often'			

A.4 Survey item translations

Table 13 reports the translations of items used in the surveys.

A.5 Pairwise cluster comparison analysis

Table 14 reports the results of post-hoc comparisons of user clusters.

Table 12: Questions about the effect of end-of-the-year holiday season to the browsing behavior, which was asked only in the last survey. Among the participants included in the dataset, 199 answered the last survey. On average, the participants did not change their daily routines or time they spent online or experience atypical stress that would affect the study.

	Survey Four
“To what extent did your daily routines change during the last month due to the holiday season?” “To what extent did you experience unusual stress due to the holiday season?”	2.38 (1.19) 2.20 (1.20) **Scale:** 1 ’not at all’ – 5 ’very much’
“Have you intentionally changed the time you spend online during the holiday season?”	“Yes, to spend less time”: 16, “Yes, to spend more time”: 61, “No”: 122

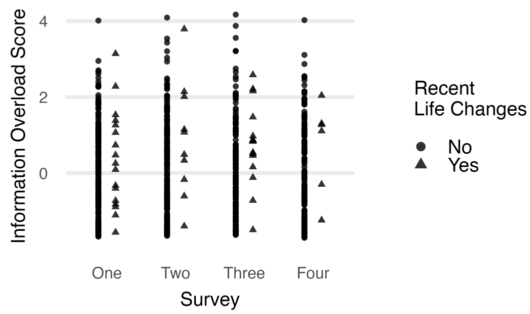

Figure 18: Recent life changes and information overload. Very few individuals reported recent life changes in each survey.

Table 13: English and German translations of the items used in the surveys.

Topic	English	German
Information Overload	- I am often distracted by the excessive amount of information I receive through my web browser. - I feel overwhelmed by the amount of information delivered through my web browser on a daily basis. - I am concerned that the amount of information that I receive through my web browser prevents me from processing the most important pieces of information. - I often feel pressured to deal with everything delivered by my web browser.	- Die große Menge an Informationen, die ich über meinen Browser erhalte, lenken mich oftmals ab. - Ich fühle mich durch die Vielzahl an Informationen, die ich täglich über meinen Browser erhalte, überfordert. - Ich bin besorgt, dass die vielen Informationen, die ich über meinen Browser erhalte, mich daran hindern, die wichtigsten Informationen zu erkennen. - Ich fühle mich oft unter Druck gesetzt, mit den vielen Informationen, die ich über meinen Browser erhalte, umgehen zu müssen.
Life situation changes	- Have there been any changes in your life situation in the last month that have had an impact on your browsing behavior?	- Gab es im letzten Monat Veränderungen in Ihrer Lebenssituation, welche einen Einfluss auf ihr Browsing-Verhalten hatten?
Changes in web browsing	- How different are your usual activities from the activities you performed online last month?	- Wie sehr unterscheiden sich Ihre gewöhnlichen Aktivitäten von den Aktivitäten, die Sie im letzten Monat online durchgeführt haben?
Use of Tracked Devices	- How often do you use these devices for work? - How often do you use these devices for personal information searches? - How often do you use these devices for entertainment?	- Wie oft nutzen Sie diese Geräte beruflich? - Wie oft nutzen Sie diese Geräte zur persönlichen Informationssuche? - Wie oft nutzen Sie diese Geräte zur Unterhaltung?
Changes in Behavior Due to the Holiday Season	- To what extent did your daily routines change during the last month due to the holiday season? - To what extent did you experience unusual stress due to the holiday season? - Have you consciously increased or decreased the time you spend online during the holiday season?	- Inwieweit haben sich Ihre täglichen Abläufe während des letzten Monats aufgrund der Weihnachtszeit verändert? - Inwieweit haben Sie untypische Belastungen aufgrund der Feiertagssaison erlebt? - Haben Sie Ihre Online-Zeit während der Ferien bewusst erhöht oder verringert?

Table 14: Games-Howell post-hoc comparisons of user clusters. Individuals in cluster C2 have significantly higher overload than other clusters as well as significantly higher average session sparseness.

Variable	Comparison	Difference	CI	p
Information Overload	C1 - C2	1.95	[1.28, 2.62]	$<.001$
	C1 - C3	0.70	[-0.31, 1.71]	0.249
	C1 - C4	0.45	[-0.16, 1.06]	0.212
	C2 - C3	-1.25	[-2.31, -0.18]	0.017
	C2 - C4	-1.49	[-2.20, -0.78]	$<.001$
	C3 - C4	-0.25	[-1.28, 0.79]	0.913
Mobile Duration	C1 - C2	1.71	[0.76, 2.67]	$<.001$
	C1 - C3	5.66	[4.36, 6.95]	$<.001$
	C1 - C4	0.70	[-0.14, 1.55]	0.131
	C2 - C3	3.94	[2.57, 5.32]	$<.001$
	C2 - C4	-1.01	[-1.99, -0.03]	0.04
	C3 - C4	-4.95	[-6.27, -3.64]	$<.001$
Desktop Duration	C1 - C2	-2.70	[-4.13, -1.28]	$<.001$
	C1 - C3	-2.68	[-4.52, -0.85]	0.002
	C1 - C4	-3.21	[-4.55, -1.87]	$<.001$
	C2 - C3	0.02	[-1.47, 1.51]	1
	C2 - C4	-0.51	[-1.16, 0.15]	0.184
	C3 - C4	-0.53	[-1.94, 0.89]	0.722
Total Duration	C1 - C2	-0.99	[-2.50, 0.52]	0.305
	C1 - C3	3.02	[0.51, 5.52]	0.014
	C1 - C4	-2.50	[-3.96, -1.04]	$<.001$
	C2 - C3	4.00	[1.68, 6.32]	$<.001$
	C2 - C4	-1.51	[-2.50, -0.52]	$<.001$
	C3 - C4	-5.51	[-7.81, -3.22]	$<.001$
Session Sparseness	C1 - C2	0.10	[0.03, 0.17]	0.001
	C1 - C3	-0.06	[-0.15, 0.04]	0.381
	C1 - C4	-0.00	[-0.07, 0.07]	1
	C2 - C3	-0.16	[-0.24, -0.07]	$<.001$
	C2 - C4	-0.10	[-0.17, -0.04]	$<.001$
	C3 - C4	0.05	[-0.04, 0.14]	0.395
Event Entropy	C1 - C2	-0.29	[-0.65, 0.07]	0.148
	C1 - C3	-0.07	[-0.50, 0.36]	0.972
	C1 - C4	-1.07	[-1.46, -0.68]	$<.001$
	C2 - C3	0.22	[-0.16, 0.60]	0.406
	C2 - C4	-0.78	[-1.10, -0.46]	$<.001$
	C3 - C4	-1.00	[-1.41, -0.59]	$<.001$