Taking 5: Work-Breaks, Productivity, and Opportunities for Personal Informatics for Knowledge Workers

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ABSTRACT

Taking breaks from work is an essential and universal practice. In this paper, we extend current research on productivity in the workplace to consider the break habits of knowledge workers and explore opportunities of break logging for personal informatics. We report on three studies. Through a survey of 147 U.S.-based knowledge workers, we investigate what activities respondents consider to be breaks from work, and offer an understanding of the benefit workers desire when they take breaks. We then present results from a two-week in-situ diary study with 28 participants in the U.S. who logged 800 breaks, offering insights into the effect of work breaks on productivity. We finally explore the space of information visualization of work breaks and productivity in a third study. We conclude with a discussion of implications for break recommendation systems, availability and interuptibility research, and the quantified workplace.

Author Keywords

Work breaks; knowledge workers; productivity; quantified workplace; personal informatics; visualization.

ACM Classification Keywords

H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION

Productivity in the workplace has long been a topic of interest for the CHI community. Much attention has been placed on understanding how and when people switch tasks, multitask, and the effects of distractions and interruptions on productivity. Yet, beyond distractions and task switching, knowledge workers intentionally (and often regularly) pause their work to “take a break”. For example, a worker can get coffee or read news online several times during a workday.

While colloquially referred to as a *break* or a *work break*, these terms have been used to describe a wide range of activities. Those include, for example, switching to a different work task [21], a midday meeting or lunch [24], a biological need (e.g. going to the bathroom, eating) [41], maintaining a habit or addiction (e.g. smoking) [32], spending time away from a screen [16,37], or exercising during the workday [38]. Not taking breaks has been shown to have potentially detrimental effects on work performance and focus [11,41] and workplace satisfaction [41].

Despite the broad understanding that breaks exist at work, there is little consensus on how break activities are defined. Specifically, there is little agreement about the characteristics (type of task, location, people involved, etc.) that make an activity a break, and what makes breaks good or bad. This is a fundamental challenge when exploring the role of breaks in the modern workplace. Further, it stands in stark contrast to our community’s rich knowledge of multitasking, task switching, and interruptions [1,9,21,23,26,42] and building tools to support them [2,11,14,18,19,20]. Filling this gap is the key scientific motivation for our work as it could uncover new opportunities for technology tools.

Exploring technologies to assist workers in understanding and managing break habits is in line with a growing interest in personal tracking and reflection on personal information (e.g. personal informatics [22]). It is viable that workers will benefit from personal tools that track work breaks and support reflection on their impact on productivity and wellbeing. Whether automatically sensed or manually logged, it will be necessary to tailor the information to the needs of self-trackers to best support reflection and action.

In this paper, we report on a series of studies: a survey of U.S.-based knowledge worker break behaviors, a diary study that captures in-situ work breaks and the activities and motivations that surround them, and an exploration of tools to help workers better visualize, and ultimately understand their break practices. Specific contributions include:

- An understanding of what knowledge workers consider to be breaks from work (and which activities they do not consider to be breaks, and why), and an understanding of what outcomes knowledge workers desire when taking a break.
- A detailed investigation of the effects of work breaks on self-reported productivity based on an in-situ diary study.
- An exploration of the potential of break logging for personal informatics, through the design and study of visualizations using diary-study participants’ data, self-observations and open questions.

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RELATED WORK

We now survey related work in defining and understanding the value of breaks, productivity and sensing in the workplace, and learning from personal data.

Defining breaks from work

Substantial research has explored how breaks affect worker productivity and focus. Breaks improve overall work performance, despite the short-term cost to productivity and overhead of task resumption [7]. Yet, the definition of 'a break' in prior literature has not been consistent. For example, in some cases, being away from a computer screen was viewed as a requirement [16,37] or treated as a proxy for determining when someone is on a break [24]. However, it is well-known that people complete non-work tasks on their work computers, such as browsing social networks [34].

Other work has studied the impact of second or minute-long rests from work, typically called *microbreaks* or *microdiversions* [11,17,27]. These rests have been shown to improve productivity [27] and increase worker retention in crowd-powered systems [11]. However, it remains unclear whether knowledge workers consider these rests to be breaks from work. In their crowd diversion system, Dai *et al.* avoid the term *break* because they believe a break is typically longer and the activity is determined by the worker [11]. To provide a clearer view of criteria that make activities breaks, we ask the following research question:s

RQ1: What do knowledge workers consider to be breaks from work?

Break-taking Objectives and Practices

Prior work has shown that frequent breaks reduce accidents and physical discomfort in industrial environments [38,39]. Researchers have also studied the role of breaks in office environments for avoiding repetitive strain injury, muscle fatigue, and excessive sedentary behavior [8,15,37,38]. There is, however, disagreement on whether short, frequent breaks are preferable to longer, infrequent breaks [10,16,37].

On the flip side, workers often forego taking breaks to maintain productivity or because of pressures in the work environment. Although Rogers *et al.* found that nurses made no additional patient-care mistakes during shifts when they were unable to take a break, they note that missing breaks promote bad eating habits (e.g. taking advantage of readily-available unhealthy snacks) and contributes to burnout [30].

Approaching the question of break-taking objectives from a personal rather than an organizational angle raises our next research question:

RQ2: What benefit do knowledge workers desire when they take a work break?

Previous studies, such as Czerwinski *et al.*'s diary study [9] and Mark *et al.*'s in situ study [24] have documented an array of workplace activities of knowledge workers. These studies also captured some of knowledge workers' break activities, such as downtime or personal tasks and social network use. Mark *et al.* report participant's valence and arousal showed no significant change after a mid-day break, but note an increase in web email and Facebook after that mid-day break [24]. In our work, we address specifically the impact of varied break activities on desired benefits and productivity:

RQ3: What breaks provide the benefits desired by knowledge workers and improve workers' productivity?

Insights gained through this question could benefit, for example, the design of break-recommendation systems that promote beneficial activities and dissuade others.

Learning from Collected Personal Data

Interest in tracking and learning from collected personal data, or personal informatics [22], has grown in the past decade. Designers and researchers have begun exploring methods for helping people learn from personal data. Visualization [6,12] and summarizing data into natural-language sentences [5,12] have been shown to be effective.

Research has also explored presentation of personal data collected in the workplace. In classic work by Begole *et al.*, intraday desktop activity logs were used to construct visualizations for group coordination [3,4]. The authors primarily discussed opportunities for computer supported cooperative work rather than self-understanding [3]. Mathur *et al.* similarly design a system that presents self-reported mood and work activity publicly, emphasizing organization-wide privacy and learning implications [25].

Recently, there have also been efforts to automatically collect and model user behavior using desktop and environmental sensing [14,24,25,42]. For instance, tools like RescueTime [29] automatically track and summarize application use over time. Zuger and Fritz [42] investigate the use of psycho-physiological sensors to automatically predict worker interuptibility.

With technology for automatically sensing activity, mood, and productivity on the horizon, we turn to how technology can help people understand their own work-break habits. To this end, we explore the research question:

RQ4: How can personal informatics best help knowledge workers learn from the breaks they take?

The remainder of this paper focused on addressing these research questions through a series of studies. Through a synthesis of the results, we discuss the implications for understanding behavior of work breaks and the value of tools that help workers track and understand break activity.

STUDY 1: UNDERSTANDING BREAKS FROM WORK

The first study focused on our first two research questions – gaining an understanding of criteria used by knowledge workers to define breaks (and whether definitions of breaks differ across workers), and an understanding of the benefits workers desire out of their breaks. Results from this study serve as foundation for understanding how breaks impact knowledge workers' wellbeing and productivity.

	AMT (N=100)	Convenience (N=47)
Age	Avg 32.8, min 21, max 64	Avg 31.8, min 20, max 81
Gender	45 Female, 55 Male	32 Female, 14 Male, 1 did not disclose
Most Common Occupations	20 computer & math 15 office & admin support 14 business & financial 11 sales	20 student 10 computer & math 4 research 3 design

Table 1. Demographics of survey respondents.

Study Method

We solicited responses through posts to social media and university mailing lists (a convenience sample) and through Amazon Mechanical Turk (AMT). We restricted the AMT task to U.S.-based respondents who had a task acceptance rate of at least 95% and had completed at least 1,000 tasks. Respondents recruited through a convenience sample were entered into a raffle for two $25 gift cards. Respondents from AMT were compensated $2.00 each. The task description stated, "*Looking to understand the practices of knowledge workers*". The first question quoted the Wikipedia definition of a "*knowledge worker*" and asked respondents to affirm that their occupation could be categorized as such.

Respondents answered a combination of choice and free-response questions. Free-response questions were open-coded by the first author. The second author independently coded 10% of the data, and both authors discussed until high agreement was reached. In total, three questions were coded: explanations of why an activity is not a work break (5 categories, Cohen's κ values between 0.74 and 1.00), desirable outcomes of breaks (9 categories, κ 0.73-1.00), and undesirable outcomes of breaks (5 categories, κ 0.59-1.00).

Respondents

In total, we received 147 responses: 100 from AMT and 47 convenience sample responses (an additional respondent who did not meet our filtering criteria was excluded). Table 1 presents a summary of demographics and the top respondent occupations. While our sample includes a wide variety of U.S.-based knowledge workers, it is certainly skewed towards technology-related professions. We quote respondents with S##, where S1-S100 and S101-S147 were recruited from AMT and convenience samples, respectively. The survey is available in the supplementary materials.

STUDY 1 RESULTS

What is, and is not, a work break

To understand which activities knowledge workers consider breaks and why, we compiled a list of 18 activities that had been considered or referred to as a work break in the literature [11,21,24,32,38]. The list contains both physical and digital activities (see Figure 1). In the survey, respondents were asked to indicate, for each activity in the list, whether they considered it to be a break from work, *regardless of whether they themselves took it*. For each activity a respondent marked as *not* a break, they were asked to briefly describe why not.

Of a total 2646 entries (147 respondents x 18 activities), 1878 were marked as "a break" and 617 (4.2 entries out of 18 activities per respondent, on average) as "*not* a break". In other words, a large proportion of activities described in prior work were not considered breaks by the respondents. As seen in Figure 1, participant opinions varied by activity. It is possible that similar criteria applied by respondents to the same activity resulted in different ratings. We thus examine respondents' open-ended descriptions of their choices.

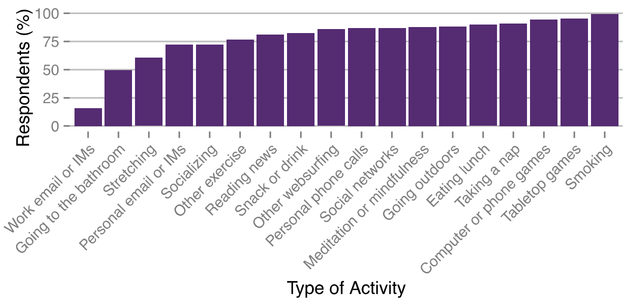


Figure 1. % of respondents agreeing activity X is a break.

Work-related activities are not breaks

One clear classification of activities that did emerge from the responses was that activities related to work were rarely considered breaks. 124/147 respondents (84%) did not consider managing work email or instant messages to be a break from their work. Work email was thought of as "*part of my job*" or "*work related*" (S10, S146, mentioned by 118 others). 7 and 5 respondents felt reading news or websurfing were related to their work, respectively. This is often required for of certain professions, such as S77, "*my job requires me to keep up with the news, especially Real Estate news.*"

This result highlights two important points. First, many of these work-related activities have been considered breaks in the literature. For instance, Jin and Dabbish use *break* to describe switching to a more desirable task [21]. As a result, this may require established implications around task management to be rethought. Second, it also illustrates an activity (e.g. reading real estate news) may be a work related task to one worker (e.g. a real estate agent) but not to another (e.g. an office assistant currently looking for a home to purchase). This has significant implication for any automatic classification of activities as being breaks. We expand on this implication in the discussion section.

Biological needs are not breaks

While not as conclusive as work tasks, 81/147 respondents (55%) indicated they did not consider an activity such as eating, getting a drink, or going to the bathroom as breaks, but rather "necessary" activities. S48 explained, "*I think of a 'break' as something one does for enjoyment or for rest,*" believing that "*going to the bathroom is something that must be done.*" Similarly, S24 said meditation is "*how I stay effective throughout the day.*"

Respondents consistently indicated that going to the bathroom, and getting a snack or drink were too short to be considered breaks (27, 10, and 10 respondents). In fact, many indicated they would sometimes continue to work while doing these activities. S132 notes, "*I can still have my eyes on the monitor and think about work while I'm stretching.*"

These results provide an important observation that physical acts, like walking to an office "break space" to get a drink, do not automatically qualify the action as a break. We next turn to understanding what positive outcome knowledge workers seek when taking a break, and what negative aspects they wish to avoid.

Desired benefits were shared, but subjective

When asked to explain what makes a break good and/or successful, 112 respondents (76%) referred to a desired mental state upon returning to work. Examples include breaks that "*cleared my mind*", where they returned "*refreshed*", "*refocused*", "*relaxed*", or "*recharged*", or that the break "*lowered my stress*." An overall theme was that workers return from a successful break feeling *ready to work*.

Respondents described different ways of returning from a break ready to work. Fifteen respondents stated the need for breaks to provide a new perspective on their current work task: "*sometimes it helps [me] to get some distance from a problem and then go back to it.*" (S147). People do not necessarily want to think about their work on their break. A successful break for S29 "*tak[es] my mind off work for a bit*", a sentiment shared by 28 others. While there is consistency in the descriptions of the qualities of a "good" break, the evaluation of each break activity is clearly subjective.

Undesirable outcomes were largely causal

For many survey respondents, undesirable outcomes of breaks were simply the inverse of desirable outcomes. They "*don't feel relaxed*" after a bad break (S42 and 34 others) or "*think about work the entire time*" (S58 and 31 others). Twenty-two respondents described a bad break as one interrupted by work, such as being "*called about work*" (S76). Some disliked "*having to talk to others about work*" during a break (S83 and 7 others).

Finally, the length of a break may lead to a break being seen as unsuccessful. Nineteen respondents described a bad break as being **too short**, such S9 "*if I do not have time to enjoy my break.*" Bad breaks can also be **too long**, "*if I take too long, or if someone starts what looks to be a long conversation*" (S21 and 19 others). In both cases, respondents referred to the length of a break in relative terms (too long/short). This suggests people have an internal notion of a desired or expected length for a break, and a conception of whether the actual length of the break aligned with that expectation. We explore the relationship between break type, break length and outcome in studies 2 and 3.

STUDY 2: A DIARY STUDY OF BREAKS FROM WORK

In our first study, we identified high variance in the types of breaks that workers take. We also learned that the value attributed to a break (e.g., feeling refreshed) can be highly subjective. Towards our ultimate goal to understand potential technology opportunities to assist workers in managing and improving their break activities, our investigation now turns to exploration of the relationship between work-breaks and the benefits they may provide to a knowledge worker's physical and mental states and productivity (expressed in RQ3).

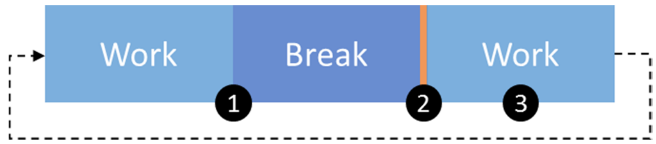


Figure 2. A conceptual flow: A work-break is a non-work activity (or activities) sandwiched between work activities. Our diary study collected self-reports about each break and its effect in three parts, indicated above.

We conducted a diary study that explores the effect of breaks on work (and work on breaks). As seen in the conceptual flow shown in Figure 2, we assume that a break is preceded and followed by work activities and is concerned with a worker's state and activities in four stages: Work and productivity *before* taking a break (*Pre-break*), activities done while on a break (*Break*), physical and mental state at the end of the break (*End-of-break*), and work and productivity *after* the break (*Back-at-work*).

Methods

To learn how different breaks affect knowledge workers' state and productivity, we created a website for logging detailed information about breaks throughout the day (Figure 3). A complete diary entry consisted of three parts (labeled 1, 2, and 3 in Figure 2) allowing us to collect rich data and enable identification of temporal (and causal) relationships:

(1) Whenever they are about to take a break, participants are asked to start a new log entry (Figure 3a) and to describe what they were working on, why they decided to take a break, and evaluate their level of productivity (Figure 3b).

(2) Upon returning from a break, participants indicate that they had returned (Figure 3c), describe what they did on their break, whether it was longer or shorter than intended, and rate their end-of-break state (Figure 3d). Participants then return to their normal work (Figure 3e).

(3) Finally, 10 minutes after resuming work, participants receive an alert asking for the final part of the entry (Figure 3f), including their current activities and productivity ratings.

This sequence helps expose the relationship between productivity before the break and the break itself and their combined effect on productivity after the break.

The website was designed for both desktop and mobile, with a text message replacing the alert on mobile. We recognized that participants might forget to begin a diary entry before going on a break and only realize it once they return. We thus allow participants to start a diary entry upon returning from a break. Using what we refer to as the "*Forgot*" dialog, participants log what they did before the break, what they did on their break, and self-report the length of the break.

Figure 3. Our desktop and mobile-friendly website for logging break activities. Study participants (a) began logging their breaks, (b) described what they were working on, (c) took their break, (d) logged what they did on the break, (e) returned to work, and (f) rated their productivity 10 minutes after they returned to work.

Diary Entries

For every break, participants recorded data in seven categories. We describe the data collected in more detail:

Work task: Collected before the break ("pre-break") and 10 minutes after resuming work ("back-at-work") as free text.

Reasons for taking a break: Collected pre-break. Participants select all reasons that apply from a list drawn from prior work [11,21,24,32,38].

Productivity levels: Collected pre-break and back-at-work. Three 7-point Likert-item questions from *much lower than normal* to *much higher than normal* with a midpoint of *about normal*: "I would rate my current ____ as…" (Work *quality*, *focus*, and *productivity*). Prior work has validated these items as reliable self-reported measures of productivity [36,40].

Type of break: Collected at end-of-break. Participants selected all activities that applied from the list of activities used in Study 1, excluding the "Other work-related activities" item. We provided an "Other" option, and these responses were independently coded in full by the first two authors (19 codes, Cohen's κ of 0.74-1.00).

Break length: Calculated at end-of-break based on the time elapsed. The length of breaks logged through the "Forgot" dialog was based on participants' self-reports.

Intended length of a break: Collected at end-of-break on a 7-point Likert question from *Much shorter than I intended* to *Much longer than intended* with a midpoint of *As I intended*.

Break quality: Collected at end-of-break. Drawing on findings from Study 1, we used three 7-point Likert-scale questions from *not at all* to *extremely*: "I feel…" (*relaxed*, *refreshed*, *ready to work*).

	Demographics (N=28)
Age	Avg 30.1, min 21, max 58
Gender	13 Male, 15 Female
Most Common Occupations	6 computer & math 6 office & admin support 4 legal 3 business & financial
Time at desk (hours)	Avg 7.6, min 5, max 12
	Diary Tool Use
Days logged breaks	Avg 8.7, min 4, max 10
Breaks logged/person	Avg 31.6, min 5, max 59
Breaks logged/person/day	Avg 3.6, min 1.25 max 5.9
	Breaks Logged (N=800)
Break duration	Avg 22.9 minutes, SD 25.6
Most Common Breaks (not mutually exclusive)	421 going to the bathroom 249 social networks 238 personal email or IMs 221 snack or drink 198 lunch 146 other websurfing

Table 2. Study 2 participants had varied occupations and most frequently logged necessary breaks.

Additional details can be found in the supplemental material.

Participants and Analysis

We recruited 28 participants for a two-week study through posts to social media on personal timelines and high school and university alumni pages (an additional participant withdrew from the study after one day and their data are not reported). No two participants were from the same organization. Participants were compensated $5 for each of the first 5 days in which they logged breaks, and $10 per day thereafter, for a maximum compensation of $75. We chose this compensation scheme to encourage prolonged participation. Table 2 summarizes demographic information, diary tool use, and the breaks logged with the tool.

Participants logged 885 breaks in total. In our analysis, we discarded 64 breaks because participants did not report coming back from them, and 21 breaks that were logged more than 30 minutes after the break was over. Of the 800 breaks we report on, 786 breaks were logged using a desktop browser and 14 (2%) were logged via a mobile device. In 570 cases (71%), participants remembered to begin logging a break before it started. The remaining 230 breaks were logged upon returning from the break via the "*Forgot*" dialog.

Across all participants, the three productivity-level ratings (*work quality*, *focus*, *productivity*) were highly correlated both pre-break (r=0.72-0.82, p<0.001) and back-at-work (r=0.80-0.84, p<0.001). We thus combine the three into a single *Productivity* rating. We found a similar high correlation in the end-of-break reports between the *relaxed* and *refreshed* break-quality ratings (r=0.76, p<0.001) and combined these ratings. The correlation of this combined rating and a participant's readiness to resume work (aka, "*ready to work*") was positive but weaker (r=0.6, p<0.001).

Inspection of break length distribution indicated a lognormal distribution, thus we applied a power transform prior to analysis. The Intended Length of a break was decomposed into two binary measures: Longer vs. Intended (true if participant responded 5-7 on Likert-scale question) and Shorter vs. Intended (true if 1-3 on Likert-scale). This is because the inverse of longer (shorter) than intended can simply be "As Intended", not necessarily shorter (longer) than intended. For analysis, we combined break into five categories: Necessary (lunch, snack or drink, bathroom), Digital (personal email or IMs, social networks, web-surfing, phone calls, news, digital games), Physical Rest (meditation, exercise, nap, stretching), Outdoors, and Social. A single break could still have multiple categories (e.g. a phone call made outdoors). Finally, no breaks of tabletop games or smoking were logged and thus do not appear in our analyses.

Except when otherwise mentioned, data were analyzed using linear mixed models with Participant ID as a random effect. We explore the effects of break factors at each stage of the conceptual flow (Figure 2) through separate models.

Limitations

While 17 participants (61%) logged a break every single day of the study, we noticed an overall decrease in the number of participants logging breaks per day ($F_{1,8}$=10.1, p=0.013, β=-0.721 fewer participants per day) and a marginal decrease in number of breaks logged per person per day ($F_{1,213}$=3.55, p=0.061) as the study progressed. While we did not find any significant effects of Day in Study on our measures, it suggests our diary may have been burdensome.

17 of the 28 participants also mentioned that the two weeks of the study were somewhat atypical, sometimes resulting in more or fewer breaks taken than normal. For example, P21 had "*fewer work duties*" and P20 was "*within my first month at a new job*", while P24 "*experienced a higher workload volume than normal*" and P5 "*was a backup for a co-worker who was on vacation*".

Our study relied on participants' self-reported data and self-assessments, while some prior work has utilized sensors [42] and desktop monitoring [24,29]. Our approached allowed us to explore a wide spectrum of break activities, many of which are away from the desk and cannot yet be reliably sensed. Our qualitative scales were all positively framed (e.g. *relaxed*, *focused*). While this simplified data entry (e.g. a higher rating always reflected a positive break or feeling), this setup may have affected results.

STUDY 2 RESULTS

To discuss our findings, we focus first on factors that may influence taking a break and the type of break taken. We then describe the breaks taken by our participants and factors that may cause a break to be longer or shorter than intended. We also examine which factors contribute to a participant feeling relaxed, refreshed, and ready to return to work at the end of the break. Finally, we examine the relationship between the break and reported productivity when back at work. We use our results to construct a detailed model (Figure 4) that describes the effect of work on breaks and breaks on work.

Productivity and the Decision to Take a Break

An initial question we ask is "How does work productivity affect a knowledge worker's decision to take a break?" To answer this question, we examined the proportion of breaks taken given the value of reported productivity before the break. Our analysis found no significant effect ($F_{1,550}$=0.07, p=0.796), suggesting that participants took breaks with similar frequency whether they felt more or less productive.

We did find, however, a significant effect of pre-break productivity on the *type of breaks* participants took. We ran a series of logistic regressions with different types of breaks as dependent variables, controlling for time-of-day and day-of-week. We found participants tended to take *Digital* breaks (such as checking personal email or visiting social networks) more often when they feel less productive (β=-0.218, Z=-2.41, p=0.016), but when feeling more productive, *Necessary* breaks (such as going to the bathroom or getting a snack) were the ones more likely (β=0.200, Z=2.19, p=0.028). Other break types were not taken significantly more or less often based on productivity.

Taking a closer look at specific categories of Digital breaks, we note participants took *Social Network* and *Websurfing* breaks more often when they felt less productive (β=-0.195, Z=-2.06, p=0.039; β=-0.218, Z=-2.22, p=0.027) and marginal significance for *Digital Games* breaks (p=0.055). We found no impact of productivity on *Personal Email*, *Phone Calls*, or *News* breaks. It is possible that these activities require temporary attention, while others are used as distraction. Indeed, many people have goals to spend less time on social networks [35].

Break Type and Desired Break Length

Recall that in Study 1, respondents described breaks that are too short or too long as unsuccessful breaks. To examine factors that may cause this, we first performed a regression with break length (log-transformed) as the dependent measure (results in Table 3). Participants logged more than one activity on 65% of breaks, so we consider the length added by each type of break. Outdoors breaks increased break length the most (β=0.497, p<0.001), while Necessary (β=0.155, p<0.001) and Physical Rest (β=0.155, p=0.009) breaks had the smallest increase. This provides an insight that break recommendation systems could suggest breaks that align with the length of break desired.

Turning to whether a break was longer or shorter than intended, we conducted logistic regressions with *Length vs. Intended* as the dependent measure. We created separate models for Shorter vs. Intended and Longer vs. Intended. We find a significant effect of break length on Longer vs. Intended (β=2.834, Z=9.55, p<0.001) and a marginal effect on Shorter vs. Intended (p=0.056). Looking at break type, *Digital* breaks and *Social* breaks (those that involve talking to others) were more likely to last longer than intended

Length of break (log)	Est.	SE	*df*	*t*	*p*
(Intercept)	0.722	0.082	493.3	8.754	<0.001***
Day of week	0.018	0.009	778.5	1.777	0.076 .
Hour at work	-0.004	0.006	789.2	-0.580	0.562
Productivity Before	0.009	0.014	789.0	0.634	0.526
Necessary Break	**0.155**	**0.035**	**790.5**	**4.398**	**<0.001*** **
Digital Break	**0.244**	**0.032**	**778.2**	**7.705**	**<0.001*** **
Social Break	**0.272**	**0.038**	**788.2**	**7.241**	**<0.001*** **
Physical Rest Break	**0.132**	**0.050**	**789.4**	**2.626**	**0.009** **
Outdoors Break	**0.497**	**0.045**	**785.0**	**10.978**	**<0.001*** **

Table 3. Regression table for Length of break.

Relaxed and Refreshed	Est.	SE	*df*	*t*	*p*
(Intercept)	3.334	0.203	325.0	16.470	<0.001***
Day of week	-0.019	0.021	771.0	-0.926	0.355
Hour at work	0.003	0.013	779.1	0.244	0.808
Productivity Before	**0.166**	**0.031**	**778.1**	**5.407**	**<0.001*** **
$\log_{10}$Break Duration	**0.306**	**0.085**	**785.2**	**3.608**	**0.003*** **
Longer vs. Intended	-0.038	0.079	780.3	-0.478	0.633
Shorter vs. Intended	**-0.534**	**0.099**	**783.7**	**-5.391**	**<0.001*** **
Necessary Break	0.118	0.079	782.1	1.485	0.138
Digital Break	-0.090	0.073	787.6	-1.237	0.217
Social Break	0.082	0.086	777.6	0.956	0.339
Physical Rest Break	**0.334**	**0.112**	**778.8**	**2.994**	**0.003** **
Outdoors Break	0.031	0.108	780.2	0.291	0.771

Table 4. Regression table for Relaxed and Refreshed rating.

Ready-to-work	Est.	SE	*df*	*t*	*p*
(Intercept)	1.543	0.216	557.3	7.152	<0.001***
Day of week	**-0.499**	**0.020**	**774.8**	**-2.482**	**0.013***
Hour at work	**-0.057**	**0.013**	**785.0**	**-4.407**	**<0.001*** **
Productivity Before	**0.162**	**0.030**	**783.3**	**5.419**	**<0.001*** **
$\log_{10}$Break Duration	**-0.171**	**0.082**	**785.9**	**-2.097**	**0.036***
Longer vs. Intended	-0.020	0.076	786.6	-0.285	0.796
Shorter vs. Intended	-0.063	0.096	786.1	-0.658	0.511
Relaxed/Refreshed	**0.613**	**0.034**	**772.4**	**18.104**	**<0.001*** **
Necessary Break	0.038	0.076	787.0	0.495	0.621
Digital Break	0.037	0.070	778.9	0.526	0.599
Social Break	0.093	0.082	784.4	1.129	0.259
Physical Rest Break	0.005	0.108	785.1	0.043	0.965
Outdoors Break	-0.012	0.103	786.1	-0.115	0.909

Table 5. Regression table for Ready-to-work rating.

Productivity after	Est.	SE	*df*	*t*	*p*
(Intercept)	1.641	0.237	489.9	6.915	<0.001***
Day of week	0.033	0.023	679.3	1.432	0.153
Hour at work	-0.012	0.014	658.8	-0.809	0.419
Productivity Before	**0.235**	**0.034**	**671.8**	**6.907**	**<0.001*** **
$\log_{10}$Break Duration	-0.028	0.090	593.9	-0.308	0.758
Longer vs. Intended	-0.154	0.085	626.0	-1.819	0.069 .
Shorter vs. Intended	0.050	0.106	649.2	0.472	0.637
Relaxed/Refreshed	**0.120**	**0.043**	**579.3**	**2.768**	**0.006** **
Ready-to-Work	**0.225**	**0.039**	**633.6**	**5.778**	**<0.001*** **
Necessary Break	0.093	0.086	613.5	10.80	0.280
Digital Break	0.051	0.076	523.5	0.671	0.503
Social Break	-0.071	0.091	663.8	-0.775	0.439
Physical Rest Break	0.188	0.115	642.7	1.632	0.103
Outdoors Break	-0.191	0.114	662.5	-1.675	0.095 .

Table 6. Regression table for Productivity after rating.

(β=0.572, Z=2.62, p=0.009; β=0.512, Z=2.03, p=0.043), and *Necessary* and *Outdoors* breaks were less likely to last longer than intended (β=-0.623, Z=-2.56, p=0.01; β=-0.773, Z=-2.44, p=0.015) for our participants. We additionally note *Physical Rest* breaks were marginally less likely to last longer than intended (p=0.071). We find break type did not significantly affect whether breaks were shorter than intended.

Refreshed, Relaxed, and Ready to Work!

We also examined what affects a person feeling relaxed and refreshed at the end of a break, and whether those affect readiness to resume work. Table 4 shows the results of a linear mixed model regression with the combined *Refreshed-and-Relaxed* score as the outcome measure.

Confirming our finding from Study 1, breaks that were shorter than intended were correlated with feeling significantly less relaxed and refreshed at the end of the break ($F_{1,784}$=29.06, p<0.001). While longer breaks were correlated with higher ratings of being relaxed and refreshed ($F_{1,785}$=13.02, p=0.003), breaks longer than intended were not (p=0.633). Taken together, these results suggest that being refreshed and relaxed is more strongly affected by breaks that are too *short*, rather than breaks that are too *long*. Looking at break types, *Physical Rest* breaks were correlated with people feeling relaxed and refreshed ($F_{1,779}$=8.96, p=0.003).

Finally, independent of break type, there was a strong correlation between productivity rating before the break and refreshed/relaxed rating at the end of the break ($F_{1,778}$=29.23, p<0.001). A possible explanation is that when a worker feels unproductive at work, it is hard for them to relax.

Considering factors influencing participants' readiness to return to work (Table 5), feeling more relaxed and refreshed was correlated with feeling more ready to work ($F_{1,772}$=327.74, p<0.001). We found a positive relationship between productivity before a break and feeling ready to get back to work ($F_{1,783}$=29.37, p<0.001). Put simply, we found that when people feel productive before a break, they feel ready to work afterwards.

While the type of break did not show a significant effect on readiness to work, we found a negative correlation between break length and readiness to work, with people slightly less ready to work after taking longer breaks ($F_{1,786}$=4.40, p=0.036). We should note that while it is reasonable to assume that long breaks leave people less ready to work, it is also possibly that when one is not ready to work, they tend to take longer breaks.

Finally, we found that participants reported feeling less ready to return to work as the day went on ($F_{1,785}$=19.42, p<0.001) and as the week went on ($F_{1,775}$=6.16, p=0.013).

The Effect of a Work-break on Productivity

For the final piece of our model, we analyze the connection between the work-break factors examined and participants' productivity, reported 10 minutes after resuming work. Of the 800 breaks reported, 627 (78%) contained back-at-work responses and were used in this analysis. We conducted a linear mixed model analysis with the combined Productivity rating as the dependent measure (see Table 6).

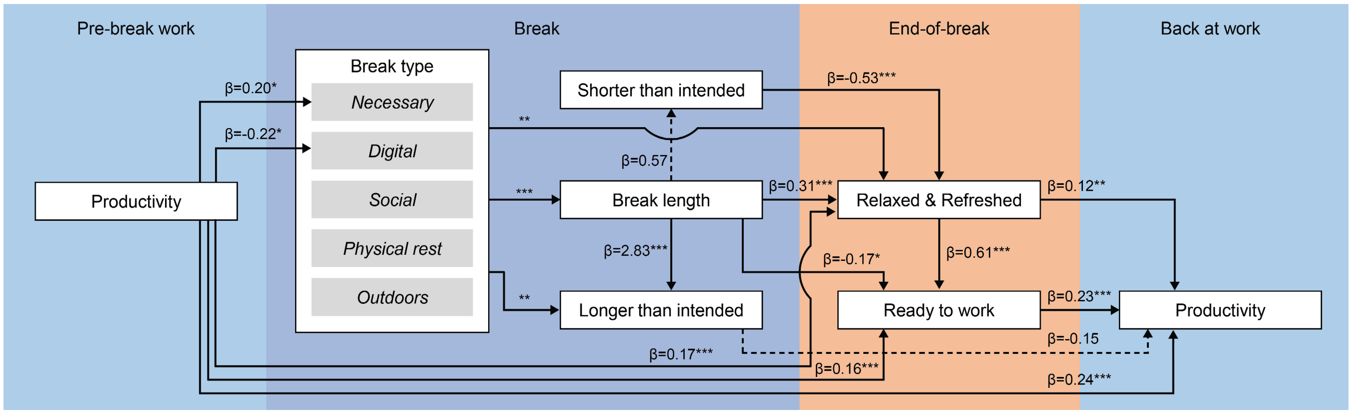


Figure 4. Regression analysis results across conceptual flow (- - - p<0.1; * p<0.05; ** p<0.01; *** p<0.001). Effects of hour-of-day and day-of-week not shown. For coefficient estimates of individual break types, please refer to tables above.

Our analysis shows significant effects of feeling *Relaxed and Refreshed* and *Ready to Work* (at the end of the break) on productivity 10 minutes later ($F_{1,579.3}$=2.77, p<.006; $F_{1,634}$=5.78, p<.001). This finding suggests that a break that leaves a knowledge worker refreshed and relaxed, and thus ready to work will positively affect their work productivity.

Looking at break type, we note marginal significance suggesting a decrease in productivity following *Outdoors* breaks. Finally, we found a correlation between productivity *before* and productivity *after* a break ($F_{1,672}$=6.91, p<.001).

Insights Gained from Logging Breaks

At the end of their two-week participation, participants completed an end-of-study survey. In this survey, we asked about their experience using the diary tool and offered them opportunities for open-ended discussion of what they learned or wished they could learn from the study. We quote participants with P##.

Participants described learning about their state after breaks. Some, for example, learned that breaks were not always beneficial. P16 found breaks "*have only a minimal effect on my productivity*", while P19 found the impact more variable: "*they don't always predictably refresh me!*"

When discussing the use of the diary, participants appreciated that it provided them more awareness of their breaks. P20 noted, "*Actually logging every little break helped me realize how much time [I was taking off].*" Fourteen participants wished they understood more about their break habits; five participants wanted to know what breaks made them more productive, wondering "*are there break types that can help me be more productive?*" (P8) and "*how did my productivity/focus/etc. change with the duration of my break?*" (P10). P19 wanted to "*find a reliable way to feel refreshed and re-energized.*" Others wanted to learn "*what times of day I generally took breaks*" (P7).

These responses, and the overall results of both studies, indicate that there is important variation in break behavior and a strong desire by workers to have tools that could help them understand and reflect on their habits. However, showing that tools that are accurate, reflective, and (most importantly) useful to workers *could* be created was still missing. Towards this, we designed a set of visualizations of break habits, based on data obtained in Study 2 and explored their potential value for workers.

STUDY 3: BREAKS AND PERSONAL INFORMATICS

While participants in our diary study learned about their habits from logging their breaks (e.g. reflection-in-action [33]), people often benefit from later reflection on personal data [13,22]. Prior work has shown visualization of personal data helps reflection for understanding and improvement [12]. We bring this work into a new domain, exploring how visualization can help people reflect on their breaks.

Visualization Design

Based on the open-ended responses of diary-study participants, we selected 13 topics in four categories for learning and reflection on breaks (Table 7). We then developed and iteratively refined visualizations for all topics in four categories:

- Overview of break habits (visualizations 1-4)
- What impacts break duration (visualizations 5-6)
- What impacts feeling refreshed after a break (visualizations 7-9)
- What impacts productivity (visualizations 10-13)

As in Study 2, we combined Refreshed and Relaxed ratings and the three Productivity ratings to reduce repetition in visualizations and outline major trends.

Visualizations were made with ggplot with Study 2 data. We used three types of plots: histograms (Figure 5a), point ranges (Figure 5b), and scatter plots with trendlines (Figure 5c, 5d). Each visualization contains a summarizing natural language caption, a technique often used in identifying patterns in personal informatics data [5,12]. These captions were automatically generated by running statistical tests at α=0.3 and interpreting the results. For histograms and point ranges, we ran Tukey HSD tests and identified categories with largest and smallest means. For scatter plots, we ran Linear Regressions and identified the

1.	Number of breaks taken each day of the study
2.	Number of breaks taken by the time of day
3.	Number of breaks taken by break duration
4.	Number of breaks taken of each break type
5.	Break duration for each break type
6.	Whether breaks were as long as intended for each break type
7.	Refreshed rating after break for each break type
8.	Refreshed rating after break by break duration
9.	Refreshed rating after break by break length as intended
10.	Change in productivity back-at-work for each break type
11.	Change in productivity back-at-work by break duration
12.	Change in productivity back-at-work by break length as intended
13.	Change in productivity back-at-work by refreshed rating after break

Table 7. We presented visualizations of 13 topics of break habits. We used three types of plots: histograms , point ranges , and scatter plots with trendlines .

sign of the coefficient. Because individual data was small, we used a high α value to identify potential trends.

Method

To evaluate the 13 visualizations, we contacted 19 of our 28 Study 2 participants who indicated willingness to be contacted and had logged breaks at least five days. 9 of the 19 participants responded and were scheduled for a phone interview. Interviewees received a $25 gift card.

Before each interview we automatically generated personalized visualizations for each participant based on his or her data from the diary study. During the interview, a participants browsed the visualizations on a webpage one at a time in the order of Table 7, but were allowed to scroll up to refer to previous visualizations at any time. We used a "think aloud" protocol, where participants were asked to describe their thoughts as they viewed the visualizations. The interviewer occasionally asked clarification questions. We additionally collected ratings for each visualization and a ranking of each visualization's value.

The participants we interviewed logged an average of 37 breaks in the diary study (min 24, max 55) over an average of 9 study days (min 7, max 10). We interviewed 6 women, 3 men. Their average age was 32.8 (min 21, max 58). Interviews lasted 57 minutes on average (min 37, max 85).

STUDY 3 RESULTS

Starting to track one's own behavior is often the result of a desire to change the behavior, understand it, or out of curiosity [13,31]. When reviewing their breaks, our participants exhibited similar perspectives. P16 and others wanted an overview of their break habits "*to me, the basic stuff is much more important*." Others, however, wanted to identify habits to act on "*based on these sort of outcomes or plots, how could I change my habits about breaks?*" (P3).

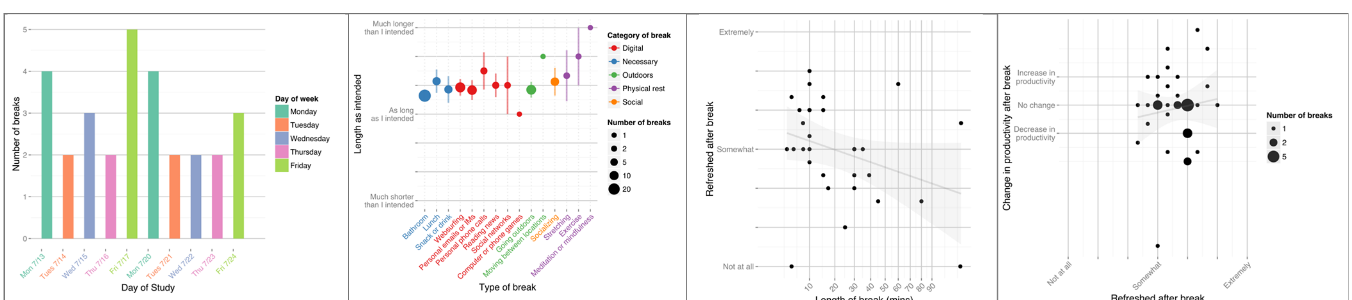
Consistent with prior work [12], different visualizations provided different value to each participant. Importantly, participants found the visualizations complementary; when looking at her visualizations, P13 stated "*I probably get more out of seeing them together than separate in isolation.*"

Identifying Break Trends

Visualizations helped participants identify break-taking trends. P13 learned when she took breaks "*I didn't know that my break habits drop in the afternoon.*" P10 learned that "*most of my breaks were a little bit shorter than I intended, which I didn't know.*" P16 was surprised to learn "*how little my breaks refreshed me… I would have thought that in most instances it would.*"

Participants ranked visualizations that contained information about trends more highly. However, some participants found the absence of a trend as important as the presence of one. For example, P10 stated, "*there's no particular pattern here, but that also counts as something worth noting.*" P3 found this frustrating, and wished she found something prescriptive: "*I wish… I could pinpoint 'oh my gosh, when I take longer breaks I feel much more refreshed.' Then I should always go out to lunch.*"

Although participants found value in captions describing trends, they did not always align with people's intuition. For P24, "*I see exercise is saying no change to a slight decrease in productivity, I don't know if I agree with that. I found that more energizing really*". Still, some participants valued seeing data reflecting a belief different from what they expected "*I would have expected that if I felt more refreshed*



You took more breaks on **Mondays** and **Fridays** than other days. (a)

Physical rest breaks tend to be longer than you intended more than other breaks. (b)

Longer breaks tend to leave you **less refreshed**. (c)

There doesn't seem to be a relationship between returning from a break refreshed and changes in productivity. (d)

Figure 5. Example visualizations and natural-language captions presented to Study 3 participants. These correspond to Table 7 visualizations (a) 1, (b) 6, (c) 8, and (d) 13, respectively.

then I would have been more productive, but based on this, that is not what's happening" (P10).

From Reflection to Action

As participants looked through the visualizations, they identified ways to change their break-taking practices. P16 considered changing when he took breaks to spread them throughout the day: "*I have very few breaks after two o'clock. So I probably might be better off trying to even out my breaks more over the day.*" P28 found that "*it's pretty clear that the longer my break is, the more likely I am to not feel refreshed… I should keep my breaks a little shorter.*"

Participants mostly described changing the types of breaks that they took. P1 wondered, "*I feel like if I want to feel more refreshed, maybe I need to get up and walk around and not get sucked into technology.*" P20 identified that "*snack or drink [leaves me less refreshed] than I would expect it to be.*" He felt this was an opportunity for improvement: "*I could go back and maybe even make a change tomorrow… I'm not really getting a whole lot out of Diet Mountain Dew except 100mg of sodium and not enough caffeine.*" P20 decided at the end of the interview to try not drinking soda for the rest of the week. Participants found the visualizations describing types of breaks more actionable than the other visualizations (t_{107}=2.852, p=0.005, 95% CI 0.22-1.23 increase on a 7-point Likert scale). Participants also wanted visualizations that contained information beyond the breaks themselves, such as the specific task worked on, or their schedule. For example, P20 wished he "*had a better memory to see what my primary work task was*" on certain days of the study, while P13 thought, "*If I pulled up my calendar and saw what I was doing that week, that might be useful.*" This suggests that a system for tracking and visualizing breaks would benefit from data from sources such as a calendar or desktop logging.

DISCUSSION

We now discuss our findings and their design implications.

Implications for Break Logging Systems

As we have shown, there is no simple definition for what activities are breaks. System designers should thus not make assumptions about certain activities being breaks and other not. Moving to new locations like "break" rooms, bathrooms, or going outside cannot always be inferred as a break activity. Some people would take offense to seeing their bathroom use or personal email habits on a visualization of their breaks, while others may find this information enlightening and change their habits accordingly.

One limitation of our diary study (and similar lines of work) is that, while participants provided rich data for each break they took, we were unable to capture cases where a participant wanted to take a break but decided not to, or where a participant would have benefited from a break but did not even consider it. Indeed, capturing inaction (a choice not to make a phone call, not take a break, and not eat something you should not) is important, but nearly impossible. One possible way to log not-taking breaks would be that if a user did not take a break they normally do, the system could prompt them for the reason. This, however, would require a predictive system that uses breaks logged over time for initial training.

Implications for Break Recommendation Systems

The relationship between productivity before and after a break suggests that exploring the link between work tasks and break habits in detail is still necessary. Due to the large number of unique tasks descriptions by our participants, our models did not include individual work tasks. However, break recommendation systems should not only consider whether a work task is interruptible (as considered in prior work [2,14,19]), but also how work task influences what break activities might be more or less appropriate. While a short break remaining at a desk may preferred during a data entry task, people may seek a longer break away from their work environment in the midst of a creative task.

Implications for Availability and Interruptibility Research

One key finding from our work is the potential negative effect of disrupted breaks on productivity. Participants described breaks that are interrupted (for work, in person, etc.) as bad breaks that fail to provide the necessary reprieve from work. This finding is significant for the areas of understanding availability and disruption. Previous research has shown that people tend to overestimate the availability of another person [1] based on a range of cues that may be related to break taking (including standing, eating or drinking). This suggests that a person taking a break is more likely to be interrupted by another person. While the cost of interruption during work has been examined in depth [18,20,23,28], the cost of disrupting a break has been underexplored. Consider, for example, systems designed to predict good or bad moments for interruption (e.g., [2,14,19]) which will typically avoid interrupting a work task. These systems are often more likely to direct interruptions to a user when they are on a break, potentially eliminating the desired benefits of the break. Our work highlights the need to study the cost of disrupting breaks and to include this cost into a system's decision logic.

CONCLUSION

We contribute findings on what knowledge workers consider to be breaks and what they desire when they take a break. We report a model of break-taking behavior, surfacing break's effects on feeling relaxed and refreshed, feeling ready to work, and productivity. We finally present break tracking as a new direction for personal informatics in the workplace, developing 13 visualizations to help knowledge workers understand and act on their habits. Our work informs the design of future break logging and detection systems, research on availability and interruptability, and contributes to our understanding of knowledge worker's break habits.

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