Finding Kairos: The Influence of Context-Based Timing on Compliance with Well-Being Triggers

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Abstract. For healthy computer use, frequent, short breaks are crucial. This research investigated whether context-aware persuasive technology can identify opportune and effective moments (of high user motivation and ability to perform target behavior) for triggering short breaks fostering symbiotic interactions between e-Coaching e-Health technology and users. In Study 1, office workers rated their motivation and ability to take a short break (probed at random moments). Simultaneously their computer activity was recorded. Results showed that computer activity (time since last break; change in computer activity level) can predict moments of high and low (perceived) ability (but not motivation) to take a short break. Study 2 showed that when office workers received triggers (to take a short break) at moments of high (vs. low) ability (predicted based on computer activity), compliance increased 70%. These results show that context information can be used to identify opportune moments, at which persuasive triggers are more effective.

Keywords: Persuasive technology · Kairos · Triggers · Well-being · e-Health · e-Coaching

1 Introduction

In modern-day society, a large share of the workload has shifted from physical work to working with information [13]. Many employees gather, processes and produce information as their main task. While computers are useful tools for such knowledge workers, prolonged computer use can also lead to serious health risks [14]. Healthy working behavior is needed to guard the well-being of knowledge workers and reduce health risks. Taking regular short breaks, for instance, can help reduce the risks of repetitive strain injury [15] as well as sedentary behavior [16]. Various studies have investigated the advantages of taking short breaks (also called microbreaks) for computer workers, and characteristics of these breaks (see e.g., [17]). Research [17] shows that 30 s breaks

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from computer work have health benefits while not hampering productivity, and even improving work accuracy [18].

To help computer workers, the smart technology at which they incur risks can also be used to help them prevent it. That is, their systems can also function as e-Health technology [19] by functioning as an eCoach (see e.g., [20]), and help users adapt their behavior. Such technology would be Persuasive Technology [1–3], as it attempts to change user behavior or attitudes without coercion or deception [1, 24].

To influence human behavior, Persuasive Technology must influence determinants of behavior, and in psychological research various theories of behavior determinants have been proposed (e.g., the Theory of Planned Behavior [22], and the Motivation, Opportunity and Ability MOA model [23], see also [5], [6]). Comparable to other models, and directly applied to Persuasive Technology, Fogg's Behavior Model [2] proposed that Motivation and Ability determine the effectiveness of a persuasive trigger. Persuasive triggers (c.f., [2]) can have many different forms (e.g., text message, a sound, a growling stomach), and have in common that they can be successful in changing the user's behavior when noticed by the user, when user associates the trigger with performing the target behavior, and when the user is motivated and able to perform the target behavior.

In support of this model [2], earlier research [21] showed that appropriate localization of triggers (i.e., a manipulation of user ability to act on the trigger), and motivating contents of the trigger message (i.e., a manipulation of user motivation) influence trigger effectiveness. More specifically, in this earlier research, participants visited a virtual supermarket where product images were displayed on posters and in which triggers (to purchase a product) were presented either co-located with products (or not) and these triggers contained a motivating message (or not). Confirming hypotheses, triggers co-located with the target product led to higher sales of that product, especially when the trigger contained a motivating message. This research showed that manipulating ability and motivation (to perform the target behavior) by changing characteristics of the trigger influences trigger effectiveness.

However, trigger characteristics are only one determinant of user's ability and motivation to perform a target behavior. Perhaps even more crucial determinants of user ability and motivation can be found in the context in which behavior takes place. Characteristics of the user him- or herself, the use context, and the behavior, all have a strong influence on user ability and motivation. For example, the physical context of the user (e.g., being in a cold office) will have a dominant influence on user ability and motivation (e.g., to save energy for heating).

Therefore, in the current research we will investigate whether context information can be used to identify moments at which user motivation and ability are high, and triggering (to perform a target behavior) might be especially effective. We will focus on the use context, that is, on the variables that can be detected in the context of computer use by, specifically, computer workers. Context-aware persuasive technology might be able to identify opportune moments (at which a user's motivation and ability to perform the target behavior are high) for triggering, and use those opportune moments for effective influencing a target behavior. Thereby, this kind of technology can foster symbiotic interactions between e-Coaching e-Health technology and users, as it enables adapting output to the user regardless of his/her ability to explicitly refine his/her request (see [30], p. 4).

In two field studies, we investigated (Study 1) computer workers' motivation and ability to take a short break, their computer use context (e.g., mouse movements, keyboard presses), and (Study 2) the effectiveness of persuasive triggers to take a short break.

2 Study 1

Study 1 investigated whether context-aware technology can identify opportune moments (at which a user's motivation and ability to perform the target behavior are high). This question was investigated in the context of knowledge workers at a regular office of a research and consultancy organization. The computer activity of knowledge workers is an important part of their context, and the goal of Study 1 was to explore if this type of context could be used to predict their motivation and ability to take the desired behavior, in this case taking a short break. For this, these office workers rated their motivation and ability to take a short break (probed at random moments in time) during a working week, while simultaneously their computer activity was recorded. Data was collected using an experience sampling method [25], that consisted of two types of measures: (1) The levels of motivation and ability were gathered by asking the participants to periodically report ratings for these two factors. (2) Computer activity was recorded using key and mouse logger software on their computer system.

2.1 Methods

Participants. Six knowledge workers (as defined by [26]) participated in Study 1. All participants were employees or interns at a Dutch research and consultancy organization. The mean age of the participants (4 men and 2 women) was 27.8 years ($SD = 8.47$). All participants participated in the study without receiving any reward.

Materials. To collect the data, two software programs were installed on the participants' work computers. To collect data about the computer activity of the participants, a logger application was installed (uLog, developed by Noldus Information Technology for researchers in user-computer interaction to study computer activity behavior [27]). This software runs in the background and was used to record mouse activity (number of left clicks, right clicks, double clicks, wheel scrolls, drags, hovers; relative and total cursor distance travelled), keyboard activity (number of characters typed, special keys pressed, key combinations made and strings typed) and application activity (applications starts and exits, window switches performed). In light of privacy, no content or personally identifiable information was collected. For instance, keystrokes were recorded, but not which characters were typed.

The dataset collected by this computer activity logger software allowed us to calculate the various variables that were necessary to assess the predictive value of a user's computer activity for that user's self-reported ability and motivation to take a break. Of these variables, two variables showed to be predictors of user ability: A user's change in overall activity, and the time that a user worked since his or her last break. More specifically, to calculate a participant's change in overall computer activity, we divided the total number of events during the last 3 min by the total number of events during the last 30 s. To calculate the time that a user worked since the last break, we used the time passed after ending a period of no activity of at least 5 min.

To collect motivation and ability ratings from the participants, a self-report program was installed. This software (developed in Java) was BabylonA, which periodically administered the self-reports and recorded the responses. To ask users to rate their momentary levels of ability and motivation to take a short break, the software displayed a pop-up windows on the participant's screen (see Fig. 1).

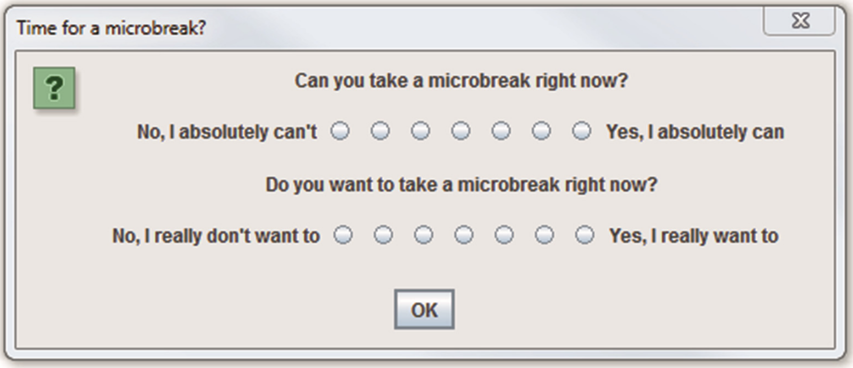

Fig. 1. The self-report pop-up question window.

To assess a user's (self-reported) ability to take a short break, the question "Can you take a microbreak right now?" was posed. Users could answers by clicking an option on a 7-point Likert scale (1 = No, I absolutely can't, to 7 = Yes, I absolutely can). To assess a user's (self-reported) motivation to take a short break, the question "Do you want to take a microbreak right now?"was posed. Users could answers by clicking an option on a 7-point Likert scale (1 = No, I really don't want to, to 7 = Yes, I really want to).

The software (BabylonA) automatically displayed these questions at random moments in time, although between two consequent pop-ups at least 20 min had to pass, and at least one pop-up had to appear every hour (to achieve optimal granularity in the data).

During the 7 workings days, participants answered the questions presented in pop-up windows 219 times (a response rate of 88%), but because (for unknown reasons) sometimes the computer activity logger application had not been running, 148 self-reports (of ability and motivation) were available for analyses. Participants' answers to the motivation and ability questions showed a positive correlation, $r(146) = .48$, $p < .001$.

Procedure. After agreeing to participate, a participant was asked to sign the informed consent form. Next, the logger application and the BabylonA application were installed on the participant's work computer. During each of seven working days, these two programs gathered data: the logger application recorded computer activity data, and the BabylonA application asked a participant for his or her ability and motivation to take a short break. After these seven days, the computer activity data and self-report response log files were collected from the computers, and the two software applications were de-installed from the participant's computer. Finally, participants were thanked for their participation and debriefed.

2.2 Results and Discussion

Results showed that a *participant's change in overall computer activity* was a significant predictor for that participant's ability rating (at that same moment in time), as indicated by a significant regression equation, $F(1,145) = 8.11$, $p = .005$, with an R^2 of .053 (a correlation of .23).

Also, results showed that the *time that a user had worked since his or her last break* was a significant predictor also for that participant's ability rating (at that same moment in time), as indicated by a significant regression equation, $F(1,137) = 16.981$, $p < .001$, with an R^2 of .110 (a correlation of .33).

A participant's change in overall computer activity and a participant's time worked since last break both are independent predictors of a participant's (self-reported) ability to take a break, as indicated by a multiple regression analysis, in which a participant's change in overall computer activity was a significant predictor (B = .084, SE = .030, Beta = .221, $t = 2.75$, $p = .007$) and also time worked since last break was a significant predictor (B = .008, SE = .002, Beta = .293, $t = 3.65$, $p < .001$).

Results provided no evidence of other relationships between a participant's computer activity and his or her ability, nor any evidence or predictive value of (elements of) a participant's computer activity and his or her motivation to take a break.

Thereby, the current findings show that participants' levels of ability (to take a short break) can be predicted using context-aware technology. That is, these results provide evidence that two context variables have predictive value for an office worker's ability to take a short break: the extent to which the user's overall computer activity has changed (during the last 3 min), and the time that has passed since the last time the user took a break (of more than 5 min).

Based on these findings, that allow identifying opportune moments (at which a user's ability to perform the target behavior is high), Study 2 investigated whether persuasive technology indeed is more effective when triggering user behavior change at such moments. So, Study 2 investigated whether a trigger to take a break would be more effective when it is presented longer after a person took his or her last break, and when it is presented right after a change in that person's overall computer activity level. Thereby, Study 2 investigated Fogg's Behavior Model [2] that proposed that (next to motivation) ability of the user to perform the behavior is a crucial determinant of the effectiveness of a persuasive trigger.

3 Study 2

To study this question, we conducted a field study in which office workers were presented with triggers (pop-up windows on screen) to take a short break. That is, their computer activity was measured, and based on the two variables identified in Study 1 (time since last break and change in overall computer activity), moments of high and low ability to take a break were identified. For each participant, half of the triggers to take a break was presented a such a moment of high (predicted) ability, and half of the triggers to take a break was presented at a moment of low (predicted) ability. We expected that triggers presented at moments of high (predicted) ability would be more effective than triggers presented at moments of low (predicted ability).

3.1 Methods

Participants and Design. Thirty-five knowledge workers (as defined by [26]) participated in the experiment. All participants were employees or interns at a research and consultancy organization (TNO), employees at an engineering consultancy company, or students at Eindhoven University of Technology. The mean age of the participants (27 men and 8 women) was 34.5 years ($SD = 12.3$). For their participation, participants received the chance to win one of three gift vouchers (of €25). All participants were presented with persuasive triggers at moments of high and of low (predicted) ability, as we manipulated this factor within participants.

Materials. As in Study 1, two software applications were used that were installed on each participant's desk computer. The application to record participant's computer activity was completely the same as in Study 1. It ran in the background, and recorded a participant's computer activity making available a dataset that was stored on the computer itself, and such that the other application could immediately use it for calculating the two variables (time since last break and change of computer activity) that are predictors of ability to take a break.

The application to present triggers to take a break to participants was developed in Java and purpose-built for this study. This application was context-aware technology, in the sense that it could read and responded to the logger application dataset in real-time. As described and identical to our procedures for Study 1, the application calculated a participant's change in overall computer activity by dividing the total number of events during the last 3 min by the total number of events during the last 30 s. To calculate the time that a user worked since the last break, it used the time passed after ending a period of no activity of at least 5 min.

To predict whether user ability would be high or low, and thereby whether a trigger to take a break should be presented or not presented, the application used thresholds for both variables. That is, based on analyses of the dataset of Study 1, this application determined that the current moment was a moment of *high* ability to take a break when both the time that had passed since the participant took a break was more than 30 min, or the participant's (current) overall level of computer activity had increased by 25%. Contrarily, this application determined that the current moment was a moment of *low* ability to take a break when both the time that had passed since the participant took a break was less than 18 min, or that the participant's (current) overall level of computer activity had decreased by 25%.

Each hour (but not within 3 min of the previous trigger) the application would present a pop-up window on the participant's screen with a trigger message to take a break (see Fig. 2). This pop-up window presented the text message "Time for a microbreak!" Participants click a button to accept (clicking a button labelled "Start!") or refuse this suggestion (clicking a button labelled "No, I can't right now", or a button labelled "No, I don't want right now"). If a participant clicked the button "Start!", That button disappeared and timer (counting down from 30 s) was shown in its place. This short break duration is the same as used by [28, 29].

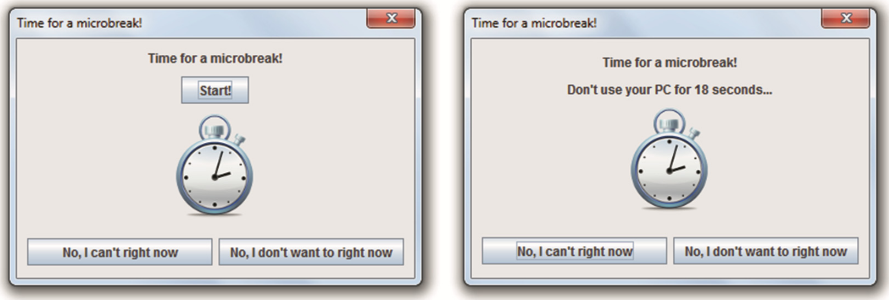

Fig. 2. The BabylonB pop-up in its initial state, as it was displayed to the participants (left) and in its state as after clicking the "Start" button (right).

To determine the moment in time at which a trigger would be displayed, at random moments in time, the application determined whether that moment was a moment of high or low ability for the participant to take a break using the two variables and their thresholds as described above. For all participants, half of these triggers (based on these thresholds) were presented at moments of (predicted) low ability, and the other half of these triggers were presented at moments of (predicted) high ability.

Overall, the persuasive trigger was presented to all participants 1007 moments, of which 420 times at a moment of high (predicted) ability and 587 times at a moment of low (predicted) ability. When participants took more than 15 s to respond to a persuasive trigger (i.e., press one of the button, see Fig. 2), we removed this response from the dataset. The reason for this is that we investigated the influence of using contextual information as ability predictor and during these 15 s the use context has changed. Also, some participants barely complied to the triggers (i.e., complied less than 6 times in total over the whole week at moments of both high and low (predicted) ability). As these participants basically had not participated in the study (and produced no data to analyze) we removed them from the dataset. After these two exclusion criteria, data from 29 participants were left to be used in the analysis.

The two dependent variables were reported compliance and actual compliance. We calculated (for each participant) the percentage of reported compliance by counting the number of times that participant clicked the 'Start!" button, and closed the window after the timer had finished, and dividing that number by the total of persuasive triggers that participant was presented with (separately for the high and low ability moment triggers). Likewise, we calculated a participant's percentage of actual compliance by checking for each reported compliance whether the logger data also indicated that the participant had not used his or her computer for 30 s (indicated by no keypresses and no mouse movement). Also this number we then divided by the total number of persuasive triggers that participant was presented with (at low and at high ability moments). Based on this analysis, we removed 52 responses (24 for the high ability condition, and 28 for the low ability condition) for which a participant has reported to start a short break but actually had continued using the computer.

Procedure. After agreeing to participate, participants were asked to sign the informed consent form. Also, each participant received a short document summarizing the procedure and presenting contact information of the researchers. Next, the logger application and the trigger presentation application were installed on the participants' work computer. During each of five working days, the logger application recorded computer activity data, and the trigger presentation application presented triggers to take a break. After these five days, the computer activity data and trigger presentation and response log files were collected from the computers, and two software applications were de-installed from all computers. Finally, participants were thanked for their participation and debriefed. The gift vouchers were randomly distributed after the experiment had finished.

3.2 Results

Confirming expectations, results showed that when a participant received a persuasive trigger at moments of high ability (predicted based on their current computer activity and an algorithm based on analyses of the dataset of Study 1) they showed higher percentages of reported compliance ($M = 47.03\%$, $SD = 29.27$) than when a participant received a persuasive trigger at moments of low (predicted) ability ($M = 28.90\%$, $SD = 27.14$), $t(28) = 4.17$, $p < .001$, *Cohen's d* = .64. The same was found for actual compliance: when a participant received a persuasive trigger at moments of high ability, percentages of actual compliance ($M = 43.72\%$, $SD = 30.16$) were higher than when a participant received a persuasive trigger at moments of low ability ($M = 25.51\%$, $SD = 26.90$), $t(28) = 4.15$, $p < .001$, *Cohen's d* = .64.

In other words, when these office workers received persuasive triggers (during their working week) at moments of high (vs. low) ability (predicted based on their current computer activity and an algorithm based on analyses of the dataset of Study 1), they performed the triggered behavior (taking a short break) about 70% more often (complying in 47.03%/43.72% versus in 28.90%/26.90% of the cases).

4 General Discussion

To investigate whether context-aware technology can identify opportune moments for influencing users using triggers (at which a user's motivation and ability to perform the target behavior are high), in Study 1, office workers rated their motivation and ability to take a short break (probed at random moments in time) during a working week, while simultaneously their computer activity was recorded. Results showed that moments of high and low (perceived) ability to take a short break can be predicted based on computer activity, while motivation could not be predicted. Two factors predicted perceived ability: time since last break, and change in overall computer activity level.

Investigating whether persuasive technology that triggers users is more effective when triggering user behavior change at such opportune moments (as identified by Study 1), Study 2 confirmed that when office workers received persuasive triggers (during a working week) at moments of high (vs. low) ability (predicted based on their current computer activity and an algorithm based on analyses of the dataset of Study 1), they performed the triggered behavior (taking a short break) about 70% more often.

Results of these two studies show that context information can be used to identify opportune moments for triggering specific behavior, and that persuasive triggers are more effective at those moments. Thereby, the current results confirm Fogg's Behavior Model [2] that proposed that (next to motivation) ability of the user to perform the behavior is a crucial determinant of the effectiveness of a persuasive trigger. Specifically, the level of ability can be used to help define what is an opportune moment, or *Kairos* (see [1]). They also confirm the theory by Fogg [2] that triggering at such an opportune moment leads to higher compliance with the target behavior.

This finding is also in line with research evidence that backs up comparable models of behavior determinants, as for example the Motivation and Opportunity as Determinants (MODE) model proposed by Fazio [4], or the Ability-Motivation-Opportunity frameworks (see e.g., [7], and also [23]). Importantly, the current research presents evidence specifically for the effectiveness of triggers by persuasive technology and thereby presents evidence in direct support of Fogg's model.

Future research can study whether use context information may be used to predict motivation to comply too. Although the current research presented evidence for a strong correlation (of .48) between user motivation and ability (to take a short break – see Study 1), future research might also developed new measures to assess user motivation and ability in ways that allow more distinction between the two concepts. Thereby, future research could study both the value of (predicted) ability and motivation for the effectiveness of persuasive triggers, and future studies could even further separate ability and opportunity. Also, future research might investigate the current research question in other and larger populations, studying the importance of interpersonal differences. Another important question is the relationship between a person's inclination to take a break and his or her actual acceptance of the trigger's message. Study 2 could not explicitly assess this inclination as such explicit assessment could have interfered with a participant's naïve motivation (or ability) to take a break. Future research might attempt to tap into this inclination without influencing users (e.g., by measuring bodily signs of tiredness) at the same time as presenting users with persuasive triggers to take a break.

The results of Study 1 and Study 2 also provide evidence for the value of context information for the timing of persuasive technology. This is in line with the expectations of authors such as Munson [7] and IJsselsteijn et al. [8], who described supposed advantages of context awareness for delivering persuasive health messages.

Besides computer activity, many other types of contexts exist. Distinctions might be made between the physical context of a user (e.g., in a hot or a cold office), the social context of a user (e.g., among friends or at the office), the mental context of a user (e.g., busy), and the user's computer use context (e.g., indicated by variables indicating computer use).For example, information about a person's cognitive load, the amount of mental effort needed to perform a task [9], could be of great value for estimating the extent to which users might be influenced, or for understanding how a user should be approached. It is easy for people to see whether their coworkers can be disturbed during a task, and technology can also be improved by being able to determine this. As Hudson et al. [10] put it, "as adults, we can typically assess someone's interruptibility very quickly and with a minimum of effort", yet computers are "almost entirely oblivious to the human context in which they operate and cannot assess whether 'now is a bad time'".

The current research makes clear that software that helps users prevent negative side-effects of repetitive movements (anti-RSI software) could present more effective persuasive triggers when taking into account the opportunity of the moment based on computer use context. Presenting triggers at the wrong moment in time, might not lead to compliance, or lower levels of compliance. Recent research suggested that using the wrong persuasive strategies might even lead to reactance effects causing users to become angry towards the persuasive technology, and even show behavior that opposes the target behavior [11].

As occupational computer use grows, so do the risks of negative health consequences due to repetitive strain injury and sedentary behavior. These risks are already widespread today, but they can be reduced by healthy working behavior. One habit that can decrease the health risks associated with both repetitive strain injury and sedentary behavior, is taking frequent short breaks during work. Encouraging such behavior with persuasive technology has several advantages, such as availability and scalability of such interventions.

The current research showed that (computer use) context information can be used to identify the best moment to present persuasive triggers, and presented evidence for the importance of appropriate timing for the effectiveness of persuasive technology. It shows how persuasive technology can function in symbiotic interaction with its user by combining computation, sensing technology, and interaction design to realize understanding between humans and computers (see [30], p. 11). Next to stimulating healthy working behavior reducing health risks associated with computer use, these insights can also help making persuasive technology (e.g., on-screen triggers) more effective for e-Coaching other kinds of behavior as for example health-related behavior pertaining to diabetes, nutrition, weight loss, and quitting smoking. Context-aware persuasive technology is a form of tailored persuasive technology, just as personalized persuasive technology (see e.g., [12]) is tailored to characteristics of people.

Insights into context-awareness increases understanding of tailoring persuasive technology (to user, user and use context, and even to affordances of the persuasive technology itself, see [21]), and thereby of maximizing the persuasive power of technology.

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