

MASTER

A matter of time

the influence of context-based timing on compliance with well-being triggers

van Schendel, J.A.

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ABSTRACT

As occupational computer use grows, so do associated risks of negative health consequences. Repetitive strain injury and sedentary behavior are prevalent among computer users and both are associated with serious health risks. These risks can be minimized by healthy working behavior. One way to decrease the health risks associated with both of these conditions is taking short, frequent breaks during work, which are called microbreaks. Encouraging such behavior with persuasive technology (PT) has several advantages. Among the advantages are the availability and scalability of such interventions.

Literature suggests that influencing people at the right time is critical to ensure the effectiveness of PT. Additionally, researchers have claimed that if a technology is aware of context, it should be able to identify such opportune moments and thereby increase compliance with the target behavior. An opportune moment to persuade, according to the Fogg Behavior Model, is one where the subject's motivation and ability to perform the target behavior are at a high level. As such, a technology that tries to persuade knowledge workers to take microbreaks, should be able to determine when the motivation and ability of those workers to take a microbreak are at a high level. However, there appears to be a lack of empirical evidence for the Fogg Behavior Model, as well as for the claims of the importance of timing for PT and the usefulness of context information in determining opportune moments.

The current research presents two studies. The first study was performed to assess whether context information (the computer activity of knowledge workers, such as the number of mouse clicks and key presses) can be used to make inferences about the level of motivation and ability to take a microbreak (e.g., overall computer activity is high, therefore the worker is too busy to take a microbreak). Six knowledge workers rated their level of motivation and ability to take a microbreak at different points in time, over the course of seven working days. Simultaneously, their computer activity was recorded. Confirming our expectations, the results show that moments of high and low (perceived) ability to take a microbreak can be partially predicted based on computer activity. More specifically, it can be based on two factors: the time since their last break and the change in their overall computer activity level. The level of motivation, on the other hand, could not be predicted based on computer activity.

Next, the second study assessed whether presenting persuasive triggers at times of high ability leads to higher compliance, compared to times of low ability. A within-subjects experiment with 35 knowledge workers was carried out over the course of five working days. Each participant was subject to two conditions: triggers presented at times of high estimated ability and low estimated ability. The conditions were interactive and based on the current computer activity of the participants. Specifically, they were based on the two contextual factors described above.

The results show that presenting triggers to take a microbreak at moments of high ability led to higher compliance with the target behavior than presenting triggers at moments of low ability. Average compliance (reported and actual) in the high ability condition was approximately 18 percentage points higher than in the low ability condition.

As such, the results provide support for the Fogg Behavior Model. The current research shows that compliance with the target behavior of a persuasive technology is significantly higher if triggers are presented at a moment of high (self-rated) ability to perform that behavior, as the Fogg Behavior Model describes. The research also provides supportive evidence for the importance of timing for persuasive technology in general, as well as the usefulness of context information for determining opportune moments to persuade. For knowledge workers specifically, qualitative information is presented that describes their preferences about microbreak timing.

Finally, theoretical and practical implications of the results are discussed, as well as possibilities for future research. The results of the current research are not only of value for the well-being of knowledge workers, but also for the many other areas in which persuasive technology is used.

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1. INTRODUCTION

In modern-day society, a large share of the workload has shifted from physical work to working with information (Statistics Netherlands, 2001; Wolff, 2005). A large share of all employees gathers, processes and produces information as their main task. While computers are useful tools for such knowledge workers, prolonged computer use can also lead to serious health risks.

Healthy working behavior is needed to guard the well-being of knowledge workers and reduce health risks. Taking regular breaks, for instance, can help reduce the risks of repetitive strain injury (Galinsky, Swanson, Sauter, Dunkin, & Hurrell, 2007) as well as sedentary behavior (Healy et al., 2008b). Encouraging such behavior with technology has several advantages, because such interventions can be available at all times and are easily scalable. Technology that tries to change the attitudes or behavior of people is called persuasive technology (Fogg, 2002).

As will be discussed in this introduction, several aspects are supposedly required to assure the effectiveness of persuasive technology. One of these is timing, which in turn is dependent on the context of the person that is subject to the persuasive technology. Literature suggests that if a technology is aware of context, it can identify appropriate moments to persuade people to change their behavior. Persuading at such opportune moments should lead to higher compliance with the target behavior. However, there is a lack of evidence to support these suggestions. Even if they are valid, earlier research has not specified what constitutes appropriate timing. It also remains unclear whether technology can identify opportune moments using context information.

If context-aware persuasive technology can indeed identify opportune moments to persuade knowledge workers to take regular breaks, those workers might be more inclined to change their behavior. And if their behavior changes, health risks due to the nature of their work may be reduced.

This chapter further explains the motivation for this research and describes the relevant research areas in more detail. It also lists the research questions and hypotheses.

1.1 *SWELL*

This research is part of the *SWELL* project, which stands for Smart Reasoning Systems for Well-Being at Work and at Home (TNO, 2015), which is in turn part of a Dutch national research program called *COMMIT* (COMMIT, 2015). The goal of the *SWELL* project is to “improve the well-being at work of knowledge workers”, where knowledge workers are defined as “people who use and produce information as their main task” (Janssen & Van Hall, 2013).

The project’s methodology is described as “the gathering of information on the physical and mental state and context of the knowledge worker, interpret this information and, through

smart reasoning, provide feedback and advice on how to improve well-being” (Janssen & Van Hall, 2013).

As part of the SWELL project, the current research focuses on well-being at work for knowledge workers.

1.2 Knowledge workers

Since the current research focuses on improving the well-being of knowledge workers, it is important to identify what well-being means for this type of worker. If the risks associated with knowledge work can be identified, ways to decrease those risks can be discussed. To investigate knowledge worker well-being, a clear description is needed of who knowledge workers really are.

One way to define knowledge workers is to contrast the nature of their work with manual work. This is what Drucker (1993) did when he described them as the worker “who puts to work what he has learned in systematic education, that is, concepts, ideas and theories, rather than the man who puts to work manual skill or muscle”.

Some authors assume a broad definition of knowledge workers, such as Thomas and Baron (1994), who regard them as “professionals who use information as their main input and whose major products are distillations of that information”, or Sellen, Murphy, and Shaw (2002), who define them as people “whose paid work involves significant time: gathering, finding, analyzing, creating, producing or archiving information”. Others are in search of a more specific definition, such as Kidd (1994), whose study results “suggest that the defining characteristic of knowledge workers is that they are themselves changed by the information they process”. This last definition contrasts knowledge workers with other office workers such as communications workers, who collect and pass on information, and clerical workers, who “apply information which is extrinsic-to them and which does not change (i.e. inform) them, e.g. company policies” (Kidd, 1994).

Much like Thomas and Baron (1994), the SWELL project defines knowledge workers as “people who use and produce information as their main task” (Janssen & Van Hall, 2013). However, no matter the definition, the processing of information is a defining feature.

At present, the main way to access, process, produce and publish information is by using a computer. In 2014, 70 percent of all employees in the Netherlands made use of computers and 65 percent of all employees made use of the internet (Statistics Netherlands, 2014). Moreover, 100 percent of all companies in the Netherlands with ten or more employees had an internet connection (Statistics Netherlands, 2014). Due to the information-processing nature of knowledge work, computer use is routine for knowledge workers. Although computers can be helpful, their use can also lead to several health risks. Two of the risks associated with computer use will be described in more detail. These are repetitive strain injury and sedentary behavior.

1.3 Repetitive strain injury

Computer use has a number of aspects that can result in health risks. Typically, working on a computer involves holding a static posture, a fixed focal distance, sustained muscle tension (holding a mouse) and repetitive movements (typing on a keyboard or regularly switching between keyboard and mouse). These aspects can become a source of negative health syndromes, importantly repetitive strain injury (Blatter & Bongers, 2002; Lim, Sauter, & Schnorr, 1998).

Repetitive strain injury (RSI) is not a single condition, but rather an umbrella term for disorders that “develop as a result of repetitive movements, awkward postures, sustained force, and other risk factors” (Yassi, 1997). These disorders are various and can be related to tendons (e.g., tendonitis), muscles (e.g., fibromyositis), joints, peripheral-nerve entrapment (e.g., carpal tunnel syndrome) and vascular syndromes (Yassi, 1997). This is why RSI can negatively affect many parts of the human body, ranging from the back, neck and shoulders to the hand, wrists, elbows, knees and ankles. Symptoms of RSI include stiffness, numbness, tingling sensations, loss of strength, loss of coordination and general pains in any of the mentioned parts of the body (Health Council of the Netherlands, 2000). The term RSI is controversial and is sometimes interchanged with the terms cumulative trauma disorder (CTD) or musculoskeletal disorder (MSD) (Van Tulder, Malmivaara, & Koes, 2007).

Occupational RSI is widespread and costly. Estimates of the prevalence of RSI among the Dutch working population range from 19 percent to 42.8 percent (Health Council of the Netherlands, 2000). Moreover, repetitive hand or arm movements among workers is increasingly common. An overview report of the Fifth European Working Conditions Survey reported not only that “exposure to repetitive hand or arm movements is by far the most prevalent risk, with 63 percent of workers reporting they have to carry out repetitive hand or arm movements at least a quarter of the time”, but also that this risk “unfortunately shows an upward trend” (Parent-Thirion et al., 2012). A study commissioned by the Dutch Ministry of Social Affairs and Employment estimated the total yearly costs due to RSI at 2.1 billion euro (Blatter et al., 2005) for the Netherlands alone.

RSI is common among computer workers. For example, Klussmann, Gebhardt, Liebers, and Rieger (2008) found a prevalence among German computer workers of 55 percent for symptoms of the neck and 38 percent for symptoms of the shoulder. Matias, Salvendy, and Kuczek (1998) cited an 8–38 percent incidence rate of carpal tunnel syndrome among computer workers, compared to 5–6 percent of “manufacturing industrial workers involved in manual repetitive tasks”. Moreover “the prevalence and severity of symptoms are significantly correlated with the amount of time spent performing computer tasks” (Galinsky et al., 2007). Women show increase risk compared to men with extended computer use (Blatter & Bongers, 2002).

For the Netherlands, a study by Blatter, Bongers, Kraan, and Dhondt (2000) found that 30.8 percent of secretaries and typists reported RSI complaints. Additionally, Massaar (1998) reported prevalence rates among Dutch “screen workers”, who are employees that spend more than two hours per day working in front of a computer screen. It appeared that 47 percent of these workers sometimes experienced complaints of the neck, shoulders, arms, fingers or wrists,

while 9 percent had these complaints often. The percentage of workers who often had complaints increased with the number of hours they spent working in front of a screen. 82 percent of all of them attributed their complaints to their computer work.

RSI can be treated in a range of different ways. Treatments that are commonly applied include exercise therapy, physical therapy, ergonomic measures, frequent rest breaks, exercise or a combination of these (Van Tulder et al., 2007).

Ergonomic adjustments can be made to the setup of work stations to reduce some of the symptoms of RSI. However, as Galinsky, Swanson, Sauter, Hurrell, and Schleifer (2000) explain, research has shown that such ergonomic measures “[do] not appear to be sufficient for completely eliminating work-induced discomfort, and in some cases, discomfort has been virtually unaffected by ergonomics interventions”. They refer to research by Winkel and Oxenburgh (1991), who “noted that since constrained shoulder/neck postures are inherently characteristic of VDT [video display terminal] work, prolonged static contractions in these muscles are probably not preventable through workstation design changes” (Galinsky et al., 2000). Instead, there is a possibility that neck and shoulder discomfort “might be relieved only by changes in work organization such as task rotation or increased rest breaks, which allow for periodic interruptions of the VDT task” (Galinsky et al., 2000).

A number of researchers have shown the benefits of taking rest breaks. Henning, Sauter, Salvendy, and Krieg (1989) found them to be “instrumental in reducing fatigue and associated performance decrements” for data entry tasks. A study by McLean, Tingley, Scott, and Rickards (2001) also looked at “keying and data entry tasks” and found a “beneficial effect of regularly scheduled ‘microbreaks’ on subjective discomfort ratings at the neck, the low back, the shoulder, and the forearm/wrist areas”. Also, the researchers found that “the introduction of a microbreak strategy had increased benefit as the duration of the computer terminal work increased”.

Researchers from the U.S. National Institute for Occupational Safety and Health summarized earlier research as follows: “Restriction of rest break opportunities during computer work has been identified as a significant risk factor for musculoskeletal symptoms and injuries. By contrast, muscle tension and discomfort are reduced, and psychophysiological arousal is increased, immediately following rest breaks.” (Galinsky et al., 2007). Their own research compared a conventional break schedule with a supplementary one, which added 5-minute breaks every hour. They found that “increases in discomfort of the right forearm, wrist and hand over the course of the work week under the conventional schedule were eliminated under the supplementary schedule” (Galinsky et al., 2000) and that “in addition to their positive effects on musculoskeletal discomfort, supplementary rest breaks also reduced eye soreness and visual blurring” (Galinsky et al., 2007).

In summary, RSI symptoms are widespread among computer workers. Although the consequences of RSI are prevalent and costly, different measures can be taken to reduce or prevent the associated health risks. One of the measures that is shown to be beneficial is taking regular breaks during computer use.

1.4 Sedentary behavior

Extended computer use typically results in extended periods of sitting down. However, sitting for extended periods of time has also been connected with negative health consequences.

Sitting in front of and working on a computer is an example of *sedentary behavior*, which is defined as “any waking behaviour characterized by an energy expenditure ≤ 1.5 METs while in a sitting or reclining posture” (Sedentary Behaviour Research Network, 2012). MET stands for Metabolic Equivalent of Task and 1 MET corresponds to lying down and doing nothing. For comparison, the energy expenditure of walking ranges from 2 to 3 METs, bicycling to work is 4-6 METs and running (at 8 km/h) is equivalent to 8 METs (Ainsworth et al., 2000).

Sedentary behavior is not the same as being inactive. Being inactive signifies a lack of physical activity in general and the term is used to describe people who do not meet physical activity guidelines, such as those set by the World Health Organization (World Health Organization, 2010).

The adverse health consequences of sedentary behavior are various. Self-reported sedentary time is associated with obesity (Foster, Gore, & West, 2006; Hu, Li, Colditz, Willett, & Manson, 2003), cardiovascular disease (Jakes et al., 2003), depression (Teychenne, Ball, & Salmon, 2010), cancer (Lynch, 2010), abnormal glucose metabolism (Dunstan et al., 2007, 2005, 2004) and metabolic syndrome (Bankoski et al., 2011). Metabolic syndrome is in turn associated with a higher risk of developing health issues such as cardiovascular disease and diabetes. Some researchers have also linked objective (as opposed to self-reported) measures of sedentary behavior to markers of metabolic risk (Ekelund, Griffin, & Wareham, 2007; Healy et al., 2008a, 2007).

Prolonged sitting was also found to be a risk factor for all-cause mortality (van der Ploeg, Chey, Korda, Banks, & Bauman, 2012). The association “appeared consistent across the sexes, age groups, body mass index categories, and physical activity levels and across healthy participants compared with participants with preexisting cardiovascular disease or diabetes mellitus” (van der Ploeg et al., 2012).

It is crucial to note that the risks of sedentary behavior are independent of physical activity, as can be seen in the results of, for instance, van der Ploeg et al. (2012). This means that even people who reach their weekly dose of exercise are still at risk. An active person who performs intensive training three times a week, but mostly sits during work or at home, is therefore open to the same risks. Thus, if one wants to reduce the risks associated with sedentary behavior, then that behavior has to be addressed directly.

Reducing sedentary behavior can be done by simply avoiding prolonged periods of sitting (Owen, Bauman, & Brown, 2009). Light activity such as walking around the office is enough to achieve an energy expenditure of over 1.5 METs, the upper limit of sedentary behavior. Authors such as Healy et al. (2008b) have shown the beneficial effects of taking regular breaks. They used accelerometers to measure the sedentary time of 168 participants, as well as the number of breaks they took. Their results showed that “independent of total sedentary time and moderate-to-vigorous intensity activity time, increased breaks in sedentary time were beneficially associated

with waist circumference, BMI, triglycerides and 2-h plasma glucose”, which are four markers of metabolic syndrome.

In conclusion, sedentary behavior presents serious health risks for knowledge workers. At the same time, prevention is relatively simple. Taking regular breaks can help reduce the risk of adverse health effects.

1.5 Microbreaks

So, both repetitive strain injuries and sedentary behavior present serious health risks for knowledge workers. Fortunately, the simple act of taking regular breaks can help to lower some of these risks.

Research by Rohmert (1973) studied the recovery effects of breaks. He found that “within the first half of the break period, fatigue will be diminished not to half of its worth but to a quarter or less”. Thus, a relatively large amount of the beneficial effects of a break can be gained in a short period of time. He also found an exponential increase of fatigue during work, meaning that it is better to have breaks sooner during work. These two findings led him to recommend “short breaks and often”, which “ensures short working periods with a small average degree of fatigue as well as the frequent experience of the high rate of recovery at the beginning of a break”.

Such short and frequent breaks are called *microbreaks* or *micropauses*, to distinguish them from for instance lunch breaks. Although extended research has been done on microbreaks and recovery, there is no consensus on their optimal duration or distribution. Some have used microbreaks only minutes apart (Byström, Mathiassen, & Fransson-Hall, 1991; van den Heuvel, de Looze, Hildebrandt, & Thé, 2003), while others used intervals of 20 and 40 minutes (McLean et al., 2001) or intervals of one hour (Henning, Jacques, Kissel, Sullivan, & Alteras-Webb, 1997). As for the duration of microbreaks, Henning et al. (1989) found that when workers could decide for themselves when to resume their tasks, their microbreaks lasted an average of 27.4 seconds. Based on this result, McLean et al. (2001) also decided to use a microbreak length of thirty seconds.

Rohmert (1973) already understood that if microbreaks were to be more widely adopted, they could not hamper worker productivity. As McLean et al. (2001) described, “when told to take frequent breaks throughout the work day, many workers fear that this will impact negatively on their work, or that it will impact on their manager’s (or co-workers’) perception of their effort”. Moreover, they pointed out that “if breaks are regimented, this may result in added stress due to frequent work interruption”. However, the findings of Rohmert (1973) confirmed that there is a point where the productivity gains from breaks would grow larger than the time lost to breaks. Thus, breaks can be organized in such a way that they can in fact increase overall productivity.

Later research confirmed these results. McLean et al. (2001) not only found that microbreaks had a “positive effect on reducing discomfort in all areas studied during computer terminal work”, but also that they “showed no evidence of a detrimental effect on worker productivity”.

Results by Galinsky et al. (2007) provided “further converging evidence that supplementary breaks reliably minimize discomfort and eyestrain without impairing productivity”. Their conclusions were that “data-entry speed was significantly faster with supplementary breaks so that work output was maintained, despite replacing 20 min of work time with break time”.

Furthermore, van den Heuvel et al. (2003) studied the effects of regular breaks on productivity and work-related neck and upper-limb disorders. They studied 268 computer workers over 8 weeks and not only found that regular breaks contributed to the perceived recovery of such disorders, but also that they led to an increase in productivity. The number of key strokes and the typing accuracy rate was “significantly higher in the intervention group with breaks [...] than in the control group”. This could be due to the reduced performance of a person who continues working without regular breaks: the number of delete key strokes was found to be “much higher in the control group than in the intervention groups”.

1.6 *E-health and e-coaching*

As mentioned before, the focus of the SWELL project is to “prevent negative long term consequences of (dis)stress by means of recovery” (Koldijk, 2014) and it tries to do so with the use of technology. An example could be a technology that helps knowledge workers to take regular breaks. In fact, such technologies already exist in different forms. Applications such as Workrave (Workrave, n.d.) and WorkPace (Wellnomics, n.d.) are designed to help computer users prevent RSI symptoms. Technologies such as these, which have the aim of improving people’s health, are called e-health applications.

E-health or eHealth is a general term and refers to any kind of ICT application used for healthcare (Gaddi, Capello, & Manca, 2014). E-health applications have received considerable amounts of interest due to the rise of ICT in general and the aging society in Western countries. For instance, it is predicted that a quarter of the Dutch population will be 65 years or older in 2030 (Alpay, Henkemans, Otten, Rövekamp, & Dumay, 2010). Additionally, “recent Dutch reports indicate that the number of people with chronic conditions will continue to rise, whereas the number of healthcare professionals will decrease” (Alpay et al., 2010; Blokstra et al., 2007). As such, greater strain will be placed on existing healthcare systems. Because the goals of e-health are “to improve health, efficiency and productivity in healthcare delivery, and the economic and social value of health” (Currie & Seddon, 2014), it is hoped that e-health can help with the increasing demand for healthcare.

One of the promises of e-health is that it can enable increased self-management for patients. For instance, patients could make use of a personal health record (PHR) system, to manage and share personal health data, or a personal computer assistant, “who provides patients with interpretation and guidance relating to the information from the PHR” (Alpay et al., 2010). That latter type of system is also referred to as an e-coach. Ideally, e-coaches help patients to be more self-sufficient and healthcare organizations to reduce costs, especially for chronic conditions. E-coaches can take on different forms, from simple text-based web interfaces to persuasive robotic assistants (Blanson Henkemans et al., 2009; Looije, Neerinx, & Cnossen,

2010). Examples are e-coaches that have been designed to provide computer-tailored physical activity and nutrition education (Kroeze, Werkman, & Brug, 2006), to deliver weight loss programs over the internet (Tate, Wing, & Winett, 2001), to help smokers quit using automatic e-mails, (Lenert, Muñoz, Perez, & Bansod, 2004) and to guide diabetes patients with text messaging (Franklin, Greene, Waller, & Greene, 2008).

One thing that e-coaches have in common is that they try to change the attitudes or behaviors of patients in order to improve their well-being. This means that such health technologies meet the definition of a persuasive technology (Chatterjee & Price, 2009; Fogg, 2002; Lehto, Oinas-Kukkonen, Pätäälä, & Saarelma, 2013). The research field of persuasive technology has developed frameworks for the design and analysis of such technologies. The existence of such frameworks makes it possible to investigate persuasive technologies in a scientific manner.

1.7 *Persuasive technology*

Persuasion has been defined as “the name we give to the type of communication that brings about change in people” (Bostrom, 1983). No longer are human beings the only ones making use of this type of communication: e-coaches are examples of technologies that try to bring about change and influence people. Accordingly, in his seminal work, Fogg (2002, p. 15) defines technology as being persuasive when it makes “an attempt to change attitudes or behaviors, without using coercion or deception”.

Fogg (2002) lists six advantages that persuasive technologies have over human persuaders. To start with, he explains that “no human can be as persistent as a machine”, since machines do not “get tired, discouraged or frustrated” and do not need to eat or sleep (Fogg, 2002, p. 7). Additionally, they can allow for increased anonymity, since people’s data is saved and interpreted by a machine and not by another human being. Other advantages are that technology can process large volumes of data, can make use of many modalities including video and hyperlinked content, can be easily scaled and that they can become ubiquitous (Fogg, 2002).

Many of these advantages are important when it comes to behavior change for health. For instance, anonymity is important since health information can be highly sensitive. Moreover, encouraging behavior such as taking regular breaks throughout the day would require a human persuader to be present all day long. This is a much more realistic task for technology. Lastly, technologies such as personal computers and smartphones are already ubiquitous in the lives of many people. Such devices are integrated into people’s lives, making them a convenient option for persuasion.

Today, many examples of persuasive technologies exist. They are used and studied in various domains, such as health (Fujinami & Riekkö, 2008; Maheshwari, Chatterjee, & Drew, 2008; Toscos, Faber, An, & Gandhi, 2006), e-commerce (Saari, Ravaja, Laarni, Turpeinen, & Kallinen, 2004), online communities (Fogg & Eckles, 2007), safety (Chittaro, 2012), energy conservation (Midden & Ham, 2008) and IT security (Forget, Chiasson, van Oorschot, & Biddle, 2008). Within the domain of health, their goals range from maintaining exercise regimens (Lacroix, Saini, & Goris, 2009) to quitting smoking (Räisänen, Oinas-Kukkonen, & Pahlila, 2008).

Fogg (2009) theorizes that “for a target behavior to happen, a person must have sufficient motivation, sufficient ability, and an effective trigger”. A trigger is the stimulus to encourage the desired behavior. Fogg (2009) suggests that the trigger has the highest chance of succeeding when it is given at a time when the subject’s motivation and ability to perform the target behavior are at a high level. Fogg (2002, p. 41) also refers to this “opportune moment” as *kairos*.

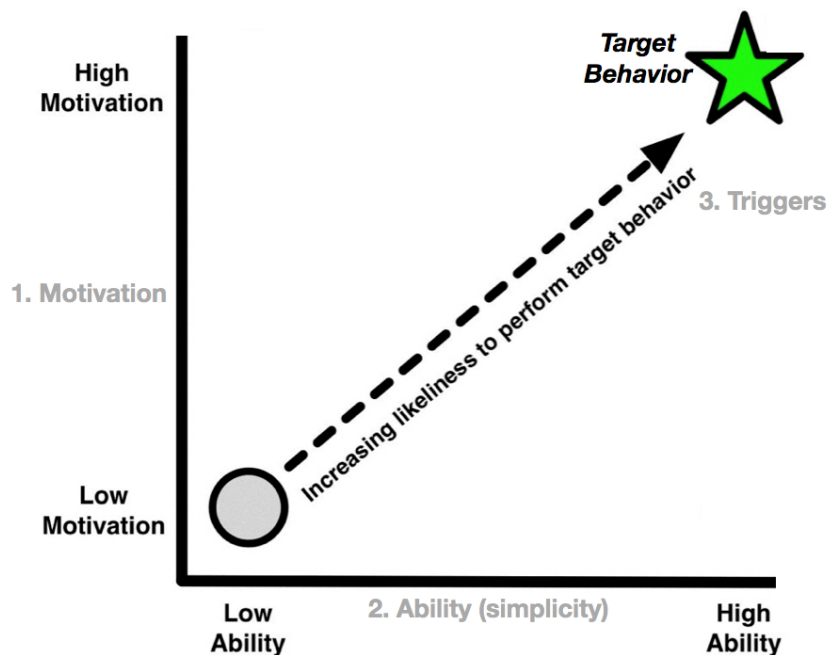


Figure 1.1: The Fogg Behavior Model (Fogg, 2009)

The three factors of *motivation*, *ability* and a *trigger* are summarized graphically in Figure 1.1, which shows the Fogg Behavior Model (Fogg, 2009). As can be seen in the figure, Fogg theorizes that when motivation and ability increase, so does the likeliness that the target behavior is performed. He also warns for the consequences if one of the two conditions is not satisfied: “When our motivation is low for that behavior, a trigger is distracting. Conversely, when we want to perform the behavior being triggered but lack ability, we feel frustrated.”

1.8 Suggestion technology and timing

One of the types of persuasive tools listed by Fogg (2002) is suggestion technology, which is “an interactive computing product that suggests a behavior at the most opportune moment” (Fogg, 2002, p. 41). A suggestion technology could, for instance, suggest to a knowledge worker that they should take a microbreak. For suggestion technology to be effective, “timing is critical” (Fogg, 2002, p. 43). Making use of the right timing means “creating a decision point at or near the time when it’s appropriate to take action”. However, the author goes on to state that there is no foolproof way to select such an appropriate moment: “in reality, the timing issues

in persuasion are not easily reduced to guidelines” (Fogg, 2002, p. 43).

As mentioned before, *kairos* is the term used for such opportune moments to persuade. One of the few studies that investigate *kairos* is the study by Räsänen et al. (2008), tried to determine *kairos* for quitting smoking. The researchers showed participants “pictures related to the dangers of smoking” and then asked the participants to rate how strongly they felt they were affected by the pictures. One of their conclusions is that, in this case, the closer to *kairos*, the larger the reported the effect of the pictures. However there seem to be a number of flaws in the study. First, the researchers used subjective ratings by the participants, by asking them how strongly they felt they were affected by the pictures. Their ratings may not correspond with their eventual actions. Second, the study seems to show a type of circular reasoning. The moment of *kairos* was determined by looking at when the reported effect was the highest, therefore it is only logical that the reported effect was highest at those moments. In conclusion, while Räsänen et al. (2008) underline the importance of *kairos*, they provide no further insight into how *kairos* can be determined.

Previous research in the SWELL project also presented evidence for the importance of timing. Wabeke (2014) used a custom-made e-coach mobile phone application to assess the effectiveness of a recommender system. The interactive software gave knowledge workers tips and recommendations throughout the working day with the aim of improving their well-being. Although the e-coach software was received positively, not all of the tips were executed. Of the tips that were rejected, 60 percent was rejected “because the moment of recommendation was somehow inappropriate” (Wabeke, 2014).

To assure the effectiveness of persuasion, the timing of persuasive triggers has to be optimized. However, timing is dependent on other factors. According to Fogg (2002, p. 43), “timing involves many elements in the environment [...] as well as the transient disposition of the person being persuaded”. Such “information that can be used to characterize the situation” is called *context* (Dey, 2001).

Illustrating the opportunities of involving context, Wabeke (2014) concludes by saying that “we also see opportunities for adopting context-aware algorithms”. Other authors have also underlined the importance of context-awareness for delivering health-related instructions. Munson (2012), for instance, discusses some of the challenges involved in designing persuasive systems for health. His view is that “mobile and context aware systems can still help us deliver tailored messaging, at the right time and right place”. IJsselsteijn, de Kort, Midden, Eggen, and van den Hoven (2006) spot similar opportunities for persuasive technology in healthcare. They predict that “new sensor technologies and algorithms that allow for context-aware computing, will make it possible to [...] deliver appropriate persuasive health-related messages to that person at the right time”.

Although very little literature could be found on the subject of context and persuasive technology, there are relevant studies in the related field of *interruptibility*. While this is not the same as persuasion, it might be helpful in determining moments when a persuasive trigger is not seen as disruptive and thus better received, possibly leading to higher compliance. For instance, Ho and Intille (2005) looked at determining interruptibility based on context information. The

hypothesis of Ho and Intille (2005) is that “prompts from mobile devices may be perceived as less disruptive if they are presented at times when the user is transitioning between different physical activities”, because they argue that “when physical transitions occur, mental transitions are also likely”. Participants carried wireless accelerometers to sense physical activity transitions, such as going from sitting down to standing up. Then, a piece of software interrupted participants “once every 10-20 minutes throughout the day, either randomly or at an activity transition” (Ho & Intille, 2005). The researchers concluded that “messages delivered at activity transitions were found to be better received” (Ho & Intille, 2005).

Another study that looked at interruptibility was done by Hudson et al. (2003), who tried to predict the interruptibility of office workers. They prompted their participants at 672 different times, asking them to rate their current interruptibility. Meanwhile, they recorded video and audio material of the participants. This material was later coded to simulate possible sensors. Among other things, data was collected about what the participants were doing and who was present. They conclude that their results are “quite promising” and that their results demonstrate that “sensor-based estimators of human interruptibility are possible”. Additionally, they believe that “overall a relatively simple set of sensors can probably be employed to achieve good results” (Hudson et al., 2003).

Context, in the case of knowledge workers, may for a large part be determined by their computer activity. Monitoring computer activity was also suggested by the participants in the study by Ho and Intille (2005): “when subjects were informed [of] the nature of the study, 5 subjects noted that the algorithm should consider monitoring their computer since there were periods during the day when they had nothing to do and were surfing the Internet”. The participants described such moments as “times when they would be extremely receptive to any interruption” (Ho & Intille, 2005). Moreover, the results of Hudson et al. (2003) put keyboard use in the top twenty sensors with the highest information gain.

1.9 Motivation and ability

Multiple researchers underline the importance of context when trying to change people’s behavior. Earlier studies have found that context can be used to determine a person’s interruptibility. However, there is a lack of evidence that shows that triggering at context-based times increases the persuasiveness of a technology. Additionally, it is unclear what exactly constitutes an opportune context-based moment in time.

One theory about what defines an opportune moment is presented in the Fogg Behavior Model Fogg (2009). As described earlier, the model describes three factors, which are motivation, ability and a trigger. Fogg (2009) claims that the effectiveness of the trigger depends on motivation and ability. Thus, triggering at an opportune moment means triggering at a moment of high motivation and high ability.

Besides the Fogg Behavior Model (FBM), there are numerous other psychological models for human behavior that include motivation and ability. One of the most notable is the theory of planned behavior (Ajzen, 1985), which is itself an extension of the theory of reasoned action

(Ajzen & Fishbein, 1980). As the theory of planned behavior (TPB) describes it, behavioral achievement (performing a certain behavior) is predicted by *behavioral intention* and *perceived behavioral control*. The model is shown in Figure 1.2.

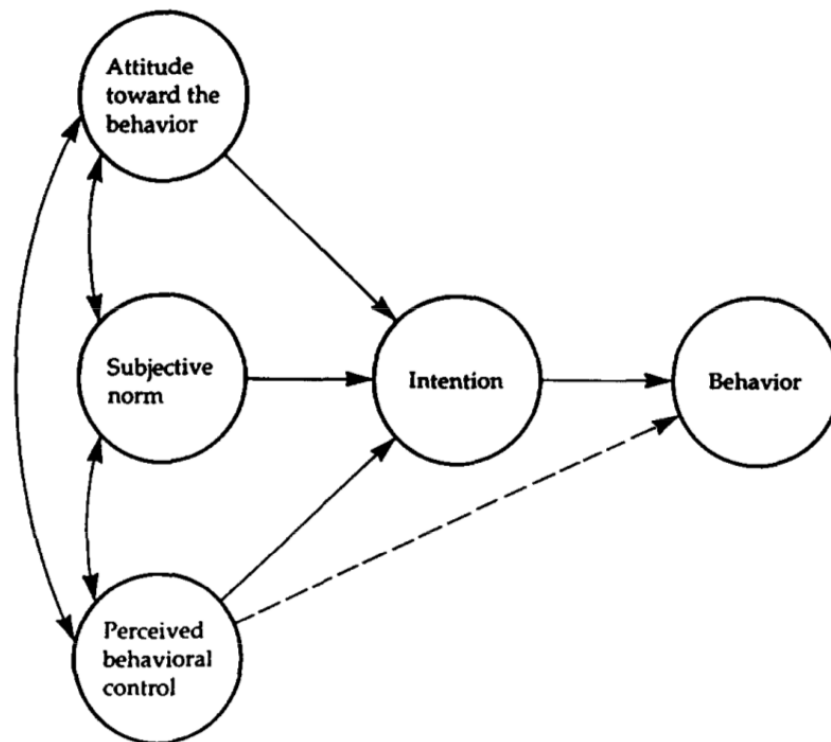


Figure 1.2: The theory of planned behavior (Ajzen, 1991)

Although Ajzen and Fishbein (1980) described perceived behavioral control as ability, it is not the same concept of ability as in the FBM. Ability as used in the FBM is what Ajzen (1991) described as “*actual control*”. Actual control has to do with a person’s physical ability to perform a behavior, or whether they have the needed time, or even whether they have enough money. Perceived control is not about such kinds of external ability, but about a person’s belief in their own ability. It is described as people’s “confidence in their ability to perform” a behavior (Ajzen, 1991). This is also known as the psychological construct of *self-efficacy* (Ajzen, 1991). It is included in TPB because it is “of greater psychological interest” compared to actual control, which is regarded as “self-evident” (Ajzen, 1991). Thus, compared to the Fogg Behavior Model, the motivational factor plays a much larger role in the theory of planned behavior (TPB).

Another well-known behavioral model that includes motivation and ability is the motivation, ability, opportunity model (Ölander & Thøgersen, 1995) or MAO. The model is shown in Figure 1.3. It was developed to predict consumer behavior. As the name suggests, the MAO model includes three determinants. The first, motivation, includes the “attitude towards and the social norms regarding the behavior” (Ölander & Thøgersen, 1995). It is therefore similar to the idea of motivation in TPB. The second determinant is “the actor’s *ability* to carry out his/her intentions” (Ölander & Thøgersen, 1995). As in TPB, this is about internal ability. Ölander and Thøgersen (1995) refer to Pieters (1991), who explains that there are two factors

to ability: task knowledge, which is “knowledge about the specific means of attaining a goal”, and habit, patterns formed by the actor that they may fall back on.

Where the MAO model differs from TPB is the addition of the third determinant, opportunity. Ölander and Thøgersen (1995) see opportunities as “objective preconditions for the behavior”, although they “acknowledge that individuals may perceive the same conditions differently and hence (subjectively) see different opportunities”.

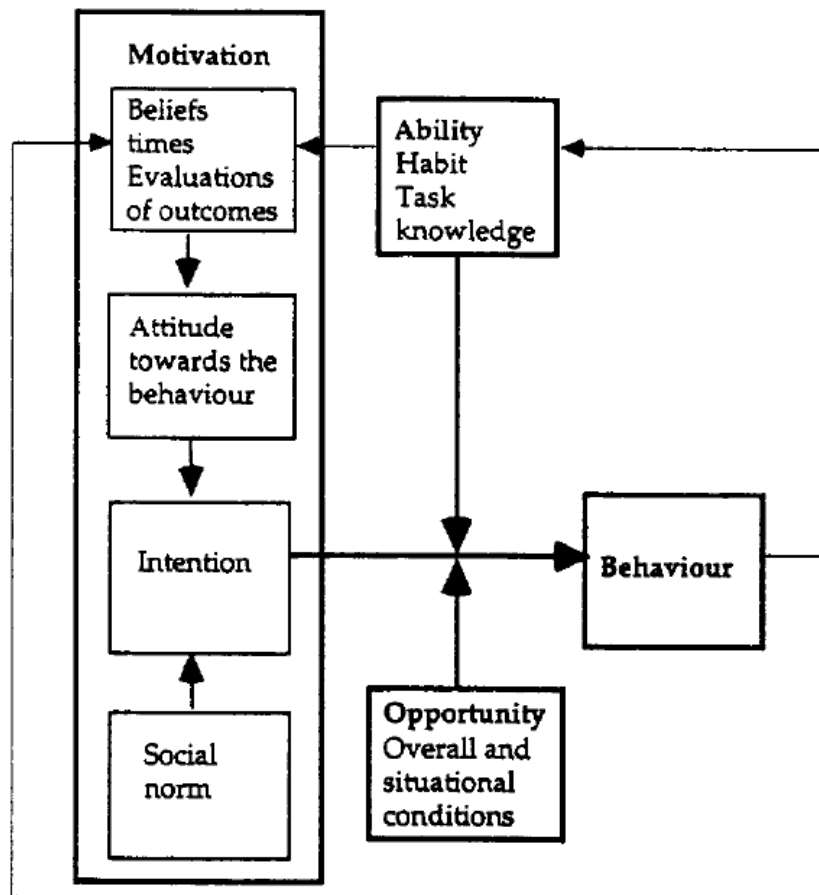


Figure 1.3: The motivation, ability, opportunity model (Ölander & Thøgersen, 1995)

An often-used example to explain behavior models is trash disposal. The target behavior is throwing trash in a trash can, instead of on the street. TPB focuses on a person’s attitude towards the behavior (the person thinks properly disposing of trash is important) and subjective norm (perceived pressure to perform the socially desirable behavior of not littering). TPB does not focus on a person’s actual behavioral control (the physical ability of the person to throw away trash) but instead looks at *perceived* behavioral control (the person believes they are able to throw away trash). This is not of particular importance for throwing away trash, but it is important for more challenging behaviors, where a person’s belief in their ability can mean the difference between success and failure.

The MAO model would describe three factors. Motivation would be a combination of a person’s attitude and social norms regarding proper trash disposal. Ability would include task

knowledge (the person knows how to throw away trash, or how to properly separate trash) and habit (the person never litters and is used to throwing trash in trash cans). Finally, opportunity would be about situational factors that are preconditions for the behavior (the presence of a trash can nearby).

In the FBM, persuasive triggers would be presented to the person. These can be implicit (the person spots a trash can) or more explicit (a sign saying “Throw away your trash here!”). The person will comply with the desired behavior, provided they have sufficient motivation (they *want* to throw away trash) and sufficient ability (they *can* throw away trash). A lack of motivation could mean that the trigger becomes distracting, while a lack of ability (not having a trash can nearby) could lead to frustration.

The above shows that the Fogg Behavior Model (FBM), which includes the two factors motivation and ability, has large similarities with the TPB and MAO models. There are two main differences. First, to our knowledge, the FBM is not as extensively tested as TPB or MAO. Second, the FBM is specifically focused on persuasion, instead of behavior. These two differences are the reasons why the FBM is the model that is used in the current research.

1.10 Research questions and hypotheses

As shown earlier, there seems to be a lack of literature investigating the effectiveness of context-based timing in persuasive technology. Yet, previous research in the SWELL project (Wabeke, 2014) found that wrong timing was the most commonly reported reason to reject a well-being tip. Wabeke (2014) therefore suggests that using context-awareness to determine opportune moments for such tips might “increase the chance that tips are followed-up”. Other researchers also spot opportunities for context-based timing in persuasive technology (IJsselsteijn et al., 2006; Munson, 2012), yet the evidence for these theories is lacking.

Therefore we propose to investigate the influence of context-based timing on compliance with well-being triggers. Fogg (2009) described opportune times for effective persuasion as times of high motivation and high ability. To our knowledge, this theory has not been empirically tested. Additionally, the current research focuses on knowledge worker well-being, which can be improved with regular microbreaks.

Therefore the main research question is defined as:

*What is the influence of triggering at times of high motivation and high ability
(versus times of low motivation and low ability)
on compliance with microbreak triggers for knowledge workers?*

The Fogg Behavior Model (Fogg, 2009) claims that triggering at a time of high motivation and high ability increases the likeliness that the subject complies with the target behavior, compared to triggering at a time of low motivation and low ability. Thus, the main research hypothesis is defined as: *triggering at times of high motivation and high ability has a positive influence on compliance with microbreak triggers.*

To answer the main research question, first a subquestion has to be answered, which is:

*What are times of high motivation and high ability
to take a microbreak, for knowledge workers?*

Answering this subquestion is the goal of Study 1. To answer it, several hypotheses will be tested. The hypotheses will predict a knowledge worker's level of motivation and ability to take a microbreak, based on their computer activity, because computer activity is suggested to be an important part of the context of a knowledge worker's environment.

Motivation to take a microbreak is hypothesized to increase over time. Research has shown that physiological strain and fatigue increase with the time a person has been working (Rohmert, 1973). Therefore, the longer someone has been working, the more they might want to take a break. If they then take a break, their motivation decreases to a minimal level. Once they continue working, motivation will again increase. Therefore, **hypothesis 1a** is defined as: *motivation to comply with a well-being trigger increases with the time a knowledge worker has been working without a break.*

Ability in the Fogg Behavior Model, as explained earlier, seems to be similar to what Ajzen (1991) described as “*actual control*”. It is therefore expected to be related to external influences. For instance: an upcoming deadline might prevent workers from taking a break, since they do not have the time to stop working. If this is the case, the worker is likely to be working quite hard, which is then reflected in his computer activity. Once a particular task is finished, and a busy period has ended, the worker might be more able to take a break. Research by Ho and Intille (2005) found that “messages delivered at activity transitions were found to be better received”. One way to spot if a worker has just finished with a task could be to look at when they close applications. Therefore, **hypothesis 1b** is: *ability to comply with a well-being trigger is higher when a knowledge worker has just closed one or more applications in the last minute.*

Previous research found that “subjects were more receptive to prompts tied with activity transitions than those presented at a random time” (Ho & Intille, 2005). As such, ability to comply with a persuasive trigger might be higher during activity transitions. Such an activity transition could be when a worker has just finished a task. An indication of this could be a decrease in their overall computer activity. Therefore, **hypothesis 1c** is: *ability to comply with a well-being trigger is higher when a knowledge worker shows decreased computer activity.*

Ability to take microbreak is expected to be at a high level when a worker is currently taking a break. Otherwise, they would not be able to do so. Therefore, **hypothesis 1d** is: *ability to comply with a well-being trigger is higher when a knowledge worker has not used the computer for 1 minute or longer.*

Finally, ability might also be influenced by the time since the previous break. A worker has limited time during a day to complete all of their tasks and therefore only limited opportunities to take a break. Thus, they are not able to take a break right after a previous one. Similar to motivation, ability might also increase with the time since the previous break. As such, **hypothesis 1e** is: *ability to comply with a well-being trigger increases with the time a knowledge worker has been working without a break.*

2. STUDY 1: DEFINING OPPORTUNE MOMENTS

The first study described in this thesis was set up to answer the research subquestion, “What are times of high motivation and high ability to take a microbreak, for knowledge workers?”.

As explained in Chapter 1, the computer activity of knowledge workers is an important part of their context. Therefore, 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 microbreak.

In this study, the computer activity of participants was recorded and compared with their levels of motivation and ability to take a microbreak, at different points in time. The data was collected using two methods. Computer activity was recorded using a keylogger. The levels of motivation and ability were gathered by asking the participants to periodically report ratings for these two factors.

The following sections describe Study 1 in more detail.

2.1 Method

Study 1 gathered data from two sources: a keylogger and periodic self-reports. The keylogger recorded computer activity data, such as mouse clicks, cursor movements and keystrokes made by the participant. The self-reports asked participants to rate their motivation and ability to take a microbreak at that particular moment in time.

This method, using a series of real-time self-reports to obtain data from participants, was based on the Experience Sampling Method (Csikszentmihalyi & Larson, 1987) or ESM. Generally, ESM uses a signal from an electronic device to prompt the participants at different points in time to have them record their experience, for instance by answering a number of questions about their current internal state. An example of a study that used ESM is research by Hudson et al. (2003) on office worker interruptibility.

ESM has several advantages over retrospective reporting, which is when participants report on their experiences after the fact. The first is that ESM is less susceptible to retrospective bias. Trull and Ebner-Priemer (2009) list some of the possible sources of this bias, such as the recency effect, where participants are more likely to report more recent effects, or the mood-congruent memory effect, where participants are more likely to report experiences “that are consistent with their current mood state” (Trull & Ebner-Priemer, 2009).

A second advantage is that collecting participant data in their natural environment “serves to increase the construct, ecological, and external validity” (Trull & Ebner-Priemer, 2009). Finally, this experiment required a way to assess the participants’ motivation and ability throughout

their working day and collect context information (in this case computer activity data), for which ESM is well suited.

A disadvantage of ESM is that the information is collected at random times. If the collection of information could be targeted, it would be more efficient, but unfortunately that is not possible for this exploratory research.

2.1.1 Participants

A total of six knowledge workers participated in Study 1. All of the participants were employees or interns at TNO. Because all of them use and produce information as their main task, they can be categorized as knowledge workers (Janssen & Van Hall, 2013). The mean age of the participants was 27.8 years ($SD = 8.47$) and 4 of the 6 were male.

Participation was on a voluntary basis. Informed consent was obtained from all participants. A copy of the informed consent form used can be found in Appendix A.

2.1.2 Apparatus and materials

To collect the data, two software programs were installed on the participants' work computers. These were a keylogger, to collect data about the computer activity of the participants, and a self-report program, which was purpose-built to periodically collect the motivation and ability ratings from the participants.

Keylogger

The keylogger was installed on the participants' work computers to record their computer activity. The specific tool used during this study is called uLog. It is developed by Noldus Information Technology for researchers in user-computer interaction to study computer activity behavior (Noldus Information Technology, 2006). The keylogger runs in the background and can record various information about the user's behavior, such as mouse clicks, cursor movements and keystrokes.

During Study 1, the keylogger was set up 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.

Self-reports

The second software program was a Java program called BabylonA, which periodically administered the self-reports and recorded the responses. The self-reports appeared as pop-up dialogs

on the participants' screens. The pop-up is shown in Figure 2.1.

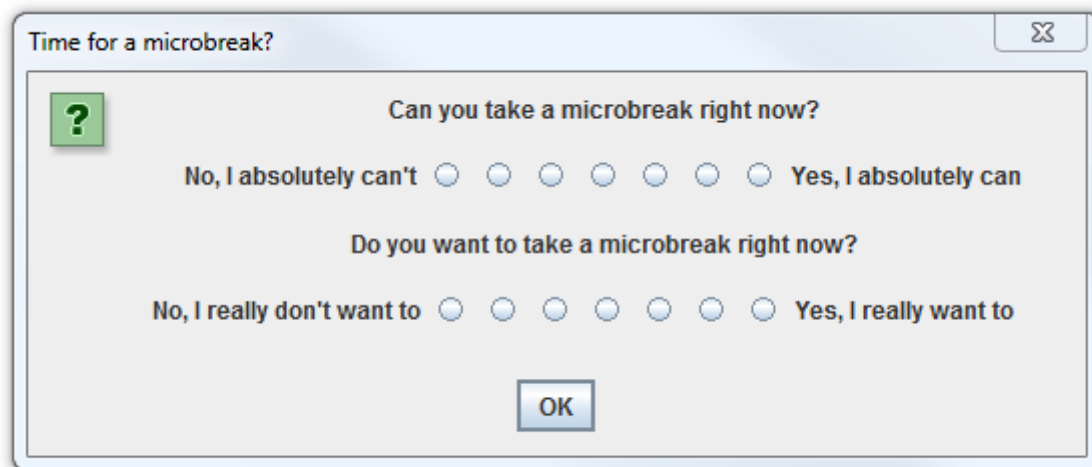


Figure 2.1: The self-report pop-up, as it appeared to the participants

The two factors, motivation and ability, were rated on a 7-point Likert scale. The Fogg Behavior Model (Fogg, 2009) does not specify how exactly these two factors should be measured or phrased. However, Fogg (2009) describes a person who has high motivation as someone who “wants” to perform a certain behavior. Likewise, a person with high ability is described as someone who “can” (versus “cannot”) perform a behavior. Thus, for the motivation factor, the question was phrased as “Do you want to take a microbreak right now?”, followed by seven radio buttons, ranging from “No, I really don’t want to” to “Yes, I really want to”. For the ability factor, the question was phrased as “Can you take a microbreak right now?”, with the answers ranging from “No, I absolutely can’t” to “Yes, I absolutely can”.

The self-reports were automatically administered by the BabylonA program. The pop-ups were displayed at randomly determined moments in time. However, two limits were applied. The first was that at least 20 minutes had to pass between subsequent pop-ups. This was done to decrease the chance that a report would be influenced by the one before it. The second limit was that at least one pop-up had to appear every hour. This was done to make sure that enough data could be gathered and a certain granularity in the data could be preserved.

2.1.3 Procedure

The keylogger and the BabylonA program were installed on the participants' work computer.

Over the course of seven working days, the participants answered periodic self-reports. The self-reports were administered roughly six times per day by the BabylonA software program. At the same time, computer activity data was recorded using the keylogger.

After the study was finished, the computer activity data and self-report responses were collected from the computers. Additionally, unstructured interviews were held with the participants to gain more insight into their working patterns and their experiences with during the

experiment.

2.2 Results

The following section describes the results obtained in Study 1. First, a preliminary data analysis gives an overview of the collected data and describes the procedures taken to prepare the data for further analysis. Following, two different types of data analysis are described, namely data mining and statistical analysis. Lastly, some qualitative information is described.

2.2.1 Preliminary data analysis

Self-reports

A total of 249 self-reports were administered, of which 219.5¹ (or 88.2 percent) were answered.

Some of the responses were given at times when the keylogger had not been running, which meant that no computer activity data for that time period had been recorded. These responses were removed from the dataset. Afterwards, 148 valid self-reports were left to be used in the analysis.

The mean rating for motivation was 3.31 ($SD = 2.00$). The mean rating for ability was 4.45 ($SD = 2.13$). Motivation and ability had a positive, medium-to-high correlation, $r(146) = .48$, $p < .001$.

Computer activity data

In total, over 360,000 computer activity events were recorded by the keylogger. To obtain the average number of events related to each self-report response, the events were aggregated in three different timespans. For each event type, the sum of the recorded events was calculated for the last 30 seconds, the last minute and the last 3 minutes before a self-report response.

The event types used as features in the analysis were the number of

- left clicks,
- right clicks,
- double clicks,
- wheel scrolls,
- mouse drags,
- mouse hovers,
- relative cursor distance travelled,
- total cursor distance travelled,
- keyboard characters typed,
- special keys pressed,
- key combinations made,
- strings typed,
- applications started,

¹ The half-answered report was a case where only the ability scale was rated, but not the motivation scale.

- applications exited and
- window switches performed.

Additionally, several features were calculated from the keylogger data. These were

- the time since the last break (where a break is defined as no activity for at least 5 minutes),
- the change in overall activity (total events in the last 3 minutes divided by the total events in the last 30 seconds), and
- the application used at the time of the pop-up.

The applications were first filtered. Activities related to non-end-user facing applications, such as the Windows background services *dllhost* and *conhost*, were removed from the dataset.

2.2.2 Hypothesis testing

Five *a priori* hypotheses had been formed. To test these hypotheses, different analyses were conducted. The hypotheses that describe a linear relationship between two variables (H1a, H1c and H1e) were tested using a linear regression analysis. The other hypotheses (H1b and H1d), which describe differences between two groups, were tested using independent-samples t-tests.

H1a: motivation to comply with a well-being trigger increases with the time a knowledge worker has been working without a break

To predict motivation based on the participants' time in minutes since their last break, a simple linear regression was calculated. The regression equation was not found to be significant ($F(1,137) = 2.615, p = .108$), with an R^2 of .019. The unstandardized coefficient for every minute since the last break was .003. Thus, **no evidence was found in support of hypothesis 1a.**

H1b: ability to comply with a well-being trigger is higher when a knowledge worker has just closed one or more applications in the last minute

To test the difference between the means of the group of cases that had 0 applications closed in the last minute and the group that had at least one application closed in the last minute, an independent-samples t-test was conducted. Although the group with at least one application closed had a higher mean ability rating, no significant difference ($t(146) = .173, p = .863$) was found between the ability ratings of the groups with 0 applications ($M = 4.44, SD = 2.11$) and ≥ 1 application closed ($M = 4.52, SD = 2.28$). Thus, **no evidence was found in support of hypothesis 1b.**

H1c: ability to comply with a well-being trigger is higher when a knowledge worker shows decreased computer activity

To predict ability based on the participants' change in computer activity, a simple linear regression was calculated. A significant regression equation was found ($F(1,145) = 8.111, p = .005$), with an R^2 of .053. Participants' predicted ability rating is equal to $3.976 + 0.084$ (change in activity). Thus, **hypothesis 1c is supported.**

*H1d: **ability** to comply with a well-being trigger is higher when a knowledge workers has not used the computer for 1 minute or longer*

To test the difference between the group of cases that had at least one event recorded in the last minute and the group that had no events recorded for at least the last minute, an independent-samples t-test was conducted. Although the latter had a higher mean ability rating, no significant difference ($t(3.90)=.598, p = .583$) was found between the ability ratings of the groups with events in the last minute ($M = 4.44, SD = 2.15$) and no events in the last minute ($M = 4.75, SD = 0.96$). Levene’s test indicated unequal variances ($F = 6.28, p = .013$), so degrees of freedom were adjusted from 146 to 3.90. Thus, **no evidence was found in support of hypothesis 1d.**

*H1e: **ability** to comply with a well-being trigger increases with the time a knowledge worker has been working without a break*

To predict ability based on the participants’ time in minutes since their last break, another simple linear regression was run. A significant regression equation was found ($F(1,137) = 16.981, p < .001$), with an R^2 of .110. Participants’ predicted ability rating is equal to $3.855 + 0.009$ (minutes since the last break). Ability ratings increased 0.009 for every minute since the last break. Thus, **hypothesis 1e is supported.**

In conclusion, the results of the statistical analysis provide support for hypotheses 1c (ability is higher with decreased computer activity) and 1e (ability is higher with a longer time since a break). Subsequently, a multiple regression analysis was run to combined these two hypotheses. This regression predicted ability, based on both the change in activity and the time since the last break.

A significant regression equation was found ($F(2,135) = 12.675, p < .001$), with an R^2 of .158 and an adjusted R^2 of .146. The participants’ predicted ability rating is equal to $3.473 + 0.008$ (minutes since the last break) $+ 0.084$ (change in activity). The coefficients, significance values and other specifics are reported in Table 2.1.

Table 2.1: Results of multiple regression, predicting ability rating based on the time since the last break and the change in activity

Variable	B	$SE(B)$	β	t	p
Constant	3.473	.265		13.123	<.001
Time since last break	.008	.002	.293	3.653	<.001
Change in activity	.084	.030	.221	2.753	.007

Thus, a knowledge worker’s self-rated ability to take a microbreak can be partially predicted based on their change in activity and the time since their last break. No significant results were found to predict self-rated motivation.

2.2.3 Data mining

Another way to predict the level of motivation and ability based on data, is to use data mining. Data mining is using specialized software to find relationships and patterns in a dataset automatically. Predictive models can then be formed, based on detected patterns. This makes it a data-driven approach, which is different from the theory-driven approach where specific hypotheses are formulated and then tested in experiments.

Hudson et al. (2003) as well as Poppinga, Heuten, and Boll (2014) used a type of data mining, decision trees, in their research. Poppinga et al. (2014) developed a model for predicting opportune moments for smartphone notifications, based on smartphone sensor data. To build the model, the researchers gathered data in a similar way as in Study 1. Using a purpose-built smartphone application they asked users at different moments during the day about their mood. Then, they used the machine learning software Weka to create a classifier that could predict opportune moments from sensor data. The resulting model, a C4.5 decision tree, had an accuracy of 77.85 percent. Not only was this accuracy higher than their baseline, it also gave insight into the types of sensor data that had the largest influence. It provided interesting information that could be used to develop a theory or improve other models.

An attempt was made to build a similar model for Study 1, which could predict the level of motivation and ability to take microbreak, based on computer activity. However, no models with acceptable performance could be developed.

Three data mining classifiers were employed to try and predict motivation and ability: a J48 decision tree, a multilayer perceptron (a type of artificial neural network) and linear regression. The machine learning software Weka was used to run them. The classifiers were tested using 10-fold cross-validation. For the J48 decision tree and multilayer perceptron, the motivation and ability variables were categorized into “low” (values 1-3), “neutral” (4) and “high” (values 5-7).

The results for all three classifiers are shown in Table 2.2. For the classification models (J48 decision tree and the multilayer perceptron) the percentage of correctly classified instances, the kappa statistic and the relative absolute error (RAE) are reported. For the linear regression model, Pearson’s r and the RAE are reported.

Table 2.2: Data mining results using three types of classifier

	J48 decision tree			Multilayer perceptron			Linear regression	
	Correct	Kappa	RAE	Correct	Kappa	RAE	r	RAE
Motivation	51.35%	-0.08	100.55%	49.32%	0.03	96.95%	-0.06	136.47%
Ability	51.35%	0.07	94.81%	56.76%	0.19	85.39%	0.1587	116.61%

As can be seen in Table 2.2, the RAE for all three classifiers was higher than 85 percent, which means that none of the three classifiers achieved acceptable performance. Additionally, the best performance of the linear regression model was not better than that of the combined multiple regression equation found earlier during hypothesis testing. As such, it does not offer any improvement.

The kappa statistic measures the agreement between the predicted categories and the true categories. A statistic of 1 indicates complete agreement, while a number of 0 indicates that the model's performance is equivalent to chance. Since the kappa statistic was 0.07 or lower for the J48 decision tree as well as the multilayer perceptron when predicting motivation, none of these models were satisfactory. The best performing classifier was the multilayer perceptron when it was used to predict ability, yet its kappa statistic of 0.19 signifies only a "slight agreement" (Viera & Garrett, 2005) with the true categories.

In conclusion, none of the data mining models showed acceptable performance. Therefore, data mining did not prove to be successful in developing a useful model for the current research.

2.2.4 Qualitative information

The unstructured interviews that were held with the participants produced some relevant qualitative information. For instance, multiple participants said they saw the two scales, motivation and ability, as having distinct meanings.

The reception of the pop-ups was mixed. The most common reasons for them to cancel a pop-up was that they had just returned from a break ("...and then that notification is there again, but I just took a break"), or that they were with someone, for instance in a meeting or during a presentation ("for instance when you're with someone, it's very bothersome").

The pop-ups were only used to collect the data and the program was not meant to function as an e-coaching application. Nonetheless, some of the participants already regarded the pop-ups as suggestions to take a short break. In fact, for some of the participants the pop-ups functioned as a positive reminder: "Sometimes the alert is there again and I thought, oh right, I've got to take a break again. [...] That's quite nice."

2.3 Discussion

2.3.1 Hypotheses

Only two of the five *a priori* hypotheses for Study 1 were supported by the results. These were hypothesis 1c (ability is higher with decreased computer activity) and 1e (ability is higher with a longer time since a break). A multiple regression was run to combine the two supported hypotheses.

The multiple regression showed that a knowledge worker's self-rated ability to take a micro-break can be partially predicted based on their computer activity. Specifically, it can be based on two factors. There are the knowledge worker's change in overall computer activity and the time since their last break.

The relative contributions of both factors to the prediction cannot be directly compared, since they are measured in different units (minutes versus computer activity events). However, the R^2 value of the "time since break" factor (.110) was larger than the one of the "change in activity" factor (.053). Therefore, it seems that the former has a larger share in determining self-rated ability.

There was only one hypothesis that tried to predict the motivation ratings (hypothesis 1a: *motivation to comply with a well-being trigger increases with the time a knowledge worker has been working without a break*). There was no evidence to support this hypothesis. Therefore, the conclusion is that the ratings for motivation could not be predicted based on the recorded computer activity. Possible causes for this and opportunities for future research are suggested in section 2.3.3.

2.3.2 Data mining

One of the goals of Study 1 was to develop a classification model that could predict motivation and ability based on computer activity. Earlier research was successful in developing models for related goals (Hudson et al., 2003; Poppinga et al., 2014). However, the results of Study 1 show that applying the same decision tree classifier as Poppinga et al. (2014) to the Study 1 dataset did not result in similar accuracies. Further attempts using classifiers based on neural networks were equally unsuccessful. As can be seen in Table 2.2, the percentage of correctly classified instances is very low. Overall, the relative absolute error for all three classifiers was high.

The resulting decision trees for motivation and ability had a very large size. The model for classifying motivation scores had a size of 45 nodes and 29 leaves (end nodes), while the model for ability had 41 nodes and 21 leaves. Such large trees could indicate overfitting, which is when a model describes noise instead of the true relationships. This can lead to poor predictive performance. With such specific models and this danger of overfitting, the low accuracies that were reported are even less acceptable.

Several attempts to improve the classifiers were made. Among these were the following:

- Categorizing motivation and ability responses into more extreme categories (i.e. only values 1 and 2 were categorized as “low” and only 6 and 7 as “high”).
- Binning the applications (e.g. “browser”, “IDE”, ...).
- Categorizing cancelled pop-ups as 0 motivation and 0 ability (the fact that they were cancelled could mean they were displayed at a highly inopportune moments)

However, these additional measures did not produce satisfactory results either. The cause of this could be a lack of scale. Poppinga et al. (2014) recorded data from 6581 notifications from 79 users, over a period of 76 days. In contrast, the dataset from Study 1 consisted of 148 cases from only 6 users, over 7 working days. An option for future research is to run more large-scale studies to train more accurate and useful classifiers.

2.3.3 Limitations and future research

Motivation could not be predicted based on the results of Study 1. Thus, the extent of its role in the Fogg Behavior Model (Fogg, 2009) remains unclear. As explained above, a lack of scale could be one of the reasons why the data mining approach was unsuccessful. Therefore one avenue for future research could be to perform a larger-scale replication of Study 1. This

way it may still be possible to develop a model for predicting knowledge workers' motivation to take a microbreak. Chapter 4 discusses the theoretical implications of not being able to predict motivation in detail.

Although motivation could not be predicted based on the results, ability could. Two of the hypotheses about the level of ability were supported by the results. Combining these hypotheses resulted in a single linear regression equation. This equation predicts knowledge workers' ability to take a microbreak based on two factors, namely their change in overall computer activity and the time since their last break. Thereby, computer activity can be used to predict times of high and low ability.

As such, further research could try to use these predicted times of high and low ability to investigate the influence of the level of ability on compliance with well-being triggers. This is in fact the aim of Study 2, which is described in the following chapter.

3. STUDY 2: THE INFLUENCE OF CONTEXT-BASED TIMING

According to Fogg (2002), one of the factors that defines an opportune moment for persuasive technology to encourage a certain behavior is the subject’s *ability* to perform that behavior. In other words, a persuasive trigger given at a moment of high ability should result in higher compliance with that trigger than one given at a moment of low ability.

Study 2 was set up to test this assertion. Because the participants’ level of motivation could not be predicted based on their computer activity, the main research question was redefined as:

What is the influence of triggering at times of high ability (versus times of low ability) on compliance with microbreak triggers for knowledge workers?

The Fogg Behavior Model (Fogg, 2009) claims that triggering at a time of high ability increases the likeliness that the subject complies with the target behavior, compared to triggering at a time of low ability. Thus, the main research hypothesis is defined as: *triggering at times of high ability has a positive influence on compliance with microbreak triggers, compared to times of low ability.*

The results of Study 1 showed that a knowledge worker’s self-rated ability to take a microbreak can be partially predicted based on their computer activity. Specifically, it can be based on their change in activity and the time since their last break. Therefore, computer activity can be used to predict times of high and low ability.

To answer the main research question, an experiment with two within-subjects conditions (*high ability* and *low ability*) was run to investigate their influence on compliance rates. The following sections describe the experiment in more detail, as well as the results and conclusions.

3.1 Method

Study 2 used a within-subjects design with two conditions. The conditions were labelled *high ability* and *low ability*, where ability refers to the participant’s predicted ability to take a microbreak.

In both conditions, persuasive triggers were shown to the participants, suggesting that they take a microbreak. However, the timing for the two conditions was different and was dependent on the computer activity context of the participants. The following section describes the conditions in more detail.

3.1.1 High and low ability conditions

The results of Study 1 showed that two factors are of importance to determine a knowledge worker’s level of ability: the time since the previous break and the change in computer activity. These two factors are labelled *TimeSinceBreak* and *ActivityChange*, respectively.

As in Study 1, *TimeSinceBreak* is defined as the time in minutes since the last pop-up or since the last period of 5 minutes or more without any computer activity. *ActivityChange* is calculated by dividing the number of events in the last 3 minutes by the ones in the last 30 seconds. As such, if the level of activity remains constant, the value of *ActivityChange* is 6.

The persuasive triggers were shown when either of the conditions was met. For this to happen, certain thresholds for both *TimeSinceBreak* and *ActivityChange* had to be met. The thresholds for the conditions are listed in Table 3.1.

Table 3.1: Thresholds for the experimental conditions

Condition	TimeSinceBreak (minutes)	ActivityChange
High ability	> 30	> 8 (25% decrease)
Low ability	3 < x < 18	< 4.8 (25% increase)

These thresholds had to be within a certain range. If they turned out to be too extreme, the conditions might never be reached and too few microbreak triggers would be shown. If they were too moderate, the two conditions would become too similar to detect a difference.

For *ActivityChange*, an increase and decrease of 25% were used. For *TimeSinceBreak*, the thresholds were partly based on the dataset from Study 1. All the *TimeSinceBreak* values from that dataset were collected in ascending order. Then, the list was divided into three equal groups and the cut points between the groups were used as thresholds. The cut point of the lowest group was at 18 minutes. The cut point of the highest group was at 77 minutes. However, that would mean more than an hour between breaks, possibly making the condition highly unlikely to occur. Instead of 77, a lower threshold of 30 minutes was set. The reason for this particular number is that it is in between the two microbreak conditions used by McLean et al. (2001). The last adjustment to the thresholds was that *TimeSinceBreak* had to be at least 3 minutes, to make sure subsequent pop-ups would not interfere with each other.

To test whether these two conditions represented *high ability* and *low ability*, the thresholds were applied to the dataset from Study 1. This resulted in two groups, one for each condition. An independent-samples t-test was conducted and a significant difference ($t(57)=3.19, p = .002$) was found between the ability ratings of the *high ability* ($M = 5.17, SD = 1.83$) and *low ability* ($M = 3.40, SD = 2.25$) groups.

3.1.2 Balancing conditions

To make sure both conditions would occur the same amount of times for each participant, the order of the conditions was determined randomly. This randomized counterbalancing was also a way of controlling for order effects. However, the nature of the conditions meant that, for instance, the *low ability* condition might occur much more often than *high ability*, because its

threshold for `TimeSinceBreak` is lower and therefore sooner met. To avoid this, the condition was switched to *high ability* if `TimeSinceBreak` grew longer than 18 minutes, and then switched back after the *high ability* pop-up was displayed. A flowchart showing all the steps taken by the BabylonB program to determine the condition can be found in Appendix B.

3.1.3 Participants

A total of 36 knowledge workers participated in the experiment. One of the participants could not be reached after the experiment to collect his data and could therefore not be included in the analysis.

The participants were TNO employees and interns from The Hague and Leiden, employees at Hi-Safe Systems, and graduate students and PhD candidates studying at Eindhoven University of Technology. The participants were selected because they can all be categorized as knowledge workers, since all of them use and produce information as their main task (Janssen & Van Hall, 2013). The mean age of the participants was 34.5 years ($SD = 12.3$) and 27 of the participants were male.

Three gift vouchers were distributed as compensation. They were awarded to three randomly selected participants. Informed consent was obtained from all participants. A copy of the informed consent form used can be found in Appendix C.

3.1.4 Apparatus and materials

As in Study 1, two software programs were installed on the participant’s work computer. The first was again a keylogger, to record computer activity data. The second was a program that presented persuasive triggers to the participants and recorded their responses. Additionally, a *post hoc* questionnaire was administered. The following sections describe the software and the questionnaire in more detail.

Software

The first of the two software programs was again a keylogger. The settings for the keylogger were the same as in Study 1. The tool ran in the background and was used to record mouse, keyboard and application activity on the participant’s work computer.

The second program, called BabylonB, was designed to be a basic persuasive technology application. It was again purpose-built for this study. The biggest difference with the BabylonA program from Study 1 was that BabylonB could read and respond to the keylogger data in real-time, making it context-aware. By monitoring the keylogger data it could calculate the two variables `TimeSinceBreak` and `ActivityChange`. Whenever either of the two conditions was reached, BabylonB would show a persuasive trigger to take a microbreak on the participant’s screen. These triggers appeared in the form of a pop-up and featured the text “Time for a microbreak!”

Participants then had to decide to accept or refuse this suggestion. If accepted, clicking the button “Start!” would make the button disappear and display a countdown of 30 seconds in

its place. This microbreak duration is the same as used by Henning et al. (1997) and McLean et al. (2001). If refused, the participant could choose between the options “No, I can’t right now” and “No, I don’t want to right now”. These two buttons were included to gather data about why the suggestion was refused: because of insufficient motivation or insufficient ability. The pop-up is shown in figure 3.1.

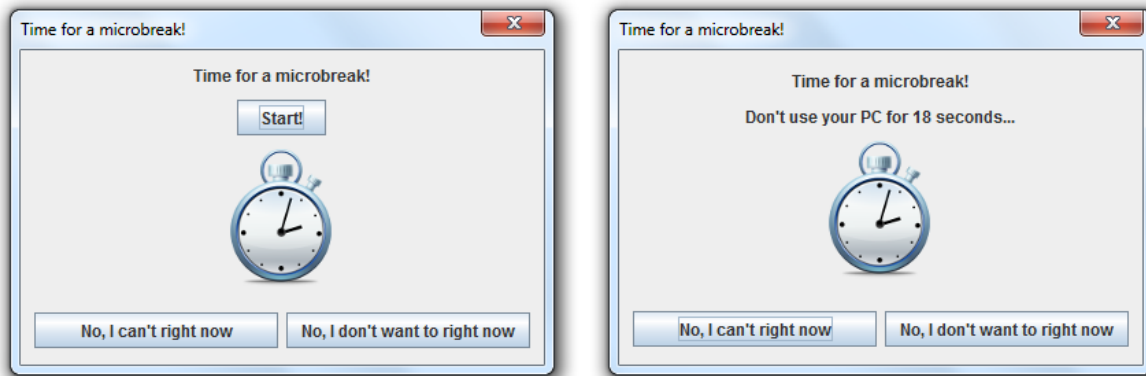


Figure 3.1: The BabylonB pop-up in its initial state, as it was displayed to the participants (left) and the pop-up after clicking the “Start” button (right)

Questionnaire

A questionnaire was developed to gather additional information about the participants and their characteristics.

The first part of the questionnaire was formed by the Utrecht Work Engagement Scale or UWES (Schaufeli & Bakker, 2003). As the name explains, this scale is designed to measure work engagement and has three subscales: vigor, dedication and absorption. These subscales, as well as the overall work engagement scale, were investigated because of their possible influence on the participants’ responses.

Second, the questionnaire gathered demographic information, such as the age and sex of the participants. It also asked the participants about their experiences with RSI, if any. The questions used were “Are you currently experiencing any RSI symptoms?” and “Do you use rest break or anti-RSI software (e.g. Workrave or WorkPace)?”.

Third, the questionnaire asked the participants about the general level of motivation and ability to take breaks during work. This was done with two statements that said “I would like to take breaks during work more regularly” and “I have the ability to take breaks during work, whenever I want”. These statements were rated on a 5-point Likert scale, ranging from “Agree” to “Disagree”.

Fourth, two additional questions asked about their experiences with the BabylonB program used during Study 2. These were the two statements ‘The pop-ups helped me to take breaks more regularly’ and “The difference between the options ‘No, I can’t right now’ and ‘No, I don’t want to right now’ was clear to me”. These were also rated on a 5-point Likert scale.

Finally, two open questions were used to ask participants “What were the most frequent reasons for you to refuse to take a break?” and “What, for you, would be a good time to take a break?”

The full questionnaire can be found in Appendix D.

3.1.5 Procedure

After explaining the procedure of the experiment to the participants, the researchers asked them for their cooperation. The participants also read and signed a form for informed consent. Every participant received a short document which contained a summary of the procedure and the contact information of the researchers.

To start the experiment, the researchers installed the keylogger and the BabylonB program on work computers of the participants. Over the course of the next five working days, the participants received persuasive triggers and could choose whether or not to follow up on them. Their answers and their computer activity were recorded.

Afterwards, the recorded responses to the persuasive triggers and the computer activity data was collected from the computers and the participants filled out the questionnaire. The gift vouchers were randomly distributed after the experiment had finished.

3.2 Results

This section describes the results and analysis of Study 2. First, the measures used to validate and clean up the data are described. Second, the main hypothesis is tested. Third, the results of the questionnaire are presented. Lastly, exploratory analysis that looks at the data in more detail is described.

A total of 1007 persuasive triggers were displayed, or an average of 6.6 per day per participant. The high ability and low ability conditions occurred 420 and 587 times, respectively. Over all participants, a total of 21,065,014 computer activity events were recorded by the keylogger.

3.2.1 Data cleaning

Several measures were taken to remove invalid data points and thereby assure accurate results.

The first of these was to remove responses where the response time was too slow. This was done to ensure the conditions were representative of high and low ability. The study investigated the role of timing and the pop-ups were displayed based on contextual information at that moment. The longer the time between the pop-up and the participant’s response, the more the context may have changed. Therefore all cases where the participant took 15 seconds or longer to respond to the pop-up were removed from the dataset. After removing these cases, around 90 percent of the dataset was left.

The second measure was to remove all participants with too few responses. Because the dependent variable was the participant’s compliance rate, expressed in percentages, too few responses would result in an imprecise number. Therefore, the participants with less than three

responses in either of the conditions, six in total, were removed from the dataset to ensure accuracy.

After data correction, data from 29 participants was left to be used in the analysis.

3.2.2 Main hypothesis: compliance with microbreak triggers

The main research hypothesis was defined as: *triggering at times of high ability has a positive influence on compliance with well-being triggers, compared to times of low ability.*

The compliance rate with well-being triggers was calculated in two ways. The first way counted the responses selected by the participants, i.e. the number of times the participants clicked “Start” on the pop-up and let the countdown finish. The second looked at their behavior, by using the keylogger data to see if the participants refrained from using their computer. In total, 52 responses (24 for the high ability condition, 28 for low ability) with “false compliance” were detected, where participants said they started a microbreak but actually continued to use their computer. However, it is worth noting that 34 of these occurred with a single participant.

A summary of the number of pop-ups and the reported and true compliance rates can be found in Table 3.2.

Table 3.2: Average number of displayed pop-ups per participant and overall compliance rates, for both conditions

Condition	Displayed	Reported compliance rate (%)	True compliance rate (%)
High ability	14.48 ± 10.68	47.03 ± 29.27	43.72 ± 30.16
Low ability	20.24 ± 16.00	28.90 ± 27.14	25.51 ± 26.90

In support of the main hypothesis, a paired-samples t-test found a significant difference ($t(28)=4.17$, $p < .001$) in **reported** compliance rates for the *high ability* ($M = 47.03$, $SD = 29.27$) and *low ability* ($M = 28.90$, $SD = 27.14$) conditions. The effect size was medium-to-large, at 0.64 (Cohen’s d).

Moreover, another paired-samples t-test found a significant difference ($t(28)=4.15$, $p < .001$) in **true** compliance rates for the *high ability* ($M = 43.72$, $SD = 30.16$) and *low ability* ($M = 25.51$, $SD = 26.90$) conditions. The effect size was medium-to-large, at 0.64 (Cohen’s d).

3.2.3 Questionnaire

The following section will summarize the responses to the questionnaire. First, a summary is given of the Utrecht Work Engagement Scale (UWES) results. Second, an overview is given of the participants’ responses to the quantitative questions. Third, a summary of the qualitative results is presented of their responses to the two open-ended questions, “What were the most frequent reasons for you to refuse to take a break?” and “What, for you, would be a good time to take a break?”.

UWES

The UWES (Schaufeli & Bakker, 2003) was part of the questionnaire. The scale was used to gather data about the participants' overall work engagement, as well as the constructs "vigor", "dedication" and "absorption". The expectation was that such factors would influence either the overall compliance rate of the participants or the difference in compliance rates for both conditions. For instance, the higher a participant's dedication, the lower their overall compliance rate could be. Or the higher a participant's absorption, the more they are bothered by interruptions, and therefore their compliance rate in the low ability condition could be much lower than in the high ability condition.

The scale consists of 17 questions. For each question, participants answer how often they feel that way on a scale of 0 ("Never") to 6 ("Always (every day)"). As per the UWES manual, the questions were combined into three subscales. The subscales vigor, dedication and absorption consist of 6, 5 and 6 questions, respectively.

The overall work engagement scale had a high level of internal consistency, as determined by a Cronbach's α of 0.897. The three subscales also showed good internal consistency, with each a Cronbach's α larger than 0.7.

Table 3.3 lists the mean scores, standard deviations and scale reliabilities for the overall scale and the three subscales. The mean scores for all scales are around four, which in the UWES scales refers to "Often (once a week)". As can be seen, the mean scores are similar for all scales. Compared to the means, the standard deviations are low, meaning that individual differences are small.

Table 3.3: Summary of UWES responses for the overall scale and subscales

Scale or subscale	No. of questions	Mean	<i>SD</i>	Cronbach's α
Work engagement (overall)	17	4.22	0.69	.897
Vigor	6	4.18	0.70	.703
Dedication	5	4.39	0.85	.869
Absorption	6	4.12	0.81	.762

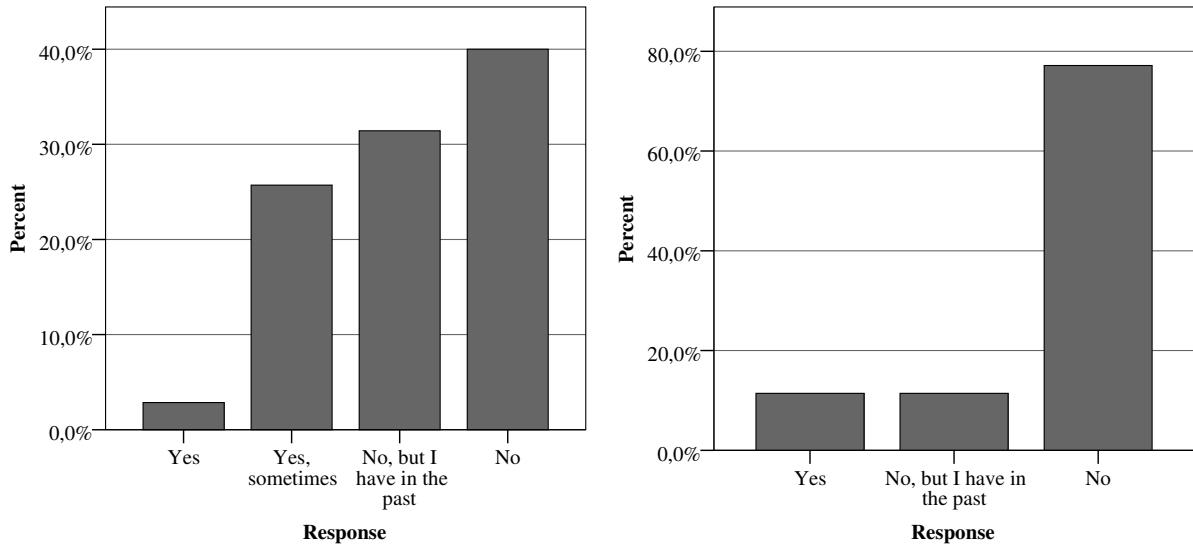
To test the influence of these factors, two multiple linear regression equations were calculated. The independent variables were the scores for overall work engagement, vigor, dedication and absorption. The two dependent variables were the participants' overall compliance rate and the difference in compliance rates of the two conditions.

Neither of the two regression equations was significant. Work engagement or its subscales were not significant predictors of either overall compliance rate ($F(3,25) = 1.426$, $p = .259$) or the difference in compliance rates ($F(3,25) = 0.372$, $p = .774$).

Quantitative results

The responses to the quantitative questions are shown in Figures 3.2, 3.3 and 3.4.

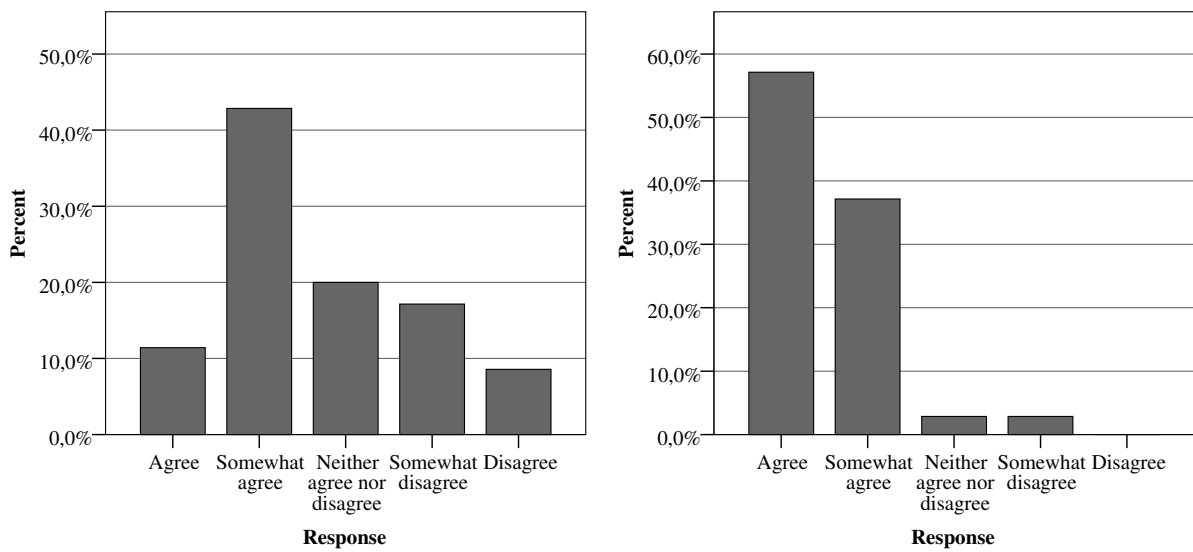
Figure 3.2a shows that a majority of the participants are currently experiencing, or have experienced, RSI symptoms. However, Figure 3.2b shows that over 75 percent have never used



(a) "Are you currently experiencing any RSI symptoms?" (b) "Do you use rest break or anti-RSI software (e.g. Workrave or WorkPace)?"

Figure 3.2: Questionnaire responses

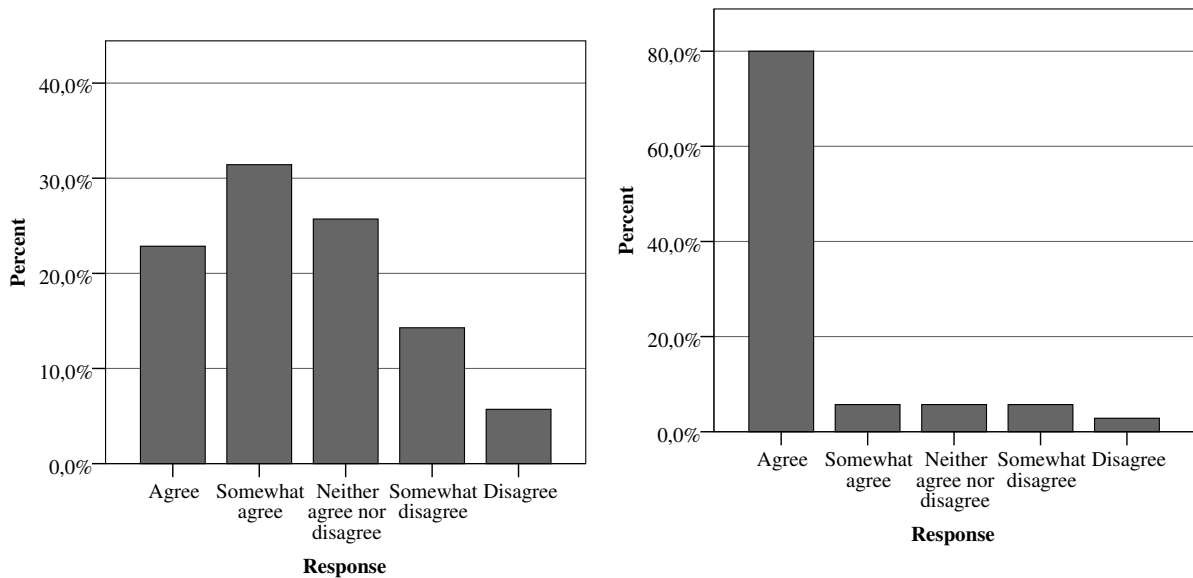
rest break or anti-RSI software.



(a) "I would like to take breaks during work more regularly" (b) "I have the ability to take breaks during work, whenever I want"

Figure 3.3: Questionnaire responses

Figure 3.3 shows the responses to the questions that asked the participants about their general level of motivation and ability to take breaks during work. As can be seen in Figure 3.3a, just over half of the participants agreed with the statement "I would like to take breaks during work more regularly". The second question asked whether they agreed with the statement "I have the ability to take breaks during work, whenever I want". As shown in Figure 3.3, over 90 percent of the participants somewhat agreed with this statement.



(a) “The pop-ups helped me to take breaks more regularly”

(b) “The difference between the options “No, I can’t right now” and “No, I don’t want to right now” was clear to me”

Figure 3.4: Questionnaire responses

Finally, Figure 3.4 shows the responses to the last two questions. Participants were divided about whether the pop-ups helped them to take breaks more regularly, as can be seen in Figure 3.4a. However, over 80 percent agreed with the statement “The difference between the options “No, I can’t right now” and “No, I don’t want to right now” was clear to me”.

Qualitative results

The final two questions of the questionnaire were open-ended. They were “What were the most frequent reasons for you to refuse to take a break?” and “What, for you, would be a good time to take a break?”

The responses to these questions were coded and a qualitative analysis is presented together with quotes by the participants.

When asked about reasons to refuse a break, 10 of the 35 participants answered that they had been in the middle of a task, thought or sentence (“I was in the middle of a thought/discussion with a colleague and didn’t want to lose it”). Moreover, 3 participants answered they were in a “good flow” (“I was just working very well and wanted to continue”).

The second most common reason to refuse them, according to 9 participants, was that they just had a break. The third most common reason to refuse a break was that there were too many pop-ups, as listed by 6 participants.

Another answer was that the participants had “no time for a break” (4 participants). Another participant answered that he “was not working very well so did not want to lose more time by taking a break”.

Finally, reasons given by only a single participant included that they had been on the telephone, had been taking notes during a meeting, or had a deadline.

When asked about good times to take a break, the participants had several suggestions.

Some of the participants had an idea about the timeframe of the breaks, for instance that the computer should suggest them every 30 minutes (3 participants) or every hour (6 participants “5 minutes each hour to get the focus back”, “each hour a small break for coffee or photocopying”). One of them argued for “no less than 90 minutes after the previous break” and two others for breaks “spread out during the day”.

A number of participants answered that it would be good if the computer responded interactively. For instance, according to two participants, the computer could suggest breaks based on a decrease in their work activity (“Software should wait for you to be idle a few seconds and then start the break”, “at a moment when work intensity decreases”). One participant would like breaks “after some time of undisturbed working”. Although the BabylonB program already had a basic degree of interactivity, one participant thought that “requests did not always seem to depend on computer usage”.

Five participants agreed that the break should be timed between tasks (“in between two files I’m working on”, “after completing mental tasks”, “between subsequent tasks”, “when I am completing one task and switching to another”).

In contrast, other participants suggested that a good time would be when they were in fact working hard (“Especially when working on something very hard (lots of typing/clicking with mouse)”, “whenever the system can detect I’m immersed (or becoming so) it should force breaks”). Both of these participants had experienced RSI symptoms before.

Several participants suggested moments that would be harder to detect by a computer, for instance “during a writer’s block”, “at a point in which I feel I am stuck at work.”, or “when I get a stiff neck.”. One participant simply answered “I can decide myself when to take a break!”. Others answers included “at a moment of low productivity”, “I prefer breaks based on my work energy” and “no fixed time, depends on my agenda”.

3.2.4 Exploratory analysis

Besides choosing to start a microbreak, the participants could also refuse the suggestion. If refused, the participant could choose between a low ability option (“No, I can’t right now”) and a low motivation option (“No, I don’t want to right now”). Additionally, the participant could directly close the dialog window to cancel it. Table 3.4 shows the ways in which the participants refused a microbreak.

Table 3.4: Ways in which the participants refused a microbreak (average percentage of all responses)

Condition	Insufficient motivation (%)	Insufficient ability (%)	Cancelled (%)
High ability	40.05 ± 32.25	12.25 ± 13.33	0.67 ± 2.53
Low ability	52.01 ± 31.25	18.48 ± 23.34	0.61 ± 1.74

A paired-samples t-test found a significant difference ($t(28)=-2.32$, $p = .028$) in the average number of cancels due to insufficient ability for the *high ability* ($M = 1.72$, $SD = 2.56$) and *low ability* ($M = 3.55$, $SD = 1.10$) conditions.

Further exploration of the results focused on the time that participants took before they started using their computer again. In half of the cases when participants complied to a microbreak trigger, they resumed working within 6 seconds of the countdown ending. The mean waiting time before using their computer again was 128.04 seconds after the countdown was done. There was no significant difference between conditions ($t(391)=-.074, p = .941$).

This shows that participants sometimes took a break that was longer than the 30 seconds from the countdown, but at other times they continued working right after the 30 seconds had passed. Thus, no conclusion can be made about whether the microbreaks should have been longer or shorter. Also, the level of ability does not seem to have an influence on break length. A higher level of ability could have had a positive influence on break length, because the breaks were started at a more suitable moment.

3.3 Discussion

3.3.1 Hypothesis

The results of Study 2 provide support for the main research hypothesis, which was defined as *triggering at times of high ability has a positive influence on compliance with well-being triggers, compared to times of low ability*. The *high ability* condition saw significantly higher compliance rates compared to the *low ability* condition. Reported compliance rates were 18.1 percentage points higher on average, while true compliance rates were 18.2 percentage points higher on average.

These results are in line with the Fogg Behavior Model (Fogg, 2009), which predicts that the higher the level of ability of the subject to perform the target behavior, the more likely they are to comply with a persuasive trigger for that behavior.

3.3.2 Questionnaire responses

The responses to the questionnaire provide insights into the characteristics and preferences of the participants.

To start, over half of the participants has experienced or currently experiences RSI symptoms, yet the majority have never used anti-RSI software before.

On the whole, the BreakTimer, even with half of the pop-ups in the low ability condition, was seen as positive. The majority of participants answered that they would like to take breaks more regularly and that the pop-ups helped them to do so.

Moreover, over 90 percent of the participants answered that they have the ability to take breaks during work, whenever they want. This is in line with expectations, because knowledge workers often have more autonomy over their work schedule compared to other workers (Drucker, 1993).

The responses by the participants to the open-ended questions contain multiple interesting ideas which can be explored. Overall, the variety in suggestions and preferences again underlines the large individual differences among knowledge workers. Some of the ideas were in line with

earlier expectations and had already formed the basis of the hypotheses for Study 1. Others were more unexpected, such as the suggestion that the computer should force breaks when the user is becoming immersed. Future research could further investigate these ideas.

Since the qualitative results were this valuable, it would have been good to learn about them before starting the experiment. Therefore, another suggestion for future research is to start a study with such a questionnaire and use the results to inform the following steps.

The responses gained with the UWES questionnaire were expected to have an influence on the results of the experiment. However, this was not found to be the case. None of the UWES scales were found to be significant predictors of the participants' overall compliance rate or the difference in compliance rates between the two conditions. Thus, no evidence was found in support of the influence of work engagement on knowledge worker compliance rates with a persuasive trigger to take a microbreak.

3.3.3 Additional conclusions

Besides the support for the research hypothesis and questionnaire results, there are more conclusions that can be drawn based on the results.

More refusals due to low ability in the low ability condition

The number of refused microbreaks due to insufficient ability was higher in the low ability condition than in the high ability condition. This is according to expectations and further evidence that the conditions truly represented low and high levels of ability.

Low false compliance rates

The difference between the reported compliance rates and the true compliance rates was small. After removing the one participant with 34 "false complies", there was an average of less than one falsely complied microbreak triggers per participant. Of course, this might be due to experiment bias: the participants were aware that they were subjects in an experiment and may have tried to do what they thought was expected of them. Nonetheless, it can be concluded that for Study 2, the number of false complies was low. When the participants reported that they would take a microbreak, they really did so.

Clear difference between the options for insufficient motivation and ability

The results of the questionnaire show that over 80 percent of the participants agreed that there was a clear difference between the two options to refuse a microbreak, "No, I can't right now" and "No, I don't want to right now". This is in line with the comments made by the participants from Study 1. It is further evidence that the factors motivation and ability are two distinguishable concepts.

Large individual differences

Both for the compliance rates and the reasons for which participants refused microbreaks, the standard deviations were quite large. As shown in Tables 3.2 and 3.4, the standard deviation can be close to, or even larger than, the corresponding means. It therefore seems that the variance in compliance rates and responses is quite large.

The qualitative results also showed a great variety of responses. As with Study 1, there appear to be large differences between individuals. This is consistent with earlier research, which found that “the opportune moment [to persuade] seems to vary between individuals” (Räisänen et al., 2008).

3.3.4 Limitations and future research

The Fogg Behavior Model (Fogg, 2009) describes three main factors for effective persuasion: ability, motivation and a trigger. In this study, triggers were presented and the predicted level of ability (high versus low) was used as the independent variable. The motivation factor was not included in the experiment. The study was carried out under the assumption that motivation would be independent from ability. However, Study 1 found a medium-to-high correlation ($r = .48$, $p < .001$) between motivation and ability. One could therefore also argue that, to some extent, the high and low ability conditions corresponded with high and low motivation, respectively. However, even if this is true, the results would still be in line with the Fogg Behavior Model, since the model describes that high motivation should also lead to higher compliance.

The generalizability of Study 2 can be assumed to be greater than that of Study 1. This is mainly because of the increased number of participants: 35 instead of 6. Additionally, the diversity among the participants was greater for Study 2. Although all the participants qualified as knowledge workers, they occupied different positions at different companies.

The execution of Study 2 faced no major issues. However, it is worth noting that for such experiments, unforeseen technical issues can always occur. In the case of this study, three participants that started the experiment could not continue due to technical difficulties. They were replaced by other knowledge workers. Additionally, finding appropriate participants proved to be difficult due to the technical requirements (for instance, using a suitable operating system).

As expected, the low ability condition occurred more often than the high ability condition, even with the efforts made to balance the two. Additionally, the standard deviation of the displayed triggers for both groups is higher than two-thirds of the mean, which again shows how large individual differences can be.

One improvement that could be made in future research is to test additional conditions. For instance, one could base conditions not only on high or low ability, but also on random timing (as done in the work by Ho and Intille (2005) and Liu (2004)), or timing that consults the knowledge worker’s electronic agenda before interrupting, or timing based on a fixed schedule determined beforehand by the knowledge worker. Additionally, the two factors that were used in to predict the level of ability (TimeSinceBreak and AbilityChange) could be examined as

separate conditions. This could be done to determine the relative influence of the two factors.

4. GENERAL DISCUSSION

The current research describes two studies. Study 1 was performed to answer the research subquestion: “*What are times of high motivation and high ability to take a microbreak, for knowledge workers?*”. The study investigated whether self-rated levels of motivation and ability to take a microbreak could be predicted, based on context information (computer activity such as mouse clicks and key presses). It was found that the level of ability of knowledge workers to take a microbreak could be predicted based on two factors: the time since their last break (TimeSinceBreak) and the change in their overall computer activity level (ActivityChange). Of these two, it seems that TimeSinceBreak has a larger influence in determining ability. The level of motivation to take a microbreak could not be predicted based on the results.

Study 2 was performed to answer the main research question: “*What is the influence of triggering at times of high motivation and high ability (versus times of low motivation and low ability) on compliance with microbreak triggers for knowledge workers?*” The hypothesis was that *triggering at times of high motivation and high ability has a positive influence on compliance with microbreak triggers*. The study used an experiment to test the influence of persuasive triggers to take a microbreak at different times. The triggers were presented whenever a time of high ability was detected or a time of low ability, based on the two contextual factors TimeSinceBreak and ActivityChange. The results of the experiment supported the main research hypothesis. It provided evidence that compliance with the target behavior of a persuasive technology is significantly higher if triggers are presented at a time of high self-rated ability to perform that behavior.

4.1 Fogg Behavior Model

The results of Study 2 showed that a persuasive trigger at a moment of high ability to perform the target behavior leads to higher compliance, compared to a moment of low ability. Therefore, the results provide evidence that support a part of the Fogg Behavior Model (FBM) developed by Fogg (2009). Specifically, the level of ability can be used to help define what is an opportune moment, or *kairos*. They also confirm the theory by Fogg (2009) that triggering at such an opportune moment leads to higher compliance with the target behavior.

The other important condition described in the FBM, motivation, could not be predicted based on the results from Study 1. Therefore, Study 2 was not able to test if a higher level of motivation also leads to higher compliance. However, a number of conclusions can still be made.

The first of these conclusions is that motivation should not be disregarded. The results

of Study 2 showed that insufficient motivation was the reason to refuse the suggestion of a microbreak in 40 or 52 percent of the cases in the high and low ability conditions, respectively. Therefore, motivation seems to be an influential factor when it comes to compliance with persuasive technology.

The second conclusion is that, according to the participants, motivation and ability were two distinct factors. A positive, medium-to-high correlation ($r = .48$, $p < .001$) between the motivation and ability ratings was found in Study 1. However, the questionnaire from Study 2 found that over 80 percent of the participating knowledge workers agreed that the difference between the options for insufficient motivation and insufficient ability was clear. This means that they should be seen as two separate concepts.

Nonetheless, the question remains as to why the level of motivation could not be predicted. Thus, the extent of its role in persuasive technology remains unclear. One option that could explain why building a model using data mining was unsuccessful, is that there was insufficient data to do so. As described earlier, the dataset used during Study 1 was much smaller compared to the one used by Poppinga et al. (2014) to build their model. If this is the case, a solution would be to perform a larger-scale version of Study 1. This could be done by examining more participants over a longer period of time. Another option would be to examine a single participant over a longer period of time, to develop a personalized model.

Another reason could be that motivation is not as easily predicted as ability, at least in the case of knowledge worker motivation to take a microbreak. This could in turn be caused by a lack of clarity for the term motivation. The Fogg Behavior Model (Fogg, 2009) describes motivation as a single concept. However, as Ryan and Deci (2000) explain, “although motivation is often treated as a singular construct, even superficial reflection suggests that people are moved to act by very different types of factors, with highly varied experiences and consequences”.

As shown in Chapter 1, there are different theoretical models that try to predict human behavior. Many contain multiple factors that, together, determine motivation. For instance, both the theory of planned behavior (Ajzen, 1991) and the motivation, ability, opportunity (MAO) model (Ölander & Thøgersen, 1995) describe motivation as *intention*. Intention is in turn determined by the subjects’ attitude towards the target behavior and subjective norms about the behavior. Other factors that are connected to motivation are *perceived behavior control* (Ajzen, 1991), which is about the subject’s belief whether or not they can successfully perform the target behavior, and the MAO model definition of *ability*, which is about task knowledge and habits.

None of these determinants of motivation are accounted for in the Fogg Behavior Model (Fogg, 2009). Extending the model with such constructs could add more detail to what is now simply described by the general term of motivation. A benefit of using more specific factors is that they can be tested more accurately and provide further insight into what determines compliance with persuasive technology. An example could be a person who is persuaded to go snowboarding. The perceived behavior control of this person could be low when it comes to this activity (they are not confident that they will make it down the hill), but their attitudes or the social norms towards the behavior might be positive (they think snowboarding is fun,

or their peers are fond of snowboarding). The result could be that they are convinced to go snowboarding, even though their overall motivation appears to be at a low level.

A more practical benefit of an extended model is that it might be easier to increase the effectiveness of the persuasive technology. If it is clear which determinant of motivation is at a low level (for instance, perceived behavioral control towards the behavior), it is also more clear what should be done to increase it (adding text saying “You can do it!”, or showing how easy snowboarding is). Thus, a more detailed model could make it more certain how to improve the design of persuasive technology and thereby make it more persuasive.

To conclude, an extended model may provide more insight into the determinants of a persuasive technology. Nonetheless, the current research provides supportive evidence for the Fogg Behavior Model. Although not all aspects of the model could be tested, the evidence suggests that presenting persuasive triggers at times of high ability to perform the target behavior leads to significantly higher compliance, compared to times of low ability. Additionally, the level of ability can be determined by introspection, since it was based on self-ratings by the participants.

4.2 *Context and persuasive technology*

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 (2012) and IJsselsteijn et al. (2006), who described supposed advantages of context awareness for delivering persuasive health messages. Furthermore, timing itself indeed seems to be “critical” (Fogg, 2002, p. 43) for the effectiveness of persuasive technology.

For the current research, the type of context used was the computer activity of knowledge workers. The experiment that was carried out used basic data about the number of recorded computer events, such as the number of mouse clicks or key presses, made by the participants in a certain time period. Although this was low-level data, as opposed to high-level data that describes what kind of task the computer users are engaged in, the results led to significantly higher compliance with the target behavior of taking a microbreak. Thus, even low-level data can lead to a significant improvement in the timing of persuasive triggers, and therefore compliance.

Another conclusion that can be made on the basis of the results from Study 1 is that it is hard to accurately predict human behavior, or even just their computer activity. However, activity recognition was not the goal of Study 1. Rather, the goal was to go skip activity recognition, and go straight from computer activity to predicting self-rated levels of motivation and ability. This approach was successful, in that it significantly increased compliance with the target behavior. Thus, this method could be useful if applied to the development of other persuasive technologies.

Besides computer activity, many other types of context exist. For example, information about a person’s cognitive load, the amount of mental effort needed to perform a task (Sweller, 1988), could be of great value. It is easy for people to see whether their coworkers can be disturbed during a task, but there is no technology which can reliably determine the same thing.

As Hudson et al. (2003) 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’”. This is also why other research in the SWELL project has focused on measuring cognitive load during tasks or on automatic recognition of the facial expressions of computer users to estimate cognitive load.

4.3 *Limitations and future research*

As mentioned in the discussion of Study 1 (section 2.3), one direction for future research could be a large-scale replication of Study 1. An extended version could examine more participants over a longer period of time. The results might be used to create a satisfactory model for predicting times of high motivation and ability. Such a model could provide insights in to what type of computer activity correlates with these two factors. These insights could lead to the development of additional hypotheses.

Moreover, it may even be useful to examine only a single participant over a longer period of time. Individual differences have proven to be large in both Study 1 and Study 2, which could also have been the reason that no satisfactory model could be developed. By studying only one participant, a personal model for that participant might be developed. If this is the case, one could imagine a learning model which adjusts to an individual knowledge worker’s habits and preferences.

Another avenue of research is to study the motivation factor more in-depth. Since the level of motivation could not be predicted based on the results of Study 1, it could not be included as a factor in Study 2. However, the results of Study 2 show that insufficient motivation was often given as a reason for not complying with a microbreak trigger. On average, 40.1 percent of all triggers in the high ability condition and 52.0 percent of the triggers in the low ability condition were refused because of insufficient motivation. Based on these results, motivation seems to be an important factor. Investigating this factor might uncover ways to greatly improve compliance with persuasive triggers.

Finally, as described earlier, the influence of other types of context information on the effectiveness of PT could be investigated. The low level data used in the experiment of Study 2 was only about how much the participants were working on their computer. But one could also look at what exactly computer users are doing, what their current stress level is, who they are with, as well as many other types of information that might determine the context of a user.

4.4 *Practical implications*

The results of this research have several implications for future applications.

During both Study 1 and Study 2, some of the participants made the remark that they found the well-being triggers bothersome. An explanation for this could be that the triggers lacked subtlety, due to their sudden appearance as pop-ups in the middle of the participants’

computer screens. One participant described them as being displayed “out of the blue”. A more understated approach is suggested for future applications. For instance, the triggers could fade in gradually or stay limited to a corner of the screen.

Existing anti-RSI software applications display break notifications to their users, in an attempt to make those users stop using their computers. Some applications, such as WorkPace, display such notifications after a set time. However, the results of this research show that timing is not a fixed factor but one that is interactive and highly dependent on context. Therefore, existing anti-RSI software could also look at the increase and decrease in the user’s activity to improve the timing of their notification and thereby increase the compliance with such break timers.

If such existing software applications, or any other persuasive technology application, would like to find the opportune time to change their user’s behavior, they could make use of the same method as the current research. The experiment has shown that self-rated ability to perform the target behavior appears to be a predictor of compliance with that behavior. Therefore, research that investigates users’ subjective ability scores could be used to identify the opportune time to persuade those users. Such research could therefore prove to be valuable for all kinds of persuasive technologies.

4.5 *Conclusion*

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 microbreaks during work. Encouraging such behavior with persuasive technology has several advantages, such as availability and scalability of such interventions.

Literature suggests that persuading people at the right time is critical to ensure the effectiveness of persuasive technology. If a technology is aware of context, it should be able to identify such opportune times and thereby increase compliance with the target behavior. The Fogg Behavior Model (Fogg, 2009) suggests that an opportune time to persuade is one where the subject’s motivation and ability to perform the target behavior are at a high level. As such, a technology that tries to persuade knowledge workers to take microbreaks, should be able to use context information to predict times of high motivation and high ability.

The current research has shown the importance of appropriate timing for the effectiveness of persuasive technology. Additionally, context information such as computer activity can be used to identify the best moment to present persuasive triggers. What constitutes appropriate timing can be determined based on the subject’s self-rated ability to perform the target behavior, as described in the Fogg Behavior Model (Fogg, 2009).

Persuasive technology can be used to stimulate healthy working behavior and thereby reduce the health risks associated with computer use. But there are many other areas where persuasive technology can improve people’s health. As described in Chapter 1, e-coaches have

been designed for various health-related issues, such as diabetes (Franklin et al., 2008), proper nutrition (Kroeze et al., 2006), weight loss (Tate et al., 2001) and quitting smoking (Lenert et al., 2004).

These are all areas that could potentially take advantage of context-awareness to improve the effectiveness of their messages. Improving compliance with such systems means improving people's health. Further research into the timing challenges for persuasive technology means, quite literally, providing people with the time of their lives.

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Appendix A – Informed consent form Study 1



Informed consent form

This document gives you information about the research “Timing for well-being tips at work”. Before the research begins, it is important that you learn about the procedure followed in this research and that you give your informed consent for voluntary participation. Please read this document carefully.

Aim and benefit of the experiment

The aim of this research is to gain insight into the working habits and preferences of knowledge workers. This information will be used to improve well-being at work for knowledge workers, as part of the SWELL project.

This research is done by Jef van Schendel, a student under the supervision of Saskia Koldijk of TNO and dr. Jaap Ham of the Human-Technology Interaction group at Eindhoven University of Technology.

Procedure

A number of times throughout the day, you will automatically be asked to answer two short questions about microbreak timing. Microbreaks are short but frequent breaks, around 30 seconds every 20 minutes, in which you can for instance get up and take a short walk. For the best results, we ask you to answer the questions as honestly and truthfully as you can. If you have not received any questions for a day or more, please contact the researcher.

Simultaneously, anonymous pc activity data will be collected using an application called uLog. For instance, the number of cursor movements and keystrokes will be recorded, but no content information such as the links you click on or the characters you type. You will have to start this data recording yourself. You will get a reminder to do so when your pc is started.

Risks

The research does not involve any risks or detrimental side effects.

Duration

The research will last approximately 5 working days.

Participants

You were selected because, as a knowledge worker, you are part of the target audience for this research.

Participant's paraph ____

Voluntary

Your participation is completely voluntary. You can refuse to participate without giving any reasons and you can stop your participation at any time during the research. You can also withdraw your permission to use your experimental data up to 24 hours after the research is finished. All this will have no negative consequences whatsoever.

Confidentiality

All research conducted at the Human-Technology Interaction Group adheres to the Code of Ethics of the NIP (Nederlands Instituut voor Psychologen – Dutch Institute for Psychologists).

We will not be sharing personal information about you to anyone outside of the research team. No video or audio recordings are made that could identify you. The information that we collect during this research is used for writing scientific publications and will be reported at group level. It will be completely anonymous and it cannot be traced back to you. Only the researchers will know your identity and we will lock that information up with a lock and key.

Further information

If you want more information about this research you can ask Jef van Schendel (contact email: jef.vanschendel@tno.nl).

If you have any complaints about this research, please contact the supervisor, dr. Jaap Ham (email: j.r.c.ham@tue.nl).

Certificate of Consent

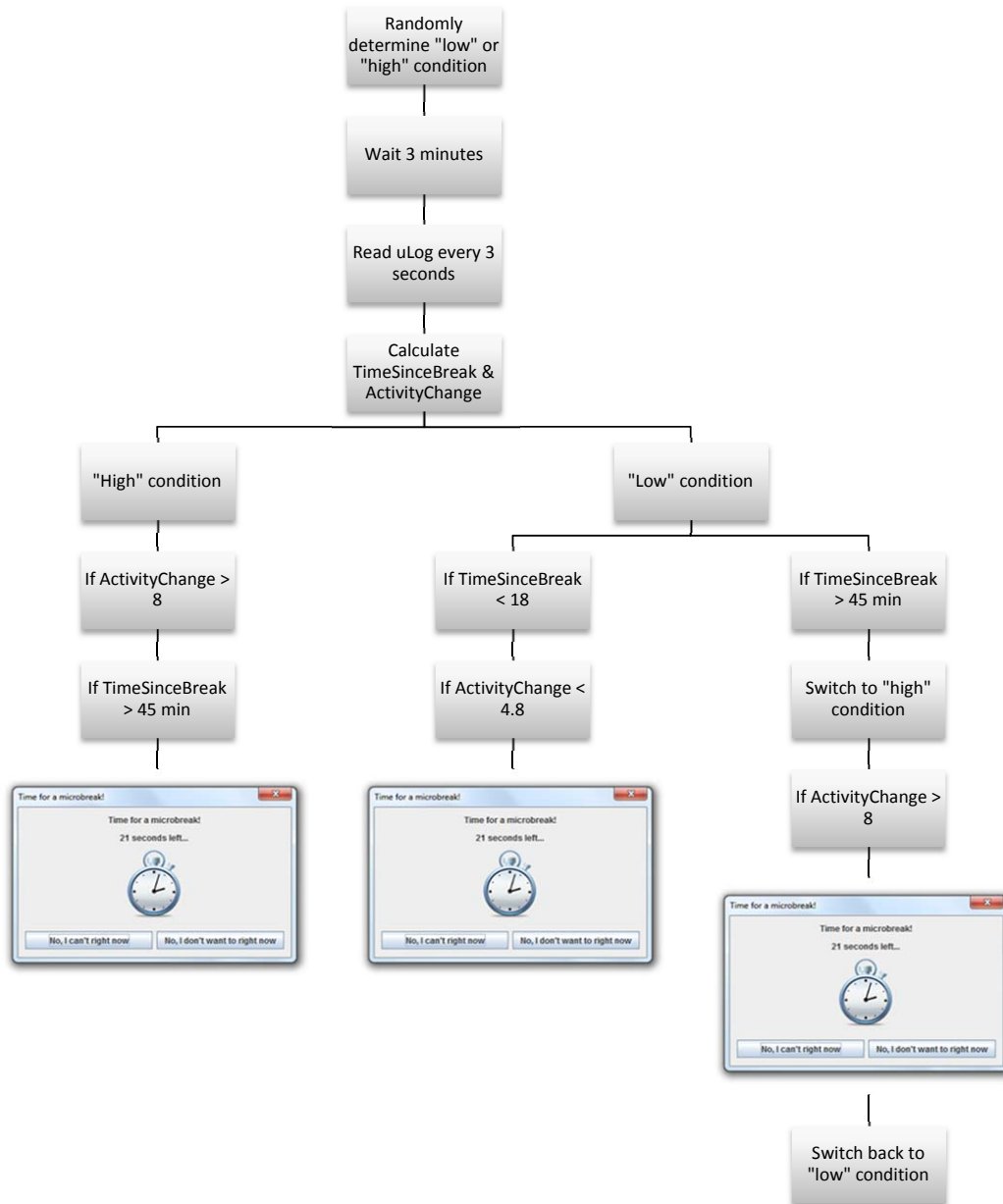
I, (NAME)..... have read and understood this consent form and have been given the opportunity to ask questions. I agree to voluntarily participate in this research carried by the research group Human Technology Interaction of the Eindhoven University of Technology.

Participant's Signature

Date

Participant's paraph _____

Appendix B - BabylonB flowchart



Appendix C – Informed consent form Study 2



Informed consent form

This document gives you information about the research “Babylon Break Timer”. Before the research begins, it is important that you learn about the procedure followed in this research and that you give your informed consent for voluntary participation. Please read this document carefully.

Aim and benefit of the experiment

The aim of this research is to gain insight into the working habits and preferences of knowledge workers. This information will be used to improve well-being at work for knowledge workers, as part of the SWELL project.

This research is done by Jef van Schendel, a student under the supervision of Saskia Koldijk of TNO and dr. Jaap Ham of the Human-Technology Interaction group at Eindhoven University of Technology.

Procedure

During your working day, a Java script will ask you to take a microbreak, which is a short 30-second break during which you refrain from using your computer. You can for instance get up and take a short walk, or do some stretching. You can choose to skip the break, but if you do, please answer why the timing was inappropriate. If you have not seen such a message for a day or more, please contact the researcher.

Simultaneously, anonymous pc activity data will be collected using an application called uLog. For instance, the number of mouse clicks will be recorded, but no content information such as the links you click. This is done automatically.

When the experiment is finished, you will be asked to fill in a short questionnaire.

Risks

The research does not involve any risks or detrimental side effects.

Duration

The research will last approximately 3 working days.

Participants

You were selected because, as a knowledge worker, you are part of the target audience for this research.

Participant's paraph ____

Voluntary

Your participation is completely voluntary. You can refuse to participate without giving any reasons and you can stop your participation at any time during the research. You can also withdraw your permission to use your experimental data up to 24 hours after the research is finished. All this will have no negative consequences whatsoever.

Compensation

Three gift vouchers, worth 10 euros each, will be handed out to three randomly chosen participants at the end of the experiment.

Confidentiality

All research conducted at the Human-Technology Interaction Group adheres to the Code of Ethics of the NIP (Nederlands Instituut voor Psychologen – Dutch Institute for Psychologists).

We will not be sharing personal information about you to anyone outside of the research team. No video or audio recordings are made that could identify you. The information that we collect during this research is used for writing scientific publications and will be reported at group level. It will be completely anonymous and it cannot be traced back to you. Only the researchers will know your identity.

Further information

If you want more information about this research you can ask Jef van Schendel (contact email: jef.vanschendel@tno.nl).

If you have any complaints about this research, please contact the supervisor, dr. Jaap Ham (email: j.r.c.ham@tue.nl).

Certificate of Consent

I, (NAME)..... have read and understood this consent form and have been given the opportunity to ask questions. I agree to voluntarily participate in this research carried by the research group Human Technology Interaction of the Eindhoven University of Technology.

Participant's Signature

Date

Participant's paraph _____

Appendix D – questionnaire Study 2

Break Timer Survey (page 1)

The following 17 statements are about how you feel at work. Please read each statement carefully and decide if you ever feel this way about your job. If you have never had this feeling, enter a '0' (zero) in the space before the statement. If you have had this feeling, indicate how often you feel it by entering the number (from 1 to 6) that best describes how frequently you feel that way.

0	Almost never	Rarely	Sometimes	Often	Very often	Always
Never	1	2	3	4	5	6
	A few times a year or less	Once a month or less	A few times a month	Once a week	A few times a week	Every day

1. _____ At my work, I feel bursting with energy
2. _____ I find the work that I do full of meaning and purpose
3. _____ Time flies when I'm working
4. _____ At my job, I feel strong and vigorous
5. _____ I am enthusiastic about my job
6. _____ When I am working, I forget everything else around me
7. _____ My job inspires me
8. _____ When I get up in the morning, I feel like going to work
9. _____ I feel happy when I am working intensely
10. _____ I am proud on the work that I do
11. _____ I am immersed in my work
12. _____ I can continue working for very long periods at a time
13. _____ To me, my job is challenging
14. _____ I get carried away when I'm working
15. _____ At my job, I am very resilient, mentally
16. _____ It is difficult to detach myself from my job
17. _____ At my work I always persevere, even when things do not go well

Break Timer Survey (page 2)

What is your age and gender?

Age: Gender: male female

Are you currently experiencing any RSI symptoms?

Yes Yes, sometimes No, but I have in the past No

Do you use rest break or anti-RSI software (e.g. Workrave or WorkPace)?

Yes No, but I have in the past No

Please indicate to what extent you agree with the following statements:

I would like to take breaks during work more regularly

Agree Somewhat agree Neither agree nor disagree Somewhat disagree Disagree

I have the ability to take breaks during work, whenever I want

Agree Somewhat agree Neither agree nor disagree Somewhat disagree Disagree

The pop-ups helped me to take breaks more regularly

Agree Somewhat agree Neither agree nor disagree Somewhat disagree Disagree

The difference between the options “No, I can’t right now” and “No, I don’t want to right now” was clear to me

Agree Somewhat agree Neither agree nor disagree Somewhat disagree Disagree

What were the most frequent reasons for you to refuse to take a break?

.....
.....
.....

What, for you, would be a good time to take a break?

.....
.....
.....