Masterarbeit

Stress Prediction for Knowledge Workers based on PC Activity and Noise Level

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April 23, 2014

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Deutsche Fassung:
Beschluss der Curricula-Kommission für Bachelor-, Master- und Diplomstudien vom 10.11.2008
Genehmigung des Senates am 1.12.2008

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Danksagung

Hiermit danke ich meinen Eltern, die mich wähend der Studienzeit immer unterstützt haben.

Ein großer Dank gilt meiner Betreuerin Dr. Viktoria Pammer vom Institut für Wissenstechnologien der Technischen Universität Graz, die mir von Anfang an stets hilfreich zur Seite stand und mich maßgeblich in allen Fragen sehr unterstützen konnte.

Ich möchte mich bei Dr. Franziska Matzer von der Medizinischen Universität Graz für Ihre Unterstützung ebenfalls recht herzlich bedanken.

Ich bedanke mich bei allen Teilnehmern an meiner Studie. Mein Dank gilt auch Dipl. Ing. Georg Sauseng vom Know-Center, der mir bei der Inbetriebnahme der Studie geholfen hat.

Ich bedanke mich beim Know-Center für die zur Verfügung gestellten Geräte und Resourcen.

Kurzzusammenfassung

Die Palette an Einflüssen, denen Personen am Arbeitsplatz, vorallem in IT getriebenen Berufen, ausgesetzt sind, ist vielfältig. Viele dieser Einflüsse verfügen über ein Potential, das die Personen in ihrer Arbeit beeinflussen kann. Untersuchungen haben gezeigt, dass diese Einflüsse der körperlichen als auch der geistigen Gesundheit schaden kann.
Im Zuge dieser Arbeit wurde eine Studie mit zwölf Teilnehmern durchgeführt. Es wurde ein System entwickelt, das die Aktivitäten von Knowledge Worker am Computer und die Umgebungslautstärke automatisch aufzeichnet. Die Aufzeichnung erfolgt mit Hilfe von Sensoren die auf dem Arbeitsplatzrechner und einem Smartphone installiert sind.
Am Arbeitsplatzrechner werden Informationen über Vordergrundfenster und Inaktivität aufgezeichnet. Bei einem Wechsel des Vordergrundfensters werden Beginn und die Dauer des Fensterfokus, der Titel des Fensters und eine eindeutige Fensternummer als Metadaten gespeichert. Inaktivität wird ab einer Minute ohne Interaktion mit dem Computer aufgezeichnet und speichert den Beginn und die Dauer.
Die Umgebungslaustärke wird über das Mikrofon eines Smartphones (Android) aufgezeichnet und die Lautstärkepegel über ein Zeitfenster von einer Minute gemittelt und gespeichert.
Die Sensoren annotieren die gesammelten Daten mit einem anonymen Teilnehmercode und laden diese in periodischen Abständen zum Server hoch. Ein Web Service nimmt die Daten entgegen und benutzt eine Key Value Datenbank um die gesammelten Daten pro Teilnehmercode zu speichern. Pro Teilnehmer werden Daten über einen Beobachtungszeitraum von zehn Tagen gespeichert.
Am Ende des Beobachtungszeitraumes berechnet die Vorverarbeitungskomponente des Systems die Kennzahlen um Arbeitszeitfragmentierung und Lärm zu approximieren. Aus den Fensterwechsel werden die Kennzahlen mit der durchschnittlichen Zeit pro Fenster und Applikation berechnet. Applikationen sind dabei Fenster mit gleichem Titel. Aus Inaktivität werden die Kennzahlen mit der Anzahl von Inaktivität zwischen ein und fünf Minuten und die Zeit von Inaktivität mit einer Dauer über zwanzig Minuten berechnet. Aus den Lautstärkepegeln werden die Kennzahlen mit dem durchschnittlichen Pegel und die Dauer, bei denen der Pegel mehr als 60 Dezibel betrug, berechnet. Die Kennzahlen werden pro Teilnehmer und Arbeitstag für fünf verschiedene Zeitfenster berechnet.
Parallel dazu wurde mit dem System das Stressempfinden des Knowledge Workers erfasst. Das Stressempfinden wurde durch Selbsteinschätzung vom Knowledge Worker manuell in das System eingegeben. Die Eingabe erfolgte zweimal täglich, einmal mittags und einmal am Ende der Arbeit. Je nach Teilnehmer konnten Daten über acht bis zehn Arbeitstage aufgezeichnet werden.
Das Ergebnis der Vorverarbeitungskomponente speichert die Kennzahlen und die Werte der Stresskalen. Mit den gespeicherten Werten wird die Korrelation der Kennzahlen mit den Werten der Stresskalen durchgeführt, um die Vorhersage des Stressempfindes zu analysieren.
Eine Korrelation der Kennzahlen mit den Stresskalen der beiden Selbsteinschätzungen in dieser Studie ergab, das eine Vorhersage des Stressempfindens mit den Kennzahlen möglich ist. Es konnte eine positive Auswirkung auf das Wohlbefinden (Stimmungslage, innere Ruhe) über alle Teilnehmer festgestellt werden, je höher die Anzahl der Inaktivitäten zwischen ein und fünf Minuten gemeinsam mit einem Lautstärkepegel über 60 Dezibel waren.

Abstract

Knowledge workers are exposed to many influences which have the potential to interrupt work. The impact of these influences on individual's, not only knowledge workers, often cause detrimental effects on physical health and well-being.
Twelve knowledge workers took part as participants of the experiment conducted for this thesis. The focus of the experiment was to analyse if sound level and computer interactions of knowledge workers can predict their self reported stress levels. A software system was developed using sensors on knowledge worker's mobile and desktop devices.
Records of PC activity contain information about foreground windows and computer idle times. Foreground window records include the timestamp when a window received focus, the duration the window was held in the foreground, the window title and the unique number identifying the window. Computer idle time records contain information about the timestamp when idle time began and the duration. Computer idle time was recorded only after a minimum idle interval of one minute.
Sound levels were recorded using an smartphone's microphone (Android). The average sound pressure level from the audio samples was computed over an one minute timeframe.
Once initialized with an anonymous participant code, the sensors record PC activity and sound level and upload the records enriched with the code to a remote service. The service uses a key value based database system with the code as key and the collection of records as value. The service stores the records for each knowledge worker over a period of ten days. After this period, the preprocessing component of the system splits the records of PC activity and sound level into working days and computes measures approximating worktime fragmentation and noise.
Foreground window records were used to compute the average time a window was held in the foreground and the average time an application was held in the foreground. Applications are sets of foreground window records which share the same window title.
Computer idle time records were used to compute the number of idle times between one and five minutes and the period of those idle times which lasted more than twenty. From the sound pressure levels the average level and the period of all levels which exceeded 60 decibels were computed. The figures were computed with the scope of an participant's working day for five different temporal resolutions.
Additionally, the stress levels are computed from midday and evening scales. Participants recorded stress levels two times a working day and entered them manually in the system. The first self report was made close to lunch break and the second at the end of an day at work. Since participants forgot to enter self assessed stress levels, the number of working days containing data of all types ranges between eight and ten.
As a result, the preprocessing component stores the measures and stress levels used by the stress predicition analysis component. The correlation of the measures with the self reported stress levels showed that a prediction of those stress levels is possible. The state of well-being (mood, calm) increased the higher the number of idle times between one and five minutes in combination with an sound pressure level not exceeding 60 decibels.

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Abbreviations

WHO	World Health Organisation
AVGW	Average Duration an Information Worker interacted with an Window, in Seconds
AVGA	Average Duration an Information Worker interacted with an Application, in Seconds
AVGS	Average Sound Pressure Level, in Decibel
DURS	Sum of Sound Pressure Level Periods exceeding 60 Decibels, in Seconds
CNTI	Number of Computer Idle Times between one and five Minutes
DURI	Sum of Idle Time Periods equal or greater than 20 Minutes, in Seconds
LEVR	Level of Relaxation
DIMP	Bi-polar Dimension of Well-Being
GS	"Feeling well/Feeling bad"
WM	"Alertness/Fatigue"
RU	"Calm/Restless"
DBC	Database Client
WIN	Window Sensor
CTL	Controller
INA	Computer Idle Time Sensor
SND	Sound Pressure Level Sensor
DB	Database

UPL	Uploader
REC	Record Service
SEL	Self Report Service
HT1	From the Beginning of Work until first Self Report
HT2	From the first Self Report until End of Work
GT	Whole Day of Work
LS1	Hour before the first Self Report
LS2	Hour before the second Self Report
CRUD	Create, Read, Update and Delete
ORM	Object Relational Mapping
MSI	Windows Installer package
APK	Android Application Package File
JSON	JavaScript Object Notation

1. Introduction

1.1. Motivation

Human beings pursue their personal activities, during their work life as well as in private settings. We will do hard in finding a person with only a single activity left on its list, waiting to be accomplished. Quite the contrary is the case. Our lifestyles keep the list of pending activities in good shape. Luckily, technology comes up with tools which support us in accomplishing activities. E.g. we collect information using web browsers regarding our next journey in a city of our choice. We communicate with workmates residing in other countries using chat programs. We store our calendar using the cloud checking appointments with different devices, anytime and anywhere. The individual picks the desired tools supporting activity management and life starts to be a successful story. Gig? In particular information workers are exposed to environmental circumstances which force them to rearrange the order of pending activities or introduce new ones. Consequently, individuals come up with strategies to manage those changes successfully but often struggle to do so. As a consequence, continuous increased levels of stress degrade personal well-being.

1.2. Goal

The goal of this thesis is to analyse the predictive power of computer interaction and ambient noise with regard to the stress level of information workers. In order to reach this goal, a multi-user multi-sensor framework was developed with sensors that a) captures noise level on Android smartphones and b) captures window switching activity on Windows PCs. An experiment was carried out, in which knowledge workers use the developed framework over a period of 10 days. Sensors do the monitoring while running on desktop computers and smartphones. They create a continous stream of foreground window and computer idle times reflecting computer interaction with the desktop computer. Further, a stream of sound pressure levels coming from the smartphone reflects ambient noise. After the experiment, the raw sensory data together with the self assessments of stress levels are aggregated into key figures. Next, the key figures from the sensors are correlated with the self assessments, once over the whole group and once for every information worker itself.

1.3. Structure of Master Thesis

Chapter 2 introduces research on interruptions, their nature and effects. The remaining chapter reports on worktime fragmentation and ambient noise as predictive factors for stress.

Chapter 3 explains the system and its components used to collect data for computing the measures and the stress levels from the knowledge workers necessary for the stress prediction analysis.

Chapter 4 states the research questions to be answered in section 4.1. Section 4.2 explains how the system internals of monitoring and storing computer interaction, ambient noise and self reports of stress. Section 4.3 describes participant's profession and how the recruiting will be done. Section 4.4 describes data preprocessing and computation of the results.

Chapter 5 presents general information of the study with respect to the participating persons and the system usage, presented in the first two sections 5.1 and 5.2. Statistics about measures approximating worktime fragmentation and ambient noise are presented in section 5.3. Section 5.4 presents the results of correlating the measures with information workers self reported stress levels across all study participants. Section 5.5 presents the correlation results for individual participants.

The outline of chapter 6 is a discussion of the results presented in chapter 5. The prediction of stress with window and application interaction times is discussed in sections 6.2.3 and 6.1.2. Sections 6.1.3 and 6.1.4 follow discussing computer idle times and section 6.1.5 discusses prediction of stress with sound pressure levels. Section 6.3 concludes with summarising the findings.

Chapter 7 reviews the goals and the findings of the thesis.

2. Worktime Fragmentation and Ambient Noise as Stress-Inducing Factors at Work

Information workers are exposed to many influences which have the potential to increase stress and strain well-being. This thesis will focus on worktime fragmentation and ambient noise as stress inducing influences. Worktime fragmentation is caused by events for example starting an conversation with an working mate, answer an telephone call, reading mail or instant messaging. Ambient noise is caused by conversations too or by office hardware like printers and air conditioning.

In most of the cases, worktime fragmentation and ambient noise claims an individuals attention and shifts focus away from the task at hand. Therefore, this thesis focus on worktime fragmentation and ambient noise as stress inducing factors at work.

2.1. Worktime Fragmentation

Unfinished tasks cause mental effort and distract the ability to maintain attention. Fragmentation is a process which causes tasks left behind suspended which may be resumed after an indefinite period of time. During this process a person switches attention away from one task to another. The sequence of actions to carry out the task at hand is divided into temporal disconnected periods.

Unfinished tasks Today the successful organisation of worklife is a challenge. Especially information work involves tasks in multiple projects that need handling of different problem statements, teammates, deadlines and so forth. Information workers face influences which exacerbate these challenges. Cost optimizing strategies of managers change working conditions and result for example in an increasing number of tasks that have to be carried out within the same time. Rapid development in technology enriches the variety of devices and applications. As soon as they become integrated in the daily routines they will additionally claim an information workers attention.

Attention is a limited resource and changing it comes at a cost. A persons capability to attend may gets exhausted when there are more and more tasks left undone.

It is not part of the human nature to leave tasks unfinished. [Zeigarnik, 1938] investigated in the phenomenon of unfinished tasks.

The well-known but unresolved Zeigarnik effect examines recall regarding to tasks and interrupted tasks. Participants walk through a list of tasks which they start to carry out one after another. About the half of the tasks were interrupted and not resumed later on. At the end participants were asked to recall the tasks. It could be observed that participants recalled interrupted tasks earlier than completed tasks. The study suggests that working on a task forces the allocation of mental resouces and a “tension system” which drives the need to complete the task. Whenever a task is finished mental resources and also the “tension system” are released. Tasks which are left undone cause the resources and the “tension system” to stay active. [Zeigarnik, 1938]

Eyrolle and Cellier [2000] show that an unfinished task interferes with the task at hand. Interference are failures in activating mental resources of the task at hand and inhibiting resources for the unfinished task. Measuring the efficiency of the task at hand shows participants need more time to get the task accomplished and made more mistakes.

2.1.1. Interruptions

Mark et al. [2005] coins the term “work fragmentation” and define it as *»a break in continuous work activity«*. An break, also being referred as “interruption”, is initiated by an event and places the person receiving the event before a decision. The person can either accept or decline the interruption. Accepting the interruption means stop working on the current task and switch to the task introduced by the interruption. Declining the interruption means to postpone or ignore it. It comes into being a conflict. If the person chooses to accept the interruption it may loose track or fail to resume the work on the interrupted task. Otherwise, if the person declines the interruption important and/or relevant ideas and information may gets lost or missed.

González and Mark [2004] conducted a study about fragmentation of information work. Results show that information workers face a highly fragmented worklife and confirm that interruptions occur continuously through out the working day. Employees of an investment management company and members of a team there took part as participants of the study. The team consists of managers, analysts and software developers who are responsible for development, test and support of financial software modules. Logged activities of the team members were divided into two categories of uninterrupted units of work, using an device or communicating with others. The sequence of units show a high switching frequency.

Figure 1 illustrates the average duration of the identified units of work for all three roles (managers, analysts, developers) combined. People spend on the average three minutes on uninterrupted units of work before they switch. Results for each role alone are similar. Considering 8 hours and 41

Events	% entire day	Avg. Time/Day (sd)	Avg. Time/ Event (sd)
Using phone[1]	5.83	0:30:22 (0:19:14)	0:02:25 (0:00:42)
Using email	9.17	0:47:46 (0:21:18)	0:02:22 (0:00:27)
Using PCs[2]	29.48	2:33:36 (1:11:23)	0:02:53 (0:01:10)
Using paper documents/books	6.80	0:35:25 (0:29:48)	0:01:47 (0:00:31)
Using other tools[3]	0.31	0:01:38 (0:03:08)	0:01:04 (0:00:15)
Talking through the walls	2.94	0:15:18 (0:14:12)	0:01:40 (0:00:24)
Interacting with people in their own cubicle	6.88	0:35:53 (0:29:25)	0:03:34 (0:01:57)
Formal meetings	14.39	1:14:58 (1:17:40)	0:41:47 (0:12:46)
Going to other cubicles	9.11	0:47:29 (0:27:21)	0:07:37 (0:03:24)
Other (unknown, personal)	15.09	1:18:39 (0:34:26)	0:17:27 (0:06:27)
All events except "Formal meetings" and "Other"	**70.52%**	**0:45:56 (0:52:03)**	**0:03:08 (0:02:27)**
All events total	**100%**	**0:52:07 (0:55:25)**	**0:08:55 (0:13:23)**

[1] Includes time spent on cell phones
[2] Includes both PCs and financial terminals – does not include email.
[3] 'Other tools' include: handheld calculator, planners, and address books

Figure 1.: Average duration of uninterrupted work

minutes on average information workers carry out 170 activities per working day.

Activities are aggregated aiming to examine fragmentation on larger units of work. González and Mark [2004] define those units as working spheres which a project would be an example. Working spheres consist of many activities which are thematically related to each other and share the same goal. Depending on the working sphere itself many people may join the team. Each member has a distinct role within the team, make use of different resources to carry out the activities. People like it to work continuously on an working sphere until it is finished. Results of Gonzalez show that people are working on ten different working spheres and spend 30 minutes for each on average per day. Working spheres are also highly fragmented. People engaged in an working sphere get interrupted 25 times per day and switch working spheres every eleven minutes on average. [González and Mark, 2004]

González and Mark [2004] observed different types of interruptions regarding a working sphere and divide them into two categories, internal and external interruptions, following Miyata and Norman [1986]. Internal interruptions stem from an persons own volition and lead to switch the task at hand. Leaving the work place to start an informal meeting with an work mate discussing an important issue which arised or having an idea to solve a problem in another task would be examples of internal interruptions. External interruptions stem from the environment surrounding a persons work place. The ringing of the telephone or the pop up of an instant message on the computer screen would be examples of external interruptions.

	Type	Average Interruptions per day (S.D)	% all types	Internal / External
Internal	Checking/Using Paper Docs	0.52 (0.86)	1.87	**49.11%**
	Checking/Using Computer	1.54 (1.47)	10.98	
	Talking t/wall	1.93 (2.15)	6.89	
	Phone call	1.14 (1.56)	4.09	
	Email use	1.04 (1.47)	7.40	
	Leaves cubicle	5.00 (2.56)	17.87%	
External	New email notif.	3.55 (3.18)	12.68%	**50.89%**
	Person arrives	6.00 (3.03)	21.45%	
	Status on terminals	0.36 (0.82)	1.28%	
	Phone ringing	2.62 (2.01)	9.36%	
	Voice message light	0.19 (0.45)	0.68%	
	Call through wall	1.33 (1.75)	4.77%	
	Reminder notification	0.19 (0.40)	0.68%	
Total		25.40 (8.23)	100%	**100%**

Figure 2.: A picture of internal and external interruptions

Figure 2 illustrates the distribution of internal and external interruptions regarding to working spheres over a day at work. The relation between internal and external interruptions is fairly balanced. Top internal interruptions are leaving the work place closely followed by starting a conversation with a work mate located nearby. Top external interruptions are persons entering the work place closely followed by email notifications. [González and Mark, 2004]

The picture changes when distributing interruptions regarding to the role of a person. Here results show that managers switch working spheres more often due to external interruptions.

Gonzalez reports that people consider the continuous switching between activities as beneficial as well as distracting. Following the study of González and Mark [2004], Mark et al. [2005] observes designated situations when interruptions are felt as notably distracting.

- People maintain a high focus at the task at hand
- Interruption occurs not at a natural breaking point of the task
- Interruption causes to switch working spheres

2.1.1.1. Temporal model of interruptions

O'Conaill and Frohlich [1995] analyse interruptions and their nature at the workplace. They define interruptions as an synchronous interaction between the initiator and the recipient. The initiator of

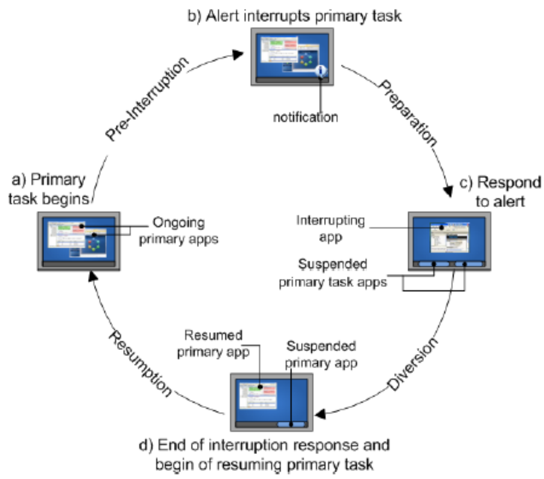

Figure 3.: Model of fragmentation

an interruption could be an person. [O'Conaill and Frohlich, 1995] presumes that the moment in time whenever such an event will occur is unpredictable and always causes the person to move the focus away from the task at hand. The proposed temporal model of interruptions by [Iqbal and Horvitz, 2007] is presented in figure 3. It outlines the process of interrupting and resuming work with a cycle of temporal consecutive phases. It supports O'Conaill and Frohlich [1995] in that it outlines the occurance of an event as the starting point of interruptions which causes a focus shift away from the task at hand.

The person starts working on an task (a). This is the beginning of the pre-interruption phase. During this phase the person maintains a (high) focus on the task. Occurance of an event (b) interrupts the person carrying out the task. At that point of time the pre-interruption phase ends and the preparation phase begins. The person performs actions that leave the interrupted task in a state that allows it to continue afterwards. The person switches focus and starts activities induced by the interruption (c) leaving the preparation phase and entering the diversion phase. In the diversion phase the person carries out the interrupting activities and possibly other peripheral activities. The diversion phase ends (d) and the resumption phase starts. During this phase the person seeks to return to the interrupted task. Recovering focus and continuing work on the task ends the resumption phase and closes the fragmentation process cycle.

2.1.1.2. Interruption Management

Interruption management deals with supporting people at work to keep track of their activities. [González and Mark, 2004, Czerwinski et al., 2004, Cutrell et al., 2001, Iqbal and Horvitz, 2007] examine applied strategies of people when dealing with interruption management. Based on that they critize systems designed to support interruption management and/or propose alternative system design guidelines.

Critics [González and Mark, 2004, Czerwinski et al., 2004] critise that interruption management is not supported well enough or is missing at all. González and Mark [2004] point out the impracticality of a company wide installed task management tool. They tracked a team of fourteen information workers of a financial software service provider company. They found that people are continuously switching between activities throughout the day but did not use the commercial task management tool. They argue that the most important reason for this is that the tool lacks being visible all the time. People instead use special folders in the inbox of the email client, printouts or post-it notes around the desk for example. Czerwinski et al. [2004] critise insufficient technical support to resume interrupted work. They found that the software people were using does not support resuming tasks, which are more complex and lengthier in duration as others, very well.

Artefacts González and Mark [2004], supported by [Czerwinski et al., 2004, Cutrell et al., 2001, Iqbal and Horvitz, 2007], coins the term artefact as an digital or analog resource which supports people in maintaining the overview and attention of their ongoing tasks. Artefacts integrate information relevant to higher level activities like projects. The idea proposed is whenever an activity gets interrupted, its state is saved, making it easier to resume work. Useful artefacts share some common characteristics:

- Permanent visibility
- Preservation of an activities state

[Cutrell et al., 2001, Iqbal and Horvitz, 2007] supports permanent visibility of artefacts. Cutrell et al. [2001] interrupt people searching a book title. The first experiment permanently displayed the description of the title at the top of the screen. In the second experiment they replaced the description with an button to request the display of the description. They found that people used the button most often after resuming from an interruption.

Iqbal and Horvitz [2007] found that people were faster resuming from an interruption if more application windows of the interrupted tasks were visible on the screen.

Inspired by the work of Czerwinski et al. [2004] Groupbarwas designed and an initial prototype implemented. Groupbar uses Windows XP Taskbar features to manage groups of windows. Users organize windows of documents, emails and other project-related resources. Each project consists of a group of windows which are always visible in the XP Taskbar. Groupbar retrieves and arranges windows when switching from one project to the other. This approach should support recovery of projects and save time when switching between projects.

O'Conaill and Frohlich [1995] proposes video diaries for recovery support. They suggest that brief audio visual sequences of the state of an interrupted task might help resume work.

Another idea proposed by O'Conaill and Frohlich [1995] is to keep the number of pending tasks small. They suggest to organize work into a lot of small, easy to solve units. Smaller units of work experience less or no interruptions. Additionally employees who accomplish many small tasks throughout a day at work might experience more positive feelings than another one working on a few complex tasks and might does not finish any of these.

There is always the opportunity to refuse an interruption O'Conaill and Frohlich [1995]. The decision of refusing or accepting an interruption is a conflicting situation Miyata and Norman [1986]. In most of the cases interruptions are accepted. The most probable reason for this is the fear of missing important information. Similar to refusing is the strategy of filtering interruptions O'Conaill and Frohlich [1995]. The filter acts as a proxy and somehow manages if the interrupting event will be forwarded to the intented receiver or not. For example the secretary of an managing employee acts as a filter. Information workers more probably will use software tools as interruption filters. Studies show that these tools only have limited success. Milewski and Smith [2000] for example let callers review the callee's state before placing the call. Unfortunately persons did not maintain their state and rendered the system ineffective. Rodenstein et al. [1999] implemented a lightweight filter prototype and found that usage of their filter does not achieve any performance gains.

Hudson et al. [2002] does not support the approach of reducing interruptions, for example by filtering methods, and favor suitable moments in time for placing an interruption for further investigation. The work of Adamczyk and Bailey [2004] support Hudson et al. [2002]. They found that interrupting a person at suitable moments in time during or between units of work have far less disruptive effects on person's emotional state and social attribution. They conclude with design guidelines of an attention manager system which identifies those moments.

Speech and office noise can have detrimental effects on task performance as well as negative effects on emotional well-being of office inhabitants [Banbury and Berry, 1998, Jones and Hughes, 2001]. Jones and Macken [1995] propose to add white noise in offices to reduce disruptive effects. They showed that an increasing number of voices from the same spatial location produce far less dispruptive effects. Nevertheless Banbury and Berry [1998] mention the "electronic masking system" of Northwood et al. [1979] which achieved only limited success in office environments Vischer [1989]. Instead Banbury and Berry [1998] suggest to adapt the acoustics of an office like use of sound isolating materials in order to make speech less intelligible.

2.1.2. Effects of Worktime Fragmentation

In 2005 a company conducted interviews and online surveys among knowledge workers in the United States. The white paper explains the estimation of costs based on the time effort caused by fragmentation. The calculation sums up the time spent for unimportant interruptions and the average recovery time from both important and unimportant interruptions. An interruption starts with the interrupting event and ends with the worker pick up the activity where one left off. Results report interruptions cause more than two hours time effort per knowledge worker per day. The survey reported 588 billion dollars lost based on the 56 million knowledge workers at this time with an average salary of 21 Dollars per hour. [Spira et al., 2005]

Beside the "time is money" function, research examines the costs of fragmentation on the performing individual itself. Negative effects on the emotional state of human beings could be observed. There is a risk that with an increase of fragmentation negative emotions also increase and stressful periods of time become more frequent. Health will suffer under continuous stress. In particular the IT section shows potential to support risk of experiencing stress like high demands on quality, high degree of self responsibilty and goals which are difficult to notice, measure or reach. [Österreichischer Bundesverband für Psychotherapie, 2014, p. 2]

2.1.2.1. Effects on task performance

Time on task One method applied by studies to quantify the effects of interruptions on task performance is measuring the time a person needs to accomplish a task, comparing the time on task with or without interrupting the person.

[Mark et al., 2008, Zijlstra et al., 1999] show that persons need less time for the same task if an interruption occurs.

Mark et al. [2008] suspend reading and answering of email with telephone calls and instant message pop ups. The interruption requests the answer of a question. One group of participants were asked questions which are contextually related to the content of the email, a second group were asked questions which are not contextually related to the content of the email. Results show that interruptions, independently of context between email and question, force persons to increase their working speed and answer emails faster.

Zijlstra et al. [1999] found a significant increase of working speed from leaving a task uninterrupted to interrupt the task once. In their experiment persons continue editing documents much faster when they were interrupted by telephone and advised an urgent request to take on.

[Gillie and Broadbent, 1989, Czerwinski et al., 2000b, Cutrell et al., 2001, Mark et al., 2005, Bailey et al., 2001] show that people need more time to accomplish the same task when getting interrupted.

Gillie and Broadbent [1989] examine effects of interruptions on the time to accomplish an task when interrupting with tasks with different degrees in complexity. Interrupting with an easy problem shows no effect on the duration to finish the interrupted task. Interrupting with more complex problems shows an significant increase of the total time to carry out the interrupted task. Gillie and Broadbent [1989] concludes that complexity of tasks induced by an interruption is an driving factor of the distracting power of interruptions. Gillie and Broadbent [1989] also examine effects of interruptions regarding time on task when cognitive processes of the task at hand are similar with those of the interrupting task. The results show an significant increase of the time on task.

Persons browsing a list of book titles need more time to find the requested title when being interrupted. An attempt to support recovery of the search, highlighting the title looked at before switching to the interrupting task, could not be shown.

Cutrell et al. [2001] examines the effects of interruptions on task performance when interrupting at different moments in time. The goal of the primary task was to find a the title of a book in a given list of titles. The task was carried out an a desktop computer. Cutrell et al. [2001] conducted two trials with different ways how the title to search for was presented to the participants. In the first trial participants were shown the exact title of the book, in the second trial participants were shown a hint consisting of a few sentences. Participants were allowed to display the hint anytime during the task with the push of a button. The search task was interrupted with an instant message popping up on the screen. The interrupting task was an arithmetical computation. They show that persons need longer to find the title when interrupting while the user is browsing in the first half of the list. In this case the participants more often used the button which displays the hint of the book title. They show that the timepoint of interrupting a task is important regarding its disruptive effects on task performance.

Mark et al. [2005] analyse work fragmentation and focus on collocation of employees. They show that employees in open plan offices need more time on average to accomplish an task in comparison to employees in small and medium sized offices. They state that employees in open plan offices are much more exposed to interrupting events.

Bailey et al. [2001] conducted an experiment where people had to solve several tasks from six different categories. They interrupted only a few of the tasks. They show that interrupted tasks took persons much more time to accomplish the task as uninterrupted tasks.

Czerwinski et al. [2000a] analyse the effects of interrupting an task with instant messages containing either relevant or irrelevant information about how to accomplish the task. The task is conducted using a desktop computer and consists of search and evaluation of a website. Participants formulate a search query based on the short description of the target website. They select the most appropriate target from the search result list and evaluate the website. Finally the website is classified into one of three categories. Instant messages pop up during the web search, some of them containing the category of the target website. Czerwinski et al. [2000a] found that interruptions caused persons to need more time to finish an task because they need more time to resume. Additionally the results show that irrelevant interruptions disrupt time on task more heavily as interruptions which contain relevant information.

Czerwinski et al. [2000a] interrupt tasks at different moments in time and analyse the effects on task performance. They follow the results of [Miyata and Norman] who found evidence that the timing of an interruption has an significant impact on the disruptive effects. They categorize an task in three temporal phases (planning, execution, evaluation). Interruptions in form of instant messages occur in one of the phases. They measured the time people need to switch from the primary task to the instant message, the time to accomplish the task described by the message and the time to recover work on the interrupted task. Czerwinski et al. [2000a] found that switching from the task to the interruption is slower when the interrupting event occurs after the planning phase. More importantly, interrupting the task at a later phase affected the time to reorient back to the interrupted task and thus decreasing task time performance.

Gillie and Broadbent [1989] could not show that people need more time to accomplish interrupted tasks. The suspension of an task with a short interruption (30 seconds) shows no effect on the total time people need to finish the interrupted task. They argue that people achieve to maintain the state of the interrupted task. They repeated the experiment and prolonged the suspension of the primary task to three minutes. Again, no effects on the interrupted task regarding the time to carry it out could be shown.

Quality of work Studies focus on the way how people conduct their work when getting interrupted. [Mark et al., 2008, Zijlstra et al., 1999] show that despite interruptions the quality of work does not diminsh.

Mark et al. [2008] suspend reading and answering of email with telephone calls and instant message pop ups. The interruption requests the answer of a question. One group of participants were asked questions which are contextually related to the content of the email, a second group were asked questions which are not contextually related to the content of the email. Mark et al. [2008] measured quality in terms of the error rate, number of words and politeness within the answer. Results show that none of the measures changed significantly between non interrupted and interrupted tasks.

Zijlstra et al. [1999] examine the error rate of an task interrupted with problems of different complexity. The results show no significant effects on the error rate of the interrupted task, regardless of wether the task is interrupted with an easy or more complex problem. The results do not support the observations regarding complexity and time on task made by Gillie and Broadbent [1989].

Banbury and Berry [1998] show that interruptions cause quality of work to diminish. They interrupted tasks with speech and ambient noise either containing speech or no speech and observe impacts on task performance. They show that not only speech but also ambient noise with and without speech caused quality of work to diminish. Participants had to solve two kind of tasks, one computational and one recall task. They measured the accuracy of the results. Their findings show that speech as well as ambient noise have detrimental effects on accuracy.

Basically people recover work after an interruption. [O'Conaill and Frohlich, 1995, Mark et al., 2005] focus on recovery of work and use it to measure the effects of interruptions. The studies show that people often do not return to interrupted tasks or even forget them at all. O'Conaill and Frohlich [1995] took video recordings of employees over one week. Analysis of the recordings reveal that persons were interrupted four times per hour on average. In more than 40 percent of the cases the persons did not return to the interrupted task immediately or on the same day. Instead, persons continue work on subsequent tasks following the task which came with the interruption. Or the interrupting task was interrupted again. Mark et al. [2005] found evidence that people do redundant work on interrupted tasks.

2.1.2.2. Effects on emotional state

In the following, studies show positive and negative effects of interruptions regarding the emotional state of individuals.

Mark et al define working spheres as higher level units of work including many activities that share a common goal. They observed working spheres of information workers with different roles (managers, analysts, deverlopers) and found out that interruptions which cause a switch between working spheres is mainly considered as a negative event. In contrast, they found some evidence that interruptions regarding the current working sphere are felt as beneficial. Mark consider interruptions which cause switching context between higher level units of work as important regarding their distracting power.

Mark et al. [2008] examine if interruptions are beneficial if the interruption and the primary task share some context. The primary task of the experiment is reading and answering emails. Interruption are trigged in between with instant messages and telephone calls. One group of participants were interrupted with questions sharing context with the primary task. Questions of the second group did not share any context with the primary task. Results show that context has no significant effects on task performance but persons changed their working behaviour.

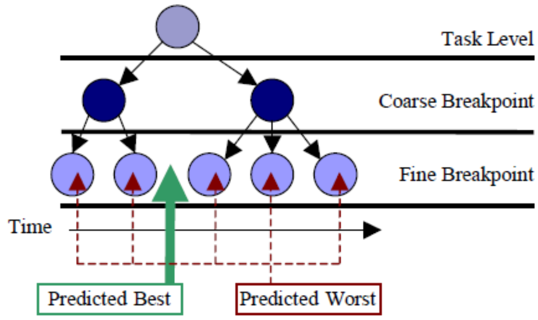

Figure 4.: Cognitive Task Model

They increased working speed resulting in a faster performing interrupted tasks. Consequently interruptions lead to higher efficiency but this change of behaviour caused effects on the emotional state. Reports show that persons experience higher levels of stress including work load, frustration and time pressure. Mark et al. [2008] state that people increase working speed to compensate the time they need to recover work on the task beforehand.

Adamczyk and Bailey [2004] examines the effects on emotional state when interrupting an activity at different moments in time. Results in this study show that predicted best moments of interruption cause fewer distracting effects as predicted worst moments. A cognitive task model is used to predict best and worse moments of interrupting events. Based on findings in event perception research the model organises activities into hierarchical units. The hierarchy consists of two levels with coarse units as the higher level parents of more fine grained units. Coarse and fine grained units are temporally and logically connected with each other and as a whole make up an activity. Figure 4 shows the schematic segmentation of an activity and highlights favourable and worse moments in time for an interrupting event. Interrupting an activity between coarse units is considered the best moment because there are more cognitive resources available for carrying out the interrupting activity. Additional they presume the focus back on the task at hand is recovered more easily because the person starts working at the beginning of the next unit. The study starts with developing a model for three tasks (editing and saving a word document, watch a video and write a summary of it, copy and save the result of a web search into a word file). The resulting models described the coarse and fine units of each of the tasks with 60 to 80 percent agreement among the participants. Based on the models participants were interrupted at predicted best, worst and random points in time with full screen pop-ups. The interrupting task was reading a news story and choosing an appropriate title out of three suggestions for it. The emotional state was captured after finishing an task and were measured with feel of annoyance, frustration, time pressure, mental effort and respectfulness. Results show a significant difference between best and worse moments. Best moments show fewer feel of negative emotions and were deemed more respectful of the task at hand.

Hudson et al. [2002] support findings of Adamczyk and Bailey [2004] and suggest that finding a good moment in time for interrupting an activity is much more useful than reducing the number of interruptions. Their study evaluates availability for being interrupted at different times during a working day. Participants report different attitudes for being interrupted depending on the time of a day. In almost all cases interruptions are associated with negative feelings. Despite of that many expect and even demand interruptions as part of the job which drive progress.

Mark et al. [2005] examines fragmentation in the workplace and explain situations where interruptions cause negative effects on personal well-being. They mention particular moments in time when an interrupting event occurs as such a situation. These moments are considered worse regarding to the breaking point of an activity. Their finding supports the observations made by Adamczyk and Bailey [2004] that worse moments of interrupting an activity are more likey to trigger distracting effects on persons emotional state. Although they present a similar model of dividing activities into hierachical units as Adamczyk and Bailey [2004] but the authors do not further explain how worse moments of interrupting relate to their model.

Bailey et al. [2001] analyses the effects of interrupting events on performance and personal well-being at different moments during an activity. Like other studies which analyse the effects on personal well-being the authors choose annoyance and mental effort as emotional dimensions but dropped frustration. Instead they take anxiety as third dimension. Participants have to accomplish three activities in a row. The interrupting events occur either in the middle or between two consecutive activities. The findings are similar to those presented in Adamczyk and Bailey [2004] and show that interruptions between activities cause less distractive effects on persons emtional state than interruptions in the middle of activities. Feel of annoyance is less when interrupting happens between two activities. Observations taken on anxiety report similar behaviour as annoyance. Anxiety is interpreted in this context as the fear to fail finishing an activity in time. The findings about the timing of interruptions and the influence of the emotional state of persons support the approach suggested by Adamczyk and Bailey [2004] to reduce negative emotions with a smart choice of breaking points.

[Mark et al., 2005, Bailey et al., 2001] report on interruptions and the perceived work load of interrupted tasks. Mark et al. [2005] observe that people start working on two to three tasks on average after an interruption. In many cases interruptions cause a much longer chain of tasks. Their findings show that people perceice a high mental effort to recover work on interrupted tasks. They report that people often forget what they have already done and do it again. Bailey et al. [2001] show that people felt much more annoyed when they were interrupted during work actitiy on tasks of higher complexity.

[Mark et al., 2008, Czerwinski et al., 2000a, O'Conaill and Frohlich, 1995, Adamczyk and Bailey, 2004] report positive effects of interruptions on the emotional state of an person. [Mark et al., 2008, Czerwinski et al., 2000a] found evidence that interruptions sharing context with the task at hand are often felt as beneficial. O'Conaill and Frohlich [1995] report that in more than 60 percent of the cases the person being interrupted received some benefit from the interruption. Adamczyk and Bailey [2004] report that person experienced more respectful emotions when interruptions were initiated at appropriate moments in time.

2.1.2.3. Effects on working behaviour

Mark et al. [2008] measured the time people spend on an task which is interrupted and observed people changing working behaviour when getting interrupted. They tried to compensate the time which they spend working on the task requested by the interruption with an increase in working speed. This change in behaviour comes at a price. People felt more stress for example time pressure and frustration.

This change in behaviour is supported with the results of Zijlstra et al. [1999]. They interrupted work of two groups, one group of professionals and one less experienced group. They observed an additional change on behaviour when getting interrupted within the group of professionals. Whenever they get interrupted they continue work for a while before changing to the interruption. This behaviour supports the statement of Iqbal and Horvitz [2007] that people spend some time on the task after an interrupting event to bring the task in an state which allows resumption of work on the task later on.

O'Conaill and Frohlich [1995] report that they measured 125 interruptions over a full working week with 4 interruptions per hour. In 30 percent of the cases they observed that people decided to continue working on something else or were not engaged in an measurable work activity.

2.2. Ambient Noise

Goines and Hagler [2007] reviews noise and its effects on human beings. The World Health Organisation (WHO) declared noise in the beginning of the seventies as an rising problem. Fourty years since then noise did not diminish from the landscape of influences with distracting power on human beings, the opposite is the case. Noise is increasing in its size, frequency, intensity and due to technological development, population growth and urbanization. In 2000, a study conducted in the United States reveals that more than thirty percent of the population is suffering under noisy conditions. In New York city, the sound level pressure in public transportation units exceeds 100 dB(A) in some extent. In relation, the sound pressure level next to a highly frequented road where a truck drives by is approximately around 85 dB(A). [Goines and Hagler, 2007]

The WHO references seven categories of detrimental impacts of noise on human beings:

- Hearing damage

- Unintelligible communication
- Sleep disorder
- Cardiovascular and physiological diseases
- Mental effects (fear, stress, nervous diseases, sickness, headaches etc)
- Work performance
- Effects on behaviour and annoyance of neighbours

In particular children and elderly persons suffer under noisy conditions. [Goines and Hagler, 2007]

As a conclusion Goines and Hagler [2007] reviews that noise per se is not the reason for negative effects on well-being but more an amplifier.

2.2.1. Intrusiveness of sound

Jones and Hughes [2001] reviews studies on the theoretical basics of sound and its distracting potential regarding to work performance and human well-being. The view that speech alone has detrimental effects is de facto obsolete. Sound sources with distinct acoustic patterns, regardless if they contain speech or not, do have distracting potential. The effects can result in decreasing task performance as well as experiencing more stressful emotions like annoyance or negative consequences for health like high blood pressure or nausea.

The ear as sentinel of the senses and its attracting power regarding attention is the main reason why sound is so intrusive.

Studies on intrusiveness of sound can be classified taking periodicy of sound into account. Studies on aperiodic sound, also called white noise, focus on the effects of intensity. Results are very inconsistent. Summarized white noise might produce moderate effects at 90dB(A) and above. Many studies focus on the effects of speech conditions which share some common properties like conducting experiments in laboratory environments, always building upon tasks which involve sequential recall and most interestingly come up with a robust error rate due to speech effects ranging between 30 and 50 percent.

Studies conduct experiments changing certain sound and/or task properties. Intensity, timing and meaning of sound are considered as unimportant properties of speech regarding its distracting power. The view that only sounds which are similar to sounds of information currently processed by cognitive resources intefere and produce detrimental effects is de-facto discarded. Sounds varying in acoustic properties like pitch, timbre and intensity are considered as the property of sound with distracting potential. The changing state theory is developed upon this fact and defines that acoustic variation transports information about order which is involuntarily processed by mental resources. This processing distracts the mental process regarding the task at hand. The order information increases markedly whenever acoustic variation increases. In this sense a single source of speech or a musical instrument are sound sources with optimal prerequisites to distract attention. [Jones and Hughes, 2001]

2.2.2. Effects of Ambient Noise

Challenging conditions for information workers to maintain focus in open plan offices motivates Smith-Jackson and Klein [2009] to examine effects of different ambient noise conditions on mental workload. Participants read documents and mark errors under quiet conditions and under two speech conditions. During the continuous speech condition two-sided conversations out of several popular movies were used as speech stimuli. In the intermittent speech condition only one side of the two-sided conversation could be heard. In the quiet condition the average intensity was between 45dB(A). In the speech conditions the average intensity was 65dB(A). Intensity measurements were taken where the participants were seated. They found evidence that people with a better ability to focus on an task experience less mental workload than people who do not focus as well on an task.

Liebl et al. [2012] interrupt tasks with ambient noise, with video sequences and a combination of both. A simulated office environment and four different kinds of tasks (arithmetic, reasoning, attention, text comprehension) were chosen as experimental setup to approximate real life working conditions. The sound pressure level of ambient noise was around 40 decibels. They measured workload, well-being, annoyance and noise after each of the tasks. Results show negative effects on emotional state when interrupting arithmetic and reasoning tasks and when interrupting with ambient noise containing speech of low intelligibility.

Leather et al. [2003] hypothesise that higher levels of ambient noise at the work place will have an impact on certain psychosocial work elements like job satisfaction, well-being and organizational commitment. Furthermore there will be an interaction between ambient noise and high job strain. Psychosocial work elements, subjective noise and job strain were collected with questionnaires. Ambient noise levels were recorded with sound level meters over two weeks. The measured noise levels ranged between 45dB(A) and 63dB(A) with an average of 55dB(A). They did not found an impact of ambient noise on any of the three psychosocial work elements but they found an interaction of ambient noise and job strain. High levels of job strain and ambient noise had an negative impact on on job satisfaction, well-being and organizational commitment. Results of the interaction between noise and job strain on personal well-being are presented in figure 5.

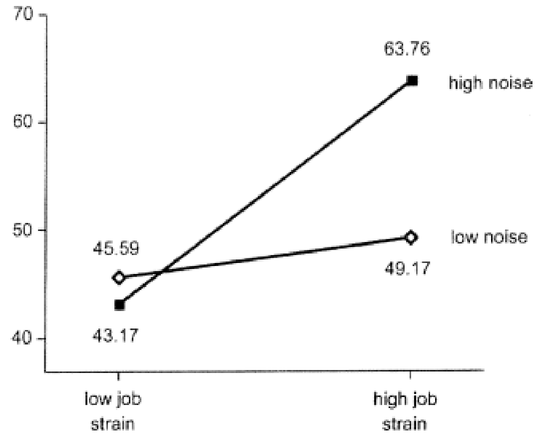

Figure 5.: Interaction of noise and job strain on personal well-being

Leather et al. [2003] conclude that ambient noise might not be stressful per se but is able to exacerbate the negative impact of stress like job strain.

2.3. Related Work

Lu et al. [2012] present StressSense, a system which recognizes stress from human voice. Their work focuses on the detection of mental stress only. Stress caused emotions are always triggered by an event. These emotions are reflected in changing certain properties of human voice. The approach of StressSense is to track the frequency of such changes and use this measure as the foundation for the final stress classification.

StressSense should be suitable for every day life usage and claims to reach that goal with the following approach. Stress detection should be done in an non invasive manner. Users of StressSense should not be forced to buy additional equipment which usually discourage people. Main drawbacks to mention here are additional financial costs and an extra device to wear. Rather StressSense should seamlessly be integrated in the daily routines and give feedback without the need of input from users. Therefore the StressSense system will use the mobile phone and its microphone as sensor for continuous and non-invasive tracking of stress. StressSense should be able to cope with different acoustic environements. Research on stress and human voice so far focus on only one particular acoustic environment. A detection system with robust results for only a single environment would render the application unuseable for every day life. The approach of StressSense employs an detection system which is able to work robustly in different acoustic environements. A simple, all purpose stress model is used whenever the person starts using the system. Over time StressSense adapts the model to the individual for robust voice bases stress detection in various real life conversational situations.

Data for evaluating the approach was recorded during an experiment with fourteen participants who had to carry out three tasks. Two tasks were considered stressful. The first task was a job interview and was conducted indoors. Participants apply for a position in the marketing division and had to answer eight questions. Subsequently the second task was to behave as an employee of the marketing division and hire new participants for future studies. The second task was conducted outdoors. The third task was considered neutral and was about reading some text. During the tasks audio was recorded with mobile phones and ground truth of stress was recorded with an galvanic skin resistance sensor mounted around the wrist. The sensor measures skin conductivity since higher stress levels cause an increase of skin conductivity. For each participant four till eight minutes of audio and stress data were collected from the job interview, 4 minutes from the marketing task and six minutes from the neutral task, three minutes indoors, three minutes outdoors.

The next step after collecting the data was evaluating importance and effectiveness of the 42 extracted features from the audio samples. They use pitch based and spectral based features for stress classification. Although intensity based features are used for stress classification they were excluded from the extracted feature set. Intensity based features require control of ambient noise and microphone settings which is impractical for this mobile application setting. After preprocess-

	Feature set A				*Feature set A B*				*Feature set A B C*			
	precision	recall	f-score	accuracy	precision	recall	f-score	accuracy	precision	recall	f-score	accuracy
universal	73.1%	58.9%	64.4%	68.6%	69.6%	70.0%	69.5%	69.6%	70.5%	74.8%	72.2%	71.3%
unsupervised	74.9%	63.4%	68.1%	70.8%	75.8%	72.1%	73.7%	74.3%	78.8%	76.8%	77.5%	77.8%
supervised	72.7%	70.3%	71.1%	71.9%	78.5%	80.1%	79.2%	79.0%	79.1%	85.0%	81.8%	81.1%
personalized	72.5%	71.9%	72.1%	72.2%	77.1%	83.1%	79.9%	79.1%	80.5%	87.1%	83.6%	82.8%

Figure 6.: Performance of universal, personalized and adaption models in indoor settings

	Feature set A				*Feature set A B*				*Feature set A B C*			
	precision	recall	f-score	accuracy	precision	recall	f-score	accuracy	precision	recall	f-score	accuracy
universal	66.1%	56.0%	60.1%	63.6%	65.7%	63.6%	64.2%	65.5%	67.0%	64.2%	65.2%	66.5%
unsupervised	67.7%	53.4%	58.8%	63.8%	68.3%	62.4%	64.7%	67.1%	76.7%	59.1%	65.7%	70.5%
supervised	66.7%	62.6%	64.2%	65.5%	72.0%	72.0%	71.7%	71.8%	75.6%	75.9%	75.5%	75.5%
personalized	66.6%	65.1%	65.7%	66.1%	72.6%	78.3%	75.2%	74.0%	76.0%	82.4%	78.9%	77.9%

Figure 7.: Performance of universal, personalized and adaption models in outdoor settings

	precision	recall	f-score	accuracy
universal	67.6%	28.2%	38.9%	57.8%
self-train	78.1%	26.4%	38.4%	60.1%
supervised	78.1%	70.1%	72.9%	74.8%
personal	65.3%	39.4%	47.7%	59.7%

	precision	recall	f-score	accuracy
universal	64.8%	60.8%	62.2%	63.6%
self-train	66.5%	59.0%	61.7%	64.6%
supervised	74.1%	77.3%	75.5%	74.9%
personal	77.4%	77.7%	77.5%	77.4%

Figure 8.: Performance of indoor and outdoor classifier in mixed settings

ing the data, stress classification was performed for indoor and outdoor datasets separately. Since features perform differently indoors and outdoors the features were selected and ranked for indoor and outdoor environments.

Four stress models were applied and compared with different feature sets in both indoor and outdoor settings. The universal stress model as the all purpose model with poorest performance expectations. The personalized model which is best in performance but poor in usability and scalability. The two adapation models which both starts with the universal model and adapts as soon as user data is available. One adaption model employs supervised adapation where the user contributes labelled data for improving the model. The second adaption model employs unsupervised adapation which utilizes unlabelled data for self improvement. Figure 7 shows that the adaption models perform nearly as good as the personalized model in the indoor setting. The picture stays similiar for the outdoor setting except for the unsupervised model which experience performance degrade against the supervised and personalized models but nevertheless performs better than the universal model.

Finally classification performance was tested under mixed conditions. It showed that the outdoor classifier performs indoor better than the indoor classifier under outdoor conditions. [Lu] suggest that classifier trained on real world data are more robust. Figure 8 shows the indoor model tested outdoor on the left and the outdoor model tested indoor on the right.

The first StressSense prototype is implemented on Android 4.0 and employs an pipeline approach to do the stress classification. At the beginning of the pipeline the recorded audio samples are processed by the sound detection module. The sound detection separates silent from non-silent audio data. Non-silent data is forwarded to the voice detection module which analyses if the sound is human speech. Finally if human speech is detected data is forwarded to the stress detection module. In the multi-threaded version on an Galaxy Nexus device, the system achieved real time performance utilizing 46 till 55 percent cpu load and an average draw of 182mA when the pipeline is fully engaged. In this case, battery life of the Nexus will last for approximately 9 hours.

Lu et al. [2012] showed that stress detection on human voice in real time on mobile devices in different acoustic environments is feasible. The current prototype implementation StressSense runs on Android 4.0 operated smartphones wihtout the need of extra equipment. Future work considers to implement an adaptive pipeline with the unsupervised adaption model for speaker adapation and the supervised model for environment adaption. Furthermore, online training of the models and speaker segmentation are open issues for the next prototype version.

Rachuri et al. [2010] presents the work on EmotionSense, a mobile sensing platform for studying human social behaviour. EmotionSense discovers relationships and effects of events (interactions, activities) on emotions and behaviour of individuals. The goal of EmotionsSense is to extract knowledge which helps social scientists to better understand these relationships and effects when conducting social and psychological studies. To achieve the goal, EmotionSense targets mobile phones as the runtime environment. Mobile phones are widespread and part of the daily life of many people. They offer an unobstrusive way of continuously collecting information on behaviour and interactions of individuals. For example no extra equipment is needed.

Regarding to social and psychological studies, the process of automatically recording and processing data processing with mobile devices omit some drawbacks of research methods applied so far. Traditional survey methods and experiments under laboratory settings for example have limited generalizability on real life settings. Incomplete self reports and diaries due to participants forgetting to log events continuously. Another important issue and concurrently advantage of mobile device usage is that individuals forget being part of a study. So far this promises results which are far less biased because participants are not aware of being constantly monitored.

After testing performance of the initial EmotionSense prototype, an experiment under real conditions was conducted to evaluate the usefulness of EmotionSense for social scientists.

Prototype The initial prototype features emotion sensing, movement detection, detection of verbal and proximity interactions among a group of individuals and an interface to programmatically change system behaviour and settings. The activation and deactivation of data recording or the definition of rules controlling data recording. A set of system components (monitors) are responsible for monitoring information about the current activity and co-location with other individuals. Monitors receive data from an mobile phone built-in sensors. Data from the accelerometer is analysed and classified into movement and non movement categories. Data from

Broad emotion	Narrow emotions
Happy	Elation, Interest, Happy
Sad	Sadness
Fear	Panic
Anger	Disgust, Dominant, Hot anger
Neutral	Neutral normal, Neutral conversation, Neutral distant, Neutral tete, Boredom, Passive

Figure 9.: Emotion clustering

the bluetooth sensor is used to detect other bluetooth devices that are in proximity. GPS signal is used to track an individual's location. The extracted knowledge is stored and requested by the inferece engine to process the facts, create and schedule actions. If the user is walking for example, the inference engine schedules an action which continuously lowers the sampling interval of the accelerometer monitor. Information from monitors and audio data serve as input for speaker and emotion recognition components.

The speaker and emotion recognition components contain a set of models used for classification. The models are created and trained offline. The speaker recognition component contains one model for each participant. At runtime the recognition components calculates the likelihood for each user for the present audio sequence. Each audio sequence is related with the model which assigns it the highest likelihood. The emotion recognition component contains models which were trained with emotional speech taken from the Emotional Prosody Speech and Transcripts library Liberman et al. [2002]. The library consists of 14 different types of emotion. The process of model assignment is the same as described previously with the speaker recognition. Rachuri et al. [2010] decided to cluster emotions into broad emotion classes because they are easier to detect and improve accuracy. Figure 9 shows the five broad emotion clusters.

Prototype performance was measured with comparing values of audio sample length against recognition accuracy, latency and energy consumption. The tests were conducted on Nokia 6210 mobile phones which were operated by Symbian. The prototype is coded in Python and C++. Audio data used was collected from 12 users over 24 hours period.

71 percent accuracy of the emotion recognition component could be achieved for broad emotion classes. Accuracy starts to converge against this value with an audio sample length equal or greater than 4 seconds. Speaker recognition achieved 90 percent accuracy at audio sample lengths greater than 4 seconds. Figure 11 shows accuracy values for emotion and speaker recognition depending on audio sample length.

Latency of both recognition components is around one minute with an audio sample length of four seconds. Measured values for energy consumption are closely around 25 joules for both components.

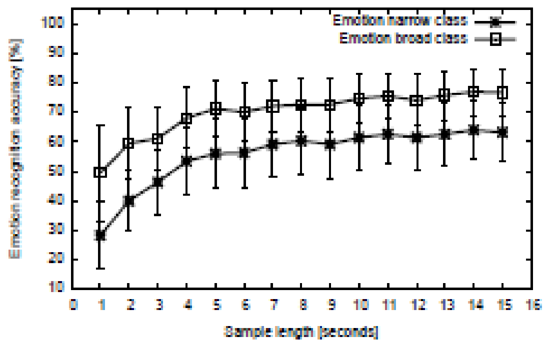

Figure 10.: Performance of emotion recognition

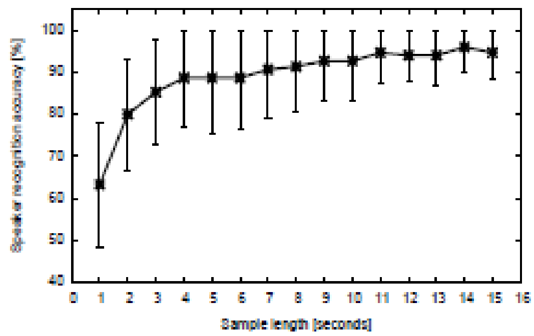

Figure 11.: Performance of speaker recognition

Real world experiment The experiment setup involves 18 users over a period of 10 days. Data recorded by EmotionSense was compared against self reports with information about activity, location, proximity and mood of an individual. Their results show different distributions of emotions detected by EmotionSense. The distribution of broad emotions detected by EmotionSense is similiar with the distribution of emotions made from the questionnaires. Rachuri et al. [2010] conclude with improvements regarding noise robustness, real-time feedback and interactive help for users.

Lane et al. [2012] envision the need of tools for effective self management of overall well-being. People choose lifestyles which often affect health in an negative way. In most cases people are not aware of these effects and consequently miss to change behaviour towards a more preferable direction. Lane et al. [2012] argue that smartphone applications enabling feedback on personal health help individuals maintain a more healthier lifestyle in the long run. Smartphones enable a new generation of personal health and well-being applications. They are powerful devices with a wide range of sensors like accelerometer, compass, GPS, gyroscope, microphone and camera. Intelligent combination of sensory data offers recognition and inference about an individuals behaviour in real-time. Further features of mobile devices referenced by Lane et al. [2012] as enabler for successful health applications are global delivery of applications via app stores, minimal configuration efforts due to automated knowledge extraction techniques and valuable feedback with intuitive visualisations.

Regarding their vision of an future personal health management application, Lane et al. [2012] point out some limitations of systems so far. Most systems consider only one dimension of behaviour influencing health like stress or diet. Lane et al. [2012] suggests that a wide range of behaviours monitored and integrated in systems are necessary and essential for valuable feedback. Some systems already take this into account but require to manually input information. This approach is likely to appear impractical for daily usage. The third key challenge they envision is to provide feedback in a way the user easily can understand. Systems fail because they lack presenting results in an valuable fashion.

Lane et al. [2012] propose that future person health management applications monitor health in multi dimensions, in an automated way using smartphones and provide valuable feedback with intuitive visualisations. They present their work on BeWell, a mobile phone application which tackles those challenges. BeWell runs on smartphones monitoring well-being along three dimensions, physical activity, sleep and social interaction. Their approach to relate behaviour with well-being of an individual is estimating a score. BeWell measures behaviour with the amount of sleep, the amount of physical activity and the amount of social interactions per day. For each value, representing a particular behaviour, BeWell infers the score. The score, a value between zero and 100, indicates an individual's performance on that behaviour. A score of 100 on sleep indicates that an individual matches its performance on that behaviour very well, for example averaging eight hours sleep per day.

Monitoring sleep, physical activity and social interactions Although sleep is not only influenced by quantity but also by quality aspects, BeWell recognizes only sleep duration. Sleep classification is performed on phone usage patterns including frequency and duration of phone recharge, ambient sound pressure levels and periods when the phone is stationary. From the classification results periods of sleep are calculated. Too much sleep as well as lack of sleep is considered when estimating the score for sleep behaviour for a single day. The initial model defines seven hours of sleep as ideal, nine hours as the upper and five hours as the lower limit of acceptable sleep duration.

Physical activity is classified extracting features from GPS and accelerometer sensors. BeWell classifies physical activity into walking, running, driving and stationary categories. The period of physical activity for a single day is converted into the metabolic equivalent of task (MET) value. The MET value is a physiological measure expressing the energy cost of physical activities [wikipedMET2014]. The estimation function uses the MET value of the physical activity of a particular day and the MET values for upper and lower limits. The values for upper and lower limits are high-end and minimum periods of time for physical activity. The values range between 300 and 150 minutes per week. From the MET values the score on physical activity behaviour per day is calculated.

BeWell chooses social isolation as behaviour to estimate the score on social interaction of an individual. Studies show that social isolation correlate with basic forms of human contact like visiting friends and relatives. BeWell uses the microphone of the smartphone to extract features from audio samples and classify periods of audio into voiced and non-voiced categories. Social isolation is measured based on the duration of voiced periods. An experiment involving ten persons were conducted to find an empirical value for the upper limit being involved in conversations per day. The lower limit was simply set to zero.

BeWell performs sensing, feature extraction, classification (sleeping, walking, talking, ...), data storing, data uploading tasks on Android operated smartphones. The tasks are carried out in the background and do not need the attention of the user. Sensory data come from built-in GPS, accelerometer and microphone hardware. Uploads of data reside in an cloud based server infrastructure.

Feedback on well-being is provided by two visualisations, one particular designed for the smartphone and another designed as web application. For the smartphone, an ambient display was designed to provide feedback over the overall well-being in an intuitive way. The design uses the mobile phone wall paper which is seen everytime the user starts interacting with the phone. Consequently, the user is continuously informed about its personal state of well-being. The ambient display presents each dimension of well-being as an animal in an aquatic ecosystem, illustrated in figure 12. Tapping the view inserts a litte box with the estimates of the scores for each dimension, sleep, physical activity and social interaction. The turtle represents behaviour of sleep, the clown fish represents behaviour of physical activity and the school of yellow fish represent behaviour on

Figure 12.: Animals in an aquatic ecosystem representing dimensions of well-being

social interaction.

The web application offers the users a diary like visualisation. Beside viewing collected sensor data it allows editing for example correction of misclassified activities or adding activities which could not be recognized. Scores are updated continuously with uploads of data and user inputs via the web application.

Benchmark resource consumption of the BeWell smartphone application shows that it is suitable to run on off the shelf smartphones. BeWell, with all tasks active, can co-exist with other resource intensive applications (web-browser, audio playback). Battery life is reduced by 40 percent on average which means 15 hours of usage until recharge which is acceptable for daily usage. Evaluation of accuracy was performed with data collected from ten persons. Each person weared the smartphone on the same location on the body (at the hip using a holster). Results for sleep classification show $\pm$ 1.5 hours accuracy of sleep duration. Social interaction classification shows an 14 percent overestimation due to misclassification of ambient sound as conversations, for example watching television. Similarily, classification of physical activities show an average error of 22 percent.

[Ayzenberg] present a system labelling social interaction events recorded on an mobile phone with stress levels from an biosensor. A calendar like visualisation on the mobile phone colors days in green, orange or red, each color representing a specific level of stress. The intent of their work is to inform users about their responses in social interaction and to trigger reflection. Ultimately, users improve social interaction behaviour due to their process of reflection and decrease stressful situations.

Social interactions monitored by the system are phone calls, email, SMS and face-to-face meetings. Face-to-face meetings are extracted from the phone calendar or manually triggered by the user. Answering an incoming call for example would be the start of an event “phone call” and hanging up the end of the event. In parallel, the start and stop of an event triggers the start and stop of the biosensor. The biosensor, worn on the wrist, records electrodermal activity (EDA). EDA is the best known unobstrusive indicator of stress activation but it is not a reliable measure to distinct between positive and negative stress. Therefore, contextual data like the events described earlier, is necessary to gain deeper knowledge about the positive or negative nature of an situation.

Recorded event and EDA data is analysed remotely with an stress recognition system. The system infers the stress level value based on an event and EDA data. A precondition before the system is ready to use is that it must be calibrated by the user. During calibration the user answers questions about its emotional state for selected events. After calibrating the system is finished the user is questioned about its stress level only if confidence is low and at random points in time to preserve good accuracy.

The system was evaluated by a single user reporting well about the system regarding recalling past stressful situations.

3. Approach: Ubiquitous Sensing to Observe Worktime Fragmentation and Ambient Noise

The approach of this thesis is to approximate worktime fragmentation and noise with data records from information workers and their environment at the workplace. A study should investigate if information worker's self assessed stress levels can be predicted by the approximations.

3.1. Approximating Worktime Fragmentation

Records of foreground windows and computer idle times will be captured by monitoring the interaction between information worker and desktop computer.

3.1.1. Foreground Window Events

Monitoring foreground window events deals with applications which the user selected to interact with. Modern desktop operating systems support users with handling multiple activities at a time. Usually an activity is represented by an application displayed in an window. Every time an application is chosen to be interacted with, the operating system brings its associated window in the foreground and gives it the input focus. Recognizing and collecting information about such window events allows to create an chronological history of user interactions with application windows.

3.1.2. Computer Idle Time Events

Monitoring computer idle times deals with inactivity regarding interaction between user and desktop computer. Usually interaction happens through mouse and keyboard input. Computer idle time is characterized through temporal periods in which a user does not interact with the desktop computer in any form [1]. If the time interval between two consecutive input events exceeds a certain threshold, the time interval is associated with inactivity. Within this experiment, two particular time intervals are considered relevant with respect to computer idle times. The first interval ranging from one to five minutes and the second ranging above 20 minutes. Idle time intervals from **one to five minutes** are considered as distracting as well as intervals ranging **above 20 minutes** are considered as not computer related activities like meetings or lunch breaks for example. Intervals ranging from five to twenty minutes are discarded. Recognizing and collecting information about such time intervals allows to create an chronological history of computer idle times.

The frequency of switching windows respectively applications will be computed from the chronological history of user interactions with application windows. Those measures will be used for approximating worktime fragmentation in terms of interruption frequency, both internal and external.

Further, frequency as well as periods of computer idle times will be computed from the chronological history of computer idle times. Those measures will also be used for approximating worktime fragmentation in terms of interruption frequency.

Both kinds of measurements are considered suitable as approximations since interruptions are the driving factor of worktime fragmentation.

3.2. Approximating Noise

Records of sound pressure levels will be captured by information worker's smartphones.

3.2.1. Sound Pressure Level Events

Monitoring sound pressure levels deals with ambient noise an individual experiences at the workplace. Stationary devices like air condition and printers, ringing phones, work mates talking with each other for example are frequently occuring sources of ambient noise, particular in open plan offices. These sources continuously change intensity of an individuals experienced sound level. Smartphones offer an ideal opportunity to measure intensity of ambient noise in proximity of an working individual. The built-in microphone delivers an continuous stream of audio samples. The stream is divided into short temporal sequences which are used to calculate the average sound pressure level within this time. The sequence of audio samples is a set of values

$$\{x_1, x_1, ..., x_n\} \tag{3.1}$$

[1] This does not necesserily mean that the user is not working at all.

The root mean square value of the sound pressure for a sequence of audio samples is calculated by the formula:

$$p_{rms} = \sqrt{\frac{1}{n}(x_1^2 + x_2^2 + ... + x_n^2)} \tag{3.2}$$

Finally, the sound pressure level is calculated by the formula:

$$L_p = 10\log_{10}\frac{p_{rms}^2}{p_{ref}^2} = 20\log_{10}\frac{p_{rms}}{p_{ref}}dB \tag{3.3}$$

Calculating and collecting information of average sound pressure levels allows to create an chronological history of intensity. An average sound pressure level and the period of time during the sound level exceeded 60 decibels will be computed from the chronological history of intensity. Those measures will be used for approximating noise. Sound level pressure is a simple kind of measure but comes with inaccuracies. There will be no distinction between background speech and white noise for example although background speech is more disruptive.

3.3. Self assessments of stress

Information workers will report on their stress level twice a day. The reports serve as the golden standard for analysing the measures with regard to stress prediction.

3.4. Evaluation of stress prediction

A group of information workers will participate in a study over ten working days. Records of foreground windows, idle times, sound pressure levels and self reports of stress levels will be captured. After the ten days period the measurements approximating worktime fragmentation and noise are computed for each working day. Finally, the prediction of stress with these measures is analysed for the whole group and for every single participant.

3.5. Ubiquitous Sensing System

The information worker and its environment are continously monitored by a sensor system distributed on desktop computer and smartphone. The system comprises three sensors observing worktime fragmentation and ambient noise. Basically, a sensor in the context of this thesis is a software application which listens to a specific kind of event. On the desktop computer, two sensors will listen to foreground window and computer idle time events. On the smartphone, a sensor will listen to audio sample events from the microphone. Further, a sensor distributes its events to a repository. The repository resides in the web and persists the events coming from a sensor.

3.5.1. System Architecture

The system architecture follows a client server approach which differs from others following an holistic approach. [Rachuri et al., 2010, Lu et al., 2012] for example present systems running on a mobile device which are capable to recognize stress or emotions. Both systems follow an holistic approach which means that everything necessary to perform recognition is done on the device. Technically speaking these systems implement a fully-fledged data processing pipeline on a mobile device to monitor and classify well-being of individuals.

Adapting the approach of other studies [Rachuri et al., 2010, Lu et al., 2012] the proposed system will leverage in situ mobile and desktop computing devices and integrate in the daily routines of working individuals in an unobstrusive way. Main advantages of this approach are improved accuracy, usability and more accurate observations Rachuri et al. [2010]. Further this design approach is very important to ensure the feasibility of the study since the system will run under real conditions in IT driven businesses.

Figure 13 illustrates the client server architecture of the system depicting the data processing pipeline where data flows through a chain of consecutive components, similar to the previously described systems. Components either push data forward to components or pull data from the preceeding component.

The data processing pipeline consists of several components where data flows in a sequential fashion from one component to the other. Each component within the pipeline creates, distributes, transforms and/or analyses data in some way and forward it to the next component. [Rachuri et al., 2010] for example classify audio sequences in silence and non-silence categories. Subsequently non-silence sequences are forwarded in the pipeline, silent sequences are discarded.

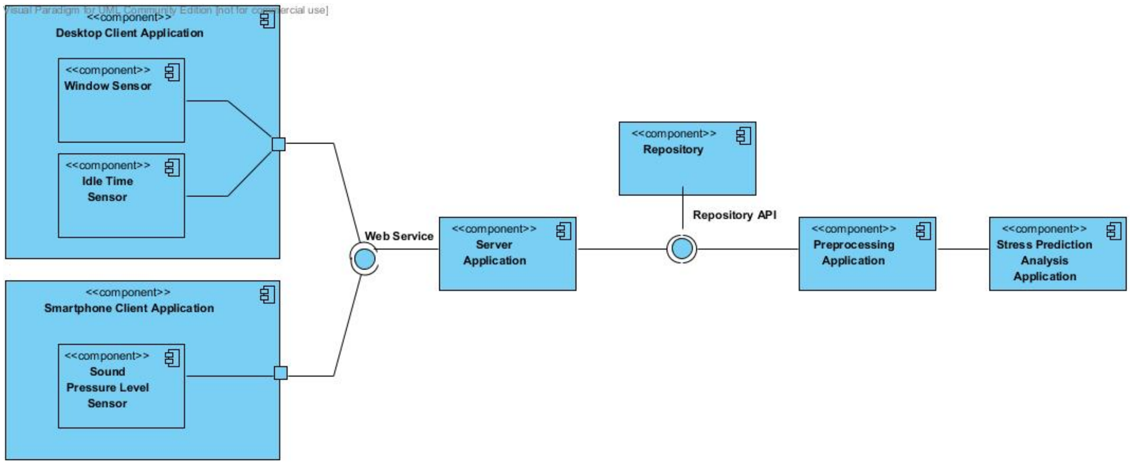

Figure 13.: Components of the System Architecture

3.5.2. Monitoring Components

The desktop and smartphone applications are the monitoring components of the system. They create foreground window, idle time and sound pressure level events and push them forward to the server application component.

Desktop Client Application Traces of computer interactions are monitored with an application running on the desktop computer. The desktop application collects information about foreground windows, foreground applications and computer idle times.

The Window Sensor Component, further refered to as Window Sensor (WIN), listens for events generated by the operating system. WIN gets notified whenever the foreground window changes and also when the title of the foreground window changes. For each notification WIN creates an record containing an identifier of the window, window title, timestamp of record and type of event. The window title is hashed using an implementation of the *MD5 algorithm*[1]. The event type is set depending on the notification sent.

WIN stores new records in a collection until the collection reaches its maximum size. In this case WIN delegates the full collection to the application controlling component, further refered to as Controller (CTL). CTL enriches the collection with information about WIN, the participant and the server. CTL triggers the command to store the enriched record in the database which is located locally on the client. Information about the participant contains the participant code. Information about the web service contains the URL of the server's web service module and the REST call to

[1]Create a MD5 Hash from a string - Visual C-sharp Developer Center `http://tutorials.csharp-online.net/Create_a_MD5_Hash_from_a_string`

trigger when uploading the record.

The Idle Time Sensor Component, further refered to as Computer Idle Time Sensor (INA), periodically measures the duration between the last two events of user machine interaction. Whenever the measured duration exceeds the threshold of computer idle time, INA creates an record containing the timestamp indicating the start of idle time, duration of idle time and the event timestamp. The procedure of collecting and delegating records applied is equal to the one of the WIN component [1,2].

Figure 14 shows the enriched version of an record of the WIN component serialized in JSON, Figure 15 respectively of the INA component[3]. The root part of both records has the same structure and consists of the participant code, the timestamp of record and the type of sensor. As mentioned before, this information is added by the CTL component. The field “sensorRecord” contains the collection of sensor events.

The records array of WIN contains foreground window changes and changes of window title. In this example the first three records are foreground window changes. The fourth record indicates a change of window title. This can be seen due to the equality of window identifiers but inequality of hashed window titles of the third and fourth record. The fifth record is again a change of foreground window and the sixth record a change of window title.

The records array of INA contains an inactivity record. In this example the collection consists of one record of inactivity with an duration of more than two minutes.

The data archive module, further refered to as Database (DB), uses *sqlite-net*[4] for initializing the database at first application start as well as reading and writing records at runtime. *sqlite-net* is an open source library to store data in SQLite 3 databases. Particular design features offered by its API are simple methods for executing Create, Read, Update and Delete (CRUD) operations and an Object Relational Mapping (ORM) layer working well with the data model of the application. These features were considered highly beneficial and eased work a lot.

The number of pending records stored in the database are periodically requested by the CTL component. Whenever pending records are available CTL delegates the records to the uploader module, further refered to as Uploader (UPL), taking care of uploading the records. UPL creates an HTTP request, sets the record as payload and send the request to an web service.

UPL reports success or failure of uploading an record back to CTL. In the case of a successful upload CTL delegates the deletion of the record to DB. If the upload of an record fails, due to a

[1] WIN and INA collect records to maintain low frequency of database operations.

[2] CTL stores records on the client host to maintain low resource consumption and to lower risk of losing data.

[3] JSON is the chosen serialization format between data monitoring and data archiving components.

[4] praeclarum/sqlite-net GitHub `https://github.com/praeclarum/sqlite-net`

```
{
    "participantCode": "d34de",
    "timeStamp": "2013-10-25T10:29:37.3664148Z",
    "type": "KnowSEnsor.Application.Sensors.FocusSensor",
    "sensorRecord": {
        "timeStamp": "2013-10-25T10:29:37.3654147Z",
        "events": [
            {
                "systemLevelEvent": "EVENT_SYSTEM_FOREGROUND",
                "timeStamp": "2013-10-25T10:24:53.752193Z",
                "windowHandle": 983776,
                "windowText": "a68534fa0df3384c41de969075ac022c"
            },
            {
                "systemLevelEvent": "EVENT_SYSTEM_FOREGROUND",
                "timeStamp": "2013-10-25T10:24:55.938318Z",
                "windowHandle": 65658,
                "windowText": "d41d8cd98f00b204e9800998ecf8427e"
            },
            {
                "systemLevelEvent": "EVENT_SYSTEM_FOREGROUND",
                "timeStamp": "2013-10-25T10:25:00.8415985Z",
                "windowHandle": 131608,
                "windowText": "a603905470e2a5b8c13e96b579ef0dba"
            },
            {
                "systemLevelEvent": "EVENT_OBJECT_NAMECHANGE",
                "timeStamp": "2013-10-25T10:25:15.2834245Z",
                "windowHandle": 131608,
                "windowText": "8d777f385d3dfec8815d20f7496026dc"
            },
            {
                "systemLevelEvent": "EVENT_SYSTEM_FOREGROUND",
                "timeStamp": "2013-10-25T10:29:30.1930045Z",
                "windowHandle": 787190,
                "windowText": "deb2fe88c09ad9bf7f3f3af3fd63716a"
            },
            {
                "systemLevelEvent": "EVENT_OBJECT_NAMECHANGE",
                "timeStamp": "2013-10-25T10:29:37.3644147Z",
                "windowHandle": 787190,
                "windowText": "18cd6ffae5abaf0f73aba2b547d213e3"
            }
        ]
    }
}
```


Figure 14.: JSON plots of enriched records collected by Window Sensor Component


```
{
    "participantCode": "d34de",
    "timeStamp": "2013-10-25T14:55:01.2193906+02:00",
    "type": "KnowSEnsor.Application.Sensors.IdleSensor",
    "sensorRecord": {
        "timeStamp": "2013-10-25T14:55:01.2193906+02:00",
        "events": [
            {
                "idleDurationInSeconds": 139.73,
                "timeStamp": "2013-10-25T14:54:53.9039722+02:00",
                "timeStampIdleStart": "2013-10-25T14:52:25.2864221+02:00"
            }
        ]
    }
}
```


Figure 15.: JSON plots of enriched records collected by Idle Time Sensor Component

broken internet connection for example, CTL stops and postpones the upload of pending records to a later point in time [12].

With the first start of the desktop client application a window pops up requesting the participant to enter the participant code. This information is required to initialize the application and further to relate records of window and computer idle time sensors to an participant. The window shows a few lines of text with a short explanation of how the code is created and gives an example. Below the example is the field where the code can be entered. The bottom line of the window contains the buttons to acknowledge the input or to cancel and quit the application. Acknowledging the participant code closes the window and starts the application. From this moment on, the application works independently and does not request the attention of the participant anymore.

Installing the desktop client application involves downloading, installing and initializing the application. Initialization is done with and only with the first start of the application. The major goal of the installation process is to keep the time effort for participants as low as possible. Downloading the client application is done via a website hosting the installation package. Installing and removing the application follows common window standards. Therefore, the application comes as an Windows Installer package (MSI). The *Windows Installer XML toolset*[3] was used to create the package. It is free and open source software, offers easy configuration of the installation package from XML source code and integrates into the build process. Time effort during initialization is minimized with everything coming preconfigured like the URL of the webservice where records are uploaded, except the participant code. The participant code is mandatory and must be provided to initialize and further run the application.

Tests of the desktop client application were performed to prove same behaviour on different Windows platforms. The tests involved installing, initializing and running the application on the test platform for approximately an hour. The *VMWare Player virtualization platform*[4], which is free for non-commercial use, provides a possibilty to run different instances of Microsoft Windows operating systems on virtual machines. All the tests could be carried out on the same physical machine and reduced time efforts of testing a lot. *modernIE*[5] is a website targeting web developers who want to test under different versions of Internet Explorer. The site offers ready to use virtual machines for the VMWare Player platform for free. Table 1 lists the windows operating systems used to perform the test runs.

Smartphone Client Application Traces of working environment are monitored with an smartphone application. The smartphone application runs on top of the Android operating system and

[1] CTL sets the length of the time interval in case of an failure during upload of an record to **one minute**.

[2] CTL sets the length of time intervals between upload trials in case of no pending records to **ten minutes**.

[3] WiX Toolset `http://wixtoolset.org/`

[4] VMware Player Plus: Easiest Way to Run a Virtual Machine `http://www.vmware.com/products/player/`

[5] Interoperability, Browser and Cross-Platform Testing | Modern.IE `http://www.modern.ie/`

Operating system	Virtual machine
Windows 7 Enterprise 32-bit	i5 3.2GHz 4GB RAM
Windows XP Professional, Service Pack 3	i5 3.2GHz 0.5GB RAM
Windows Vista Enterprise, Service Pack 2	i5 3.2GHz 1GB RAM
Windows 8.1 Preview	i5 3.2GHz 1GB RAM

Table 1.: Tests of the desktop client application

collects information about the sound pressure level.

The Sound Pressure Level Sensor, further refered to as Sound Pressure Level Sensor (SND), uses the Android Media API[1] to read audio samples from the microphone. Properties of the audio stream are 8kHz sampling rate, 16-Bit PCM audio samples, mono channel. SND reads and processes chunks of audio samples with a frame size of one second. The mean sound pressure level is calculated for each chunk of samples and stored together with the timestamp in a collection of sound pressure level records. Whenever the collection reaches its maximum size of records, SND delegates the storage of the collection to an module, further refered to as CTL. CTL triggers the command to store the collection in the database which is located locally on the client. Before continuing reading chunks, SND verfifies if the user interface wants to be notified about the current value of the sound pressure level. If so SND sends an notification [23].

The data archive module, further refered to as DB, uses *greenDAO*[4] for initializing the database at first start of the application as well as for reading and writing records of sound pressure levels at runtime. *greenDAO* is an open source tool for storing data in SQLite on Android. It offers an object-oriented API which maps Java objects to database tables (ORM) and hides nasty work from the application developer like writing SQL and parsing query results.

At application start CTL delegates uploading of pending sound pressure level records to a module, further refered to as UPL. UPL periodically queries DB for pending records and limits the result size to a reasonable limit[5]. The result containing the collection of records are serialized in JSON, together with the current timestamp and participant code. UPL creates an HTTP request, sets the JSON as payload and send the request to the server. If upload is successfully finished UPL triggers DB to mark the records as uploaded[6].

For the first start of the mobile client application the same applies as previously mentioned for the

[1] android.media | Android Developers `http://developer.android.com/reference/android/media/package-summary.html`

[2] SND collects records to maintain low frequency of database operations.

[3] CTL stores records on the phone to lower risk of losing data held in memory and to ensure remote storage of records despite missing network connectivity.

[4] greenDAO - Android ORM for SQLite `http://greendao-orm.com/`

[5] UPL limits the number of pending records for an upload to avoid memory exhaustion on the mobile device.

[6] UPL sets the duration between upload trials in any case to five minutes.

Device	Android version
HTC Hero	Android 2.1
Samsung Galaxy S	Android 2.2
HTC Nexus One	Android 2.3.6
Samsung Nexus S	Android 4.1.2
LG Nexus 4	Android 4.2
Samsung Galaxy S4	Android 4.2.2

Table 2.: Tests of the mobile client application

desktop client. Acknowledging the participant code initializes the application and displays the sound pressure level. From this moment on, the application works independently and does not request the attention of the participant anymore.

For the smartphone client the same procedure and goals regarding installation applies as for the desktop client. The final Android Application Package File (APK) was created using a self signed certificate. Android requires applications to be digitally signed by the application's developer. The self signed certificate was created using the *keytool* application which is part of the Java SDK[1]. The signed APK file of the mobile client application was hosted in the download section of the study's website.

Since it was not known what Android versions operate the mobile devices of the participants, tests on different Android versions were carried out to prove consistent application behaviour. The tests involved installation, initialization and running the application. Table 2 presents the list of devices and Android versions used to perform the test runs.

3.5.3. Archiving Components

The server application is the archiving component of the system. It receives and stores the events from the desktop and smartphone clients.

Web Service Module: Receiving Events Part of the server application is the web service module, further refered to as Record Service (REC). REC offers an API for the desktop and mobile phone clients to distribute events. Further, it delegates the storage of the events to the repository service module.

[1] keytool - Key and Certificate Management Tool`http://docs.oracle.com/javase/7/docs/technotes/tools/windows/keytool.html`

Resource	URI
Foreground Window	http://<server name and port>/moodsense/upload/windowfocus/{user}
Computer Idle	http://<server name and port>/moodsense/upload/idle/{user}
Sound Pressure Level	http://<server name and port>/moodsense/upload/soundlevel/{user}

Table 3.: Server Web Interface

REC is a web service and uses *restlet*[1] to host the API. *restlet* is an open source Java framework for building RESTful Web APIs. With the start of REC, REC configures the internal HTTP server component of *restlet* to listen and accept data of three resources. The resources reflect foreground window, computer idle and sound pressure level events. Table 3 presents the API with the resource URI for each type of event. [2].

The API allows only adding events into the archive which is reflected by accepting only HTTP POST calls. Calls on URIs starting with *http://<server name and port>/moodsense/upload/windowfocus/* are routed to the resource handling foreground window events. Calls on URIs starting with *http://<server name and port>/moodsense/upload/idle/* are routed to the resource handling computer idle events and calls on URIs starting with *http://<server name and port>/moodsense/upload/soundlevel/* are routed to the resource handling sound pressure level events. *{user}* is the variable part at the end of each resource URI. The client applications replace *{user}* with the participant code. REC configures the HTTP server component of *restlet* that it knows how to route calls to a resource, independently of the value *{user}* is replaced with.

Repository Service Module: Storing Events Also part of the server application is the Repository Service Module, further refered to as Database Client (DBC). Whenever the web service module receives an request coming from one of the client applications, it extracts the participant code from the request URI and reads the JSON document with the event data from the request payload. Next, the web service module delegates storing the participant code together with the JSON document to the repository service module. DBC establishes a connection to the database. The database stores for each participant code a collection of JSON documents. As soon as the connection is established, DBC gets the collection of documents for the participant code extracted before and appends the document to the collection.

DBC and the database are part of *MongoDB*[3]. *MongoDB* is an open source NoSQL database. It offers a Java library for storing JSON-style documents in a MongoDB database instance.

[1] Restlet Framework - RESTful web API framework for Java `http://restlet.org/`
[2] At runtime <*server name and port*> is replaced by the real name and port of the server host.
[3] MongoDB `http://www.mongodb.org/`

4. Study Design

The outline of this chapter starts with stating the research questions of this thesis and continues with the experimental setup of the study explaining how the study will answer this questions.

4.1. Research Hypotheses

A study will be conducted which provide approximations of worktime fragmentation and ambient noise on the one hand and on the other self reported stress levels of information workers. The analysis of context between the approximations and the stress levels should provide insight into *»Are the applied measures for approximating worktime fragmentation and ambient noise suitable for predicting stress levels of information workers?«*. In addition, the following hypothesis should be verified:

> *»HYP1: High frequency of window switching indicates increased levels of stress«*

> *»HYP2: High frequency of application switching indicates increased levels of stress«*

> *»HYP3: High frequency of computer idle times between one and five minutes are distracting and causes stress«*

> *»HYP4: Low periods of computer idle times above 20 minutes indicate increased levels of stress«*

> *»HYP5: High degree of above average sound pressure level is noise and causes stress«*

> *»HYP6: Long periods of sound pressure levels above 60 decibels is noise and causes stress«*

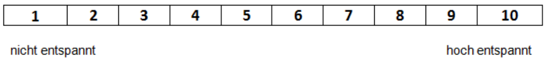

Figure 16.: Scale with ten levels of relaxation

4.2. Data Collection

The system introduced in section 3.5 continously monitors information workers and their environment at the workplace. After installation, the client applications require the attention of information worker's only at initial start. Initialization requires the participant code to be entered. Afterwards the application's user interface disappears and runs in the background. Rebooting the desktop and smartphone operating system's will automatically restart the applications and does not require information worker's attention again, during the whole period of ten working days.

The monitored foreground window, idle time and sound pressure level events by the client applications are stored by the server application of the system. The server application needs no configuration at the client side. It is hosted by the Knowledge Technologies Institute at Technical Univerty Graz.

4.2.1. Self Reports of Stress Levels

Stress levels are reported twice a day, the level of relaxation scale at midday and the multi dimensional scale with end of work. The midday report is shorter than the evening report to avoid burden participants with too much question answering. This daily procedure is repeated for ten working days.

Self reporting will be done manually by the participants via the study's website. There, the links to the web browser based surveys are provided. The workflow of the surveys starts with a screen requesting the participant to enter its participant code. Depending what survey was selected beforehand, the screen for entering the level of relaxation or the screen for entering multi dimensional scale of mental well-being is shown. When the participant finishes a survey, the hosting survey application archives the collected data.

4.2.1.1. Midday Report

The survey in the middle of a day at work contains a scale with ten levels, illustrated in Figure 16. Each level indicates the level of relaxation (LEVR) an individual experiences at a concrete point in time. The left end of the scale labelled "1" marks no relaxation. The right end of the scale labelled "10" marks full relaxation.

GS	1	zufrieden
	8	gut
	4	schlecht
	11	unwohl
WM	2	ausgeruht
	10	munter
	5	schlapp
	7	müde
RU	6	gelassen
	12	entspannt
	3	ruhelos
	9	unruhig

Figure 17.: The bipolar dimensions and the related adjectives

4.2.1.2. Evening Report

The survey with end of work acquires an individuals emotional state with respect to three bipolar dimensions of mental well-being. The three dimensions

- “Feeling well/Feeling bad” (GS)
- “Alertness/Fatigue” (WM)
- “Calm/Restless” (RU)

reflect the current emotional state of an individual.

Figure 17 presents each dimension with its four adjectives, two belonging to the positive pole and two belonging to the negative pole of the dimension. A five level scale is used to estimate the extent an individual experiences the state described by an adjective. The left end of the scale labelled “1” marks “do not agree” where as the right end of the scale labelled “5” marks “fully agree”. The score for each dimension is computed with summing up the values for positive and negative poles. The computed sum sets the dimension in relationship with either one of the two poles.

4.3. Study Participants

The target group of participants are information workers whose daily work life involves working with a desktop computer and are using a smartphone for private and/or business activities. As a precondition for participation the desktop computer needs to be operated by Microsoft Windows and the smartphone requires Android as operating system.

Participants will be invited per email to take part in the study. The mail contains the invitation for participation and a document in the attachment with an explanation of the most important facts about the study. Interested persons were kindly asked to read the document before making a decision about participation.

The document explaining the details of the study also mentions the minimalistic approach concerning privacy. Data distributed by the client applications is archived at the Knowledge Technologies Institute at University of Technology Graz. Although data is sent plain text it contains no personal and no work related information. Personal information is discarded with the use of an participant code. Work related information is discarded with hashing sensible data. The participant code is further used to maintain discernibility between data records of different participants.

4.4. Data Analysis

4.4.1. Computing Measures approximating Worktime Fragmentation and Ambient Noise

The measures for approximating worktime fragmentation and ambient noise are

- the average duration an information worker interacted with an window (AVGW)
- the average duration an information worker interacted with an application (AVGA)
- the number of computer idle times between one and five minutes (CNTI)
- the sum of idle time periods equal or greater than 20 minutes (DURI)
- the average sound pressure level (AVGS)
- the sum of sound pressure level periods exceeding 60 decibels (DURS)

Within the scope of a day at work, the measures are computed for each information worker over five temporal scopes:

- from the beginning of work until first self report (HT1)
- from the first self report until end of work (HT2)
- the whole day of work (GT)
- the hour before the first self report (Hour before the first Self Report (LS1))
- the hour before the second self report (Hour before the second Self Report (LS2))

The scope of a day at work in this experiment is framed with the date and time stamp of the first foreground window event and the date and timestamp of the second self report. Working days which miss either one of the self reports or miss desktop and/or smartphone records are discarded.

The preliminary step of computing the measures over the five temporal scopes involves preprocessing informations worker's events received from the client applications. Given a particular working day, the process creates histories for foreground window, inactivity and sound pressure level events.

4.4.1.1. Preprocessing Events

Events are stored by the server application in a collection of events belonging to a particular information worker. Preprocessing creates event sequences of foreground window, computer idle time and sound pressure level events for each working day. Each event sequence is chronologically ordered[1]. The common properties of an event in a sequence are the date and time stamp of recording (UNIX time instance) and information to which temporal scopes (HT1, HT2, GT, LS1, LS2) the event falls into. Properties common to foreground window events are the window title and the duration in seconds the window was kept in the foreground. The property common to computer idle time events is the idle time in seconds. The property common to sound pressure level events is the A weighted sound pressure level in decibel.

4.4.1.2. Computing Measures

Based on the event sequences the measures are computed.

[1] Events recorded before the beginning of work or after end of work will be discarded

Participant	Working Day	Time Frame	AVGW	AVGA	CNTI	DURI	AVGS	DURS
B07JM	2013-12-03	HT1	14.1	129.4	23.0	2906.0	51	3443.0
B07JM	2013-12-03	HT2	10.4	86.4	7.0	0.0	51.0	3054.0
B07JM	2013-12-03	GT	12.2	114.1	30.0	2906.0	51.0	6497.0
B07JM	2013-12-03	LS1	9.7	38.1	1.0	2906.0	66.0	2943.0
B07JM	2013-12-03	LS2	14.0	116.0	4.0	0.0	45.0	112.0

Table 4.: *
The measure of participant *B07JM* within the scope of working day “2013-12-03”.

AVGW	Average Duration an Information Worker interacted with an Window, in Seconds
AVGA	Average Duration an Information Worker interacted with an Application, in Seconds
CNTI	Number of Computer Idle Times between one and five Minutes
DURI	Sum of Idle Time Periods equal or greater than 20 Minutes, in Seconds
AVGS	Average Sound Pressure Level, in Decibel
DURS	Sum of Sound Pressure Level Periods exceeding 60 Decibels, in Seconds
HT1	From the Beginning of Work until first Self Report
HT2	From the first Self Report until End of Work
GT	Whole Day of Work
LS1	Hour before the first Self Report
LS2	Hour before the second Self Report

Two measures from the sequence of foreground window events are computed. The first measure stores the average time a window was kept in the foreground. The second stores the average time an application was kept in the foreground.

Two measures from the sequence of computer idle time events are computed. The first measure stores the count of idle time periods lasting between one and five minutes. The second stores the sum of idle time periods equal or greater than 20 minutes.

From the sequence of sound pressure level events two measures are computed. The first measure stores the average sound pressure level and the second the sum of sound pressure level periods exceeding a threshold of sixty decibels.

Table 4 shows the measures of participant *B07JM* for working day “2013-12-03”.

Computing Measures from Foreground Window Events In the following, the algorithms computing the measures from foreground window events, 1 and 2, are presented. Both algorithms take the sequences of foreground window and computer idle time events within the scope of working day as input. Further both algorithms consider idle time periods to be excluded from the period an window was in the foreground. For example there is an event w_a followed by an event w_b in the foreground window sequence. w_a starts at *07:44:02* and w_b starts at *07:47:25*. w_a was kept in the foreground for *03m:25s*. There is also an event i_a in the idle time sequence starting at

07:45:08 lasting *01m:23s*. This means that user interaction of the event w_a stopped after a minute for a bit more than a minute. The user resumed interaction and switched focus to the window in event w_b a minute later. The actual duration of event w_a is *02m:02s*.

Algorithm 1: GETAVERAGETIMEWINDOW computes average time a window kept in the foreground respectively the selected time frame

Input: The sequence $H_w = \{w_1, w_2, \ldots, w_n\}$ of foreground window events.
The sequence $H_i = \{i_1, i_2, \ldots, i_m\}$ of idle time events.
The selected timeframe t $\in T = \{\mathrm{HT1}, \mathrm{HT2}, \mathrm{GT}, \mathrm{LS1}, \mathrm{LS2}\}$
Output: The average time a window kept in the foreground

begin
    windowEventCount = 0
    durationWindowEvents = 0
    for $i \leftarrow 1$ ***to*** n **do**
        if $timestamp(w_i) \subseteq t$ **then**
            $windowEventCount \leftarrow windowEventCount + 1$
            $durationWindowEvents \leftarrow durationWindowEvents + duration(w_i)$
        end
    end
    durationIdleTimeEvents = 0
    for $j \leftarrow 1$ ***to*** m **do**
        if $timestamp(i_j) \subseteq t$ **then**
            $durationIdleTimeEvents \leftarrow durationIdleTimeEvents + duration(i_j)$
        end
    end
    averageTimeWindow = 0
    if $windowEventCount > 0$ **then**
        $averageTimeWindow \leftarrow \frac{durationWindowEvents - durationIdleTimeEvents}{windowEventCount}$
    end
    return $averageTimeWindow$
end

Computing Measures from Idle Time Events In the following, the algorithms computing the idle time measures, 3 and 4, are presented. Both algorithms take the sequence of idle time events within the scope of a working day as input.

Computing Measures from Sound Pressure Level Events In the following, the algorithms computing the sound level pressure measures, 5 and 6, are presented. Both algorithms take the sequence of sound pressure level events within the scope of a working day as input.

Algorithm 2: GETAVERAGETIMEAPPLICATION computes average time an application was kept in the foreground respectively the selected time frame

Input: The sequence $H_w = \{w_1, w_2, \ldots, w_n\}$ of foreground window events.
The sequence $H_i = \{i_1, i_2, \ldots, i_m\}$ of idle time events.
The selected timeframe t $\in T = \{\mathrm{HT1}, \mathrm{HT2}, \mathrm{GT}, \mathrm{LS1}, \mathrm{LS2}\}$
Output: The average time an application was kept in the foreground

```
begin
    applicationCount = 0
    durationWindowEvents = 0
    durationIdleTimeEvents = 0
    A = ∅                                   // The set of applications
    for i ← 1 to n do
        if timestamp(w_i) ⊆ t then
            A ← A ∪ windowhandle(w_i)
            durationWindowEvents ← durationWindowEvents + duration(w_i)
        end
    end
    durationIdleTimeEvents = 0
    for j ← 1 to m do
        if timestamp(i_j) ⊆ t then
            durationIdleTimeEvents ← durationIdleTimeEvents + duration(i_j)
        end
    end
    applicationCount ← | A |
    averageTimeApplication = 0
    if applicationCount > 0 then
        averageTimeApplication ← (durationWindowEvents − durationIdleTimeEvents) / applicationCount
    end
    return averageTimeApplication
end
```

Algorithm 3: GETCOUNTIDLETIMEDISTRACTIONS computes the count of idle time periods lasting between one and five minutes respectively the selected time frame

Input: The sequence $H_i = \{i_1, i_2, \dots, i_m\}$ of idle time events.
The selected timeframe t $\in T = \{\mathrm{HT1}, \mathrm{HT2}, \mathrm{GT}, \mathrm{LS1}, \mathrm{LS2}\}$
Output: The number of computer idle times between one and five minutes

begin
  countIdleTimeDistractions = 0
  fiveMinutesInSecs = 300
  for $j \leftarrow 1$ ***to*** m **do**
    if $timestamp(i_j) \subseteq t$ **then**
      if $duration(i_j) <= fiveMinutesInSecs$ **then**
        $countIdleTimeDistractions \leftarrow countIdleTimeDistractions + 1$
      end
    end
  end
  return $countIdleTimeDistractions$
end

Algorithm 4: GETDURABOVEINACTIVITYTHRESHOLD computes the sum of idle time periods equal or greater than 20 minutes respectively the selected time frame

Input: The sequence $H_i = \{i_1, i_2, \dots, i_m\}$ of idle time events.
The selected timeframe t $\in T = \{\mathrm{HT1}, \mathrm{HT2}, \mathrm{GT}, \mathrm{LS1}, \mathrm{LS2}\}$
Output: The sum of idle time periods equal or greater than 20 minutes

begin
  durationAboveThresholdInSecs = 0
  twentyMinutesInSecs = 1200
  for $j \leftarrow 1$ ***to*** m **do**
    if $timestamp(i_j) \subseteq t$ **then**
      if $duration(i_j) >= twentyMinutesInSecs$ **then**
        $durationAboveThresholdInSecs \leftarrow$
        $durationAboveThresholdInSecs + duration(i_j)$
      end
    end
  end
  return $durationAboveThresholdInSecs$
end

Algorithm 5: GETAVERAGESOUNDPRESSURELEVEL computes the average sound pressure level in decibel respectively the selected time frame

Input: The sequence $H_l = \{l_1, l_2, \ldots, l_k\}$ of sound pressure level events.
The selected timeframe t $\in T = \{\mathrm{HT1}, \mathrm{HT2}, \mathrm{GT}, \mathrm{LS1}, \mathrm{LS2}\}$
Output: The average sound pressure level in decibel

begin
  sumLevels = 0; countLevels = 0; **for** $j \leftarrow 1$ ***to*** k **do**
    if $timestamp(l_j) \subseteq t$ **then**
      $countLevels \leftarrow countLevels + 1$
      $sumLevels \leftarrow sumLevels + level(l_j)$
    end
  end
  averageSoundPressureLevel = 0; **if** $countLevels > 0$ **then**
    $averageSoundPressureLevel \leftarrow \frac{sumLevels}{countLevels}$
  end
  return $averageSoundPressureLevel$
end

Algorithm 6: GETDURABOVESOUNDPRESSURELEVELTHRESHOLD computes the sum of sound pressure level periods exceeding 60 decibels respectively the selected time frame

Input: The history $H_l = \{l_1, l_2, \ldots, l_k\}$ of sound pressure level events.
The selected timeframe t $\in T = \{\mathrm{HT1}, \mathrm{HT2}, \mathrm{GT}, \mathrm{LS1}, \mathrm{LS2}\}$
Output: The sum of sound pressure level periods exceeding 60 decibels

begin
  durationAboveThresholdInSecs = 0; threshold = 60 `// The set of applications`
  for $j \leftarrow 1$ ***to*** k **do**
    if $timestamp(l_j) \subseteq t$ **then**
      if $level(l_j) > threshold$ **then**
        $durationAboveThresholdInSecs \leftarrow durationAboveThresholdInSecs + 1$
      end
    end
  end
  return $durationAboveThresholdInSecs$
end

4.4.2. Computing Scores of Stress Level Reports

The scores are computed from midday and evening stress level reports containing:

- The Level of Relaxation (LEVR)
- The Bi-Polar Dimensions of Well-Being (GS, WM, RU)

The survey application hosting the self reports provide an export function. The export function is applied twice, once for the midday scale and once for the evening scale. As a result, computing the scores based on the export creates a file, storing the scores for each scale enriched with the participant code and the date and time stamp of reporting.

4.4.2.1. Computing Scores of Midday Report

The self report at the middle of a day consists of a single numerical value representing the extent of relaxation. The numerical is equal to the score which will be taken for data correlation.

4.4.2.2. Computing Scores of Evening Report

The self report at the end of a day at work consists of twelve adjectives belonging to one of three above mentioned bi-polar dimensions of well-being. Each adjective is represented by an numerical value. The lowest possible value is 1 expressing no agreement and the highest possible value is 5 expressing total agreement. The value of an dimension is calculated from the values of the four adjectives belonging to that dimension. The adjectives of the negative pole are re-encoded so that high negative assessments become low values and vice versa. Higher values of an dimension reflects a more positive state and lower values a more negative state. The resulting formula for calculating the value for an dimension is:

$$Dim = \sum Item_{pos} + \sum 6 - Item_{neg} \tag{4.1}$$

The $Item_{pos}$ variable represents the value for an adjective belonging to the positive pole of the dimension. The $Item_{neg}$ variable represents the value for an adjective belonging to the negative pole of the dimension.

The final step of computing the scores of self reported stress levels is the creation of a file containing the scores. The scores contain the values of the level of relaxation and the values of the three bipolar dimensions. Table 4.4.2.2 shows the values of participant *B07JM* for five working days.

Participant	Working Day	GS	WM	RU	LEVR
B07JM	2013-12-02	15	8	14	5
B07JM	2013-12-03	11	11	9	2
B07JM	2013-12-04	12	8	12	5
B07JM	2013-12-06	13	8	11	5
B07JM	2013-12-09	13	11	11	2

Table 5.: *
Computed stress level scores.

GS	“Feeling well/Feeling bad”
WM	“Alertness/Fatigue”
RU	“Calm/Restless”
LEVR	Level of Relaxation

Column LEVR contains the relaxation values where as columns GS, WM and RU contain the bi-polar dimension values.

4.4.3. Merging Measures and Scores

The last step before correlation merges the measures approximating worktime fragmentation and ambient noise and scores of stress level reports of all study participants into one file.

4.4.4. Data Correlation

In this thesis, the results of data correlation will provide numerical values about the context of worktime fragmentation and ambient noise and with information workers’s self reported stress levels. Preprocessing data resulted in ten variables divided in two categories. Six variables belonging to the category for working behaviour and environment C_{wbwe} and four variables belonging to the category for participant’s emotional state C_{emo}. The task of data correlation is determining the strength of relationship between variables of the two categories.

The pearson correlation coefficient was chosen as data correlation method, based on the review of the hypothesis, presented in section 4.1. Each of the hypothesis relate a measure approximating worktime fragmentation or ambient noise with a stress level score. Further, each relation assumes a linear pattern whereas increasing the variable of one kind results in increasing the variable of the other kind. Consequently, the pearson correlation coefficient was chosen to examine the strength of linear relationship.

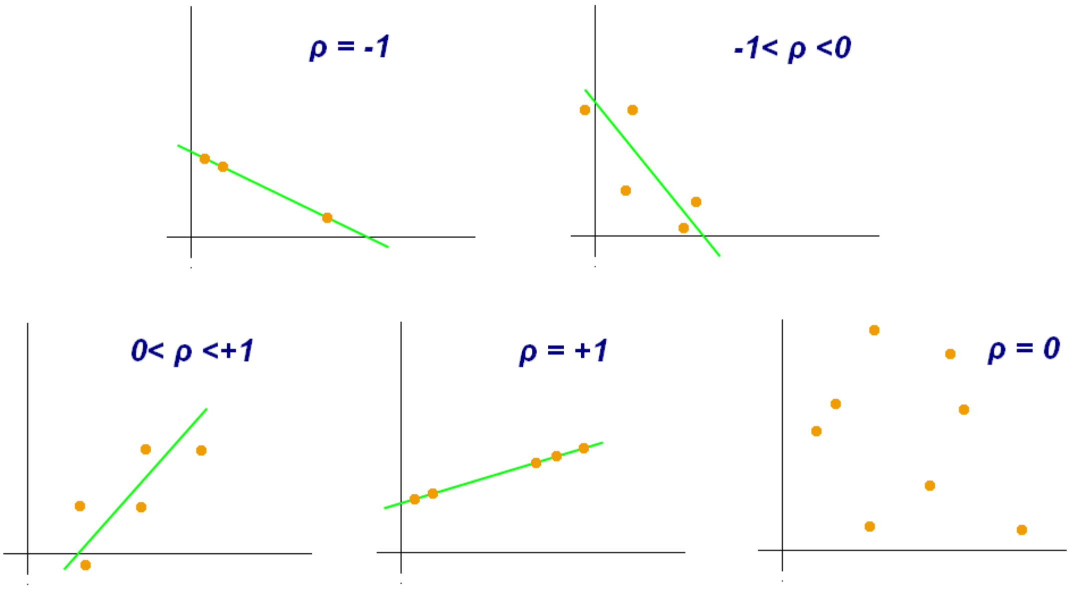

Figure 18.: Scatter plots for correlation coefficients ρ

Pearson Correlation Coefficient The Pearson correlation coefficient ρ_{XY} between two variables X and Y is defined as the fraction of co-variance and variance:

$$\rho_{XY} = \frac{cov(X,Y)}{\sqrt{var(X)var(Y)}} \tag{4.2}$$

[Guyon and Elisseeff, 2003]. The coefficient ρ_{XY} is a measure of dependency of the two variables X and Y and ranges between $+1$ and -1. A positive correlation (value close to $+1$) means a strong dependency between X and Y. As one variable increases in value the other variable also increases in value. Similarly, if a variable decreases in value the other also decreases in value. A negative correlation (value close to -1) also means a strong dependency of X and Y but the direction in which variables change is different. As one variable increases in value the other variable decreases in value and vice versa. A correlation coefficient near to zero means a weak dependency between X and Y. Figure 18 shows the distribution of X and Y values for different correlation coefficients in an exemplary manner.

Significance Level of Pearson Correlation Coefficient The significance level for ρ_{XY} is based on

$$t = \rho_{XY}\sqrt{\frac{W_{XY}-2}{1-\rho_{XY}^2}} \tag{4.3}$$

which, under the null hypothesis, is distributed as a t with $W_{XY}-2$ degrees of freedom. W_{XY} is the sum of weights of cases used in computation of statistics for variables X and Y. The significance level is two-tailed.

Statistical Analysis Tool The statistical analysis tool SPSS[1] was used to compute the Pearson correlation coefficients.

[1] IBM SPSS software `http://www-01.ibm.com/software/analytics/spss/`

5. Results

5.1. Study Participants

15 persons were invited to participate in the study. In one case participation was cancelled because the desktop computer is not operated by Microsoft Windows. In two other cases the company internet access rules forbids remote data transmission. Finally, twelve persons, comprising five male and seven female participants, took part in the study.

Participants are distributed over seven companies, six located in Graz, the capital of Styria, federal state of Austria and one person working in a company located in Germany. The companies include research centers and service providers for industries in different sectors like energy, telecommunication and automated systems. Participants could be described as information workers who are involved in many projects and different teams. Common activities include project management, software development, paper writing, formal and informal meetings and teleconferences for example. Participants are located in small as well as medium sized and open plan offices.

5.2. Usage of Ubiquitous Sensing System

Participants used the system 8.9 working days on average.

Several participants requested an update of the mobile client application since network connectivity was not available or not desired while working. In this case, events are stored in the database on the mobile phone without being uploaded. The update of the mobile client provides the possibility to upload all pending sound pressure level events with the push of a button.

Further, several participants requested to stop sound pressure level monitoring on the smartphone client. The problem was that the application continued running after leaving the workplace. As a consequence, smartphone's battery life was exhausted significantly faster than usual. An update of the mobile client application provided the feature to manually stop monitoring sound pressure level events.

		AVGW	AVGA	CNTI	DURI	AVGS	DURS
N	available	107	107	107	107	89	89
	missing	0	0	0	0	18	18
mean value		7.3	68.2	11.4	2897.5	43.5	1659.0
standard deviation		3.5	42.4	8.6	3138.8	9.5	2469.2
min		1.8	18.5	0	0.0	24	2
max		20.3	264.0	35	11871.1	60	11968

Table 6.: *
Descriptive statistics of measures approximating worktime fragmentation and ambient noise over the temporal scope HT1.

AVGW	Average Duration an Information Worker interacted with an Window, in Seconds
AVGA	Average Duration an Information Worker interacted with an Application, in Seconds
CNTI	Number of Computer Idle Times between one and five Minutes
DURI	Sum of Idle Time Periods equal or greater than 20 Minutes, in Seconds
AVGS	Average Sound Pressure Level, in Decibel
DURS	Sum of Sound Pressure Level Periods exceeding 60 Decibels, in Seconds
HT1	From the Beginning of Work until first Self Report

5.3. Descriptive Statistics

Table 6 illustrates mean value, standard deviation, minimum and maximum values of the measures approximating worktime fragmentation and ambient noise. The values were computed over the temporal scope HT1.

Table 7 illustrates mean value, standard deviation, minimum and maximum values of the measures approximating worktime fragmentation and ambient noise. The values were computed over the temporal scope HT2.

Table 8 illustrates mean value, standard deviation, minimum and maximum values of the measures approximating worktime fragmentation and ambient noise. The values were computed over the temporal scope GT.

		AVGW	AVGA	CNTI	DURI	AVGS	DURS
N	available missing	105 2	105 2	106 1	106 1	84 23	85 22
mean value		25.8	209.1	10.6	2930.2	42.0	1181.0
standard deviation		61.5	518.8	8.4	6361.0	9.4	2188.4
min		1.4	3.2	0	0.0	22	0
max		430.6	3370.2	35	53308.0	66	13370

Table 7.: *
Descriptive statistics of measures approximating worktime fragmentation and ambient noise over the temporal scope HT2.

AVGW	Average Duration an Information Worker interacted with an Window, in Seconds
AVGA	Average Duration an Information Worker interacted with an Application, in Seconds
CNTI	Number of Computer Idle Times between one and five Minutes
DURI	Sum of Idle Time Periods equal or greater than 20 Minutes, in Seconds
AVGS	Average Sound Pressure Level, in Decibel
DURS	Sum of Sound Pressure Level Periods exceeding 60 Decibels, in Seconds
HT2	From the first Self Report until End of Work

		AVGW	AVGA	CNTI	DURI	AVGS	DURS
N	available missing	107 2	107 2	107 1	107 1	89 23	90 22
mean value		18.8	181.4	21.9	5800.3	42.9	2756.0
standard deviation		49.1	514.5	12.7	7594.4	8.9	3670.6
min		1.4	3.2	0	0.0	22	2
max		430.6	3370.2.3	35	53308.0	66	13370

Table 8.: *
Descriptive statistics of measures approximating worktime fragmentation and ambient noise over the temporal scope GT.

AVGW	Average Duration an Information Worker interacted with an Window, in Seconds
AVGA	Average Duration an Information Worker interacted with an Application, in Seconds
CNTI	Number of Computer Idle Times between one and five Minutes
DURI	Sum of Idle Time Periods equal or greater than 20 Minutes, in Seconds
AVGS	Average Sound Pressure Level, in Decibel
DURS	Sum of Sound Pressure Level Periods exceeding 60 Decibels, in Seconds
GT	Whole Day of Work

5.4. Results across all Study Participants

5.4.1. Correlation of Measures with Midday Scores

The midday scores are correlated with the measures approximating worktime fragmentation and ambient noise, once with the measures representing the time from the beginning of work until midday report (HT1) and once with the measures representing the hour before midday report (LS1).

The correlation matrices show an significant negative correlation between the level of relaxation and the average duration an information worker interacted with an window. The Pearson correlation cofficient for timeframe HT1 shows $\rho = -0.216$ ($p = 0.028, N = 104$) and for timeframe LS1 $\rho = -0.228$ ($p = 0.020, N = 104$). Dependency of the other variables show no significant correlation. Table 41 shows the results for the measures of both timeframes.

5.4.2. Correlation of Measures with Evening Scores

The evening scores are correlated with the measures approximating worktime fragmentation and ambient noise, once with the measures representing the time from the midday report until evening report (HT2), once with the measures representing the hour before the evening report (LS2) and once with the values representing a whole day at work (GT).

The correlation matrices for temporal scope HT2 show an significant positive correlation between the number of idle times lasting between one and five minutes and the bi-polar dimension "calm/restless" (RU) with an Pearson correlation cofficient of $\rho = 0.212$ ($p = 0.029, N = 106$). Further, HT2 show an significant negative correlation between the time where sound pressure level exceeded 60 dB and the bi-polar dimension "alertness/fatigue". In this case, the Pearson correlation cofficient is $\rho = -0.287$ ($p = 0.008, N = 85$).

The correlation matrices for temporal scope LS2 show no significant correlation.

The temporal scope over a whole working day shows three significant correlations. The number of idle times lasting between one and five minutes positively (CNTI) correlates with the bi-polar dimensions "feeling well/feeling bad" (GS) and "calm/restless" (RU). The Pearson correlation coefficient between CNTI and GS is $\rho = 0.264$ ($p = 0.006, N = 107$). The coefficient between CNTI and RU is $\rho = 0.200$ ($p = 0.039, N = 107$). Further, GT shows an significant negative correlation of the duration of sound pressure level periods exceeding 60 decibels and the bi-polar dimension "alertness/fatigue" (WM) with an Pearson correlation cofficient of $\rho = -0.329$ ($p = 0.002, N = 90$).

		HT1	LS1
		Correlation Values	Correlation Values
AVGW	ρ	-0.216^{*}	-0.228^{*}
	p	.028	0.020
	N	104	104
AVGA	ρ	-0.117	-0.150
	p	0.236	0.130
	N	104	104
CNTI	ρ	-0.154	-0.073
	p	.118	0.464
	N	104	104
DURI	ρ	-0.145	-0.053
	p	0.143	0.595
	N	104	104
AVGS	ρ	-0.131	-0.175
	p	0.221	0.100
	N	89	89
DURS	ρ	-0.177	-0.091
	p	0.097	0.394
	N	89	89

Table 9.: *
Correlation results across all participants for the midday scale over the temporal scopes HT1 and LS1. Note: * The correlation is significant at a level of 0.05 (two-tailed).

AVGW	Average Duration an Information Worker interacted with an Window, in Seconds
AVGA	Average Duration an Information Worker interacted with an Application, in Seconds
CNTI	Number of Computer Idle Times between one and five Minutes
DURI	Sum of Idle Time Periods equal or greater than 20 Minutes, in Seconds
AVGS	Average Sound Pressure Level, in Decibel
DURS	Sum of Sound Pressure Level Periods exceeding 60 Decibels, in Seconds
HT1	From the Beginning of Work until first Self Report
LS1	Hour before the first Self Report

		HT2			LS2			GT		
		GS	WM	RU	GS	WM	RU	GS	WM	RU
AVGW	ρ	0.130	0.148	0.071	0.119	0.165	0.145	0.110	0.159	0.077
	p	0.185	0.130	0.469	0.226	0.090	0.139	0.258	0.101	0.433
	N	106	106	106	106	106	106	107	107	107
AVGA	ρ	0.105	0.147	0.091	0.101	0.160	0.149	0.096	0.178	0.078
	p	0.286	0.133	0.355	0.303	0.102	0.128	0.323	0.066	0.426
	N	106	106	106	106	106	106	107	107	107
CNTI	ρ	0.158	−0.029	0.212*	0.100	0.065	0.143	0.264**	−0.025	0.200*
	p	0.106	0.767	0.029	0.306	0.506	0.143	0.006	0.797	0.039
	N	106	106	106	106	106	106	107	107	107
DURI	ρ	0.115	0.052	−0.142	0.035	0.003	−0.020	0.156	0.056	−0.147
	p	0.240	0.594	0.146	0.723	0.974	0.841	0.109	0.568	0.131
	N	106	106	106	106	106	106	107	107	107
AVGS	ρ	−0.193	−0.120	−0.171	−0.110	−0.150	−0.098	−0.170	−0.156	−0.184
	p	0.079	0.278	0.120	0.337	0.187	0.391	0.111	0.145	0.085
	N	84	84	84	79	79	79	89	89	89
DURS	ρ	−0.114	−0.287**	−0.145	−0.012	−0.199	−0.005	0.026	−0.329**	0.005
	p	0.301	0.008	0.186	0.915	0.077	0.963	0.811	0.002	0.964
	N	85	85	85	80	80	80	90	90	90

Table 10.: *
Correlation results across all participants for the evening scale over the temporal scopes HT2, LS2 and GT. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

AVGW	Average Duration an Information Worker interacted with an Window, in Seconds
AVGA	Average Duration an Information Worker interacted with an Application, in Seconds
CNTI	Number of Computer Idle Times between one and five Minutes
DURI	Sum of Idle Time Periods equal or greater than 20 Minutes, in Seconds
AVGS	Average Sound Pressure Level, in Decibel
DURS	Sum of Sound Pressure Level Periods exceeding 60 Decibels, in Seconds
HT2	From the first Self Report until End of Work
LS2	Hour before the second Self Report
GT	Whole Day of Work

		GS	WM	RU
GS	ρ	0.218*	0.264**	0.338**
	p	0.026	0.007	< 0.001
	N	104	104	104

Table 11.: *
Correlation results of level of relaxation with bi-polar dimensions. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

GS	"Feeling well/Feeling bad"
WM	"Alertness/Fatigue"
RU	"Calm/Restless"

5.4.3. Correlation of Midday Scores with Evening Scores

The midday scores are correlated with the evening scores.

Table 11 presents the correlation matrix between level of relaxation and each of the bi-polar dimensions. GS correlates with dimension GS with an Pearson correlation coefficient of $\rho = 0.218$ ($p = 0.026, N = 104$). The coefficient with dimension WM shows $\rho = 0.264$ ($p = 0.007, N = 104$) and with dimension RU $\rho = 0.338$ ($p < 0.0001, N = 104$).

5.5. Results for Individual Participants

The correlation results for the study's participants are given in Appendix A.

5.5.1. Correlation of Foreground Window Measures

There were no significant **negative** correlation results between foreground window measures and stress level scores.

Table 12 presents the selection of significant **positive** correlation results between foreground window measures and stress level scores.

Participant	Temporal Scope	Measure	Score	ρ	p	N
G04FW	HT1	AVGW	LEVR	0.680*	0.030	10

Table 12.: *
Positive correlations of foreground window measures with stress level scores. Note: * The correlation is significant at a level of 0.05 (two-tailed).

HT1	From the Beginning of Work until first Self Report
AVGW	Average Duration an Information Worker interacted with an Window, in Seconds
LEVR	Level of Relaxation

Participant	Temporal Scope	Measure	Score	ρ	p	N
G04UJ	HT1	CNTI	LEVR	−0.697*	0.017	11
G18EJ	HT2	DURI	RU	−0.905*	0.002	8

Table 13.: *
Negative correlations of computer idle time measures with stress level scores. Note: * The correlation is significant at a level of 0.05 (two-tailed).

HT1	From the Beginning of Work until first Self Report
HT2	From the first Self Report until End of Work
CNTI	Number of Computer Idle Times between one and five Minutes
DURI	Sum of Idle Time Periods equal or greater than 20 Minutes, in Seconds
LEVR	Level of Relaxation
RU	"Calm/Restless"

5.5.2. Correlation of Computer Idle Time Measures

Table 13 presents the selection of significant **negative** correlation results between computer idle time measures and stress level scores.

Table 14 presents the selection of significant **positive** correlation results between computer idle time measures and stress level scores.

Participant	Temporal Scope	Measure	Score	ρ	p	N
G04UJ	HT2	DURI	GS	0.615*	0.044	11

Table 14.: *
Positive correlations of computer idle time measures with stress level scores. Note: * The correlation is significant at a level of 0.05 (two-tailed).

HT2	From the first Self Report until End of Work
DURI	Sum of Idle Time Periods equal or greater than 20 Minutes, in Seconds
GS	"Feeling well/Feeling bad"

5.5.3. Correlation of Sound Level Measures

Table 15 presents the selection of significant **negative** correlation results between sound pressure level measures and stress level scores.

Participant	Temporal Scope	Measure	Score	ρ	p	N
F26FM	HT1	AVGS	LEVR	-0.674^{*}	0.033	10
F26FM	HT1	DURS	LEVR	-0.741^{*}	0.014	10
G16MF	HT1	DURS	LEVR	-0.652^{*}	0.030	11
G16MF	HT2	AVGS	GS	-0.717^{*}	0.046	8
F14LL	HT2	DURS	WM	-0.771^{*}	0.043	7
G18EJ	HT2	DURS	RU	-0.746^{*}	0.033	8

Table 15.: *
Negative correlations of sound pressure level measures with stress level scores. Note: * The correlation is significant at a level of 0.05 (two-tailed).

AVGS	Average Sound Pressure Level, in Decibel
DURS	Sum of Sound Pressure Level Periods exceeding 60 Decibels, in Seconds
LEVR	Level of Relaxation
GS	"Feeling well/Feeling bad"
WM	"Alertness/Fatigue"
RU	"Calm/Restless"
HT1	From the Beginning of Work until first Self Report
HT2	From the first Self Report until End of Work

Table 16 presents the selection of significant **positive** correlation results between sound pressure level measures and stress level scores.

Participant	Temporal Scope	Measure	Score	ρ	p	N
O06AE	HT2	DURS	GS	0.799^{**}	0.010	9

Table 16.: *
Positive correlations of sound pressure level measures with stress level scores. Note: ** The correlation is significant at a level of 0.01 (two-tailed).

DURS	Sum of Sound Pressure Level Periods exceeding 60 Decibels, in Seconds
GS	"Feeling well/Feeling bad"
HT2	From the first Self Report until End of Work

6. Discussion

6.1. Discussion of Results Across All Study Participants

6.1.1. Switching Windows

The results of window and application interaction times did not support the hypothesis HYP1 (see section 4.1) that many window switches cause higher stress levels. Quite the contrary seems to be the case. During the first half of a day at work, the perceived level of relaxation and the average time spent interacting with an window shows a negative correlation. This means that a high frequency of switching windows in an early phase of an day at work is beneficial and increases well-being.

A reason for this could be that people want to accomplish their tasks as early as possible having a precise mental picture of what they want to achieve for today. Consequently, a high task focus is maintained right away from the beginning. A comparison of the average time people spent interacting with an window shows a large difference between the first and the second half of an working day. During the first half people spent 7.3 seconds on average with an minimum of 1.8 seconds and an maximum of 20.2 seconds interacting with an window. During the second half people spent 32.7 seconds on average with an minimum of 1.4 seconds and an maximum of 787.2 seconds interacting with an window. Table 17 illustrates frequencies of time spent interacting with an window for the temporal scopes HT1 and HT2.

The increased working speed in the first half of the day suggests that people know they get

	HT1	HT2
∅	7.3s	32.7s
min	1.8s	1.4s
max	20.2s	787.2s

Table 17.: *
Frequencies of time spent interacting with an window in the first and second half of an day at work.

HT1	From the Beginning of Work until first Self Report
HT2	From the first Self Report until End of Work

	CNTI		AVGS		DURS	
	HT1	HT2	HT1	HT2	HT1	HT2
∅	11.4	10.6	43.5	42.0	26m:45s	18m:11s
min	0	0	24.0	22.0	0	0
max	35	35	60.0	66.0	3h:19m:28s	3h:42m:50s

Table 18.: *
Frequencies of inactivities and sound pressure level in the first and second half of an day at work.

CNTI	Number of Computer Idle Times between one and five Minutes
AVGS	Average Sound Pressure Level, in Decibel
DURS	Sum of Sound Pressure Level Periods exceeding 60 Decibels, in Seconds
HT1	From the Beginning of Work until first Self Report
HT2	From the first Self Report until End of Work

interrupted more often during that part of the day. Consequently, they adapt working behaviour and increase working speed. Nevertheless, the assumption that people get more interrupted in the first half is not supported with our findings. The average number of idle times which we consider as having distracting effects on people's task focus do not differ significantly between the first and second half of an working day. Also, the average sound pressure level and the time the sound pressure level exceeded 60 decibels did not show any evidence of interruptions taking place more often in the first half. Table 18 illustrates frequencies of idle times and sound pressure level measures for the temporal scopes HT1 and HT2.

From an analysis of the working hours, we found that two participant's are engaged in an part-time employment. The average working hours of those two persons is *5h:25m:32s* compared to *8h:13m:30s* of the remaining ten persons. We wanted to know if those person's experience a much stronger relationship between level of relaxation and time spent interacting with an window during the first half of an working day. The correlation shows no significance. Hence we found no evidence that the part-time employed information worker differ in their experience than the ones with full-time employment regarding the level of relaxation.

The second half of an working day shows a positive correlation between time spent interacting with an window respectively application and the bipolar dimension GS. This suggests that people can cope with a higher frequency of switching windows and applications in the first part of the day but feel annoyed if that level continues in the second half of the day. This is rather a trend because the correlation between the window and application measures and the stress level score of dimension GS shows no statistical significance.

6.1.2. Switching Applications

Switching applications did not reveal any relationship with information workers's emotional states and so did not support hypotheses HYP2 (see section 4.1).

6.1.3. Short Term Idle Times

We hypothesised that times of computer idle times between one and five minutes are interruptions with mostly distracting effects on the emotional state of information workers (see HYP3, section 4.1). Telephone calls, instant messaging or conversations with working mates are examples we had in mind for such short term inactivities. During the first half of a day until midday report we found no evidence that confirms the hypothesis. Nevertheless, we observed a minor trend into that direction. The average number of idle times from the beginning of work until midday report is 11.4. We divided participants in two groups. The first one consisting of those with more than twice the average value. From this group (N=18) we calculated an average relaxation level of 5.1. The second group (N=88) with less than 23 inactivities until midday report has an average relaxation level of 6.3. However, the correlation of the number of idle times between one and five minutes and the level of relaxation shows no significance. This trend diminished during the hour before midday report (LS1) and changed during the second half of the day. Changing means that participants experience more calm when the frequency of short term idle times increases. The correlation between CNTI over an whole working day repeats the context with calm and further introduces context with dimension GS meaning that participants feeling more well with increasing frequency of short term idle times. Although we do not know the nature of those idle times, they are more likely to be beneficial and have positive effects on the emotional state of the participants, although participants do not like to experience those breaks too much in an early phase of an day at work. This goes in line with our previous statement that participants maintain a high focus and like to keep frequency of switching windows high during that time of a day.

6.1.4. Long Term Idle Times

We hypothesised that idle times lasting more than twenty minutes are breaks of a positive nature regarding individual's well being. However, the results did not support hypothesis HYP4 (see section 4.1).

6.1.5. Ambient Noise

The average sound pressure level averages at 43 decibels and reaches 66 decibels at the maximum, which is quite moderate. None of the timeframes shows a significant relationship with the emotional states of participants and did not support hypothesis HYP5 (see section 4.1).

We found a relationship between the time the sound pressure level exceeded 60 decibels and participant's level of fatigue. The longer participant's are exposed to that level or above the more they felt tired at the end of a day at work, supporting our hypothesis HYP6 (see section 4.1). Notable, the exposure did not show any accompanying effects which cause participant's feeling more bad or more restless. Therefore we suggest that this relationship has a positive influence on participant's well-being. The longer exposure times are most probably a sign of much social interaction, formal and informal meetings, small talk and so forth. This demands participant's mental resources in a positive manner and cause a pleasant feeling of fatigue. Complementary, the positive effects of short term idle times on information workers's feeling and calm levels fit perfectly into this picture.

Summarising the previously described relationship, working days with a high frequency of social interactions cause information workers to get tired but reward them with positive effects on their well-being.

6.2. Discussion of Results for Individual Participants

6.2.1. Foreground Window Measures

We found one participant supporting the hypothesis that high frequency of window switching indicates increased levels of stress. The result together with the results across all participant's suggest that the foreground window measures do not approximate worktime fragmentation well and are therefore not suitable for predicting stress of information workers.

6.2.2. Computer Idle Time Measures

A single correlation supports the hypothesis that idle times between one and five have an negative influence on information worker's emotional state. Further, a single correlation supports the hypothesis that the sum of idle time periods above 20 minutes are beneficial for well-being. The result together with the results across all participant's suggest that the idle time measures do not approximate worktime fragmentation well and are therefore not suitable for predicting stress of information workers.

6.2.3. Sound Level Measures

The measures approximating ambient noise support the hypothesis H5 and H6 (see section **??**). The result together with the results across all participant's suggest that the noise measures do approximate worktime fragmentation well and are therefore suggested to be suitable for predicting stress of information workers.

6.3. Summary

The measures approximating worktime fragmentation did not support any of the hypothesis.

In contrast to the measures approximating worktime, sound level pressures above 60 decibels, approximating ambient noise, suggests to be suitable measure to predict increases levels of stress. Together with the findings of short term breaks, the results denote a work life pattern which suggests that information workers who are open to short term social interactions will be rewarded with more positive effects on emotional state than others whose work life is more of an isolated style.

7. Conclusion

Worktime fragmentation and ambient noise are stress inducing factors at work. The goal of this thesis was to predict information worker's stress level with approximations of worktime fragmentation and ambient noise.

In the study conducted for this thesis, a ubiquitous sensing system was implemented to monitor knowledge workers and their environment. The multi platform, multi sensor system comprising desktop and smartphone devices collected and uploaded PC activity and sound level data from knowledge workers over a period of up to ten days at work. Despite the rapid growth of stored records, with several gigabytes of volume at the end of the study, the key value database did not show significant performance loss while executing read and write operations. The selection of the participant code as the key and the collection of all records as the value did not fit well with the queries of the preprocessing component. A key value design matching the queries of the preprocessing component would simplify the code computing the measures. Storing the participant code, working day and type of sensor in the key for example would allow to query all foreground window events for a chosen code and day.

Based on the results from the preprocessing, measures approximating worktime fragmentation and noise were correlated with the stress levels. The correlation was done over the whole group of participants and on an individual level. For the whole group, correlating the measures until midday did not show any stress inducing effects. No stress inducing effects regarding switching windows and computer idle times were found from midday until evening and for the whole day at work. Results show increased levels of fatigue if the sound pressure level exceeds 60 decibels over longer periods of time. Further, a high frequency of switching windows correlated with an increased level of relaxation until midday. Higher levels of inactivities between one and five minutes cause knowledge workers to feel better and more calm when leaving work. Based on these results, inactivity and sound level measures seem to be suitable to predict the emotional state of knowledge workers. Results on the individual level support the hypothesis that window switching frequency as well as short term idle times causes negative effects on well-being.

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A. Appendix

A.1. Participant B07JM

		HT1
		LEVR
AVGW	ρ	0.426
	p	0.341
	N	7
AVGA	ρ	0.618
	p	0.139
	N	7
CNTI	ρ	−0.456
	p	0.304
	N	7
DURI	ρ	−0.105
	p	0.822
	N	7
AVGS	ρ	−0.099
	p	0.832
	N	7
DURS	ρ	−0.216
	p	0.641
	N	7

Table 19.: Correlation results of window activity, soundlevel and idle time with the level of relaxation for timeframe HT1. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

		HT2			GT		
		GS	WM	RU	GS	WM	RU
AVGW	ρ	−0.205	−0.448	−0.046	−0.242	−0.550	−0.051
	p	0.660	0.313	0.922	0.602	0.201	0.914
	N	7	7	7	7	7	7
AVGA	ρ	−0.307	−0.377	−0.039	−0.517	−0.326	−0.258
	p	0.504	0.404	0.934	0.234	0.475	0.576
	N	7	7	7	7	7	7
CNTI	ρ	0.240	0.229	0.415	0.435	−0.272	0.245
	p	0.605	0.621	0.354	0.329	0.555	0.596
	N	7	7	7	7	7	7
DURI	ρ	0.275	0.005	−0.150	0.537	0.122	0.083
	p	0.551	0.991	0.748	0.214	0.794	0.859
	N	7	7	7	7	7	7
AVGS	ρ	−0.148	0.281	−0.415	0.089	0.507	−0.222
	p	0.752	0.542	0.354	0.849	0.245	0.633
	N	7	7	7	7	7	7
DURS	ρ	0.017	0.183	−0.081	0.338	0.247	0.136
	p	0.971	0.694	0.863	0.458	0.593	0.771
	N	7	7	7	7	7	7

Table 20.: Correlation results of window activity, soundlevel and idle time with bipolar dimensions for timeframes HT2 and GT. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

A.2. Participant O06AE

		HT1
		LEVR
AVGW	ρ	−0.024
	p	0.951
	N	9
AVGA	ρ	−0.085
	p	0.827
	N	9
CNTI	ρ	−0.141
	p	0.718
	N	9
DURI	ρ	−0.002
	p	0.995
	N	9
AVGS	ρ	−0.092
	p	0.813
	N	9
DURS	ρ	0.139
	p	0.720
	N	9

Table 21.: Correlation results of window activity, soundlevel and idle time with level of relaxation for timeframe HT1. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

		HT2			GT		
		GS	WM	RU	GS	WM	RU
AVGW	ρ	0.137	0.050	−0.125	0.159	0.051	−0.116
	p	0.726	0.899	0.748	0.683	0.896	0.766
	N	9	9	9	9	9	9
AVGA	ρ	0.083	0.075	−0.151	0.085	0.078	−0.154
	p	0.832	0.849	0.699	0.829	0.843	0.693
	N	9	9	9	9	9	9
CNTI	ρ	−0.365	−0.313	0.104	−0.355	−0.364	0.303
	p	0.335	0.413	0.790	0.348	0.335	0.428
	N	9	9	9	9	9	9
DURI	ρ	−0.111	0.314	−0.503	−0.039	0.283	−0.510
	p	0.776	0.410	0.168	0.920	0.461	0.160
	N	9	9	9	9	9	9
AVGS	ρ	0.102	0.255	−0.411	0.005	0.133	−0.529
	p	0.794	0.508	0.272	0.989	0.733	0.143
	N	9	9	9	9	9	9
DURS	ρ	−0.799**	0.318	−0.644	−0.789*	0.169	−0.700*
	p	0.010	0.405	0.061	0.011	0.663	0.036
	N	9	9	9	9	9	9

Table 22.: Correlation results of window activity, soundlevel and idle time with bipolar dimensions for timeframes HT2 and GT. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

A.3. Participant F14LL

		HT1
		LEVR
AVGW	ρ	−0.149
	p	0.724
	N	8
AVGA	ρ	−0.024
	p	0.955
	N	8
CNTI	ρ	−0.620
	p	0.101
	N	8
DURI	ρ	0.162
	p	0.701
	N	8
AVGS	ρ	−0.236
	p	0.573
	N	8
DURS	ρ	−0.273
	p	0.513
	N	8

Table 23.: Correlation results of window activity, soundlevel and idle time with level of relaxation for timeframe HT1. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

		HT2			GT		
		GS	WM	RU	GS	WM	RU
AVGW	ρ	0.188	0.440	0.435	0.372	0.653	0.141
	p	0.655	0.276	0.282	0.364	0.079	0.739
	N	8	8	8	8	8	8
AVGA	ρ	−0.188	−0.439	0.140	0.345	0.393	0.093
	p	0.655	0.276	0.741	0.403	0.336	0.827
	N	8	8	8	8	8	8
CNTI	ρ	−0.125	−0.614	−0.221	−0.447	0.116	−0.554
	p	0.769	0.105	0.599	0.267	0.784	0.154
	N	8	8	8	8	8	8
DURI	ρ	−0.606	0.039	−0.683	−0.119	0.227	0.010
	p	0.111	0.927	0.062	0.779	0.589	0.981
	N	8	8	8	8	8	8
AVGS	ρ	−0.035	−0.484	0.263	−0.292	−0.368	−0.381
	p	0.941	0.271	0.569	0.483	0.370	0.352
	N	7	7	7	8	8	8
DURS	ρ	−0.151	−0.771*	−0.169	−0.458	−0.081	−0.467
	p	0.747	0.043	0.717	0.254	0.849	0.244
	N	7	7	7	8	8	8

Table 24.: Correlation results of window activity, soundlevel and idle time with bipolar dimensions for timeframes HT2 and GT. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

A.4. Participant F26FM

		HT1
		LEVR
AVGW	ρ	-0.165
	p	0.629
	N	11
AVGA	ρ	-0.230
	p	0.496
	N	11
CNTI	ρ	0.050
	p	0.884
	N	11
DURI	ρ	0.388
	p	0.238
	N	11
AVGS	ρ	-0.674^{*}
	p	0.033
	N	10
DURS	ρ	-0.741^{*}
	p	0.014
	N	10

Table 25.: Correlation results of window activity, soundlevel and idle time with level of relaxation for timeframe HT1. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

		HT2			GT		
		GS	WM	RU	GS	WM	RU
AVGW	ρ	0.378	0.004	−0.060	0.372	0.653	0.141
	p	0.281	0.992	0.868	0.364	0.079	0.739
	N	10	10	10	8	8	8
AVGA	ρ	0.382	0.410	0.203	0.345	0.393	0.093
	p	0.276	0.239	0.574	0.403	0.336	0.827
	N	10	10	10	8	8	8
CNTI	ρ	0.432	−0.093	−0.146	−0.447	0.116	−0.554
	p	0.185	0.785	0.669	0.267	0.784	0.154
	N	11	11	11	8	8	8
DURI	ρ	−0.162	−0.040	0.059	−0.119	0.227	0.010
	p	0.635	0.907	0.864	0.779	0.589	0.981
	N	11	11	11	8	8	8
AVGS	ρ	0.167	0.098	0.219	−0.292	−0.368	−0.381
	p	0.624	0.774	0.517	0.483	0.370	0.352
	N	11	11	11	8	8	8
DURS	ρ	0.060	0.420	0.067	−0.458	−0.081	−0.467
	p	0.860	0.198	0.844	0.254	0.849	0.244
	N	11	11	11	8	8	8

Table 26.: Correlation results of window activity, soundlevel and idle time with bipolar dimensions for timeframes HT2 and GT. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

A.5. Participant G04FW

		HT1
		LEVR
AVGW	ρ	0.680*
	p	0.030
	N	10
AVGA	ρ	0.424
	p	0.222
	N	10
CNTI	ρ	0.571
	p	0.085
	N	10
DURI	ρ	−0.042
	p	0.907
	N	10
AVGS	ρ	0.475
	p	0.525
	N	4
DURS	ρ	−0.152
	p	0.848
	N	4

Table 27.: Correlation results of window activity, soundlevel and idle time with level of relaxation for timeframe HT1. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

		HT2			GT		
		GS	WM	RU	GS	WM	RU
AVGW	ρ	0.173	−0.556	0.145	0.123	−0.613	0.065
	p	0.633	0.095	0.689	0.735	0.060	0.859
	N	10	10	10	10	10	10
AVGA	ρ	0.174	−0.566	0.127	0.149	−0.586	0.098
	p	0.630	0.088	0.727	0.680	0.075	0.789
	N	10	10	10	10	10	10
CNTI	ρ	−0.626	−0.512	−0.242	−0.469	−0.488	−0.125
	p	0.053	0.130	0.501	0.172	0.152	0.730
	N	10	10	10	10	10	10
DURI	ρ	−0.013	0.091	−0.394	0.091	0.175	−0.062
	p	0.972	0.802	0.260	0.802	0.629	0.866
	N	10	10	10	10	10	10
AVGS	ρ	0.350	0.167	0.350	0.405	0.291	0.669
	p	0.772	0.893	0.772	0.595	0.709	0.331
	N	3	3	3	4	4	4
DURS	ρ	−0.683	−0.532	−0.683	−0.151	−0.038	0.743
	p	0.522	0.643	0.522	0.849	0.962	0.257
	N	3	3	3	4	4	4

Table 28.: Correlation results of window activity, soundlevel and idle time with bipolar dimensions for timeframes HT2 and GT. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

A.6. Participant G04UJ

		HT1
		LEVR
AVGW	ρ	0.002
	p	0.995
	N	11
AVGA	ρ	−0.416
	p	0.204
	N	11
CNTI	ρ	−0.697*
	p	0.017
	N	11
DURI	ρ	−0.466
	p	0.148
	N	11
AVGS	ρ	0.094
	p	0.811
	N	9
DURS	ρ	0.333
	p	0.382
	N	9

Table 29.: Correlation results of window activity, soundlevel and idle time with level of relaxation for timeframe HT1. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

		HT2			GT		
		GS	WM	RU	GS	WM	RU
AVGW	ρ	0.192	−0.026	0.036	0.202	−0.003	0.032
	p	0.572	0.939	0.916	0.551	0.993	0.926
	N	11	11	11	11	11	11
AVGA	ρ	0.202	−0.061	−0.019	0.204	−0.007	−0.013
	p	0.552	0.859	0.956	0.547	0.984	0.969
	N	11	11	11	11	11	11
CNTI	ρ	−0.306	0.317	−0.466	−0.175	0.225	−0.562
	p	0.360	0.341	0.148	0.606	0.506	0.072
	N	11	11	11	11	11	11
DURI	ρ	0.615*	0.166	0.392	0.654*	0.246	0.340
	p	0.044	0.626	0.233	0.029	0.466	0.307
	N	11	11	11	11	11	11
AVGS	ρ	0.067	−0.391	0.264	0.105	−0.588	0.313
	p	0.864	0.298	0.493	0.787	0.096	0.412
	N	9	9	9	9	9	9
DURS	ρ	0.340	−0.085	0.246	0.470	−0.260	0.503
	p	0.371	0.829	0.524	0.201	0.499	0.168
	N	9	9	9	9	9	9

Table 30.: Correlation results of window activity, soundlevel and idle time with bipolar dimensions for timeframes HT2 and GT. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

A.7. Participant G16MF

		HT1
		LEVR
AVGW	ρ	−0.077
	p	0.821
	N	11
AVGA	ρ	−0.439
	p	0.177
	N	11
CNTI	ρ	0.101
	p	0.768
	N	11
DURI	ρ	−0.305
	p	0.362
	N	11
AVGS	ρ	−0.481
	p	0.134
	N	11
DURS	ρ	−0.652*
	p	0.030
	N	11

Table 31.: Correlation results of window activity, soundlevel and idle time with level of relaxation for timeframe HT1. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

		HT2			GT		
		GS	WM	RU	GS	WM	RU
AVGW	ρ	0.581	0.221	0.411	0.620*	0.327	0.504
	p	0.061	0.515	0.209	0.042	0.326	0.114
	N	11	11	11	11	11	11
AVGA	ρ	0.061	0.146	−0.102	0.055	0.277	−0.123
	p	0.859	0.668	0.766	0.872	0.410	0.718
	N	11	11	11	11	11	11
CNTI	ρ	0.066	0.071	−0.114	0.668*	0.546	0.555
	p	0.848	0.836	0.739	0.025	0.083	0.076
	N	11	11	11	11	11	11
DURI	ρ	−0.184	0.016	−0.030	0.058	0.455	0.265
	p	0.589	0.962	0.929	0.865	0.160	0.432
	N	11	11	11	11	11	11
AVGS	ρ	−0.717*	−0.350	−0.610	−0.243	0.202	−0.178
	p	0.046	0.395	0.108	0.500	0.576	0.624
	N	8	8	8	10	10	10
DURS	ρ	−0.258	−0.358	−0.393	−0.251	−0.181	−0.355
	p	0.503	0.343	0.296	0.457	0.595	0.284
	N	9	9	9	11	11	11

Table 32.: Correlation results of window activity, soundlevel and idle time with bipolar dimensions for timeframes HT2 and GT. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

A.8. Participant G18EJ

		HT1
		LEVR
AVGW	ρ	0.371
	p	0.365
	N	8
AVGA	ρ	0.438
	p	0.278
	N	8
CNTI	ρ	0.591
	p	0.123
	N	8
DURI	ρ	-0.072
	p	0.865
	N	8
AVGS	ρ	0.459
	p	0.252
	N	8
DURS	ρ	0.370
	p	0.367
	N	8

Table 33.: Correlation results of window activity, soundlevel and idle time with level of relaxation for timeframe HT1. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

		HT2			GT		
		GS	WM	RU	GS	WM	RU
AVGW	ρ	−0.241	−0.320	0.069	−0.278	−0.305	0.034
	p	0.566	0.440	0.872	0.505	0.462	0.936
	N	8	8	8	8	8	8
AVGA	ρ	−0.287	−0.305	0.024	−0.297	−0.297	0.018
	p	0.490	0.462	0.955	0.475	0.475	0.966
	N	8	8	8	8	8	8
CNTI	ρ	−0.573	−0.390	−0.078	−0.113	−0.202	0.412
	p	0.137	0.340	0.854	0.790	0.632	0.310
	N	8	8	8	8	8	8
DURI	ρ	−0.623	−0.536	−0.905**	−0.593	−0.710*	−0.290
	p	0.099	0.171	0.002	0.122	0.048	0.485
	N	8	8	8	8	8	8
AVGS	ρ	−0.196	0.033	−0.638	−0.311	−0.291	−0.579
	p	0.642	0.938	0.089	0.454	0.484	0.133
	N	8	8	8	8	8	8
DURS	ρ	−0.382	−0.238	−0.746*	−0.427	−0.613	−0.654
	p	0.351	0.570	0.033	0.291	0.106	0.078
	N	8	8	8	8	8	8

Table 34.: Correlation results of window activity, soundlevel and idle time with bipolar dimensions for timeframes HT2 and GT. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

A.9. Participant H12EA

		HT1
		LEVR
AVGW	ρ	−0.547
	p	0.204
	N	7
AVGA	ρ	−0.405
	p	0.368
	N	7
CNTI	ρ	−0.335
	p	0.463
	N	7
DURI	ρ	0.522
	p	0.229
	N	7
AVGS	ρ	0.366
	p	0.419
	N	7
DURS	ρ	0.340
	p	0.456
	N	7

Table 35.: Correlation results of window activity, soundlevel and idle time with level of relaxation for timeframe HT1. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

		HT2			GT		
		GS	WM	RU	GS	WM	RU
AVGW	ρ	−0.099	−0.073	−0.280	0.159	0.051	−0.116
	p	0.833	0.877	0.542	0.683	0.896	0.766
	N	7	7	7	9	9	9
AVGA	ρ	0.502	0.224	0.864*	0.085	0.078	−0.154
	p	0.251	0.629	0.012	0.829	0.843	0.693
	N	7	7	7	9	9	9
CNTI	ρ	−0.253	−0.598	−0.553	−0.355	−0.364	0.303
	p	0.584	0.156	0.198	0.348	0.335	0.428
	N	7	7	7	9	9	9
DURI	ρ	0.482	0.231	0.137	0.457	−0.259	0.046
	p	0.273	0.618	0.770	0.303	0.575	0.922
	N	7	7	7	7	7	7
AVGS	ρ	−0.540	−0.542	−0.405	−0.117	−0.685	−0.620
	p	0.211	0.209	0.367	0.803	0.090	0.137
	N	7	7	7	7	7	7
DURS	ρ	0.059	−0.200	−0.221	−0.052	−0.563	−0.381
	p	0.900	0.667	0.633	0.912	0.188	0.399
	N	7	7	7	7	7	7

Table 36.: Correlation results of window activity, soundlevel and idle time with bipolar dimensions for timeframes HT2 and GT. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

A.10. Participant O28ES

		HT1
		LEVR
AVGW	ρ	0.023
	p	0.950
	N	10
AVGA	ρ	0.109
	p	0.764
	N	10
CNTI	ρ	0.218
	p	0.545
	N	10
DURI	ρ	−0.186
	p	0.607
	N	10
AVGS	ρ	−1.0
	p	0.0
	N	2
DURS	ρ	−1.0
	p	0.0
	N	2

Table 37.: Correlation results of window activity, soundlevel and idle time with level of relaxation for timeframe HT1. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

		HT2			GT		
		GS	WM	RU	GS	WM	RU
AVGW	ρ	0.462	0.375	0.246	0.405	0.365	0.279
	p	0.179	0.285	0.493	0.246	0.300	0.435
	N	10	10	10	10	10	10
AVGA	ρ	0.477	0.384	0.243	0.436	0.385	0.272
	p	0.163	0.274	0.499	0.208	0.273	0.447
	N	10	10	10	10	10	10
CNTI	ρ	0.388	-0.429	-0.102	0.172	0.018	-0.068
	p	0.268	0.216	0.780	0.635	0.960	0.852
	N	10	10	10	10	10	10
DURI	ρ	-0.063	-0.068	-0.535	0.305	-0.101	-0.451
	p	0.862	0.852	0.111	0.391	0.781	0.191
	N	10	10	10	10	10	10
AVGS	ρ	-1.0^{**}	1.0^{**}	-1.0^{**}	-1.0^{**}	1.0^{**}	-1.0^{**}
	p	0.0	0.0	0.0	0.0	0.0	0.0
	N	2	2	2	2	2	2
DURS	ρ	-1.0^{**}	1.0^{**}	-1.0^{**}	-1.0^{**}	1.0^{**}	-1.0^{**}
	p	0.0	0.0	0.0	0.0	0.0	0.0
	N	2	2	2	2	2	2

Table 38.: Correlation results of window activity, soundlevel and idle time with bipolar dimensions for timeframes HT2 and GT. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

A.11. Participant V01MR

		HT1
		LEVR
AVGW	ρ	-1.0
	p	0.0
	N	2
AVGA	ρ	1.0
	p	0.0
	N	2
CNTI	ρ	-1.0
	p	0.0
	N	2
DURI	ρ	-1.0
	p	0.0
	N	2
AVGS	ρ	-1.0
	p	0.0
	N	2
DURS	ρ	-1.0
	p	0.0
	N	2

Table 39.: Correlation results of window activity, soundlevel and idle time with level of relaxation for timeframe HT1. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

		HT2			GT		
		GS	WM	RU	GS	WM	RU
AVGW	ρ	−0.656	−0.984*	−0.165	−0.638	−0.609	−0.196
	p	0.344	0.016	0.835	0.246	0.276	0.752
	N	4	4	4	5	5	5
AVGA	ρ	−0.613	−0.997**	−0.009	−0.673	−0.868	0.209
	p	0.387	0.003	0.991	0.213	0.056	0.736
	N	4	4	4	5	5	5
CNTI	ρ	−0.329	−0.317	0.310	−0.848	−0.707	0.085
	p	0.671	0.683	0.690	0.070	0.182	0.891
	N	4	4	4	5	5	5
DURI	ρ	−0.163	0.281	−0.782	−0.133	−0.296	0.025
	p	0.837	0.719	0.218	0.831	0.628	0.968
	N	4	4	4	5	5	5
AVGS	ρ	0.024	0.061	−0.265	0.151	0.246	−0.406
	p	0.970	0.922	0.667	0.808	0.690	0.498
	N	5	5	5	5	5	5
DURS	ρ	−0.346	−0.034	−0.436	0.150	0.374	−0.581
	p	0.568	0.956	0.463	0.810	0.536	0.304
	N	5	5	5	5	5	5

Table 40.: Correlation results of window activity, soundlevel and idle time with bipolar dimensions for timeframes HT2 and GT. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

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		HT1
		LEVR
AVGW	ρ	0.114
	p	0.754
	N	10
AVGA	ρ	0.460
	p	0.181
	N	10
CNTI	ρ	−0.311
	p	0.381
	N	10
DURI	ρ	−0.048
	p	0.895
	N	10
AVGS	ρ	0.280
	p	0.466
	N	9
DURS	ρ	0.126
	p	0.747
	N	9

Table 41.: Correlation results of window activity, soundlevel and idle time with level of relaxation for timeframe HT1. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).

		HT2			GT		
		GS	WM	RU	GS	WM	RU
AVGW	ρ	0.006	−0.158	0.105	0.052	−0.066	0.057
	p	0.986	0.664	0.772	0.886	0.856	0.877
	N	10	10	10	10	10	10
AVGA	ρ	−0.036	−0.228	0.148	0.013	−0.100	0.033
	p	0.920	0.527	0.683	0.972	0.784	0.928
	N	10	10	10	10	10	10
CNTI	ρ	−0.209	−0.463	−0.488	−0.207	−0.431	0.674*
	p	0.563	0.177	0.152	0.567	0.214	0.033
	N	10	10	10	10	10	10
DURI	ρ	−0.292	0.004	−0.527	0.464	0.130	0.657*
	p	0.413	0.991	0.118	0.177	0.720	0.039
	N	10	10	10	10	10	10
AVGS	ρ	−0.577	−0.559	0.595	0.311	0.199	0.894**
	p	0.134	0.150	0.120	0.416	0.608	0.001
	N	8	8	8	9	9	9
DURS	ρ	−0.600	−0.668	0.359	0.138	−0.106	0.861**
	p	0.116	0.070	0.383	0.723	0.786	0.003
	N	8	8	8	9	9	9

Table 42.: Correlation results of window activity, soundlevel and idle time with bipolar dimensions for timeframes HT2 and GT. Note: ** The correlation is significant at a level of 0.01 (two-tailed). * The correlation is significant at a level of 0.05 (two-tailed).