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WIND
WIRTSCHAFTSINFORMATIK
UNIVERSITÄT ROSTOCK

(Don't) Repeat Yourself!

Concepts and Tools for Desktop Activity Logging

Prof. Dr. Michael Fellmann

Agenda

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- **Introduction**
  - Why activity and time tracking matters
  - Prospects of Desktop Activity Logging
- **Fundamentals of Desktop Activity Logging**
  - How to log activities – principles and tools
  - Prototypical logging system for research
- **Advanced Analytics**
  - Methods for classification and prediction
  - Integration of ontological knowledge
- **Empirical Perspective**
  - User acceptance of logging
  - Willingness to complete small surveys
- **Conclusion and Outlook**

Why Activity Logging Matters

Time as the (probably) most precious resource

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- **On the importance of time:** time can be spent once and (in contrast to money) there is no refund possible in case we allocate it to the wrong topics
  → **Time is precious**
- **Knowing how personal time is spent** is an **important requirement** for **improving personal effectiveness/ efficiency** and goal achievement
- **It is not easy to remember** the quantity of time spent on a particular project or activity. Psychological studies suggest that
  - **Time flies** when we are fully engaged
  - **Time "stretches"** in boring situations

→ **Desktop activity logging can record accurate logs for PC-based activities**

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Desktop Activity Logging

is the process of

continuously saving time-related data

about tasks that the user is performing on his/her

desktop using a computing device.

Synonym: Desktop Activity Tracking

Challenges of Desktop Activity Logging

Overview

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- **The Problem with current tools** is that they
  - either require a **high manual effort**

    OR
  - primarily **focus on software usage,** not *on which topic* the user is working on (few tools try to implement automated classification, e.g. via screenshots, OCR, NLP and classification methods)

    OR
  - are **domain-dependent** such e.g. for software engineering, help desks, …

Manual trackers, e.g. via Excel, Harvest

Automated trackers, e.g. RescueTime

Ticket systems, e.g. Bugzilla, Jira

→ IT-support for general-purpose desktop activity logging is still evolving

→ Logging has huge potentials also outside fixed work setting / domains

Use Case 1: Self-Reflection Support

Prospects of Desktop Activity Logging

Use Case 1: Self-Reflection Support

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- **The need for self-reflection**
  - Increased **flexibility** (time and location) and **intensification** of work
  - Increased problems due to **mental illness** which has increased by **144%** within the last decade (Bundesregierung, 2019, via Zeit online)

  → **Self-reflection & management is important**

- **Log data analysis can support reflection about**
  - Weekly **working hours**, time spent different **categories of activities** (e.g. doc. creation, organizing, communication) or on **documents/projects** (if project information is given/ can be inferred)
  - **Working patterns**, such as most productive days, typical time-slots for activities etc.

  → **Desktop Activity Mining as a new sub-field**

Reflection does not *directly* support work
→ **Work support needed**

Use Case 2: Smart Assistance

Prospects of Desktop Activity Logging

Use Case 2: Smart Assistance – more like a butler, less like a robot

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- **The need for smart assistance**
  - **"Smart"** implies some **clever independent action**, but the user is still in control of it
  - In **weakly-structured contexts** this seems a better fit than automation-focused RPA (robotic process automation) tools

- **Log data analysis can be leveraged e.g. for**
  - **prediction of relevant files, folders, applications** to ease navigation and work
  - **autocomplete**, **autosuggest** or **autofill** based on information extraction from relevant files logged during user's work

  → **Smart assistance as "digital third hand" to mechanize the trivial part of tasks**

However: A good butler in real-life may make suggestions (proactively or on request)
→ **Recommendations needed**

Use Case 3: Recommendation Service

Prospects of Desktop Activity Logging

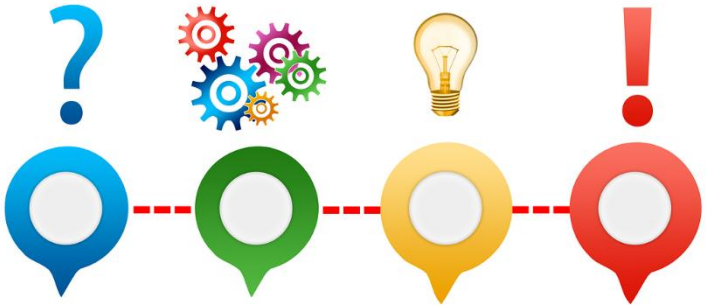
Use Case 3: Recommendation Service

- **The need for recommendations**
  - It is well known in psychology that there is a **huge difference** between **self-reflection** and **self-development**: the former is a sort of precondition, but does *not* imply the latter
  - Habits, delayed gratification or stress may lead to *not* live up to one's own intentions

  → **Recommendations may serve as an intervention to foster doing/not doing sth.**

- **Log data analysis in conjunction with data about the user's goals can be leveraged to**
  - **provide recommendations** for work-related activities, breaks or relaxation
  - **generate reminders** if self-defined goals are missed or self-set limits are exceeded

  → **Recommendations can nudge the user to repeat/don't repeat favorable activities**



→ **Ultimately, it is about (smart) self-management**

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How to Log Activities

Basic components

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Disclaimer: Logging of desktop activities and computer data as discussed within this lecture is intended for personal use only. Much like with tracking data in the field of Quantified-Self, please make sure that you conform to all relevant legal and ethical guidelines if you plan to conduct an experiment or to implement a logging software for someone else. For the sake of a more clear focus and due to time restrictions, the lecture can not cover these important aspects.

- **Components for desktop activity logging**
  - **Key logging** – records **what is typed** via keyboard, can be implemented in hardware or software. Legal applications of key loggers are the study of writing processes.
  - **Screen recording** – records **what the user sees** on the screen, either as film or screenshot triggered by a fixed timer interval or events. A drawback is that OCR (optical character recognition) is required to get readable text out of the screenshots.
  - **Application tracking** – a broader category of tools that **track application usage** via APIs (application programming interfaces) or operating system features.
  - **Combinations of the above** – larger tracking suites **combine all of the above** in order to give a comprehensive account of what is done on a computer.

How to Log Activities

Tool categories and examples

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- **Time management and tracking**
  - Software that logs which applications are used, websites visited etc., on desktop computers as well as mobiles. Some tools allow to download collected data from the cloud.
  - Examples of sophisticated tools are **RescueTime** or SmarterTime.
    More examples on: https://www.producthunt.com/topics/time-tracking
- **General purpose computer usage tracking**
  - Software that can track a broad range of computer usage, such as keyboard & mouse, applications, files and folders, web browsing, e-mail, webcam, printing, social media, etc.
  - An example of such a tool is Spytech SpyAgent
- **Robotic Process Automation (RPA)**
  - Software that can record automatable computer activities in order to reproduce workflows. Due to increasing levels of AI use, sometimes also coined as “cognitive automation”.
  - An example is UIPath. More examples on: https://blog.aimultiple.com/robotic-process-automation-rpa-vendors-comparison/

How to Log Activities

Make or buy and activity logger?

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- **Use an existing activity logger**
  - \+ Stable and mature
  - – Data has to be downloaded from cloud, no control over data structures
  - – Large software products that require installation

- **Program an own activity logger**
  - – Less maturity compared to commercial tools
  - \+ Data can be stored locally or inserted in own database, full control over data structures
  - \+ Minimalistic installation (copy files and set parameters), hence improved transparency
  - \+ Own database with minimalistic software-sensors better accommodates to changing research requirements

→ **It has been decided to create a minimalistic prototypical desktop activity logger**

Prototypical Activity Logger

The basis: AutoIT

- **AutoIT**
  - Scripting environment to automate tasks on computers running Windows.
  - It has a library of functions and extensions and is well-documented and supported by the user community.
  - AutoIT scripts can be compiled to executables (.exe) that run without installation on any Windows computer

https://www.autoitscript.com

- **WinGetTitle() – the most important function**
  - Using this function, it is possible to acces the title of the currently active window
  - For application path and other data, further functions are available
  - There is also a “Window Spy” tool for interactive inspection of return values

Prototypical Activity Logger

Reading file paths

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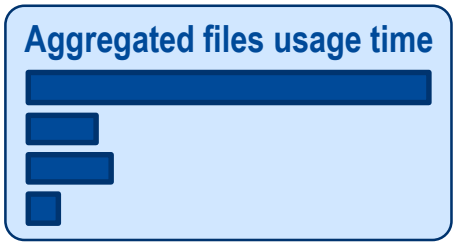
- **Why are file paths interesting?**
  - Files still tend to be organized in taxonomies with human-readable semantic labels
  - **Example:** Let us assume a directory structure

```
C:\Users\max\project\Administration
C:\Users\max\project\WP1
C:\Users\max\project\WP2
C:\Users\max\project\WPn
```



Now, we calculate usage time of documents (end-time – start-time) and then sum up the total usage time of documents for each folder within a specified hierarchical range.
If cumulated usage time of documents in "Administration" is huge compared to documents in all other folders, the user can reflect about this fact
→ It supports self-reflection

- **Two ways to read file paths**
  - Acquire a **COM-object** within the AutoIT-script, then ask this object for the filepath
  - Use the **Windows list of currently running processes** to filter and retrieve the filepath

Prototypical Activity Logger

Logging the web browser – example using Google Chrome

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- **Logging every webpage loaded in the browser**
  - Implemented as **Chrome extension**, data is sent along with a user name and token
  - The **data could be enriched** by using website classification that provide a category such as learning, news, finance, shopping. Example: https://www.brightcloud.com/tools/url-ip-lookup.php. This can be used to quantify time spent on categories such as news or social media

```
var timer;

chrome.runtime.onMessage.addListener(function (message, callback) {
    console.log("received message")
    if (message.type === "start") {
        timer = setInterval(function () {
                sendCurrentUrl(message.username)
            },
            1000
        )
    }
    if (message.type === "stop") {
        clearTimeout(timer);
    }
});

function sendCurrentUrl(username) {
    chrome.tabs.query({'active': true, 'lastFocusedWindow': true}, function (tabs) {
        if (tabs.length > 0) {
            var url = tabs[0].url;
            sendRecord(username, url);
```

Core function call of the extension

```
chrome.tabs.query({'active': true, 'lastFocusedWindow': true}, function (tabs) {
    if (tabs.length > 0) {
        var url = tabs[0].url;
        sendRecord(username, url);
    }

});
```

Prototypical Activity Logger

Logging appointments – example using MS Outlook

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- **Why are appointments interesting?**
  - # of Appointments is an **indicator for workload/stress** and supports self-reflection
  - **Activity-recommendations** should **not** be given **during meetings**

- **Logging appointment management in MS Outlook**
  - Creation, change and delete of appointments **throw events** that can be handled in **VBA**
  - Due to small amounts of data, the most simple procedure is to re-write the event list for one day if any change occurs
  - **Sample code** that creates an alert-message when an appointment has been created

```
Sub colItems_ItemAdd(ByVal Item As Object)
    Dim FocalItem As AppointmentItem
    ' Do what's needed
    Set FocalItem = Item
    MsgBox FocalItem.Subject & vbCrLf & vbCrLf _
            & "Date/time created:    " & FocalItem.CreationTime & vbCrLf _
            & "Date/time modified: " & FocalItem.LastModificationTime, _
            vbOKOnly, "Check Creation Date"
End Sub
```

Prototypical Activity Logger

…and even more data: adding smartwatch data

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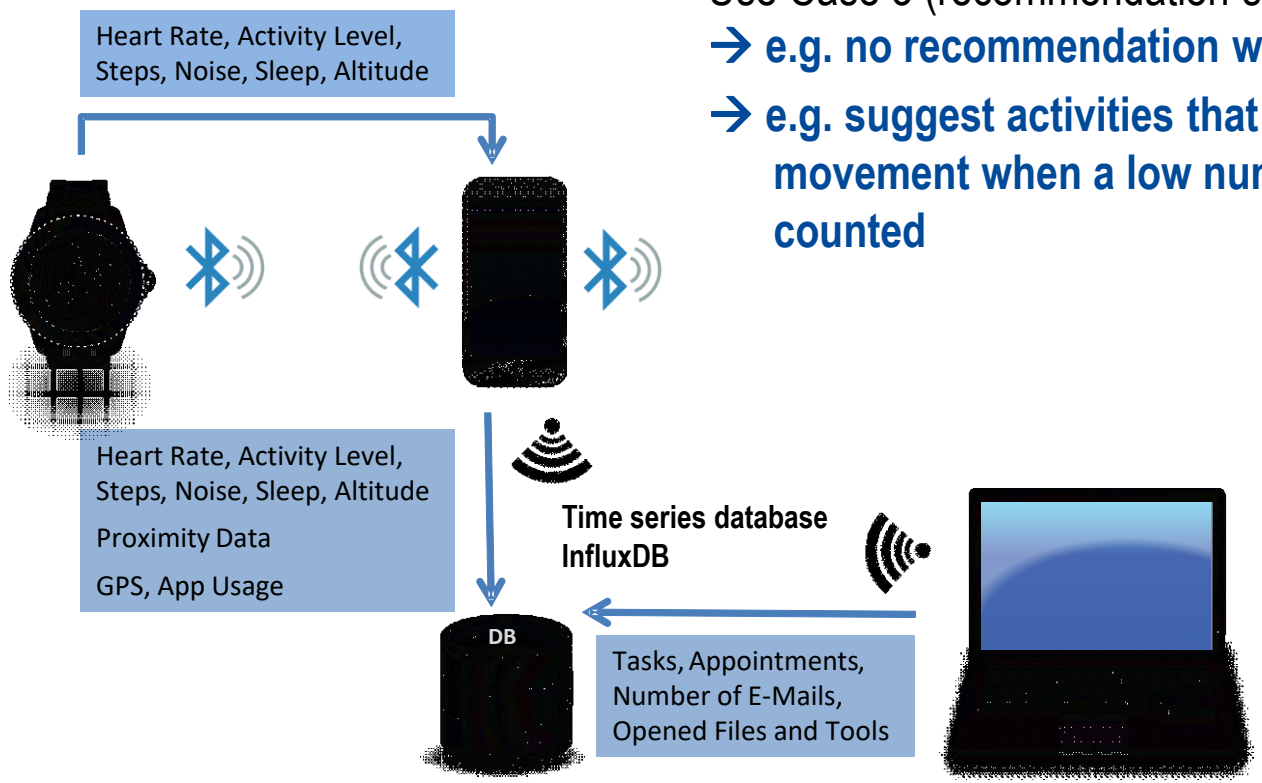
- **Technical architecture for the integration of smartwatch data**
  - Sensor data such as **calories burnt,** step counter and **heart rate** are sent via smartphone
  - Additional sensor data supports can support Use Case 1 (self-reflection) or Use Case 3 (recommendation service)

→ e.g. no recommendation when pulse is > 90

→ e.g. suggest activities that involve physical movement when a low number of steps is counted



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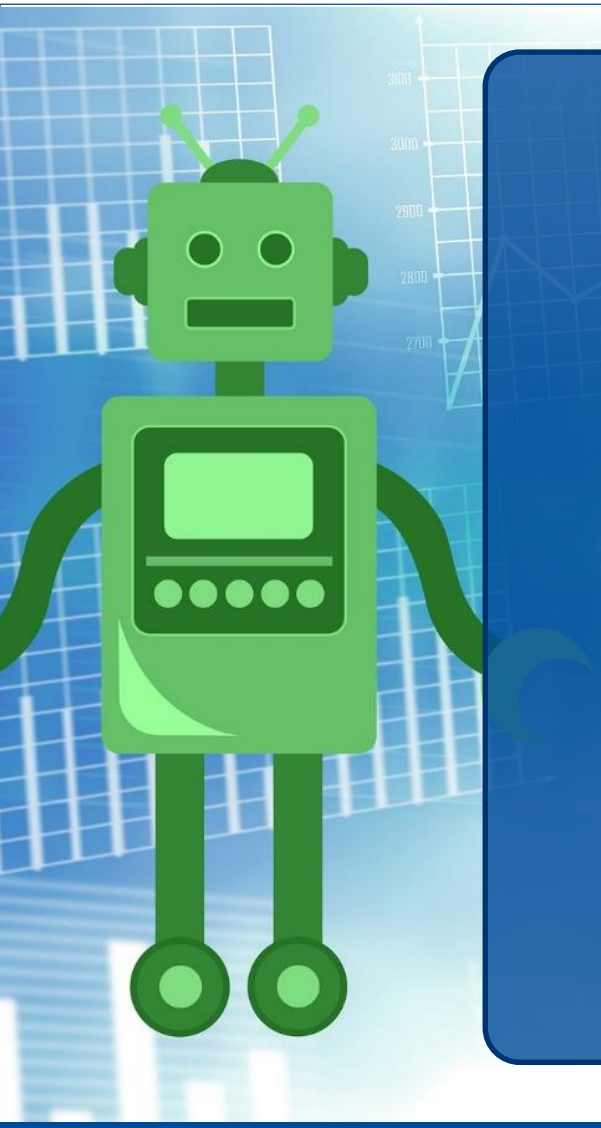
Methods for Advanced Analytics

Overview



Selected methods from Data Science

Unsupervised learning

k-means clustering

Association rule mining

Supervised learning

Regression analysis

k-nearest neighbors

Support vector machine

Decision tree

Random forest

Neuronal nets

Methods for Advanced Analytics

Sample questions to answer

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- **Use Case 1 – Self-Reflection**
  - **Q1-TASKCLS** Which tasks are occupation-related and which are done for private purposes?
  - **Q2-STRESS** What effectively causes stress during ordinary workdays?
  - **Q3-ACLUSTR** Which activity clusters exist according to length and frequency?
- **Use Case 2 – Smart Assistance**
  - **Q4-FOLPRED** What is the most likely folder to save a file?
  - **Q5-AROUTINE** Which activities occur together and form a routine?
- **Use Case 3 – Recommendation Service**
  - **Q6-ACTNEXT** Which tasks are likely to be executed next?
  - **Q7-RECACCPT** Given an activity recommendation, what is the probability of acceptance?

→ **In general, questions should reflect the needs in an application context (we plan to identify questions e.g. in a recently started project)**

Methods for Advanced Analytics

Relevance of the classification/prediction methods

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Question	*k*-means	Assoc. rule	Regress. analysis	*k*-nearest neighbor	SVM	Decision Tree	Random forest	Neural nets
Q1-TASKCLS					x	x	x	x
Q2-STRESS			x					
Q3-ACLUSTR	x			x				
Q4-FOLPRED		x						
Q5-AROUTINE	x	(x)						
Q6-ACTNEXT		x				x	x	
Q7-RECACCPT						x	x	x

Example: Applying association rule mining to predict next activity

- **Structure of the association rule learning problem**
  - Find rules such as “x and y are often purchased together in one transaction”
  - Central metrics (Source: Wikipedia)

$$\mathrm{supp}(X) = \frac{|\{t \in T; X \subseteq t\}|}{|T|}$$

Support (how frequently): supp(*X*) with respect to *T* is defined as the proportion of transactions *t* in the dataset which contains the itemset *X*.

$$\mathrm{conf}(X \Rightarrow Y) = \mathrm{supp}(X \cup Y)/\mathrm{supp}(X)$$

Confidence (how often true): The confidence value of a rule, *X* => *Y* with respect to a set of transactions *T* is the proportion of the transactions that contains *X* which also contains *Y*.

- **Characteristics of the scenario**
  - With **sequential pattern mining**, a special sub-type of finding associations was used.
  - Two algorithms **FP-growth** and **PrefixSpan** were implemented in Orange3
  - Implementations were tested on data derived from RescueTime logs.

Methods for Advanced Analytics

Example: Applying association rule mining to predict next activity

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```
665,2018-06-08 10:00:00 -0700,diva-portal.org,265,1528408800.0,36000.0
666,2018-06-08 10:00:00 -0700,raidix.slack.com,303,1528408800.0,36000.0
667,2018-06-08 10:00:00 -0700,telegra.ph,375,1528408800.0,36000.0
668,2018-06-08 10:00:00 -0700,vncviewer,127,1528408800.0,36000.0
669,2018-06-08
670,2018-06-08
671,2018-06-08
672,2018-06-08
673,2018-06-08
674,2018-06-08
675,2018-06-08
676,2018-06-08
677,2018-06-08
678,2018-06-08
679,2018-06-08
680,2018-06-08
681,2018-06-08
682,2018-06-08
683,2018-06-08
684,2018-06-08
685,2018-06-08
686,2018-06-08
687,2018-06-08
688,2018-06-08
```

Sample Input

Generated Rules

Supp	Conf	Covr	Strg	Lift	Levr	Antecedent		Consequent
0.067	0.389	0.171	0.556	4.083	0.050	saplogon, vk.com	→	mail.google.com, skypeapp
0.067	0.438	0.152	0.938	3.062	0.045	mail.google.com, vk.com	→	saplogon, skypeapp
0.067	0.483	0.138	0.862	4.055	0.050	mail.google.com, saplogon	→	vk.com, skypeapp
0.067	0.933	0.071	5.400	2.420	0.039	mail.google.com, saplogon, skypeapp	→	vk.com
0.067	0.467	0.143	1.067	3.062	0.045	saplogon, skypeapp	→	mail.google.com, vk.com
0.067	0.700	0.095	1.800	4.083	0.050	mail.google.com, skypeapp	→	saplogon, vk.com
0.062	0.867	0.071	3.667	3.309	0.043	winword, skypeapp	→	saplogon
0.062	0.433	0.143	0.767	3.957	0.046	saplogon, skypeapp	→	winword
0.062	0.650	0.095	1.850	3.689	0.045	saplogon, winword	→	skypeapp
0.048	0.909	0.052	5.000	3.471	0.034	winword, vk.com	→	saplogon
0.048	0.278	0.171	0.639	2.536	0.029	saplogon, vk.com	→	winword
0.048	0.500	0.095	4.050	1.296	0.011	saplogon, winword	→	vk.com
0.043	0.450	0.095	2.350	2.011	0.022	saplogon, winword	→	mail.google.com
0.043	0.818	0.052	5.000	3.124	0.029	mail.google.com, winword	→	saplogon
0.043	0.310	0.138	0.793	2.834	0.028	mail.google.com, saplogon	→	winword
0.043	0.250	0.171	0.500	2.917	0.028	saplogon, vk.com	→	offline time - eat/drink
0.043	0.692	0.062	4.231	2.643	0.027	vk.com, offline time - eat/drink	→	saplogon
0.043	0.900	0.048	8.100	2.333	0.024	saplogon, offline time - eat/drink	→	vk.com
0.038	0.320	0.119	0.920	2.922	0.025	vk.com, skypeapp	→	winword
0.038	0.727	0.052	3.364	4.128	0.029	winword, vk.com	→	skypeapp
0.038	0.533	0.071	5.400	1.383	0.011	winword, skypeapp	→	vk.com
0.038	0.800	0.048	2.700	6.222	0.032	chrome, jira.rd.com	→	raidix.slack.com
0.038	0.667	0.057	1.667	7.000	0.033	chrome, raidix.slack.com	→	jira.rd.com
0.038	0.615	0.062	2.077	4.786	0.030	raidix.slack.com, jira.rd.com	→	chrome

Methods for Advanced Analytics

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667,2018-06-08 10:00:00 -0700,telegra.ph,375,1528408800.0,36000.0
668,2018-06-08 10:00:00 -0700,vncviewer,127,1528408800.0,36000.0
669,2018-06-08
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673,2018-06-08
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0.067	0.933	0.071	5.400	2.420	0.039	mail.google.com, saplogon, skypeapp	→	vk.com
0.067	0.467	0.143	1.067	3.062	0.045	saplogon, skypeapp	→	mail.google.com, vk.com
0.067	0.700	0.095	1.800	4.083	0.050	mail.google.com, skypeapp	→	saplogon, vk.com
0.062	0.867	0.071	3.667	3.309	0.043	winword, skypeapp	→	saplogon
0.062	0.433	0.143	0.767	3.957	0.046	saplogon, skypeapp	→	winword
0.062	0.650	0.095	1.850	3.689	0.045	saplogon, winword	→	skypeapp
0.048	0.909	0.052	5.000	3.471	0.034	winword, vk.com	→	saplogon
0.048	0.278	0.171	0.639	2.536	0.029	saplogon, vk.com	→	winword
0.048	0.500	0.095	4.050	1.296	0.011	saplogon, winword	→	vk.com
0.038	0.615	0.062	2.077	4.786	0.030	raidix.slack.com, jira.rd.com	→	chrome

Supp	Conf	Covr	Strg	Lift	Levr	Antecedent		
0.067	0.389	0.171	0.556	4.083	0.050	saplogon, vk.com	→	mail.google.com, skypeapp
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0.067	0.483	0.138	0.862	4.055	0.050	mail.google.com, saplogon	→	vk.com, skypeapp

→ Writing e-mails or working with SAP is often followed by Skype calls

Integration of Ontological Knowledge

Definition

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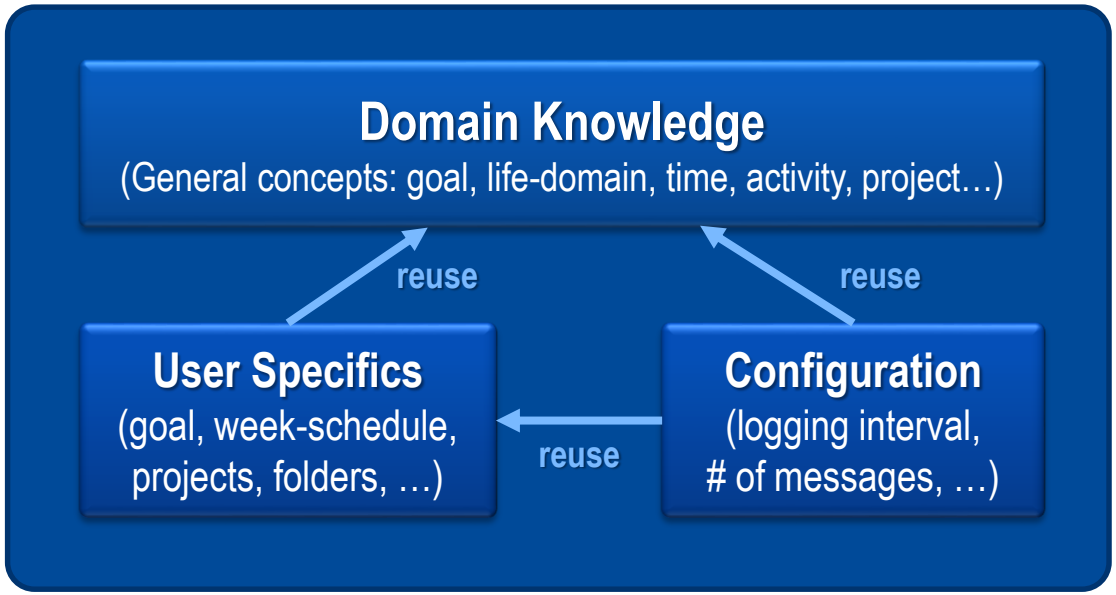
An Ontology is an „explicit specification of a conceptualization”
(Gruber 1993)

Integration of Ontological Knowledge

Purpose and structure

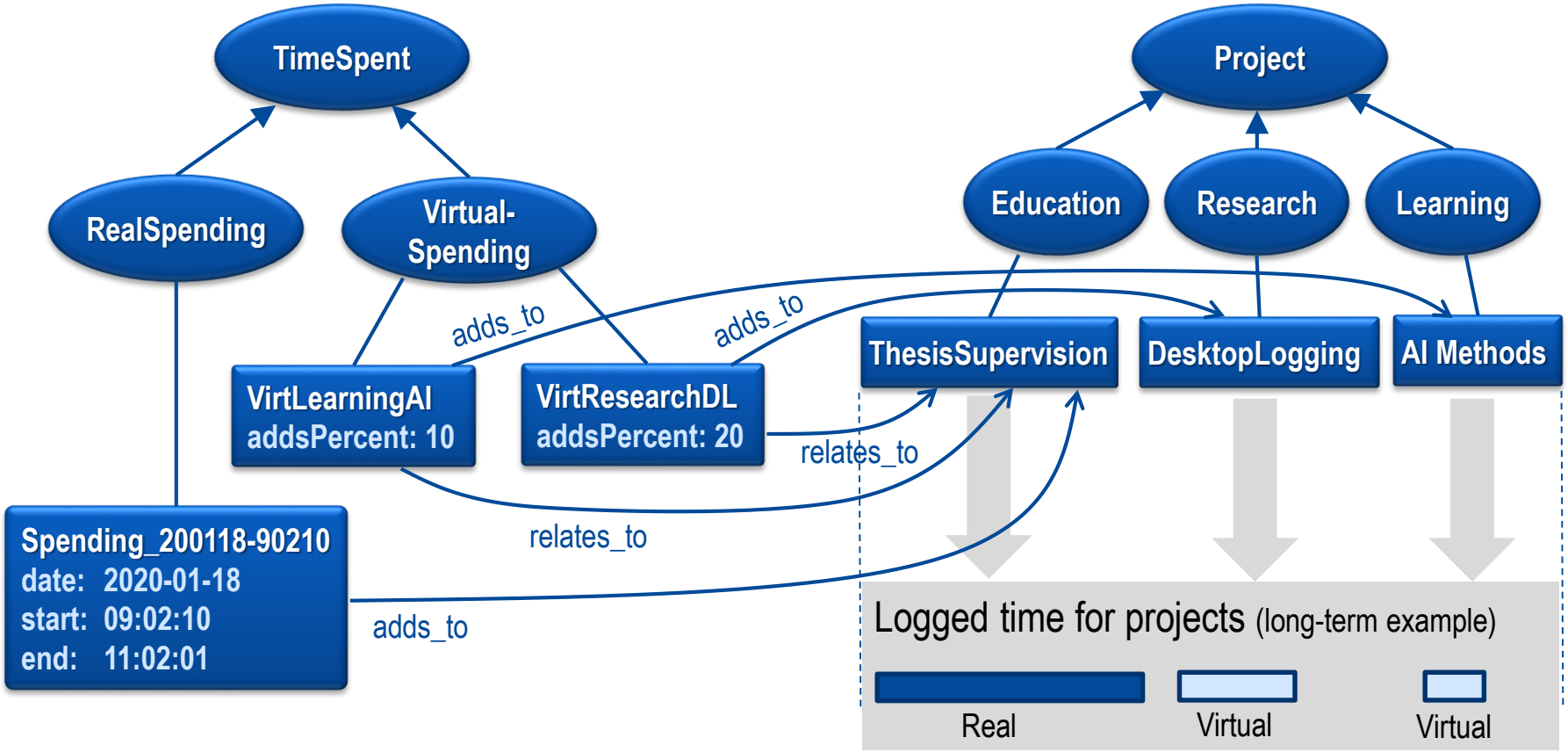
- **Why do we need an ontology?**
  - An Ontology can **conceptualize important and stable concepts** of the domain
  - It can serve as an **umbrella for domain and user-configuration knowledge**
- **High-level structure of an ontology for desktop activity logging**



Integration of Ontological Knowledge

Example: Logging “real” and “virtual” time

Core idea: Time spent is assigned to *one* primary project and to an arbitrary number of other projects of the user, where it counts as “virtual” time spending.



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Empirical question:

What is the acceptance for data logging?

Survey (Focus: Stress-sensitive Systems)

- **n = 103 complete records**
- **Age 19 – 67 years**
  (46 aged 19-29, 30 aged 30-39, 15 aged 40-49, 12 aged >49)
- 45% female, 55% male
- 92 employed, 9 stud. with part-time job, 2 non-workers

Results from the Survey

Acceptance and appraised feasibility of measurement methods

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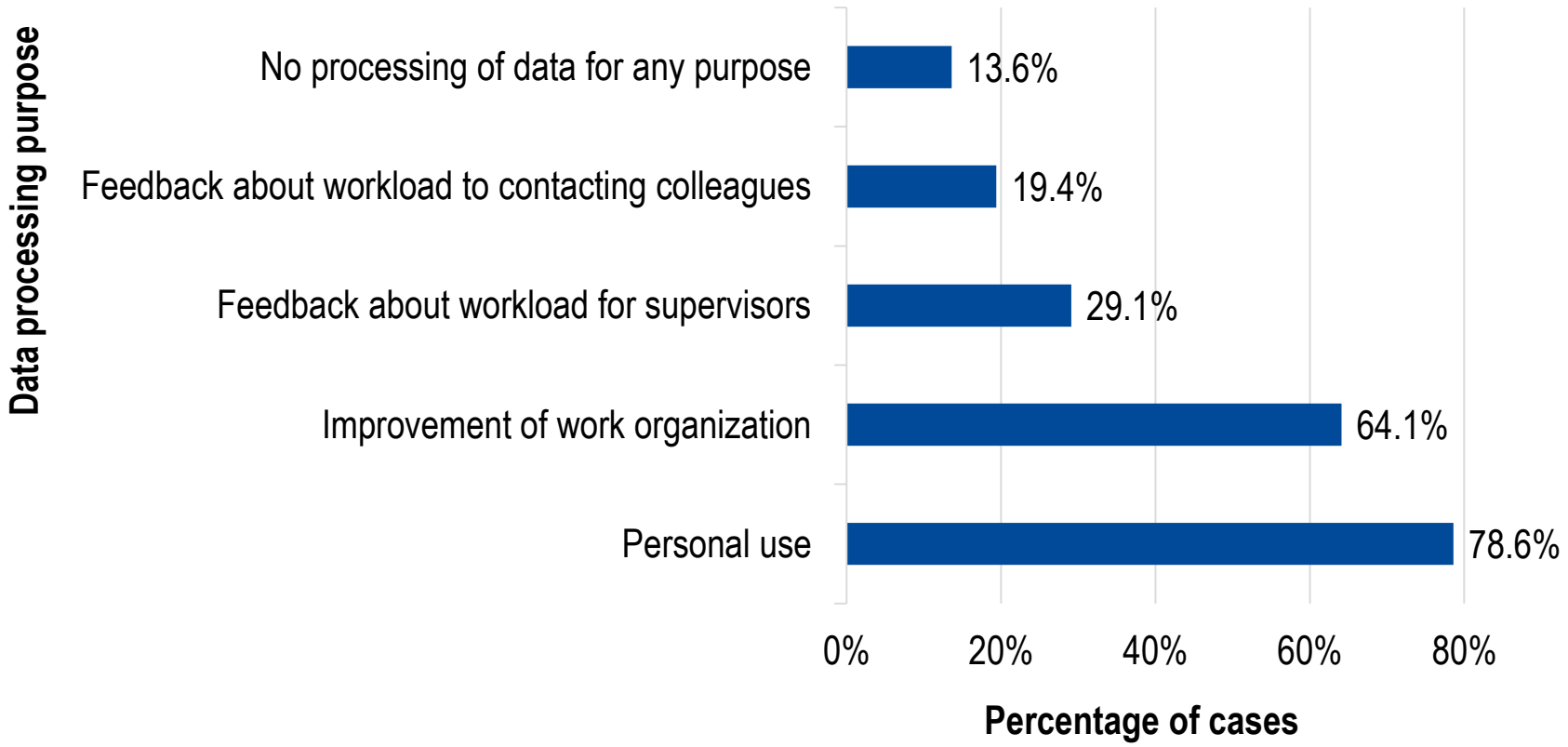
n=103		Is this data collection method feasible at your workplace?		Would you agree to the implementation of this method?	
		Yes	No	Yes	No
Neurophysio-logical data	1. Eye tracking	35.9 %	64.1 %	47.6 %	52.4 %
	2. Skin conductance measurement	32.0 %	68.0 %	34.0 %	66.0 %
	3. ECG (electrocardiogram)	31.1 %	68.9 %	41.7 %	58.3 %
Communi-cation data	4. Email / Instant messaging	43.7 %	56.3 %	60.2 %	39.8 %
	5. Phone data	43.7 %	56.3 %	54.4 %	45.6 %
Documents & Calendar	6. Appointment calendar / Work plan	50.5 %	49.5 %	**74.8 %**	25.2 %
	7. Edited documents	43.7 %	56.3 %	63.1 %	36.9 %
	8. Self-assessment questionnaire	57.3 %	42.7 %	**81.6 %**	18.4 %

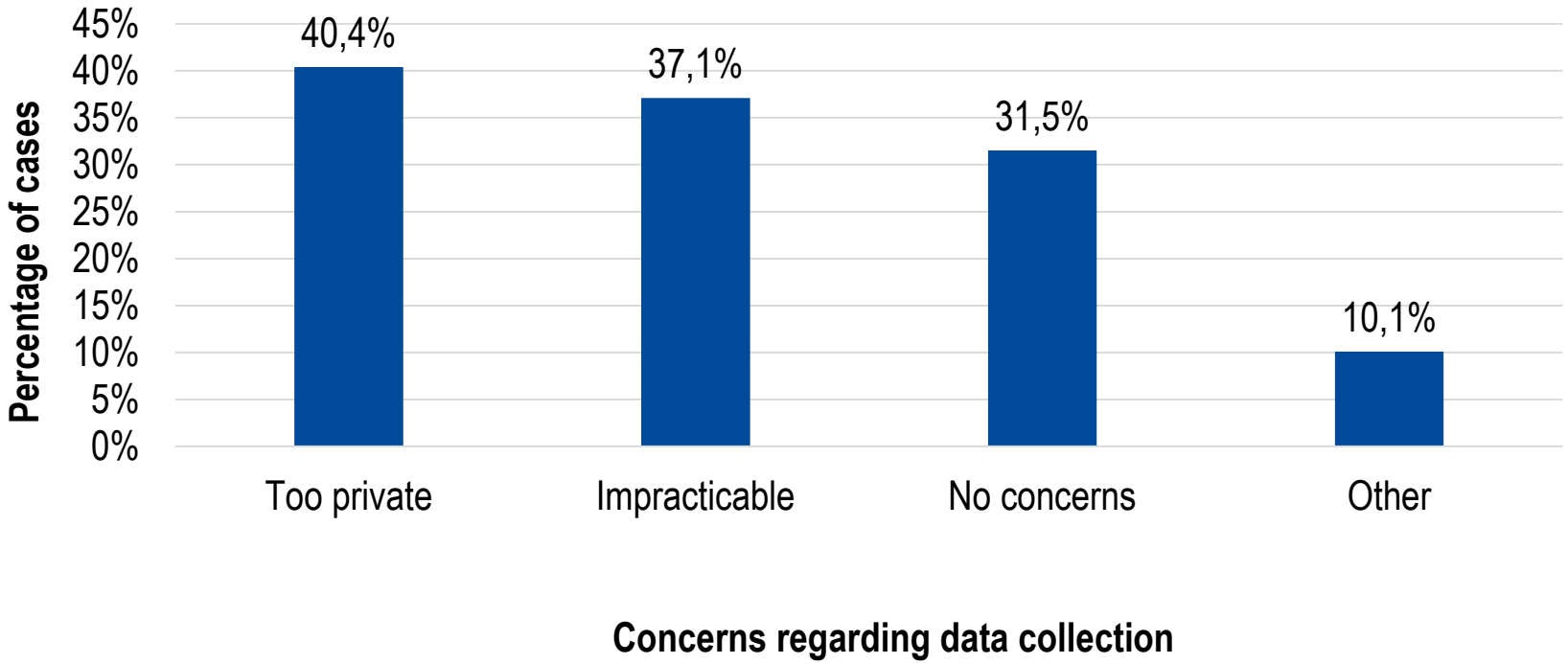
Results from the Survey

Acceptance of data processing purposes



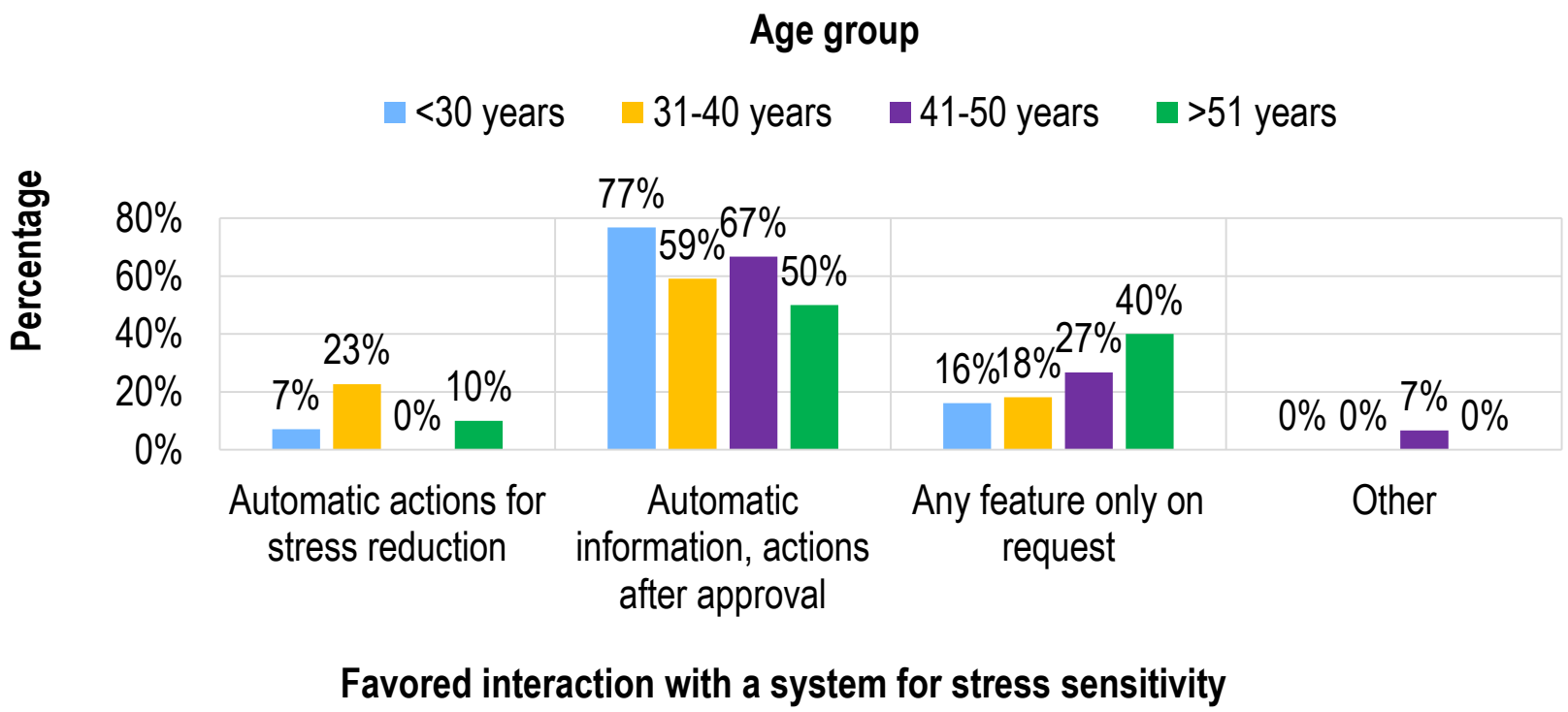
Results from the Survey

Concerns



Results from the Survey

Favored degree of automation



Empirical question:

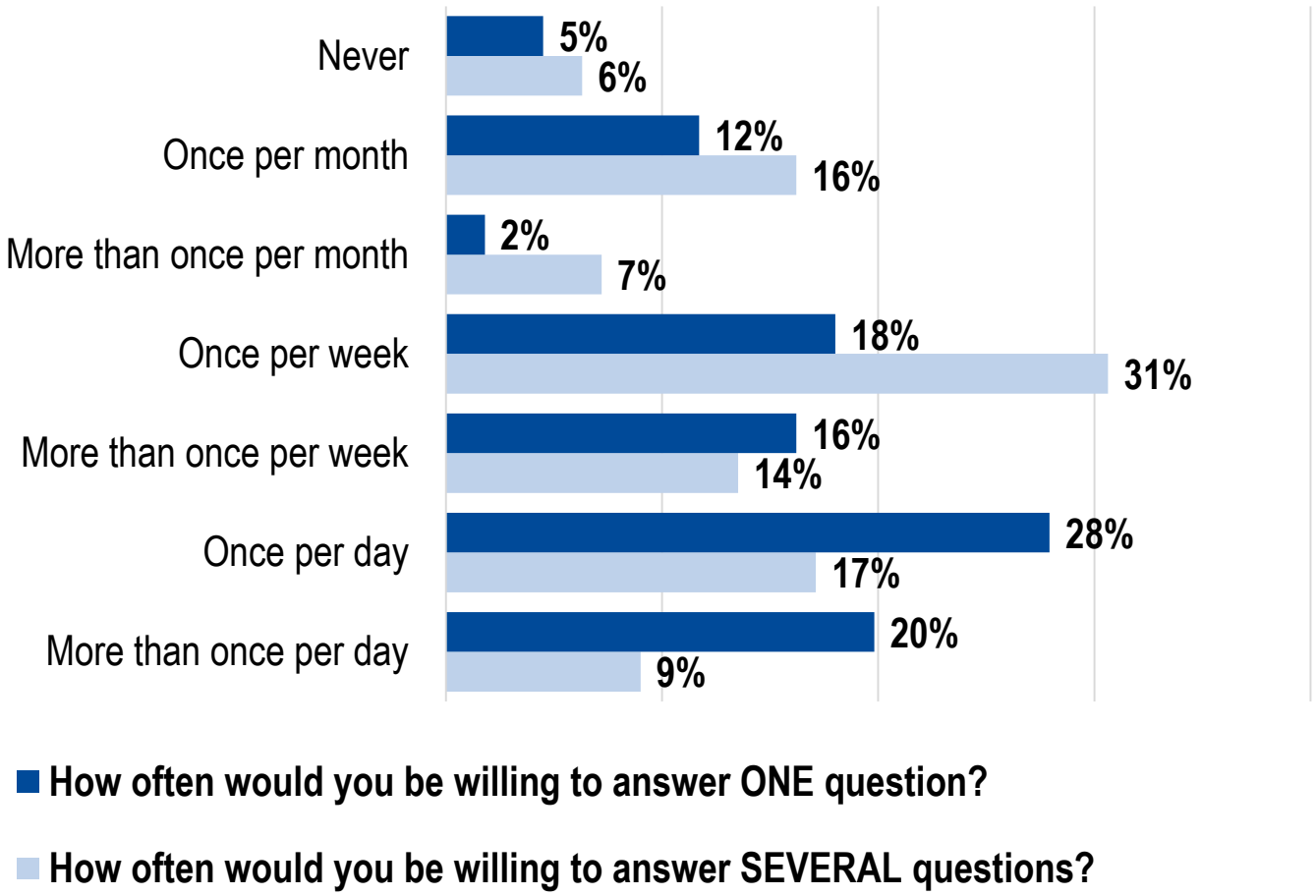
What about the willingness to cooperate with a logging tool by answering small surveys?

Survey (Focus: Assistance)

- **n = 111 complete records**
- **Age 14 – 63 years**
  (14 participants aged <21, 93 aged 21-30, 4 aged >30)
- 44% female, 56% male
- 65% students, 22% employees
- Prevalence of stress:
  78.4% were stressed within last 7 days

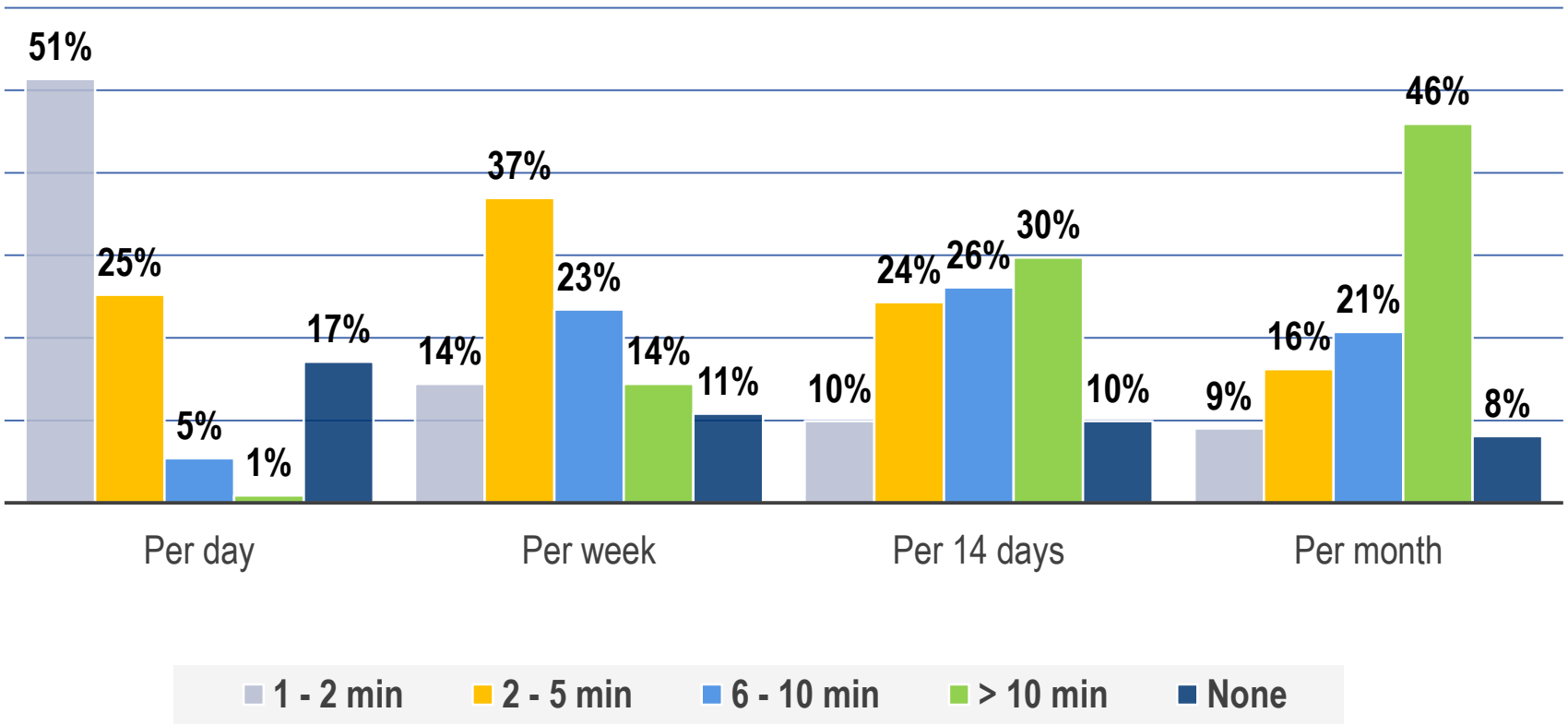
Results from the Survey

Accepted frequency to answer questions



Results from the Survey

Accepted expenditure of time to answer questions



Agenda

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- **Introduction**
  - Why activity and time tracking matters
  - Prospects of Desktop Activity Logging
- **Fundamentals of Desktop Activity Logging**
  - How to log activities – principles and tools
  - Prototypical logging system for research
- **Advanced Analytics**
  - Methods for classification and prediction
  - Integration of ontological knowledge
- **Empirical Perspective**
  - User acceptance of logging
  - Willingness to complete small surveys
- **Conclusion and Outlook**

Conclusio

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- **Desktop activity logging** implies continuously tracking computer-based activities
- It can be the **basis for use cases** such as **self-reflection** support, **smart assistance** and **recommendation services** applied in personal (office-like) working scenarios
- Research is still scarce that applies algorithms from data science
  → **Huge research opportunities when combined with data analytics/ AI**
  e.g. to fully automatically mine and label activities & projects, predict folders, stress…
- **When designing a solution**, it should be taken into consideration that users differ
  – in regard to their acceptance of data collection
  – concerning the preferred interaction mode
  → **System needs to be highly configurable**
- **Larger context:** Make use of ever increasing freedom at work ("Work 4.0") regarding time, location, topic … while considering individual resources
  → **Smart self-management to continuously prioritize work (and non-work) tasks**

The Larger Context

Desktop activity logging as a part of:

Management
"Its essential idea is that of **constant attention to details**." (Etymonline, Century Dictionary)

Smart Self-Management

Smart
"Being mentally alert; operating by **automation**" (Merriam Webster);
"(of a device) programmend so as to be capable of some **independent action**"
(Oxford Dictionary)

Self-Management
In Management: ability and activity to take **control of one's own personal and professional development** including setting goals, planning, time management, organization, learning, feedback (Wikipedia);
In Psycology: Established research field of **Self-regulation** (e.g. Journal of Self-Regulation and Regulation).

→ Smart Self-Management is the constant IT-supported planning, organization and control of personal resources to achieve personal or professional goals while at the same time paying attention to health and wellbeing.

The Larger Context

…balancing productivity and success with health and well-being

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Thank you for your attention!

– *Questions?*

Further Reading

Selected Publications

Universität Rostock

- Fellmann, M.; Lambusch, F. (2019): **Stress-Sensitive IT-Systems at Work: Insights from an Empirical Investigation.** In: Abramowicz W., Corchuelo R. (Eds): Business Information Systems (BIS 2019). Cham : Springer (LNBIP 354), pp 284-298. DOI: https://doi.org/10.1007/978-3-030-20482-2_23
- Lambusch, F.; Weigelt, O.; Fellmann, M.; Hein, S.; Poppe, M. (2020): **Personal Productivity Management in the Digital Age: Measures from Research and Use of Conventional Tools.** Track "Digital Health & Well-Being" at Int. Conf. on Wirtschaftsinformatik (WI2020), March 9-11, Potsdam, Germany. - forthcoming
- Poppe, M.; Lambusch F.; Fellmann, M.; Lichtwark, M. (2019): **IT-unterstützte Datenerfassung zur Ableitung persönlicher Produktivitätsfaktoren: eine systematische Literaturanalyse.** In: Proceedings of the Mensch und Computer 2019 Workshop on Smart Collaboration – Mitarbeiter-zentrierte Informationssysteme in der Produktentstehung. DOI: 10.18420/muc2019-ws-300-04, 8 pages.
- Weigelt, O.; Wyss, C.; Hoffmann, K.; Fellmann, M.; Lambusch, F. (2019): **Ein Bild sagt mehr als tausend Worte - Entwicklung und Überprüfung einer Piktogramm-Skala zu Human Energy.** Poster präsentiert zur 11. Tagung der Fachgruppe Arbeits- und Organisationspsychologie der Dt. Gesellschaft für Psychologie in Braunschweig.
- Fellmann, M.; Lambusch, F.; Pieper, L. (2019): **Towards Combining Automatic Measurements with Self-Assessments for Personal Stress.** In: 2019 IEEE 21st Conference on Business Informatics (CBI), July 15-17, Moscow, Russia. IEEE. DOI: 10.1109/CBI. 2019.00076, 8 pages.

Further Reading

Selected Publications

Universität Rostock

- Fellmann, M.; Lambusch, F.; Pieper, L. (2018): **IT-supported Stress Management Mediating between Sensor Data and Individual Appraisal.** In: Proceedings of the 5th international Workshop on Sensor-based Activity Recognition and Interaction (iWOAR 2018), Sept. 20-21, Berlin. ACM. DOI: 10.1145/3266157.3266223, 7 pages.
- Lambusch, F.; Fellmann, M.; (2018): **Towards Context-Aware Assistance for Smart Self-Management of Knowledge Workers.** In: Zdravkovic, J.; Grabis, J.; Nurcan, S.; Stirna, J. (Eds.) BIR Short Papers, Workshops and Doctoral Consortium, Joint Proceedings of the BIR 2018 Short Pa-pers, Workshops and Doctoral Consortium, co-located with 17th International Conference Perspectives in Business Informatics Research (BIR 2018), Stockholm, Sweden, September 24-6, 2018. CEUR-WS.org (vol-2218), 12 pages.
- Lambusch, F.; Fellmann, M.; Sauer, V. (2018): **The Data Perspective of Sensor-enabled Personal Work Support Systems.** In: Proceedings of the Workshop MCI-WS18 – Smart Factories: Mitarbeiterzentrierte Informationssysteme für die Zusammenarbeit der Zukunft, held at Mensch und Computer, September 4, Dresden, Germany. 7 pages.