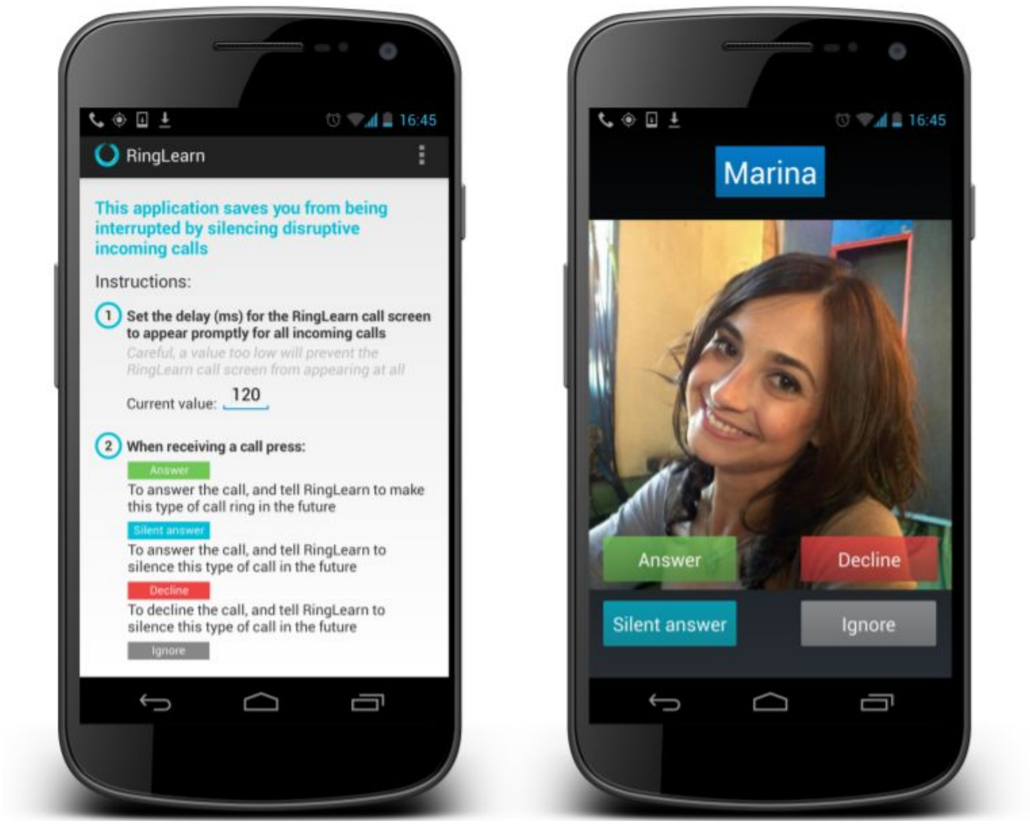
Interruptibility Analysis with Sensor Data

- Interruptibility prediction for ubiquitous systems: conventions and new directions from a growing field
  Liam D. Turner, Stuart M. Allen, Roger M. Whitaker September 2015 UbiComp '15
- Interruptibility of Software Developers and its Prediction Using Psycho-Physiological Sensors, Manuela Züger, Thomas Fritz, ACM CHI 2015
- Interrupting Drivers for Interactions: Predicting Opportune Moments for In-vehicle Proactive Auditory-verbal Tasks, Auk Kim, Woohyeok Choi, Jungmi Park, Kyeyoon Kim, Uichin Lee, ACM IMWUT 2018

Timing Matters

How Busy Are You? Predicting the Interruptibility Intensity of Mobile Users, ACM CHI 2017

Timing Matters



Who schedules?

- Sender scheduling
- Receiver scheduling

Mitigating? (decreasing ringtone volume, or flashing an LED light)

Learning to recognize disruptive smartphone notifications, MobileHCI 2014

Timing Matters

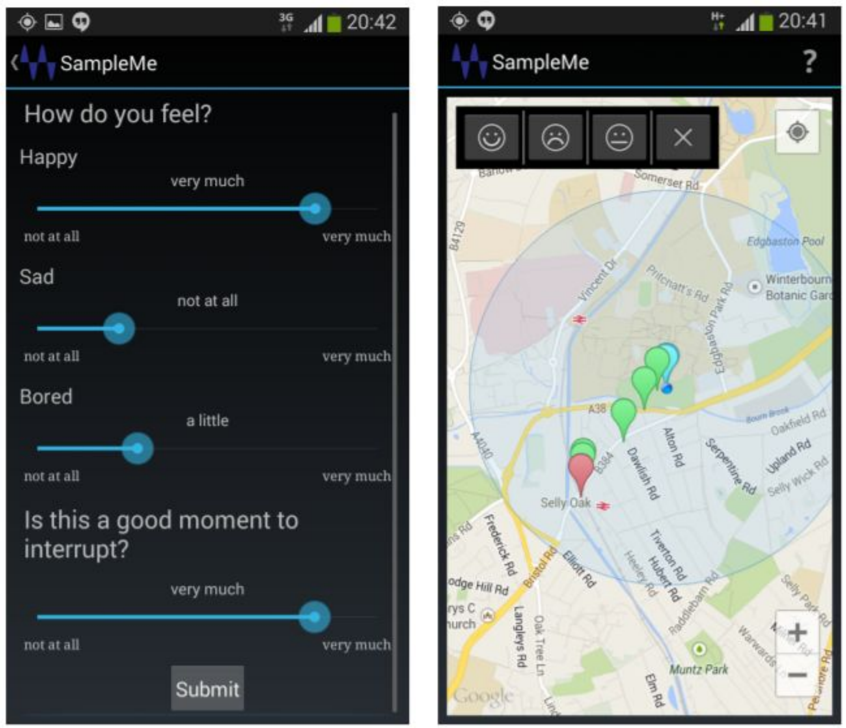
- Interrupted **after** completing two of three primary tasks **vs. during** two of three primary tasks (Bailey et al., 2001)
- Interruption has **a disruptive effect** on both a user's **task performance** and **emotional state** (e.g., **annoyance**, **anxiety**)
- Degree of disruption depends on the **user's mental load (task difficulty)** at the point of interruption

Bailey, B. P., Konstan, J. A., and Carlis, J. V. The effects of interruptions on task performance, annoyance, and anxiety in the user interface. In Proc. INTERACT'01 (2001), 593–601

Defining Interruptibility

- Physiological ability to switch focus
  - assessing the cognitive workload of the user at the time of interruption, and their capacity to receive it
  - mental workload on the user can be assessed using EEG or pupil size event
- Cognitive affect on task performance
  - ability or overhead to switch from an existing task to an interruption and then re-engage back to previous task
  - elapsed time to regain focus after the interruption, commonly referred to as resumption lag, measured through software events
- User sentiment towards the interruption
  - subjective metrics captured on a Likert scale using self reports (ESM); e.g., emotion, good timing?, how disturbing?

ESM Questions

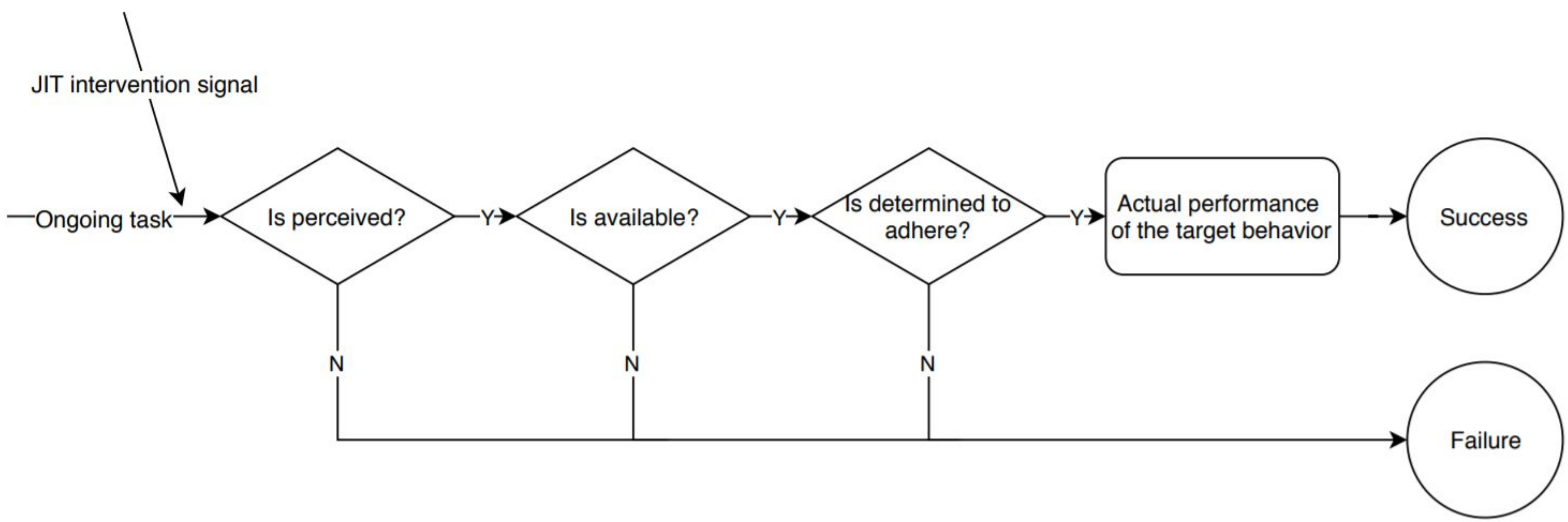


(a) Survey. (b) Emotion map.

InterruptMe: Designing Intelligent Prompting Mechanisms for Pervasive Applications, https://www.cs.bham.ac.uk/~pejovicv/docs/Pejovic14UbiComp.pdf

Interruptibility modeling

- Decision Stages in Multi-Stage Receptivity Model



"Multi-Stage Receptivity Model for Mobile Just-In-Time Health Intervention"
Woohyeok Choi, Sangkeun Park, Duyeon Kim, Youn-kyung Lim, Uichin Lee, IMWUT 2019

Scenario for Interruptibility

- Controlled environment
  - The experiment takes place in a static laboratory setting, involving simulations of activities and interruptions. Users are typically compensated for their time, but not always
- Explicit in-the-wild
  - The experiment takes place in situ around the daily lives of participants. However, the user is continually aware of the experiment. The participants are typically incentivized through compensations for their time, but not always
- Implicit in-the-wild
  - The experiment takes place in situ around the daily lives of participants. The experiment is often embedded through other features that the participant finds useful, providing more natural incentive

Data Collection

- Context
  - Smartphone sensors: e.g., HW sensors or SW APIs
  - Physiological sensors: e.g., physical state or activity
  - Environmental sensors: e.g., sound or motion in a room or car
  - Software events: e.g., active windows, keyboard and mouse activity
  - Calendar schedules
  - Temporal logs: e.g., user actions
  - Spatial logs: e.g., GPS or connections to antennas
- Latent
  - Self reports: e.g., experience sampling or post-experiment surveys
  - Qualitative feedback: e.g., post-interviews
  - Third party observer reports: e.g., in situ observation or video annotations
  - Physiological sensors: e.g., mental state or workload

Features

- User Features
  - Pupil size events, EEG events, emotion, learning style, personality, time until next calendar event
- Environment Features
  - Coarse location, fine location, other people present, states e.g. door open/closed, cell tower id, Wi-Fi SSID, nearby Bluetooth, wireless signals, smartphone ringer state, smartphone screen covered, smartphone orientation, ambient noise
- Interruption Features
  - Content e.g. text or phone number, task complexity, number of queued interruptions, time between interruptions

Features

- User and Environment Features
  - Time of day, day of week, month, user is in conversation, user's current activity, user is present, software events, unusual environment to be in, frustration level, stress, level of annoyance respiration, ambient sound, car movement, human motions, smartphone motions or acceleration, PC active and inactive time
- User and Interruption Features
  - Social relation, interruption frequency, content desirability, perceived mental effort, perceived task performance, resumption lag, perceived timeliness of delivery, number of primary task errors, primary task duration, elapsed time to switch to interruption, primary task complexity, interruption timestamp, interruption duration, perceived time pressure, previous or next task cue presented, elapsed time before user reaction, influence from social contexts

InterruptMe: Designing Intelligent Prompting Mechanisms for Pervasive Applications

https://www.cs.bham.ac.uk/~pejovicv/docs/Pejovic14UbiComp.pdf

Modeling & Testing

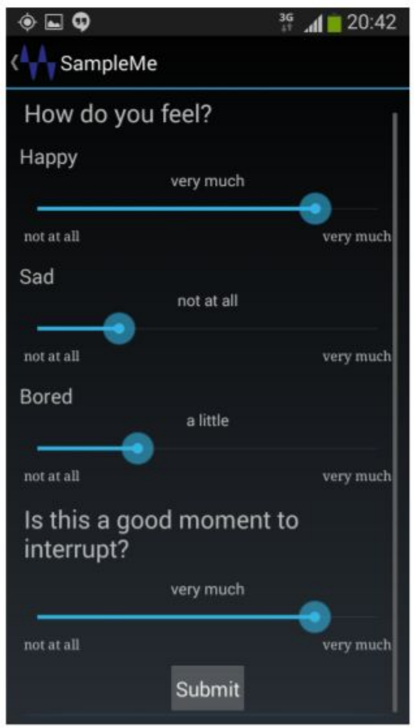
- Finding important features
- Training offline vs. online (active learning)
- Personalization vs. composite models
- Mobile implementation (e.g., Android, iOS)

Defining Interruptibility

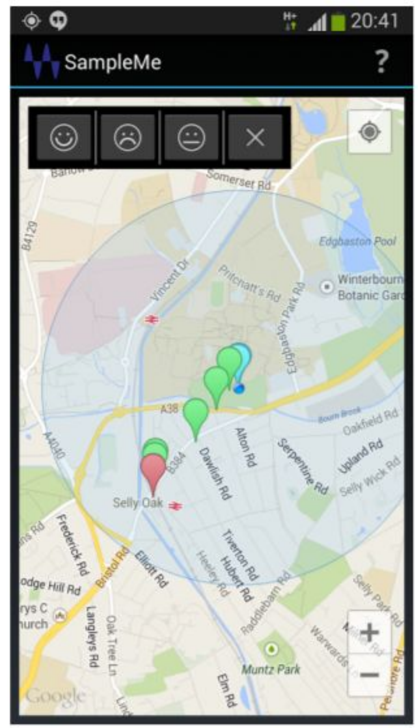
- **Reaction presence**: to predict if a recipient will react to an interruption
- **Time to reaction**: to predict if a recipient will react to an interruption within a given time interval
- **Sentiment**: to predict a recipient's attitude towards a moment in which a notification comes

- *Binary labeling is possible by setting thresholds*

ESM Questions

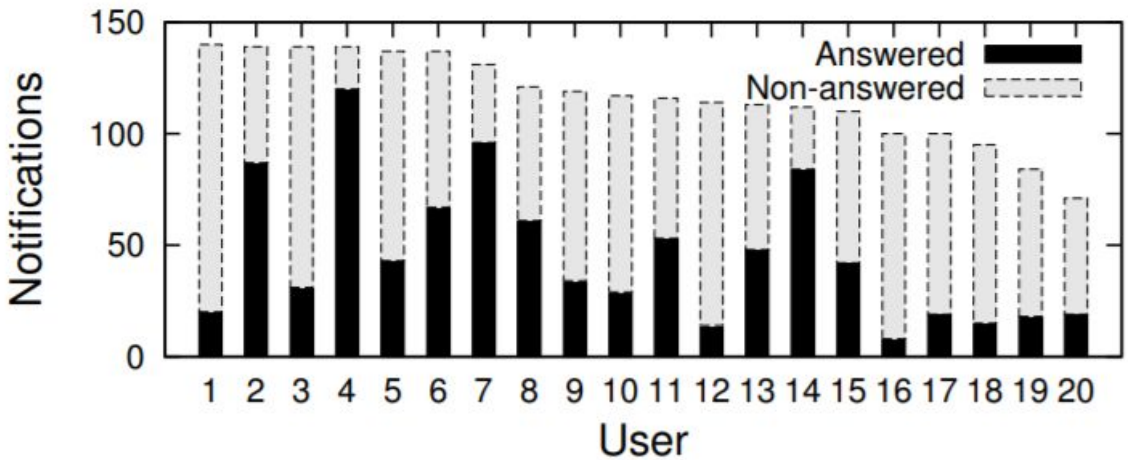


(a) Survey.



(b) Emotion map.

SampleMe Dataset



Sentiment	Not at all	A little	Some	Very much
Interruptions	1700 (72.84%)	377 (16.15%)	150 (6.43%)	107 (4.58%)

Table 4. Distribution of sentiment in the SampleMe dataset. A large majority of messages were not answered (we assign such interruptions as *not at all* appropriate) or arrived at moments that users labelled as *not at all* appropriate.

Group	Features
Time	Time of day, weekend indicator, time into experiment.
Accelerometer	Mean, variance and mean crossing rate of the accelerometer readings. Activity variation around the notification time.$^{\#}$ Activity change from notification to response.$^{*+}$
Location	Descriptive location: "Residential", "Work", or "Public". Location change from notification to response.$^{*+}$ Bluetooth fingerprint change from notification to response.$^{*+}$ WiFi fingerprint change from notification to response.$^{*+}$
Company*	Company indicator: "alone", "not alone".
Activity Engagement*	Descriptive activity: "Work related", "Leisure", or "Maintenance". How important is the activity? How interesting is the activity? How challenging is the activity? How skilled is the user wrt the activity? How concentrated the user is? User's desire to do something else.
Emotions*	How happy, sad, angry, frightened and neutral user is?

Table 1. Feature groups from the SampleMe dataset. Marked with * are features available for answered notifications only; marked with $^{+}$ are characteristic for a context change from notification to reaction; marked with $^{\#}$ characterize variation of context at the notification time.

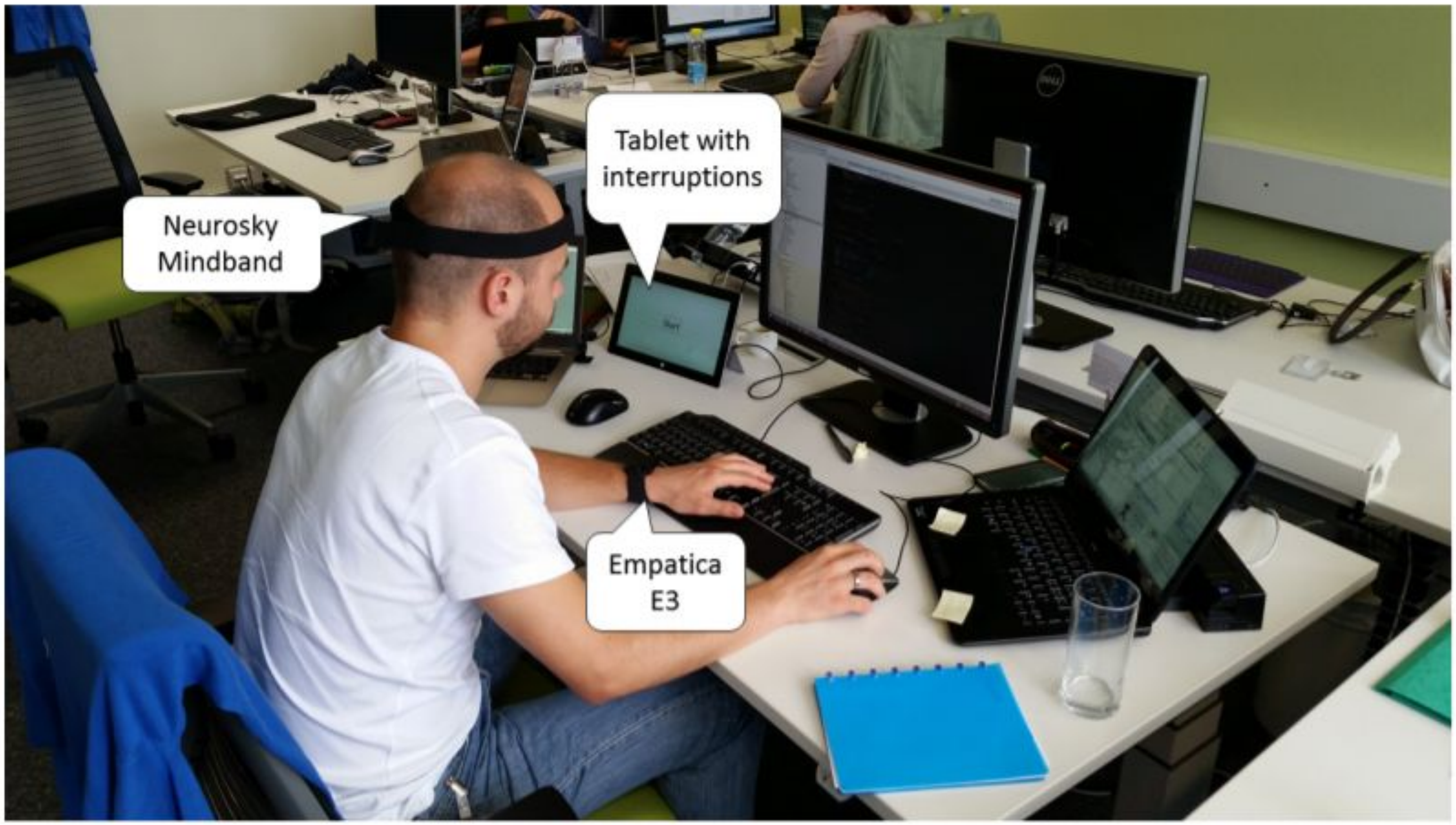
Interruptibility of Software Developers and its Prediction Using Psycho-Physiological Sensors

Manuela Züger, Thomas Fritz

ACM CHI 2015

https://dl.acm.org/citation.cfm?id=2702593

Psycho-Physiological Sensors



Psycho-Physiological Sensors

- EEG and Eye-Related Measures
  - Dry electrodes placed on the forehead reading signals mainly from the pre-frontal cortex
  - 512Hz as a raw wave and as a wave filtered for noise
- Skin- and Heart-Related Measures
  - Skin conductance is measured down to 0.1µS at a frequency of 4Hz
  - Photoplethysmograph is an optical sensor for measuring blood volume pulse (BVP), which can be used to compute interbeat interval (IBI) and heart rate (HR)

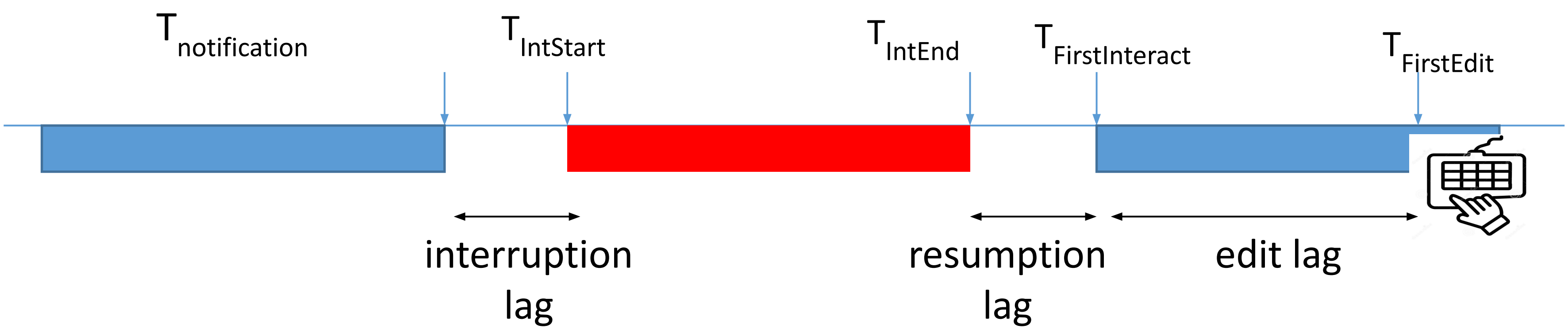
Interruption Task

- **Adding Circles.** The first task is to add a drawable figure, namely a circle, to the Draw application. The task requires to add a button with a provided icon to the toolbar and code to draw the circle. As there is already a feature for drawing an ellipse, code can be reused and the main difficulty is to identify the right places where new code needs to be inserted.
- **Adding Hexagons**. The second task is similar to the first one, but requires to add a hexagon instead of a circle. Knowledge obtained in the first task could be reused, however, drawing a hexagon is more difficult and requires knowledge in geometry. As an optional help, a document with explanations of the geometry of a hexagon was provided.
- **Adding Text and URL.** The third task is to add text and a clickable URL into an existing message dialog. The main task difficulty is to locate the right place in the code for implementing the functionality, and to get familiar with the Java API on message dialogs as well as user interface components

Interruption Task: ESM

- For the question set part, the tablet application prompted participants to rate
  - **perceived disturbance** from 1 (not at all disturbing) to 5 (very disturbing)
  - **interruptibility** at the time of the notification from 1 (highly interruptible) to 5 (not at all interruptible)
  - **mental workload** at the time of the notification from 1 (very low) to 5 (very high)

Interruption, Edit and Resumption Lag



(Interruption style:
negotiated coordination)

Interruption style: negotiated vs. immediate coordination

Outcome Measures

- Ground truth: both the interruptibility ratings and the interruption lag could serve as ground truth for defining interruptibility
- **Mental load** and perceived disturbance as secondary measures
  - cf. Psycho-physiological sensors (e.g., ECG, EMG) were also used to measure mental load

Results

Sensor	Used Features
EEG	α [2L, 5L], α/γ [2F], α/δ [2F], β [2L, 2F, 5L, 5F], β/α [2L, 2F, 5L], β/γ [2F, 5F], β/δ [2F, 5F], β/θ [2L, 5L], γ [2L, 2F, 5L, 5F], γ/α [2L, 2F, 5L], γ/β [2F, 5F], γ/δ [2F, 5F], γ/θ [2F, 5L], δ [5L], δ/β [2L, 5L], δ/γ [2L, 2F, 5L], δ/θ [2L, 5F], θ [2L], θ/α [2L], θ/δ [2L], $\beta/(\alpha+\theta)$ [2F, 5F], Mean Attention [2F, 5F], Stdev Attention [2F], Min Meditation [2L]
Photoplethys-mograph	Mean Peak Amplitude BVP [2F], Sum Peak Amplitude BVP [2L, 5L], Max Peak Amplitude BVP [5F], Mean HR [2F], IBI PNN20 [2L, 2F], IBI NN50 [2F],
Temperature	Mean Temperature [2L, 2F, 5L, 5F]
EDA	Mean Phasic Peak Amplitude EDA [2L, 5L], Sum Phasic Peak Amplitude EDA [2L, 5L], Phasic Peak Frequency EDA [2L, 5L]

Table 4. Most predictive features for Naïve Bayes classification for per instance cross-validation, and their use in the classifiers (2L/2F: lab/field study two states, 5L/5F: lab/field study five states).

Results

Truth	Prediction: interruptible	Prediction: not interruptible
interruptible	58.9 / 88.2	1.1 / 10.8
not interruptible	5 / 19	7 / 21
F_{lab}	0.95	0.70
F_{field}	0.86	0.58

Table 2. Confusion matrix for Naïve Bayes classification into two states using per instance cross-validation for lab and field study (lab / field) with individual class accuracies (F-measure)

Truth	Prediction: 1	2	3	4	5
1	1.2 / 2.4	1.9 / 12.4	2.8 / 2.2	1.1 / 1	0 / 1
2	1.5 / 3.2	9.5 / 22	13.4 / 6.5	0.5 / 2.3	0.1 / 11
3	1.9 / 2.9	7.7 / 12.7	18 / 5	0.4 / 3.1	0 / 11.3
4	1 / 1.9	2 / 4.3	1.2 / 6.6	0.2 / 5.3	2.6 / 6.9
5	0.1 / 0.1	0.1 / 2.3	1 / 1.7	1.1 / 0.5	2.7 / 10.4
F_{lab}	0.19	0.41	0.56	0.04	0.52
F_{field}	0.16	0.45	0.18	0.28	0.37

Table 3. Confusion matrix for Naïve Bayes classification into five states using per instance cross-validation for lab and field study (lab / field) with individual class accuracies (F-measure)

Interruptibility vs. Mental Load & Lags

- Positively correlated with the participants' ratings of the perceived disturbance and the mental load (Pearson's $r > 0.7$, $p<0.0001$)
- Positively correlated with the interruption lag for the lab study (Pearson's $r=0.382$, $p<0.001$)

Interview Results

- Learning more about the cost of interruptions at certain moments and possible tool support
- Asked participants to rate certain situations that we identified in previous literature from 1 (strongly like) to 5 (strongly dislike)
- **(timing)** Found that participants like interruptions at the end of a task (1.5 ± 0.6) but not in the middle (4 ± 0.7), as well as they dislike them when the mental load is high (5 ± 0) and/or the current task is difficult (4.4 ± 0.9)
- **(situation)** In situations where participants are stuck and are not making any progress, they feel more mixed about interruptions (2.9 ± 1.2) and several participants dislike interruptions in these situations although they stated that interruptions would usually be beneficial for their task and for gaining a different perspective

Interview Results

- Kind of support they desired for interruptions such as a tool that displays interruptibility to co-workers; for instance, by using a lamp (mentioned by 7 participants), and a tool that turns interruptions on or off based on the current mental load (mentioned by 5 participants)
- In particular, support for in-person interruptions is more needed than for computer based ones since they are generally perceived more disruptive and cannot be ignored
- However, participants also commonly mentioned that important interruptions should not be blocked even in situations of extremely high mental load, and that the company culture should be respected by the tool, e.g., a tool should not prevent interactions that foster team spirit.

Interaction as Sensor Data

- Multimodal sensor data?
  - Biometric sensors (Heart rate/HRV)
  - Mobility/Physical activities
  - Digital traces (computer/phone) & contextual data (e.g., calendar)

- Feature extraction:
  - **User input (keystrokes, mouse clicks/scrolls/moves)**
  - **Applications: app categories (IDE, email, messengers, etc.)**
  - **App switching**
  - Calendar (meetings)
  - Heart (HR/HRV)
  - Movements (steps)
  - Circadian Rhythm (time/sleep)

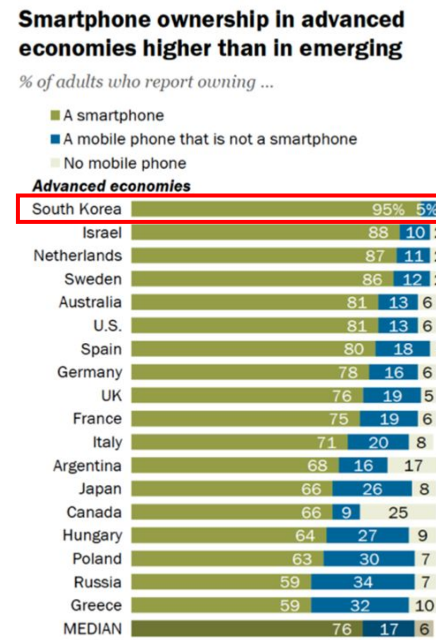
- Multi-modal sensing helps:
  - Fibit+Polar: 68%
  - Computer: 74%
  - Computer+Fitbit/Polar: 76%

Sensing Interruptibility in the Office: A Field Study on the Use of Biometric and Computer Interaction Sensors https://dl.acm.org/citation.cfm?id=3174165

FocusMore: We are living in a world surrounded by digital devices

Digital devices

Digital devices around us



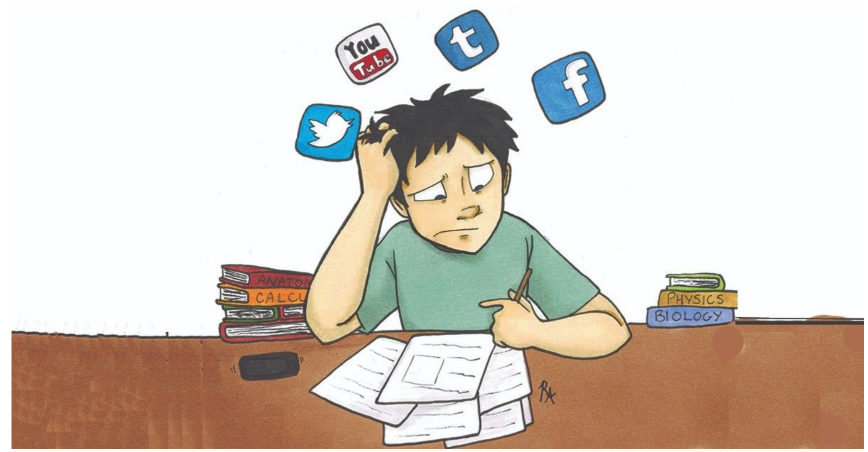
Smartphone ownership

Image from https://www.ocu.org/tecnologia/telefono/noticias/fiabilidad-satisfaccion-tecnologia
Image from https://www.pewresearch.org/global/2019/02/05/smartphone-ownership-is-growing-rapidly-around-the-world-but-not-always-equally/

Smartphones are useful But, it can interrupt daily activities

- Excessive and irrelevant notifications (Lee et al. 2014)
- Increasing the cognitive load (Lavie 2010)
- Making more prone to errors and distractions (Park et al. 2017)

External interruptions



- Habitual use due to its functionalities and pervasive accessibility to online content (Oulasvirta et al. 2012)
- Can lead to off-task phone use such as checking social media or playing games (Glassman et al. 2015)

Internal interruptions

Smartphone is one of the most common causes of distraction in daily lives

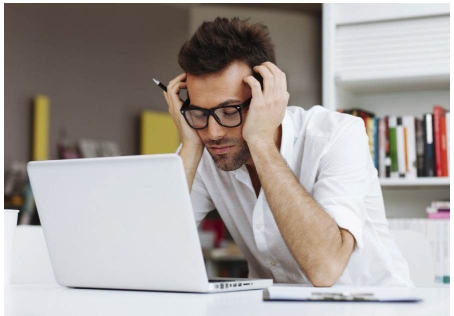
Smartphone use in classroom

Many college students are using their smartphone in classroom where they should concentrate without distraction *(Fukuzawa et al. 2016)*

Smartphone activities irrelevant to the class may affect students' learning negatively *(Levine et al 2012; Chen and Zheng 2016)*

Smartphone is one of the most common causes of distraction in daily lives

Academic performance
(Junco and Shelia 2012; Chen and Zheng 2016)

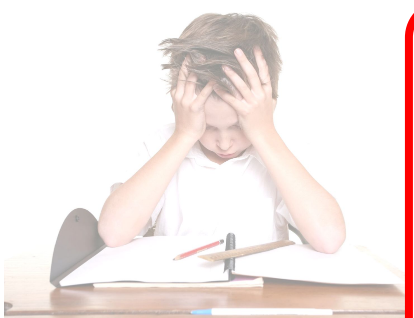


Productivity
(CareerBuilder 2016)

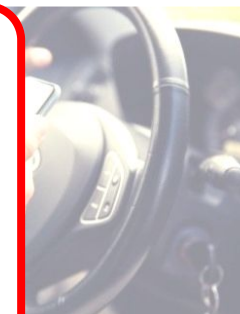
Social interaction
(Ko et al. 2015; Park et al. 2017)

Safety
(Delgado et al. 2016)

Smartphone is one of the most common causes of distraction in daily lives



Smartphone distraction should be managed!



Academic performance
(Junco and Shelia 2012; Chen and Zheng 2016)

(CareerBuilder 2016)

(Ko et al. 2015; Park et al. 2017)

(Delgado et al. 2016)

Existing coping strategies for handling distractions

DND mode
Digital wellbeing

DND mode
ScreenTime

Mobile OS systems provide various distraction management tools

Commercial applications also provide distraction manage features such as blocking app use or handling external interruptions (Lyngs et al. 2019)

Lyngs, Ulrik, et al. "Self-Control in Cyberspace: Applying Dual Systems Theory to a Review of Digital Self-Control Tools." Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. 2019.

Existing coping strategies for handling distractions

- Users should manually configure the system for distraction management
- Not flexible because it does not consider dynamic users' contexts

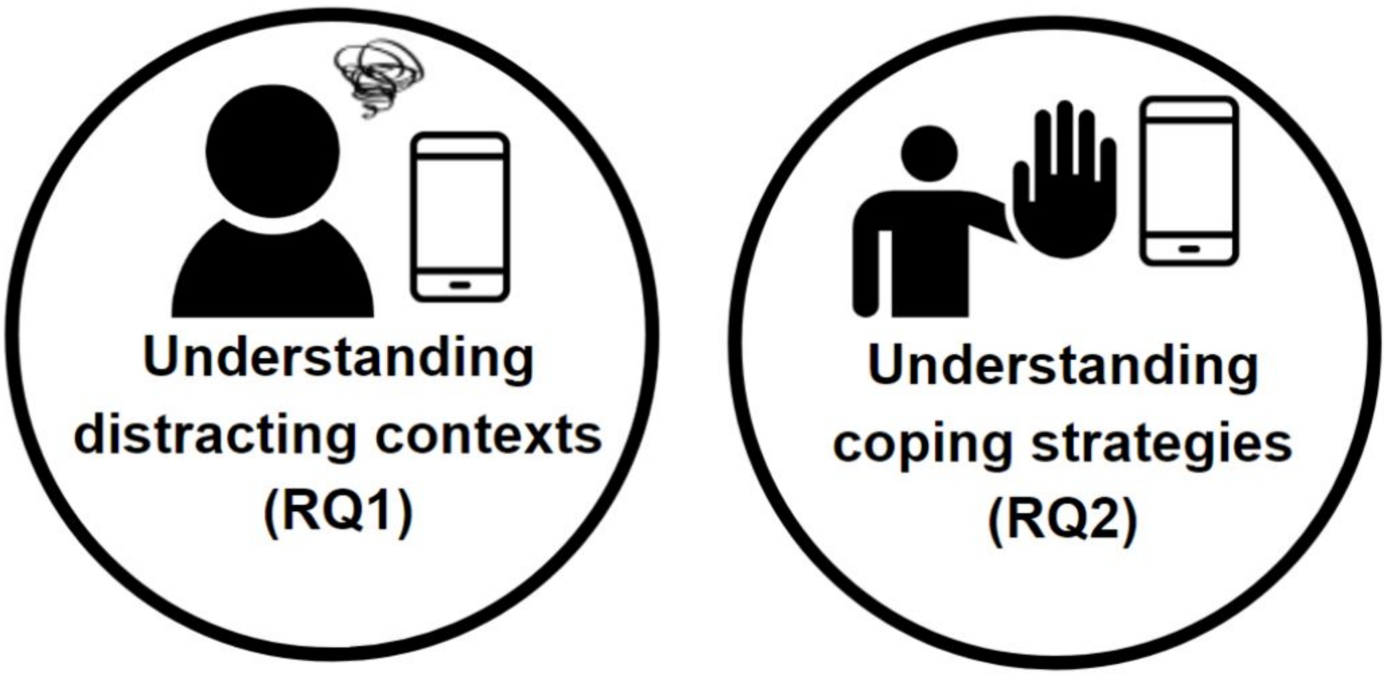
Mobile OS sy ... Android) provide various distraction management tools

... provide distraction manage features such as blocking app use or handling notifications *(Lyngs et al. 2019)*

Lyngs, Ulrik, et al. "Self-Control in Cyberspace: Applying Dual Systems Theory to a Review of Digital Self-Control Tools." Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. 2019.

Understanding distracting contexts and coping strategies

Purpose of the research:



Overall Study procedure

Understanding
distracting contexts
and coping strategies

__Done in last year (2020)__
(Published in IMWUT 2020 Nov.)

⇨

Designing
a context-aware
distraction management
system

In progress

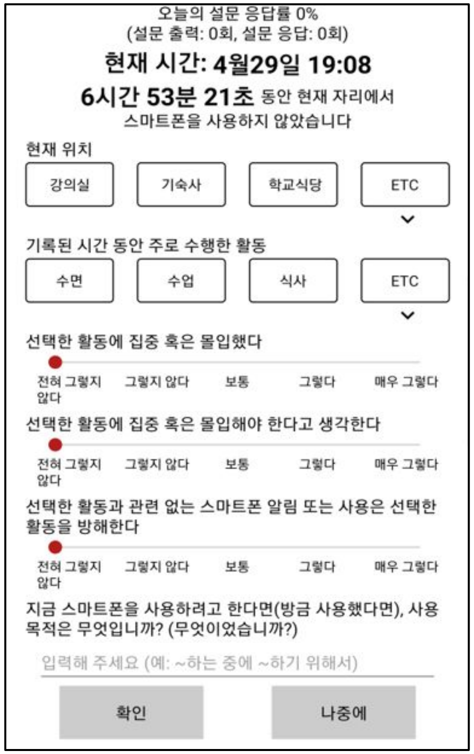
⇨

Evaluating
the system in the field

To do

For understanding distracting contexts (RQ1)

- **Developing a mobile ESM (Experience Sampling Method) application**
  - Collecting *in-situ* user contexts and experience of smartphone distraction
    - Representative user contexts (e.g., current location, ongoing activity) *(Abowd et al. 1999)*
    - Perceived smartphone distractions
- **Data collection**
  - 3 weeks of period
    - The total of 9,180 responses collected from 34 participants
  - Interview (n=15)
    - How the participants are distracted by smartphones



ESM screen

For understanding coping strategies (RQ2)

- **Online survey**
  - Asked participants write rules for distraction management (i.e., coping strategies)
  - Examples of collected rules:
    - *“When arriving at the laboratory, set all notifications silence” (Rule 28)*
    - *“Block all apps except the web browser app in the library”* (Rule 91)

- **Data collection**
  - The total of 231 distraction management rules were collected from 34 participants

User generated distraction management rule

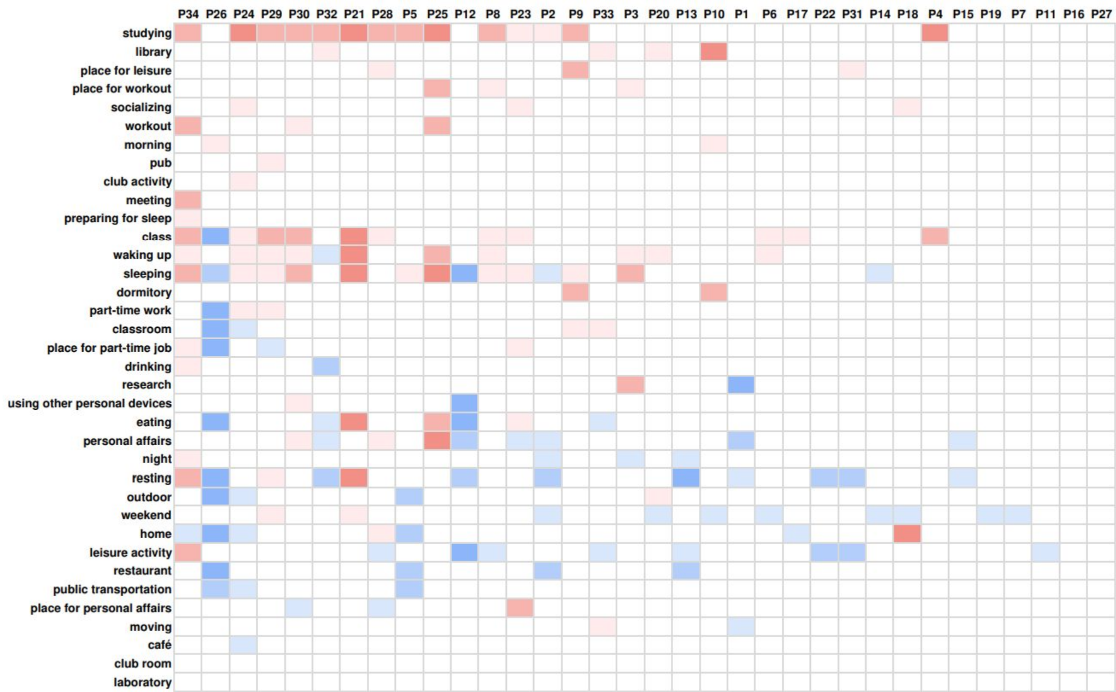
Results (RQ1)

- **Analysis of ESM data:**
  - **Diversity of distracting contexts**
    - Many contexts were reported, other than intuitively well-known contexts where people need concentration (e.g., studying, class)

	Perceived smartphone distraction level (normalized range: 0 to 1)					
	Male			Female		
Independent variables	β	p-value		β	p-value	
Time context						
weekend	-0.03	0.002	**	0.01	0.752	
night	0.00	0.777		-0.03	0.176	
morning	0.00	0.887		0.00	0.811	
Location context						
café	0.00	0.781		-0.04	0.028	*
classroom	0.00	0.992		-0.07	0.036	*
club room	-0.01	0.597		-0.03	0.126	
dormitory	0.01	0.566		-0.07	0.082	
home	-0.07	<0.001	***	-0.21	<0.001	***
laboratory	0.02	0.341		-0.07	0.103	
library	0.00	0.776		-0.02	0.386	
outdoor	0.00	0.683		-0.11	<0.001	
place for leisure	0.03	<0.001	***	0.03	0.14	
place for part-time work	-0.05	0.054		-0.04	0.218	
place for personal affair	-0.02	0.014	*	-0.04	0.014	*
place for workout	0.03	0.031	*	0.00	0.903	
public transportation	-0.04	<0.001	***	-0.12	<0.001	***
pub	0.02	0.196		-0.05	0.008	**
restaurant	-0.01	0.347		-0.08	0.001	**
Activity context						
class	0.29	<0.001	***	0.19	<0.001	***
club activity	0.08	<0.001	***	0.02	0.211	
drinking	-0.02	0.218		-	-	
eating	0.03	0.125		0.06	0.022	*
leisure	-0.01	0.276		0.03	0.17	
meeting	0.04	<0.001	***	-	-	
moving	-0.04	0.001	**	0.01	0.421	
part-time work	0.10	<0.001	***	0.07	0.049	*
personal affair	0.03	0.006	**	-0.04	0.107	
preparing for sleep	0.02	0.095		-0.03	0.102	
researching	0.16	<0.001	***	0.02	0.652	
resting	0.03	0.110		0.03	0.191	
sleeping	0.14	<0.001	***	0.11	<0.001	***
socializing	0.06	<0.001	***	0.01	0.811	
studying	0.33	<0.001	***	0.32	<0.001	***
using other personal devices	0.07	<0.001	***	-0.04	0.034	*
waking up	0.11	<0.001	***	0.10	<0.001	***
workout	0.03	0.039	*	-0.01	0.693	
marginal R^2	0.177			0.154		
conditional R^2	0.454			0.440		

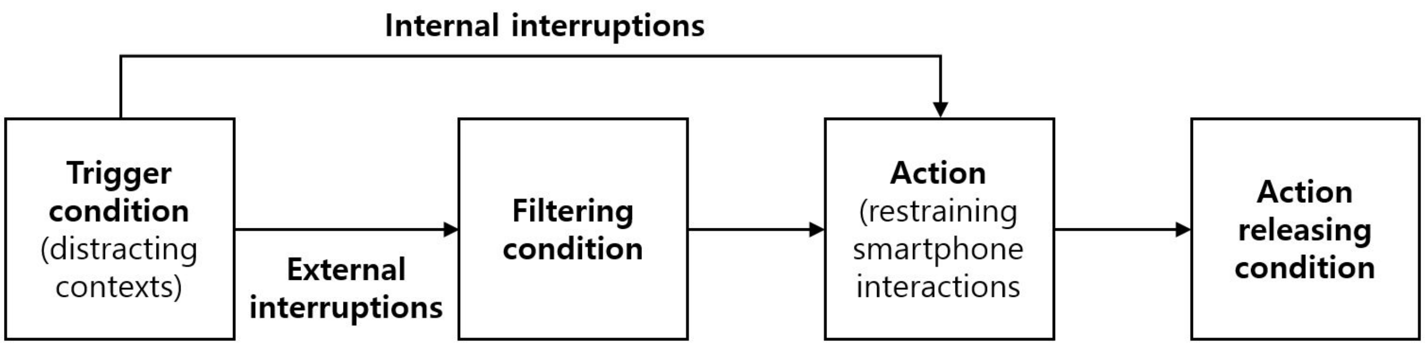
Results (RQ1)

- **Analysis of ESM data:**
  - **Individual differences in perceiving smartphone distraction**
    - Each participant had a different range of contexts
    - Participants perceived smartphone distraction differently, even in same contexts



Results (RQ2)

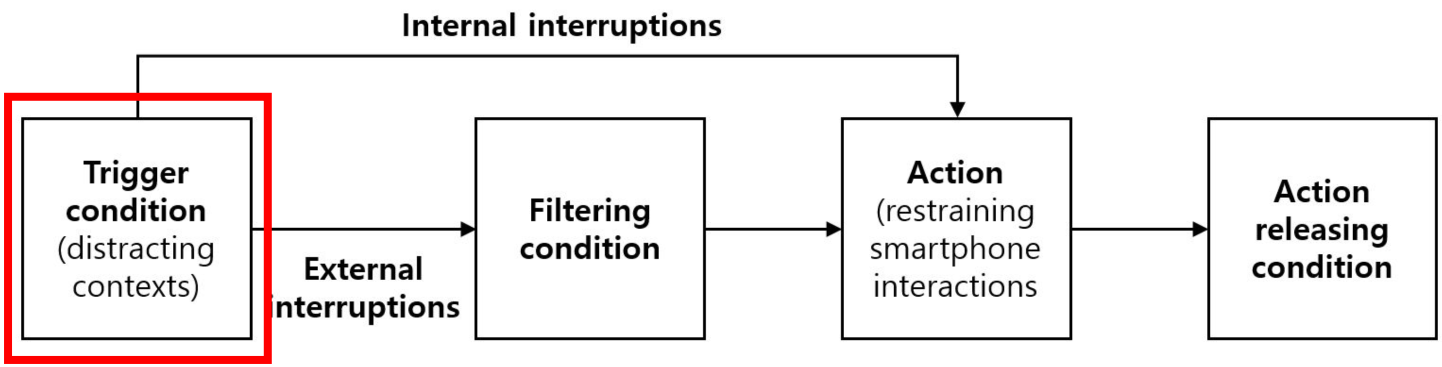
- **Found four main components that constitute the distraction management rules:**
  1. **Trigger condition:** When system actions for handling distraction is triggered?
  2. **Filtering condition:** How to filter external interruptions (e.g., receiving notification from specific apps or persons)
  3. **Action:** What coping strategies will be provided? (e.g., blocking app, changing ringer mode)
  4. **Action releasing condition:** How / When actions will be released? (e.g., automatically? vs. manually?)



Structure of the rule for distraction management rules (abstracted)

Results (RQ2)

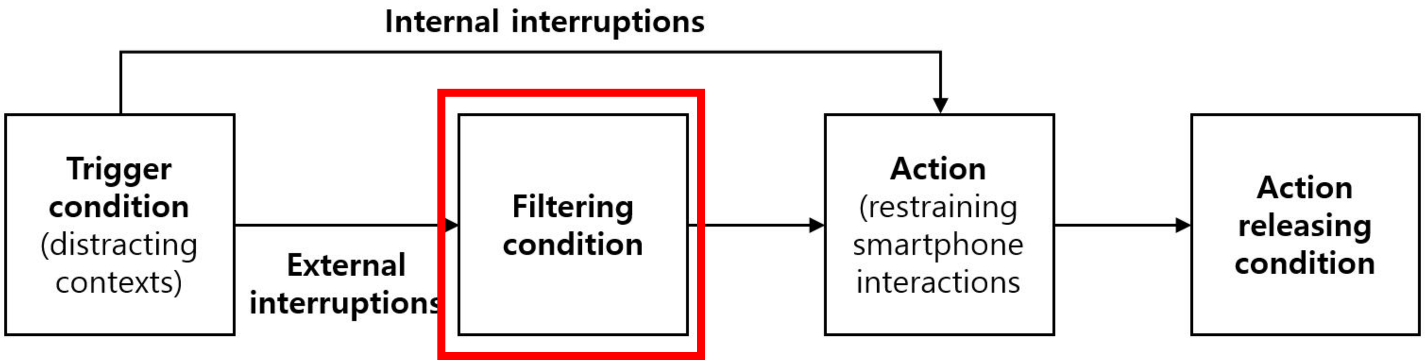
- **Found four main components that constitute the distraction management rules**
  - **Trigger condition**
    - Two types of trigger conditions:
      - (1) The environment around users (e.g., location, activities, time, social situation)
      - (2) Goal for phone usages (e.g., limited duration or frequency)
    - High level of ambiguities:
      - Different expression form for same concepts (e.g., activity vs. time, and event vs. state)
      - Different level of abstraction for concepts (e.g., After sleep time vs. from 01:00~06:00)



Structure of the rule for distraction management rules (abstracted)

Results (RQ2)

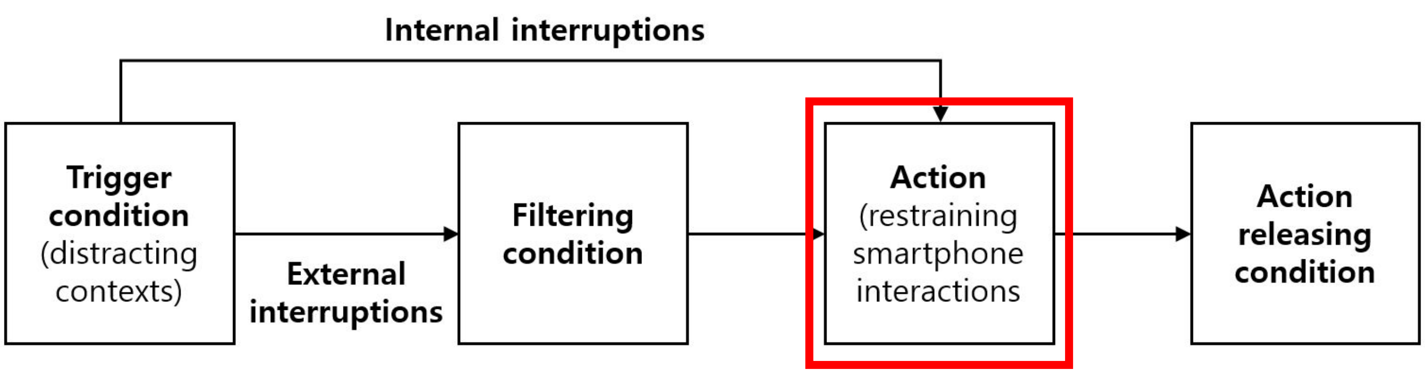
- **Found four main components that constitute the distraction management rules**
  - **Filtering condition**
    - Three main filtering conditions
      - (1) Where did the notification or the incoming call originate? (e.g., app, person)
      - (2) What topic is related to external interruptions? (e.g., work-related)
      - (3) What are arrival patterns? (e.g., 3 times within 10 minutes)



Structure of the rule for distraction management rules (abstracted)

Results (RQ2)

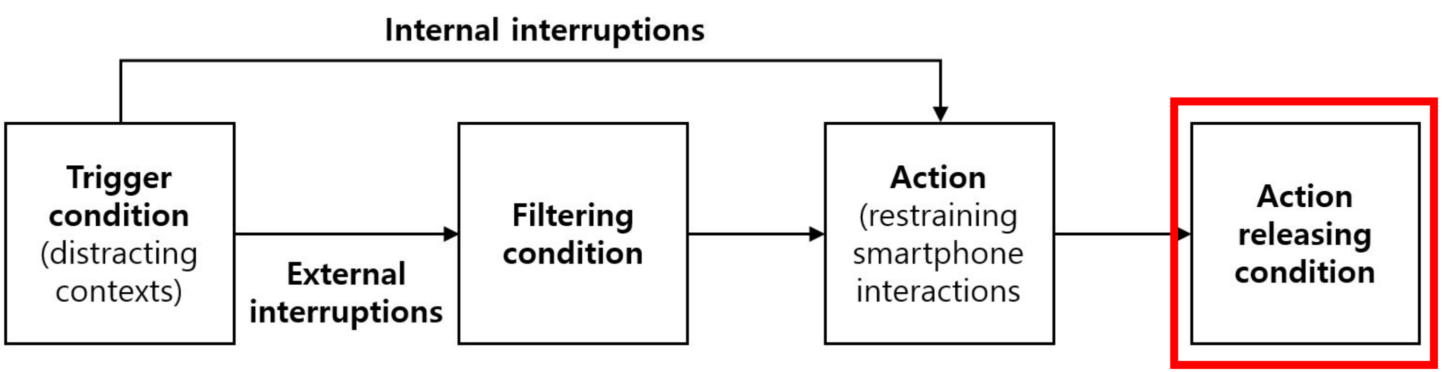
- **Found four main components that constitute the distraction management rules**
  - **Action**
    - Three types of action:
      - (1) Managing external interruptions (e.g., hide, silence)
      - (2) Locking phone or app usage (e.g., pausing certain apps, giving warning message)
      - (3) Changing a phone's state (e.g., turning on DND mode, changing ringer mode, level of sound or brightness)



Structure of the rule for distraction management rules (abstracted)

Results (RQ2)

- **Found four main components that constitute the distraction management rules**
  - **Action releasing condition**
    - Two types of action releasing condition:
      - Passive release (releasing actions when the trigger condition is no longer satisfied)
        - In many cases, rules missed conditions for releasing actions (e.g., when entering the library)
      - Active release
        - When the user tries to release the action, even if the trigger condition is still satisfied (e.g., temporary use, lockout task)



Structure of the rule for distraction management rules (abstracted)

Designing a context-aware distraction management system (in progress)

- **Next steps:**
  - Performing test with the system in the campus
  - Evaluating usefulness, user experiences and usability of the system

A field test in the campus

Summary

- Interaction timing matters (negotiated vs. immediate coordination)
- Negative impacts on a user's task performance and emotional state (e.g., annoyance, anxiety)
- Degree of disruption depends on the user's mental load (task difficulty) at the point of interruption
- Scenarios for interruptibility (Controlled vs. explicit/implicit in-the-wild)
- Data for prediction (e.g., context, latent data)
- Psycho-physiological sensors (e.g., EEG, EDA, ECG) can be used for interruptibility prediction