Hooked on Smartphones: An Exploratory Study on Smartphone Overuse among College Students

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Smartphone Overuse

Smartphone Overuse

Excessive smartphone use can be pathological and addictive

Technological addiction:
non-chemical (behavioral) addiction
(Griffiths, 1995)

Human-machine interaction contains inducing and reinforcing features that promote addictive behaviors

Related Work & Motivation

Psychology work mostly studies scale development, and psychological factors (Kim 2012, Carbonell 2012)

Usage measurement work analyzes general usage patterns (Falaki 2010, Böhmer 2011)

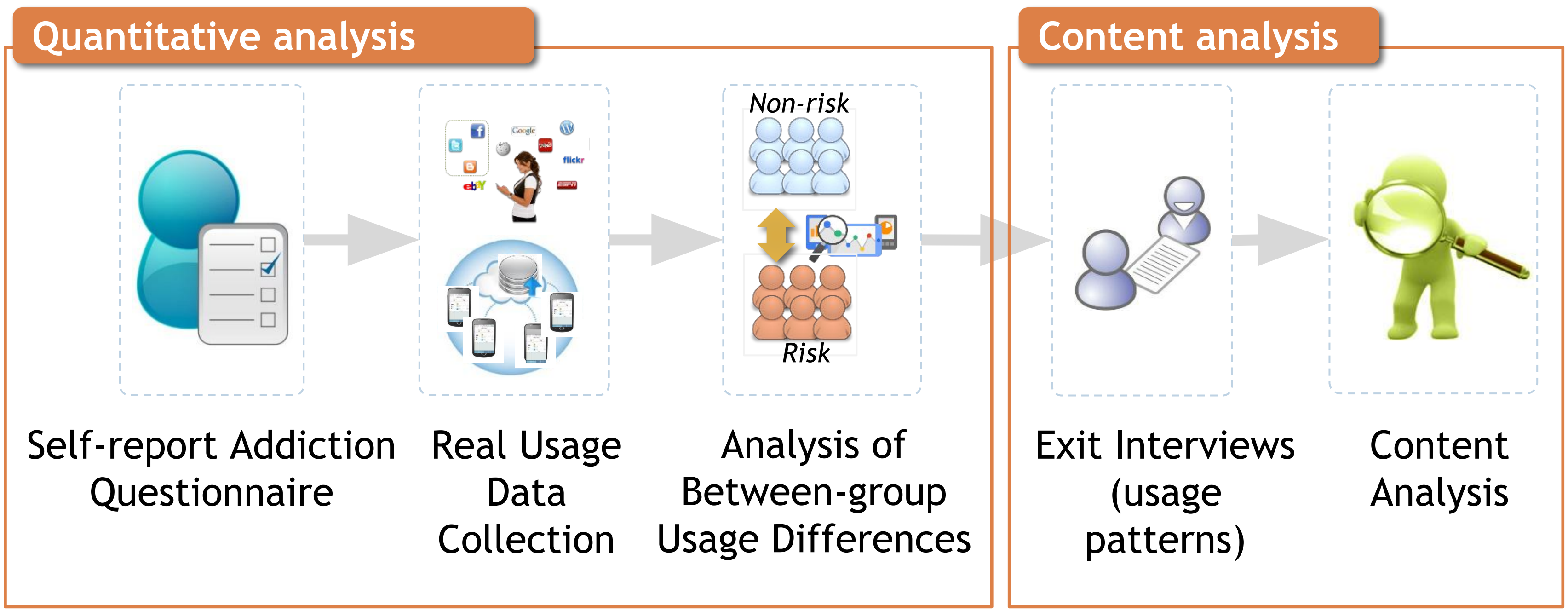
Recent HCI studies on smartphone overuse:

- College students' practices of managing overuse (Ames 2013)
- Habits of update checking (emails, friend availability sharing) (Oulasvirta 2012)

Yet, lack of understanding on detailed usage behaviors related to problematic usage of smartphones

Research Overview

Identify detailed usage behaviors related to problematic usage of smartphones



Methodology: Participants

95 college students in a large univ. (Fall, 2012)

(67 males; and 28 females)

Avg. age of participants: 20.6 (SD 1.7)

Avg. participation duration: 26.8 days (SD 9.5)

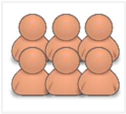
(more than 60,000 hours of usage data)

Methodology: Self-Report Data

Smartphone addiction scale (Kim et al., 2012)

Interference	"My school grades (or work productivity) dropped due to excessive smartphone use."
Virtual world orientation	"Using a smartphone is more enjoyable than spending time with my family or friends."
Withdrawal	"It would be distressing if I am not allowed to use my smartphone."
Tolerance	"Even when I think I should stop, I continue to use my smartphone."

(15 items, based on well-known DSM-IV's addiction factors)



Risk group
(# users = 36)

Non-Risk group
users = 59

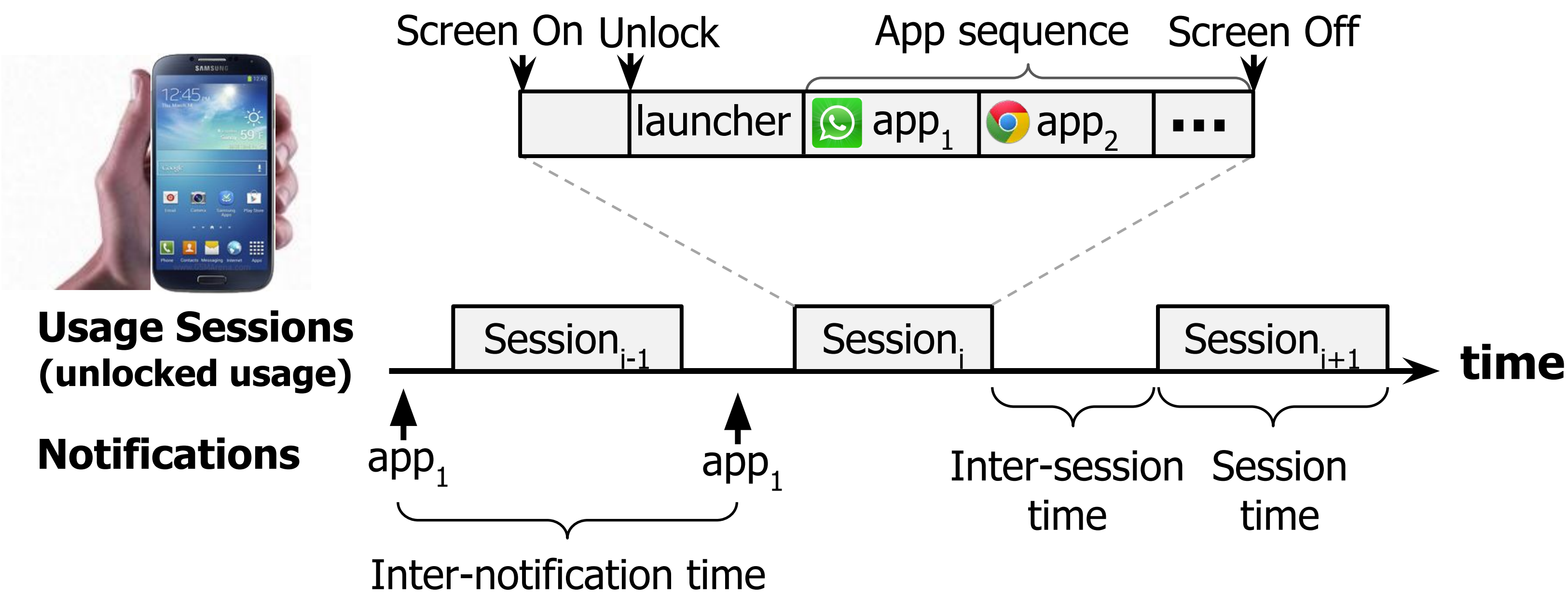
Methodology: Usage Logging

Developed *SmartLogger*, an unobtrusive logging tool, leveraging Android's accessibility service

Logging fine-grained usage data:

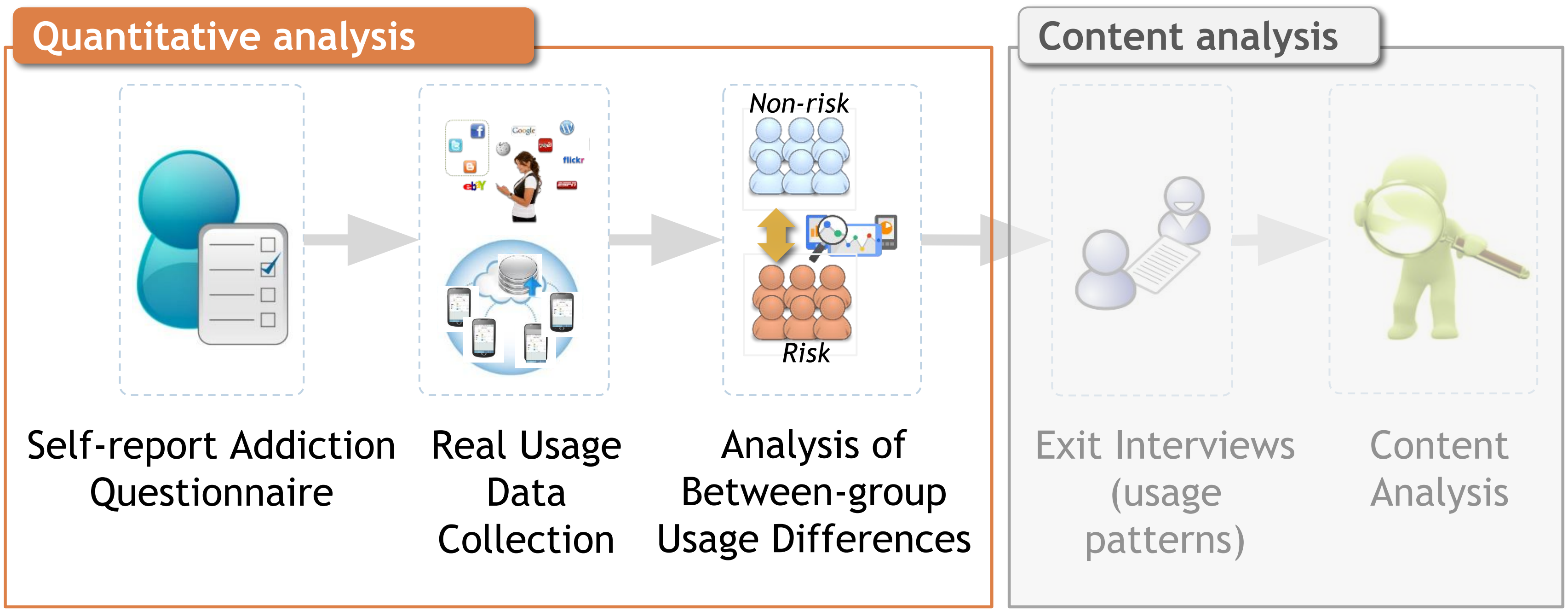
- System events (power on/off, screen on/off/unlock, battery status changes)
- App events (active/inactive apps; touch/text input events; web browsing URLs; notifications)
- Telephone events (call/SMS, ringer mode changes)

Methodology: Usage Analysis



Usage Difference Analysis

1. Overall usage pattern analysis
2. Category-specific usage pattern analysis



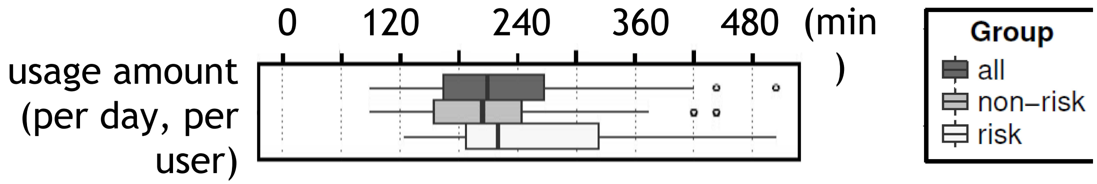
Usage Difference Analysis

1. <u>Overall usage pattern analysis</u>
2. Category-specific usage pattern analysis

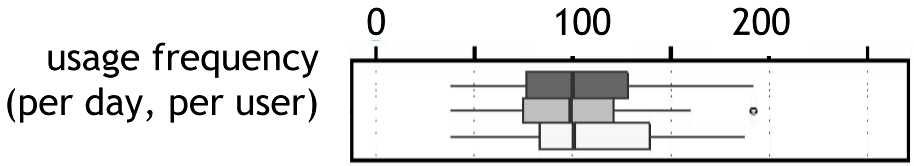
Overall Usage Patterns	Aggregated Usage	Usage time per day
		Session frequency per day
	Session-level Usage	Session time (usage time per session)
		Inter-session time
		Number of apps used per session
		Entropy of top-k apps' usage time/frequency distributions (k = 5, 10, 50)
		Usage time and frequency of top 1/2 apps
	Diurnal Usage	Usage time, session frequency, and session time: night (0~6), morning (6~12), afternoon (12~18), and evening (18~24)

Overall Usage Differences
Usage time & frequency

Daily usage amount: risk 253.0 vs. non-risk 207.4 (p=.011, Cohen's d=0.45)



Daily usage freq.: risk 111.5 vs. non-risk: 100.1 (p=.146, Cohen's d=0.31)



Risk group spent more time than non-risk group, tending to use devices more frequently & to engage in longer sessions

Overall Usage Differences
Skewness of app usage

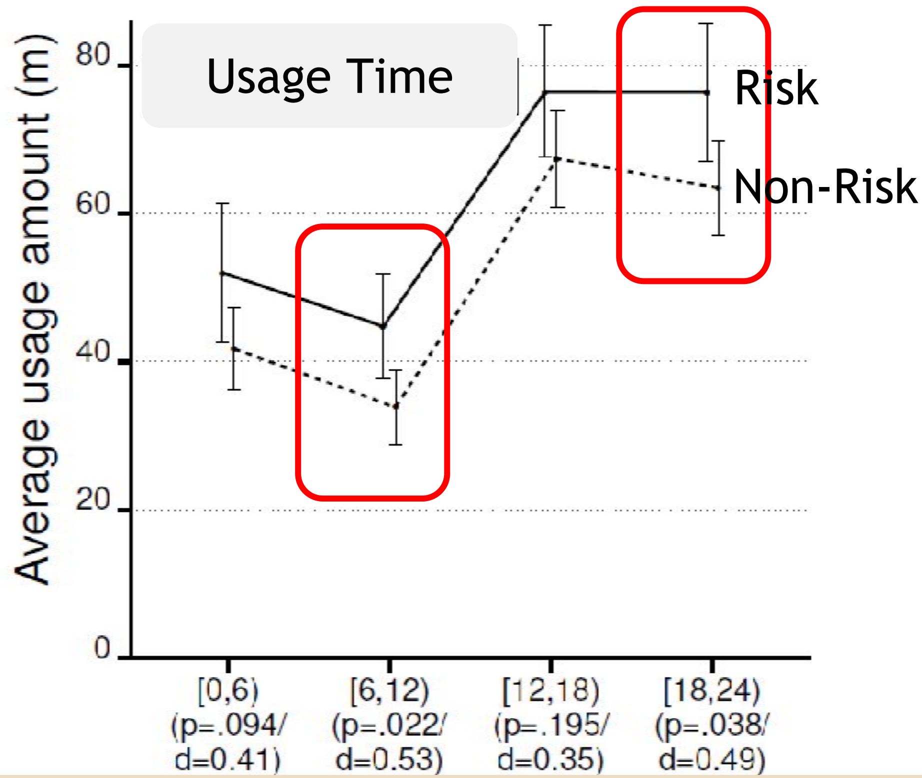
Usage of top-*k* apps skewed (exponential dist)

Notable differences found on usage of top-1/2 apps
- 1st app (risk 97.8 vs. non-risk 69.9 m, $p=.003$, Cohen's $d=0.66$)
- 2nd app (risk 47.4 vs. non-risk 37.5 m, $p=.058$, Cohen's $d=0.43$)

Entropy of top-5 apps differs (risk 1.85 vs. non-risk 1.96)

More skewed usage observed in the risk group users

Overall Usage Differences
Diurnal usage differences



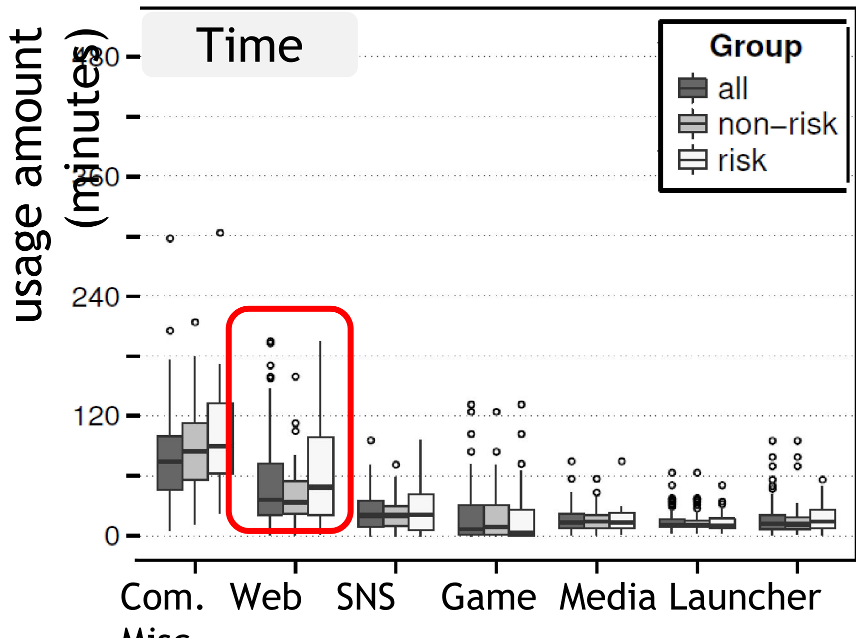
Diurnal usage difference exists: i.e.,
Risk group spent more time during morning/evening

Usage Difference Analysis

1. Overall usage pattern analysis
2. Category-specific usage pattern analysis

Category-Specific Usage Patterns	Comm.	Usage time and app frequency of communication, usage time and freq. of {MIM, SMS, email, call}, inter-MIM time
		Diurnal usage: usage time, app frequency, and session time of communication apps: night (0~6), morning (6~12), afternoon (12~18), and evening (18~24)
		Internal vs. external sessions: number of sessions per day, app sequence length per day, session duration per day/session, app sequence length per session
	Web Browser	Usage time and app frequency of web, web content, inter-web time
		Diurnal usage: usage time, app frequency, and session time of web-browsing apps: night (0~6), morning (6~12), afternoon (12~18), and evening (18~24)

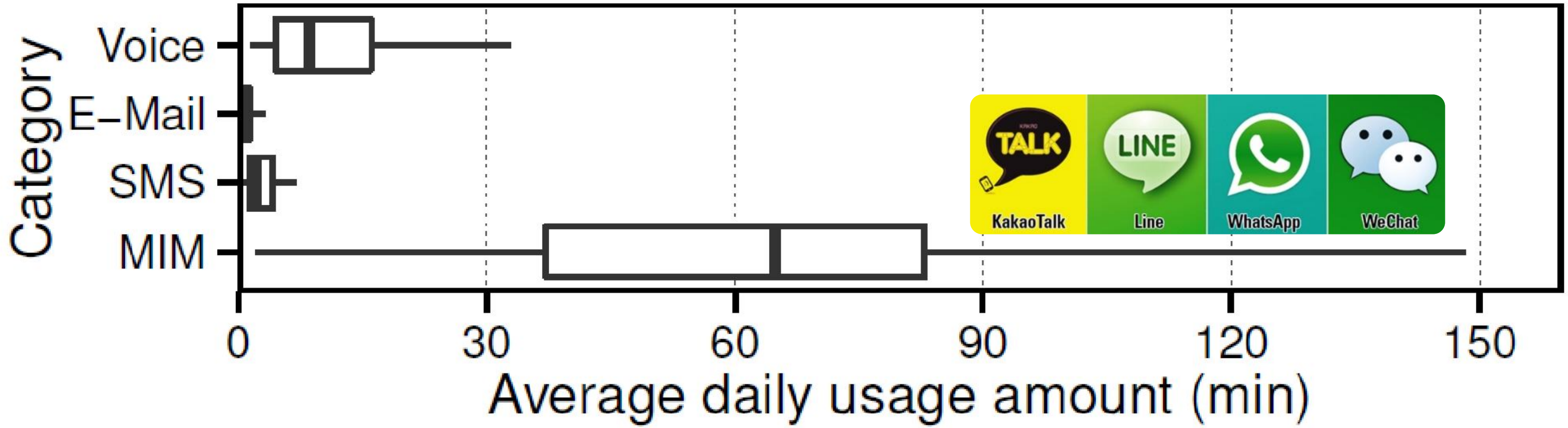
Category-specific Usage Difference



** Used a simplified app category based on existing app categories from app stores*

Category-specific usage: risk group tended to use longer, but significant difference observed only in web

Comm. Usage Differences
comm. app usage



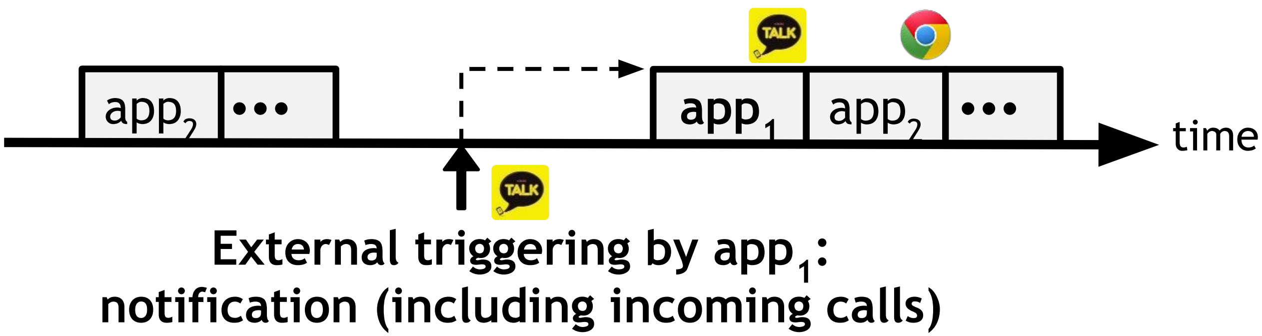
Mobile instant messaging (MIM) is dominating

- KakaoTalk is the most popular MIM in Korea
- MIM usage time (Risk: 75.6 vs. Non-Risk: 65.8, n.s.)
- MIM usage freq (Risk: 91.2 vs. Non-Risk: 76.9, n.s.)

Comm. Usage Differences
Externally-triggered session usage

Will externally-triggered session usage differ?

- Major external triggers: mobile instant messaging (KakaoTalk), SMS, calls, facebook (mostly comm. category)
- # notifications per day: Risk: 451.8 vs. non-risk: 378.5 (n.s.)



Here, if the subsequent session includes app_1, we assume that app_1 triggered smartphone usage

Comm. Usage Differences
Externally-triggered session usage

Significant differences on MIM-triggered sessions

- Aggregated app seq. length per day
  (risk: 88.7 vs. non-risk: 63.9, $p=.031$, Cohen's $d=0.50$)
- Aggregated session duration per day (s)
  (risk: 4978.9 vs. non-risk: 3661.5, $p=.030$, Cohen's $d=0.50$)

MIM acts as external cues for usage, causing overuse

Web Usage Differences

Significant difference in usage amount
(risk: 67.14 m vs. non-risk: 41.14 m, $p=.012$, Cohen's $d=0.61$)

Selected each user's top-10 visited sites and manually classified sites (e.g., portal, search, forums, news)

Significant differences in web portal usage and trending issue search (more frequent visits by risk group)

Excessive page visits by several risk group users (checking updates of online communities; e.g., 414, 166, 97 pages per day)

Risk group spent more time on the web consuming various types of online content

Usage Difference Summary

Risk group usage

Spending more time with their smartphones

Diurnal usage differs

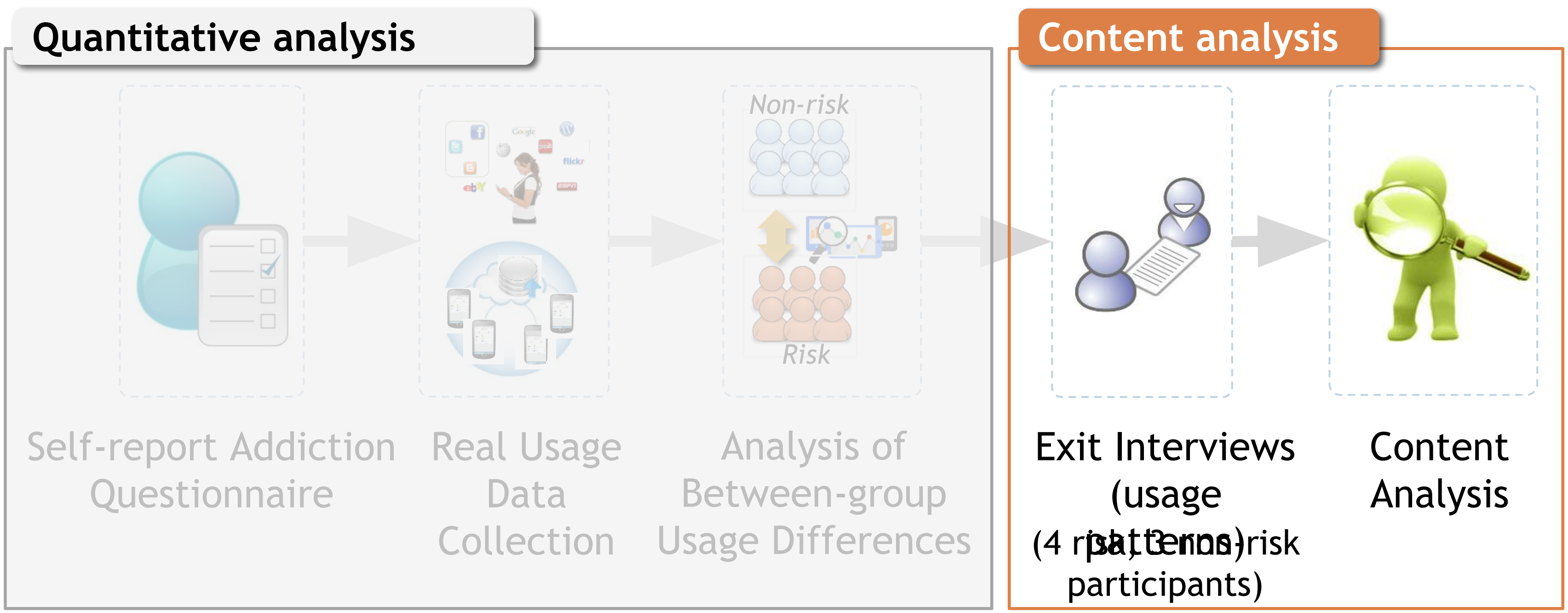
More skewed app usage

More usage on MIM-trigged sessions (external cues)

Spending more time on online content consumption

Themes of Problematic Usage
Interview data analysis

To supplement usage analysis results and to gain better understanding about usage behavior related to smartphone overuse



Themes of Problematic Usage
Interview data analysis

Felt more compelled to check their smartphones

“ *I keep paying attention, because I feel like new messages may have arrived.* ”

“ *When I’m dating or hanging out with friends, KakaoTalk messages make me feel nervous.* ”

Themes of Problematic Usage
Interview data analysis

Less conscious/structured smartphone usage behavior (showing lack of self-regulation)

It’s not like I plan to use my smartphone, but I just turn on my smartphone unconsciously.
I once used my smartphone to wake myself up in the morning. I got up at 9AM, but it turned out it was already 11AM.

I don’t have any thoughts when using my smartphone. ... At that moment, [I’m] without any sense of time.

Themes of Problematic Usage
Interview data analysis

Less conscious/structured smartphone usage behavior (showing lack of self-regulation)

“ *I use my smartphone for about 20 minutes before going to bed. I take care of messages piled up in KakaoTalk, and check Facebook, and webtoon updates at 11:30 PM. After checking that, I'm done!* ***(Non-risk group user)*** ”

Automatic Identification

Apply machine learning techniques to test the feasibility of the risk-group classification

Usage features:

- General set contained the general usage features such as the usage time/frequency, top-*k* entropies, and sequence length
- Temporal set included the diurnal usage features for aggregated usage and category-specific usage
- Category set included the category-level usage features (no temporal aspects)
- External set included all of the usage features for the external sessions

Automatic Identification

Category-specific usage patterns enable accurate identification of risk-group users

Feature set	Acc. (%)	Pre.	Rec.	F-score	Classifier
All	81.05	.816	.811	.813	DT
General	72.63	.723	.726	.724	DT
Category	87.37	.874	.874	.874	DT
Temporal	78.95	.792	.789	.790	DT
ExtCue	64.21	.622	.642	.632	NB
ExcludeGeneral	85.26	.863	.853	.858	DT
ExcludeCategory	80.00	.806	.800	.803	NB
ExcludeTemporal	77.89	.782	.779	.780	DT
ExcludeExtCue	81.05	.816	.811	.813	DT

Weka v3.6: Decision Tree (DT), Naive Bayes (NB), and Support Vector Machine (SVM)
Feature selection: Information gain algorithm

Conclusion

Identified usage patterns related to problematic usage

- Usage amount, skewness of top-*k* apps, diurnal usage, MIM-triggered usage, web usage

Uncovered common themes of problematic usage

- Compulsion of checking updates
- Limited self-regulation (less conscious/structured usage)

Demonstrated the feasibility of automatically identifying risk-group users via machine learning

- Category-specific usage enables accurate classification

Ongoing Work:

- Doing a comparative analysis of different datasets
- Designing intervention s/w for smartphone overuse

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