

Understanding Behind the Smile of Emotion Workers: Detecting After-Call Stress in Call Agents

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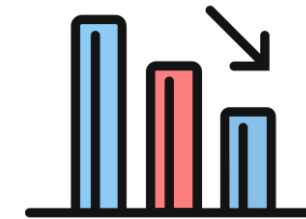
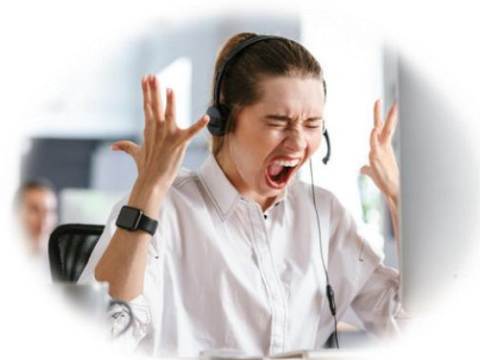
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Risks of Repetitive Emotional Workload at Call Centers

Repetitive emotional workload of call agents cause high stress

Stress degrades task performance and prolonged exposure poses long-term health risks



Performance
Drop

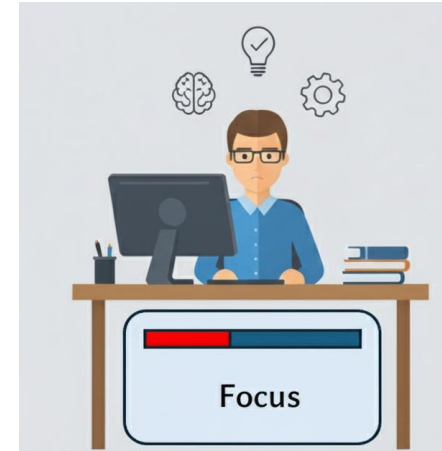


Mental health
risks

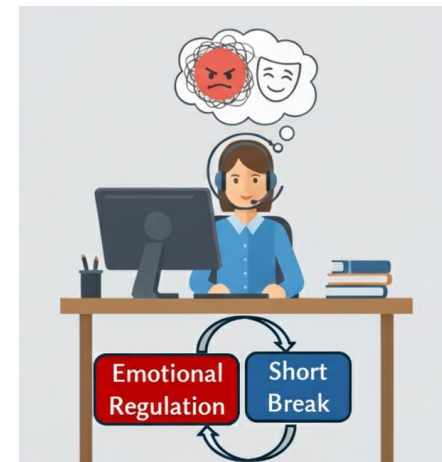
Constant emotion regulation
following company's display rules

Data-driven Stress Monitoring in HCI Contexts

- So far data-driven stress monitoring mainly focused on knowledge workers
- However, there's a lack of exploration on emotional labor contexts
- For ecological validity, we need to consider real work contexts: i.e., work procedures and data types



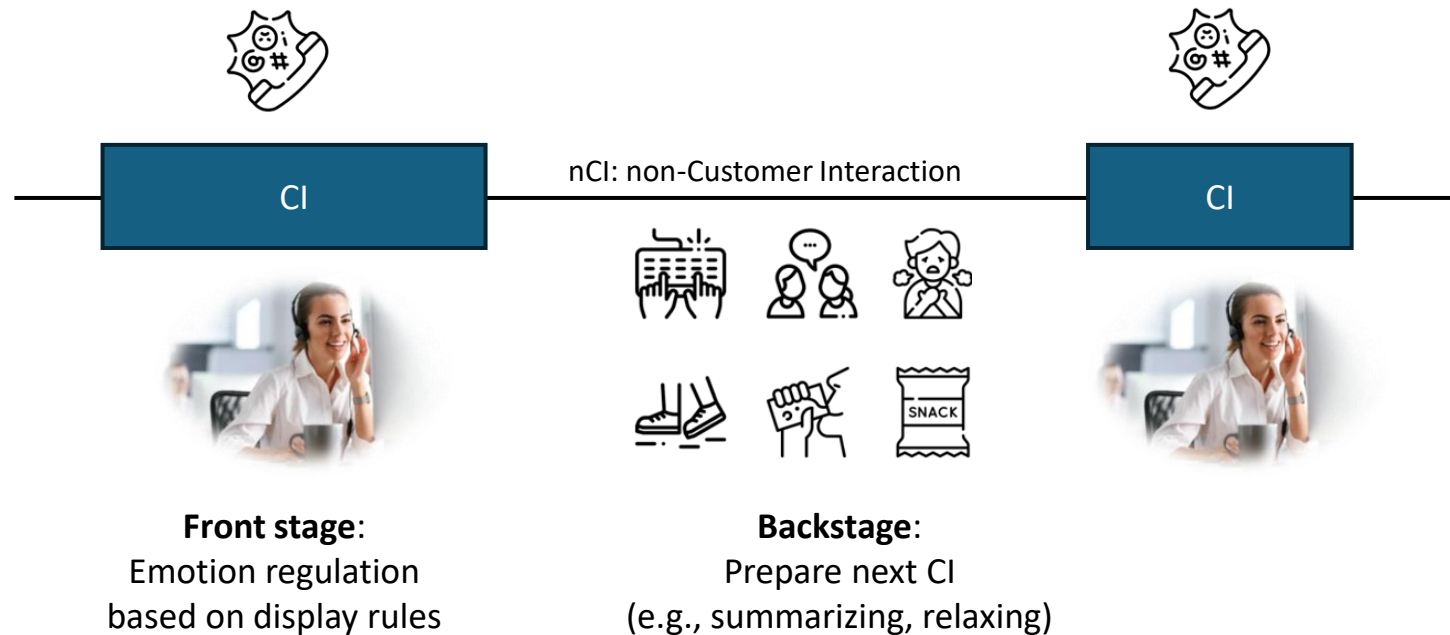
Digital traces of knowledge work:
wearable sensing, email logs, calendar entries, desktop activities



Emotional labor:
Work procedures & Data availability

Repetitive Nature of Emotional Work

CI: Customer Interaction
nCI: non-Customer Interaction

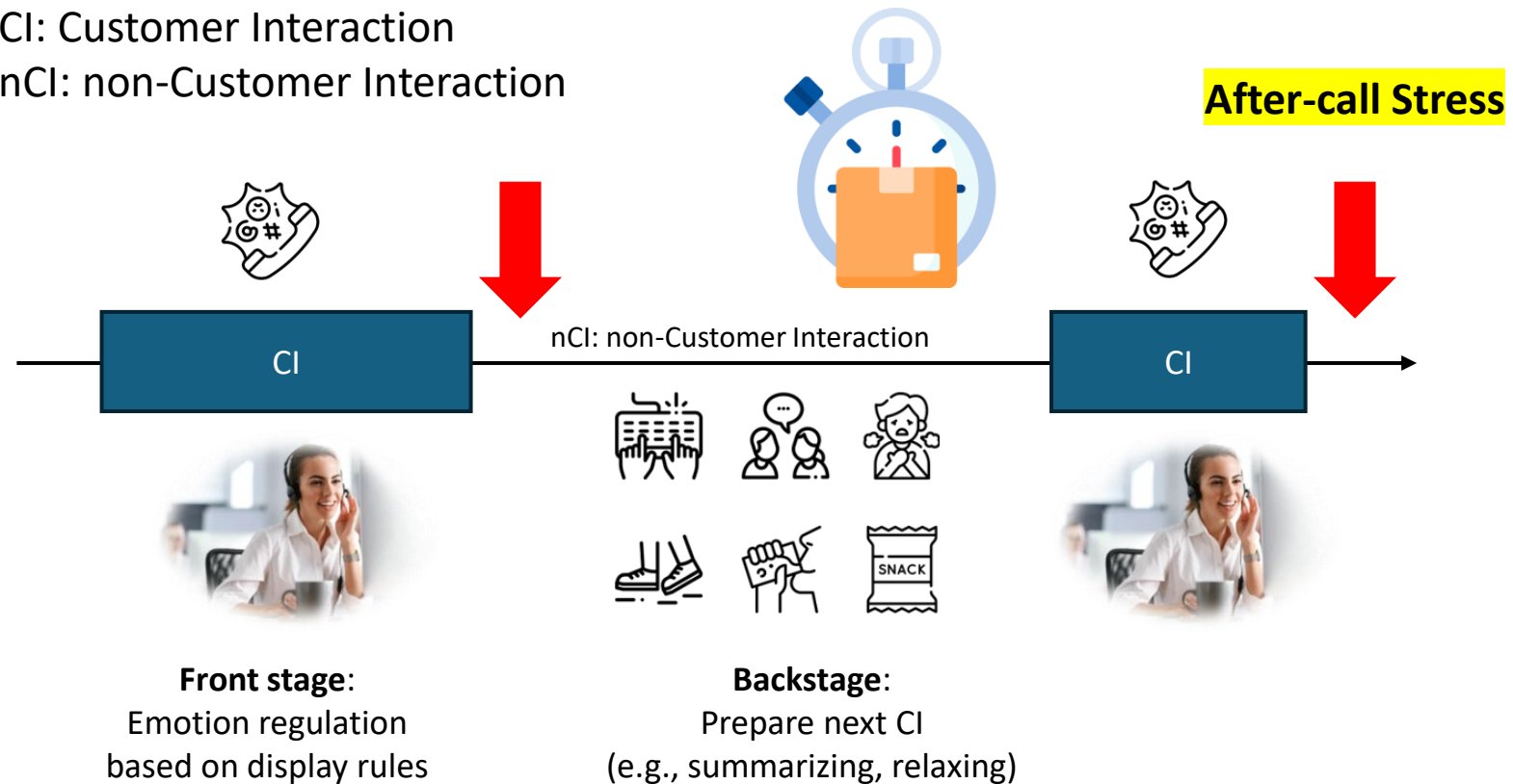


Insights: Cyclic work nature generates structured task logs that differ from knowledge-work traces

Self-Tracking After-call Stress for Worker's Stress Management



CI: Customer Interaction
nCI: non-Customer Interaction



Task aligned stress tracking is an essential step toward designing effective strategies to protect workers from excessive stress and improve well-being (e.g., JIT interventions)

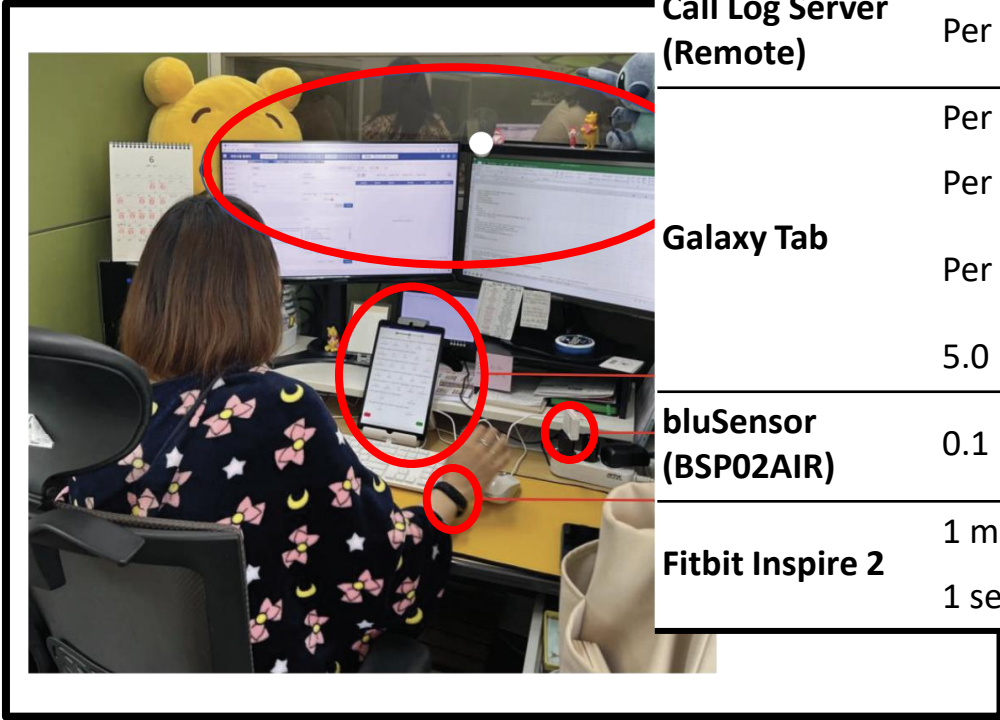
Research Goal



RQ1: Can we detect after-call stress by combining passive sensing data with call-center task logs, while respecting the task-aligned cycle of emotional labor?

RQ2: Beyond prediction performance, can interviews with call agents help us better understand the factors related to after-call stress?

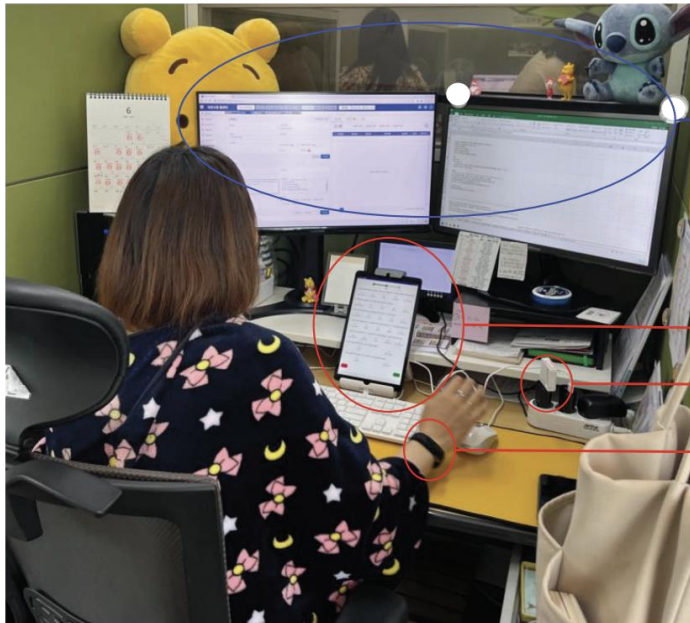
Data Collection Methods



Device	Freq	Sensing Type	Data type	Data
Call Log Server (Remote)	Per call	Passive sensing	Task	Call start time, call duration, question (text), answer (text), agreement, complaint
Galaxy Tab	Per call	Self reported	Behavioral	Eating, drinking
	Per call	Self reported	Psychological	Stress, arousal, valence, surface acting
	Per day	Self reported	Daily baseline	Daily health condition, stress, arousal, valence, bedtime, wake-up time
bluSensor (BSP02AIR)	5.0 Hz	Passive sensing	Behavioral	Desktop activity (x, y, and z)
	0.1 Hz	Passive sensing	Environmental	CO ₂ , humidity, temperature
Fitbit Inspire 2	1 min	Passive sensing	Behavioral	Step counts
	1 sec	Passive sensing	Physiological	Heart rate

Collected sensor data and self-report data
 from 18 call agents for 4 weeks
 at a city hall call center in South Korea

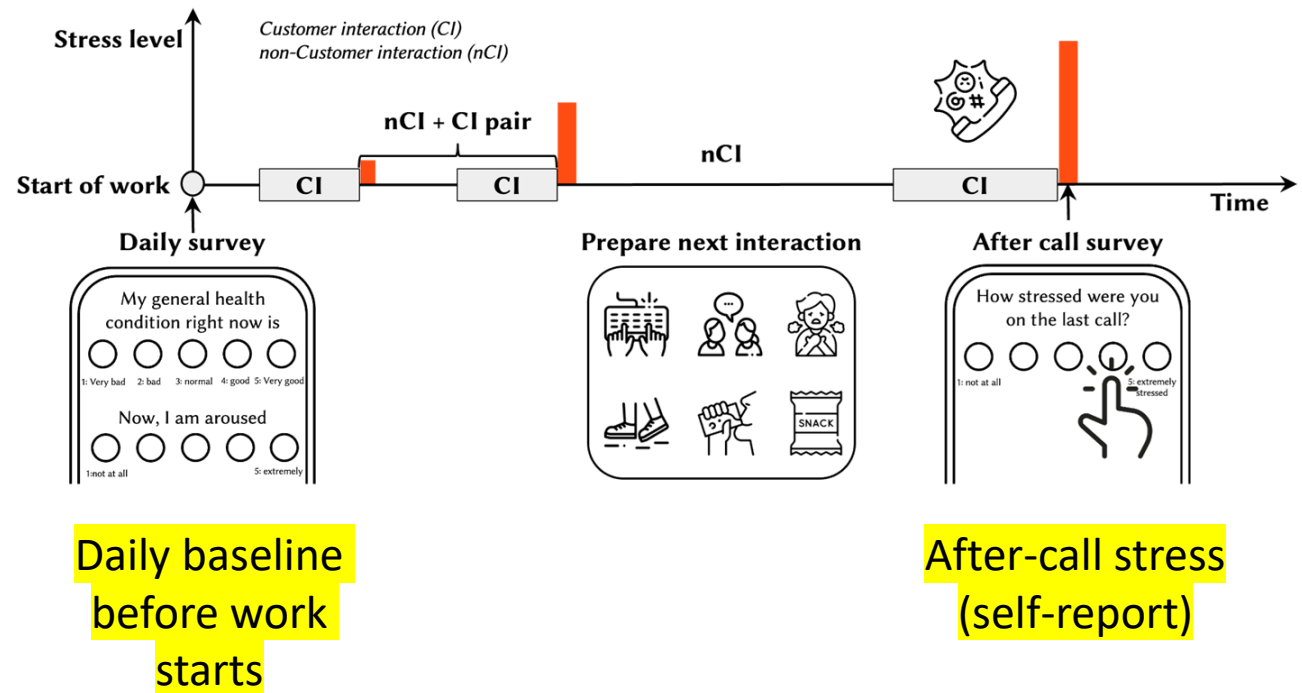
Data Collection Methods



- Call log server
- Tablet
- Environmental sensor
- Wrist band

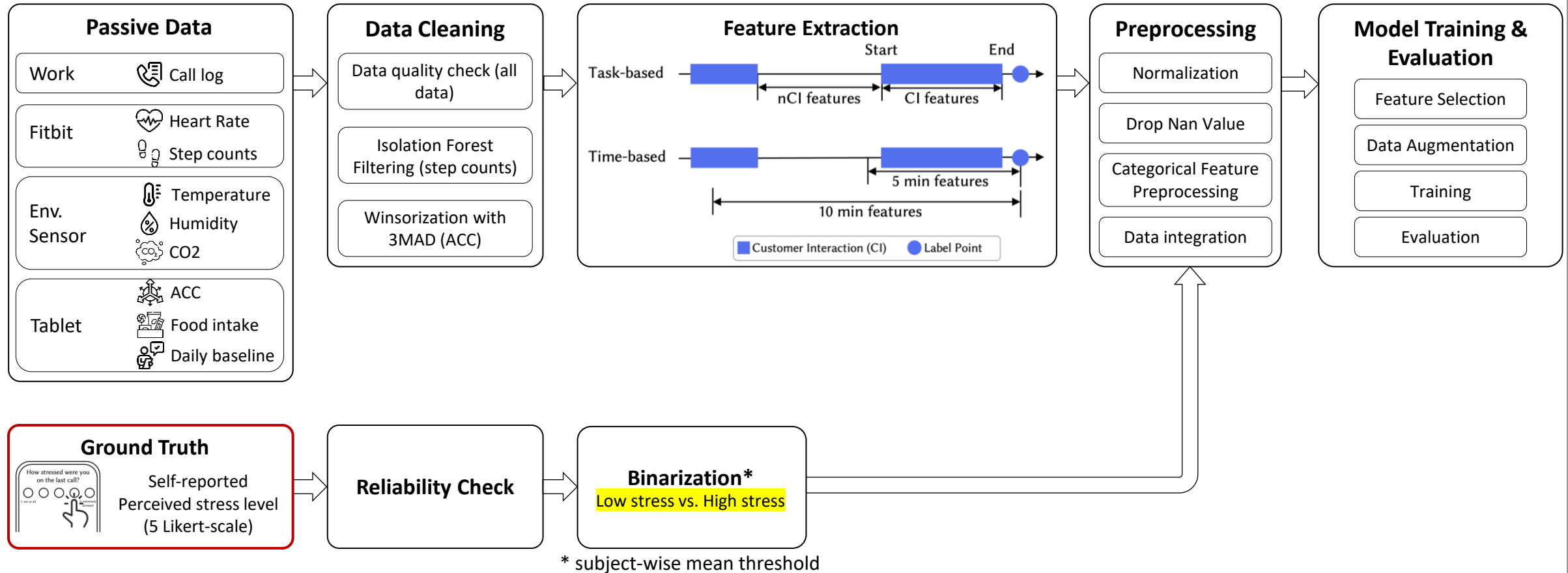
Collected sensor data and self-report data
from 18 call agents for 4 weeks
at a city hall call center in South Korea

Daily workflow for self-report data collection



⇒ 7,442 self-reports

Data Analysis Methods

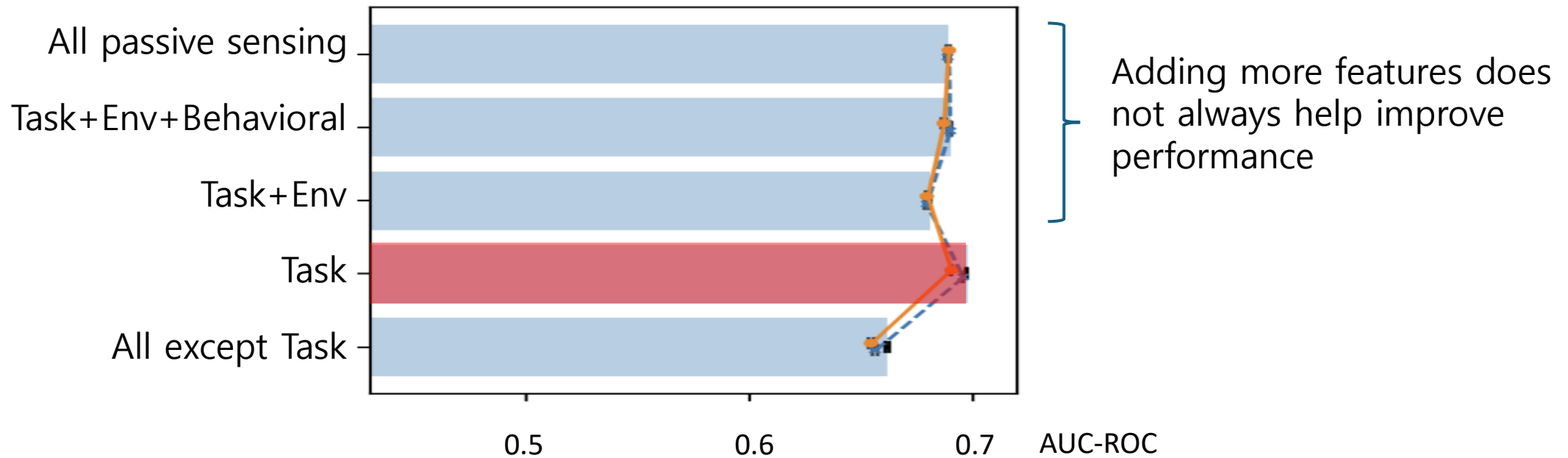


Results – Task Alignment Matters for Stress Detection

	Exact alignment	Close alignment	Non-alignment (too large window size)				
	Task-aligned		Time-based				
		5-min	10-min	15-min	20-min	25-min	30-min
ROC-AUC mean (STD)							
RF	0.685 (0.090)	0.692 (0.082)	0.671 (0.080)	0.642 (0.074)	0.616 (0.074)	0.610 (0.067)	0.605 (0.0638)
XGBoost	0.679 (0.085)	0.686 (0.088)	0.664 (0.083)	0.637 (0.082)	0.625 (0.072)	0.613 (0.078)	0.599 (0.057)
CatBoost	0.661 (0.094)	0.673 (0.085)	0.656 (0.085)	0.627 (0.084)	0.600 (0.086)	0.591 (0.075)	0.594 (0.072)
LDA	0.661 (0.079)	0.663 (0.081)	0.643 (0.078)	0.617 (0.071)	0.599 (0.069)	0.593 (0.066)	0.589 (0.065)
SVM	0.623 (0.104)	0.624 (0.106)	0.612 (0.099)	0.584 (0.099)	0.567 (0.093)	0.560 (0.094)	0.546 (0.092)
DT	0.576 (0.071)	0.601 (0.066)	0.577 (0.068)	0.583 (0.047)	0.536 (0.031)	0.523 (0.039)	0.547 (0.044)
TabNet	0.658 (0.039)	0.676 (0.035)	0.636 (0.030)	0.612 (0.048)	0.587 (0.042)	0.595 (0.025)	0.587 (0.015)

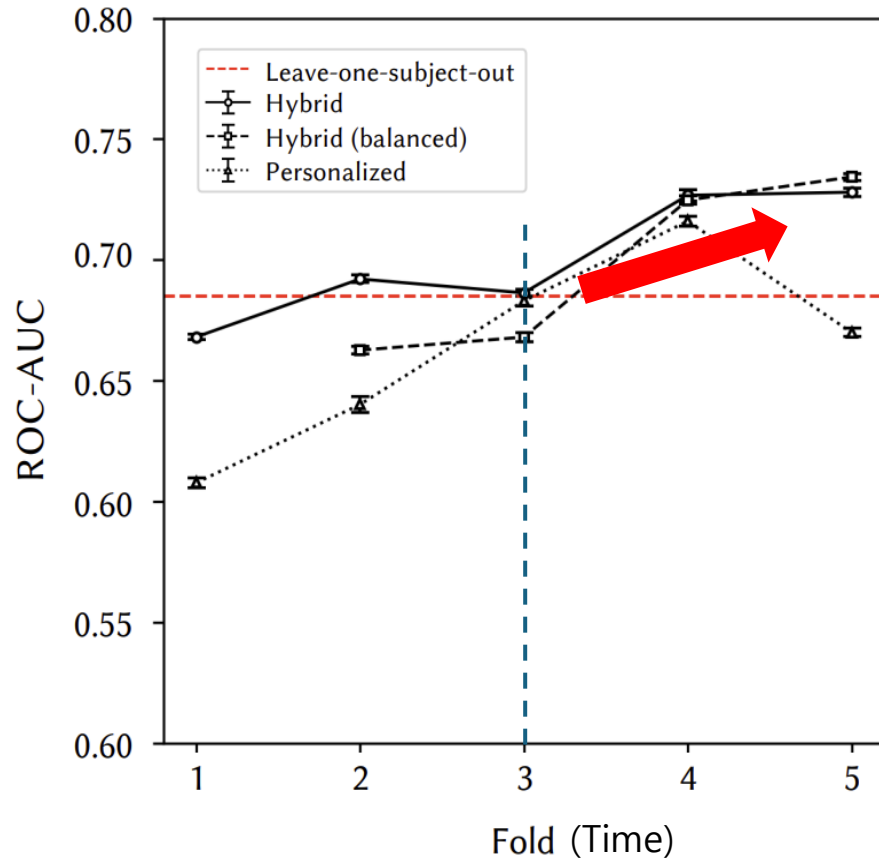
More effective to segment data according to the work contexts, rather than using broad, generic time windows

Results – Task-log Features Considered Important



Task logs should not be treated as secondary context.
Instead, they should be considered **first-class sensors** in this work setting

Results – Personalization Improves Detection Performance



After-call stress detection should not rely only on a one-size-fits-all population model, but it should adapt to individuals

* Metric : Mean (\pm SD) of AUC, # experiments per fold = 30
* Time-serious cross-validation

Understanding Factors Related to After-class Stress Dynamics

- **Semi-structured interview (N = 13) after data collection**
 - 1) **What triggers stress** during customer interaction (CI) ?
 - 2) How do you **respond to stressful conversations** during CI?Q
 - 3) **What do you do after a stressful CI** during non-customer interaction (nCI)?
 - 4) Besides stressful CI, **what other factors influence** your perceived stress level after a call?

Results – Diversity of Stress Triggers

Findings 1 Diverse stress triggers within similar customer interactions

- **Ambiguous problem description**

“Even though it’s stressful when the customer is unpleasant, it’s even more challenging when they inquire without knowing their issue. The process of figuring it out is complicated, and it becomes harder if they are not cooperative.”

- **Expectation of emotional support**

“After venting for about 11 minutes ... they said,

‘Talking about it like this has made me feel a bit better.’ That really hurt me.”

- **Rejection of proposed solutions or misunderstanding** of the caller on the suggested solution

→ **Implication:**

Future modeling may need to go beyond simple call metadata and incorporate more content-level representations of customer interactions.

Results – Different Approaches During Stressful Interactions

Findings 2 Different approaches while engaging with stressful customer interactions

- **Disengagement driven by helplessness**

"I slump and zone out because there is nothing I can do in the middle of the call."

- **Active coping strategies during the call**

*"Even though I know it's inappropriate, I make **rude gestures** or mouth **profanities directed** at the customer." "Just let him talk, and I take out a piece of paper and **write down song lyrics**."*

*"I **drink water** to cool down."*

→ Implication:

Need for personalization: even when we observe similar or related behavioral signals, their meaning may differ across individuals

Results – Variability in Recovery Patterns

Findings 3 Variability in recovery patterns during nCI intervals

- Agents use **different reset strategies** during non-customer interaction (nCI)
 - talking with colleagues, sitting quietly, deep breathing, typing forcefully, having snacks/cold drinks
 - leaving the seat or office when stress is overwhelming

“Getting up from my seat usually means I'm really stressed, and I need to step out..”

→ **Implication:**

Can't treat non-customer interaction (nCI) segment as a uniform resting period.
Recovery is personal, and systems need to account for that variability.

Results – Other Influential Personal and Environmental Factors

Findings 4 Other influential factors related affecting after-call stress

- Agent's personal and environmental context matters
 - Personality, coping style, task preference, physical conditions (e.g., sore throat, menstrual cycle)
 - Environmental factors (e.g., noise, background chatter)

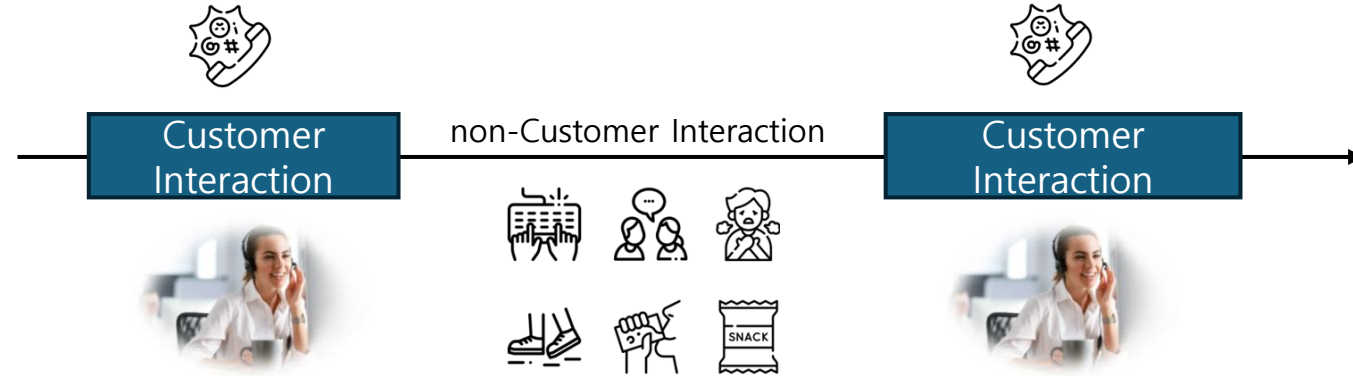
“Too loud colleagues or background chatter influence my task”

*“I feel burden when I response to the customer in overly quite environment,
because everyone can listen my voice”*

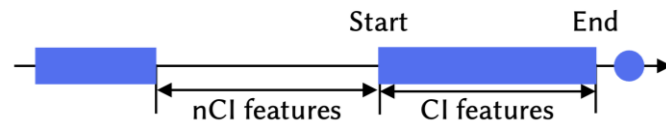
→ Implication:

Even within the same person, stress signals can vary depending on the day and the surrounding conditions

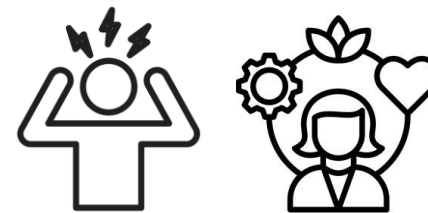
Key Findings



Task Logs as First-Class Sensors



Task-Aligned Segmentation for Feature Extraction



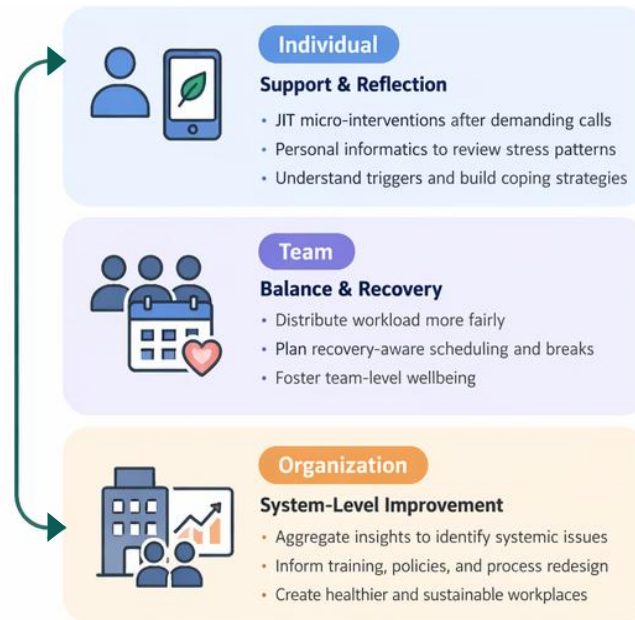
Stress Factors, Coping and Recovery Patterns

Personalization for Mitigating Inter-/Intra-Personal Variability

Implications for System Design



Adopt Progressive Sensing with Minimal Intrusion



Designing Closed Loops: Sensing → Intervention

Risks to Consider



Ethics: Sensing Should Empower Workers, Not Monitor Them

Design Principles



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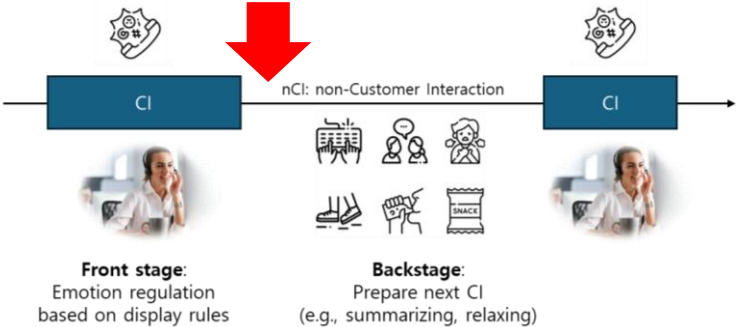


Key Findings

- Task Logs as First-Class Sensors
- Task-Aligned Segmentation as Modeling Principle
- Personalization for Mitigating Inter-/Intra-Personal Variability



After-call Stress



Implications

- Adopt Progressive Sensing with Minimal Intrusion
- Designing Closed Loops: Sensing → Intervention
- Ethics: Sensing Should Empower Workers, Not Monitor Them

