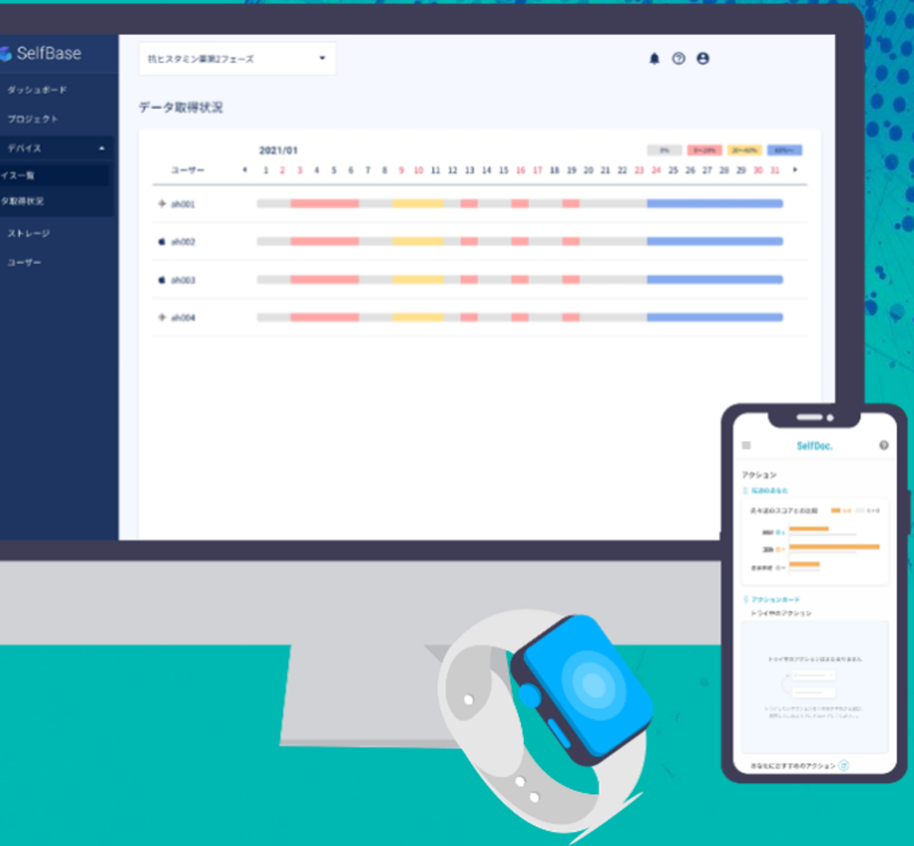
phuse·virtual

Single Day Event

Toshikazu Fukami, *TechDoctor*



Digital Biomarker Development Using Wearable Devices and its Application to Occupational Medicine

phuse.global

Medical care × Data

Wearable Device (IoT)

Healthcare service

Health Examination

data acquisition

bigdata

- **heartrate**
- sleep

analoge data

- questionnaire
- Examination

platform

data stock・preproccessing（formatting, correlation）
SelfBase

analysis

Medical Data Analysis（Neuronal Activity Assessment）
SelfBase

Keio University medical department Psychiatry and Neuroscience department

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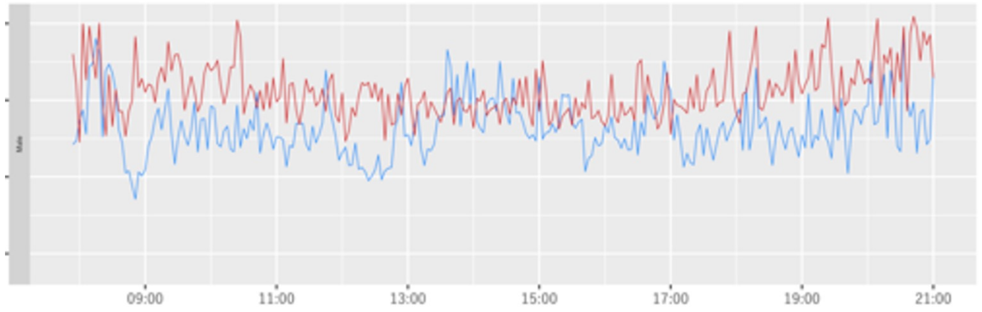
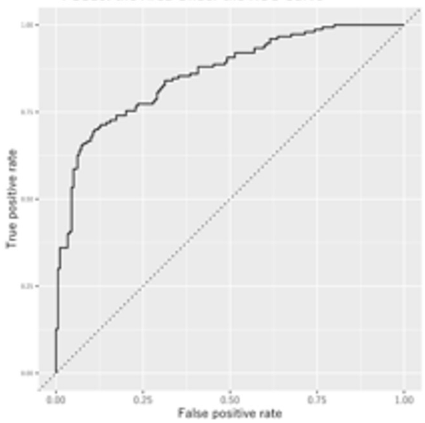
Algorithm for estimating high-stress individuals was developed by the research team.

Significant differences in the level of autonomic nervous system activity between those who are highly stressed and those who are not.



（By PSS-10）Stress level High（25%）
（By PSS-10）Stress level Low（25%）

Create a model that achieves a certain level of accuracy with respect to generalization performance, etc. (additional validation with an increased number of N is necessary)



.metric	.estimator	.estimate
accuracy	binary	0.7781155
precision	binary	0.7583893
recall	binary	0.7533333
spec	binary	0.7988827
f_meas	binary	0.7558528
pr_auc	binary	0.8528222
roc_auc	binary	0.8587337

About TechDoctor

TECH DOCTOR

Verify the accuracy of data from various sensing devices and make it available for dBM development

sensing device

wearable device

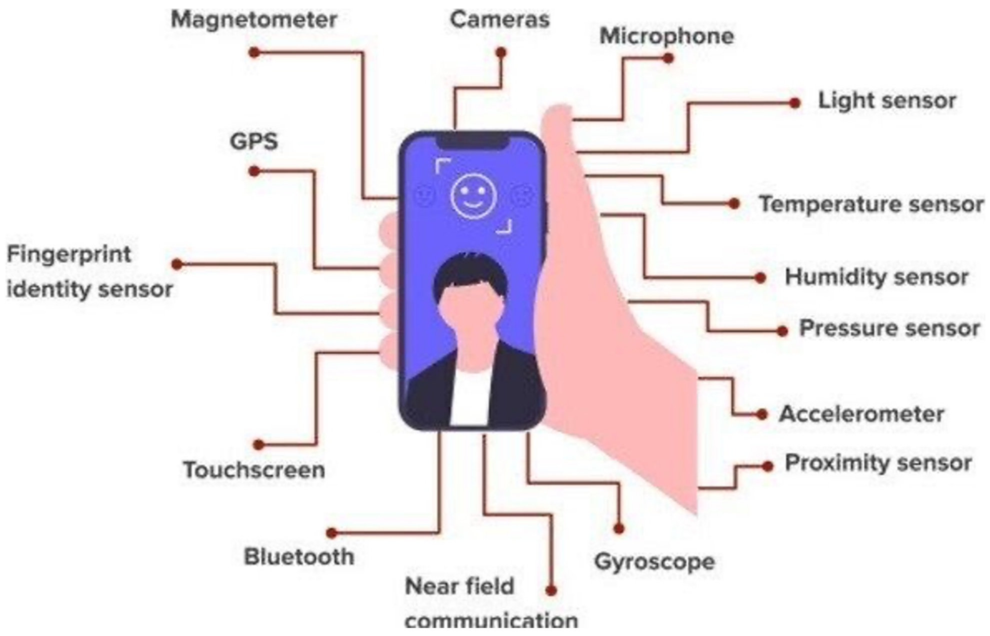
wearable devices for long-term measurement

low burden and high accuracy

table of contents

digital Biomarker (dBM)

“Digital phenotyping”



https://www.hsph.harvard.edu/onnela-lab/research/

Digital Health, Mobile and Wearable Devices for Participatory Health Applications
2021, Chapter 3, Pages 33-54

What is a digital biomarker ?

Digital biomarkers are defined as objective, quantifiable physiological and behavioral data that are collected and measured by means of digital devices such as portables, wearables, implantables, or digestibles.

(https://www.karger.com/Journal/Details/271954)

Digital Biomarker Generation Process

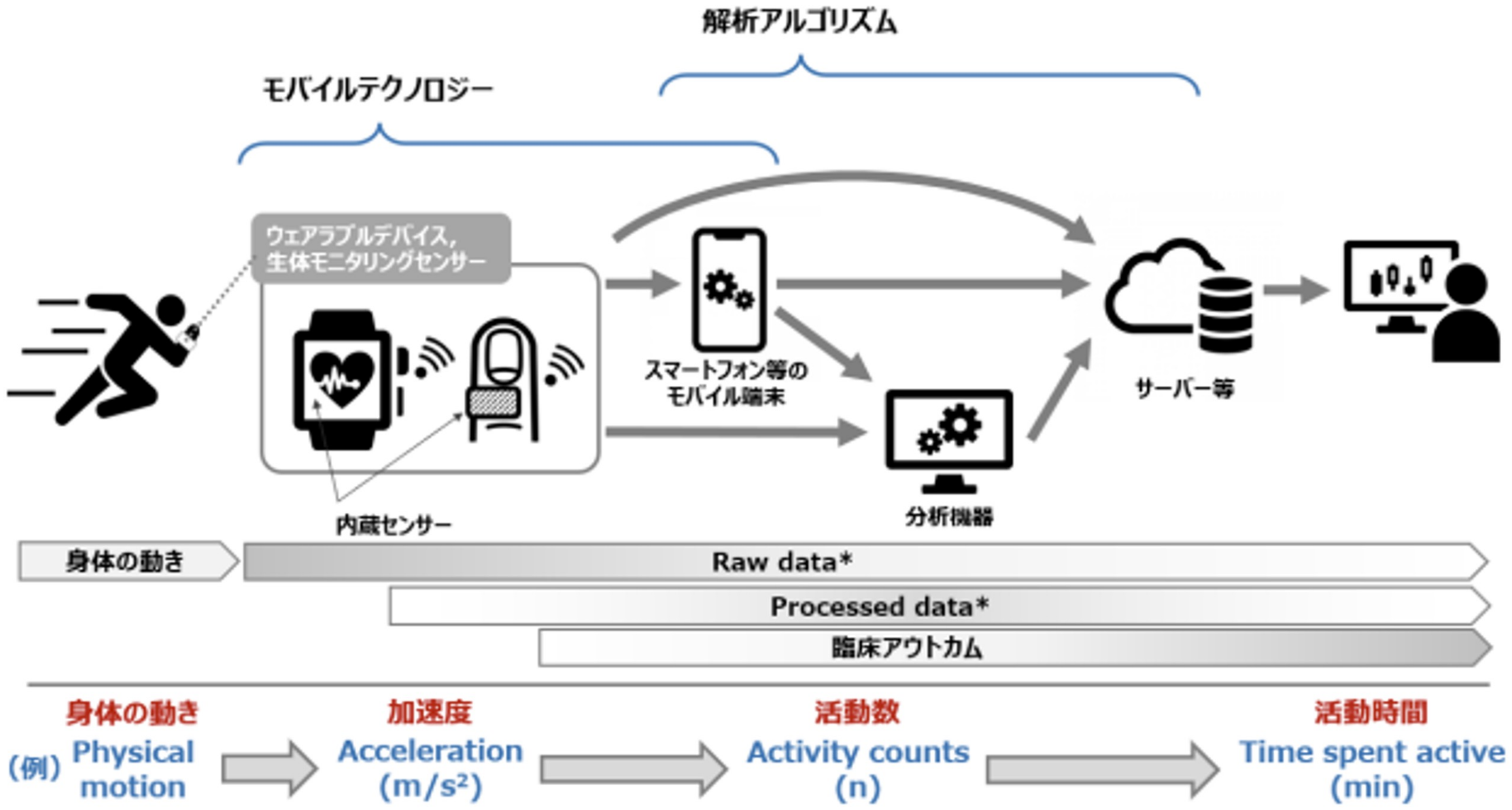


図 2-1 デジタルデバイスによるデータ取得から dBM が生成されるまでの過程

***Raw data や Processed data のまま dBM として活用される場合もある**

※医薬品開発におけるデジタルバイオマーカー(dBM)の利用と要件
2022年4月 日本製薬工業協会 医薬品評価委員会　臨床評価部会 タスクフォース1

Three important steps in dBM generation

Verification

Analytical Validation

Clinical Validation

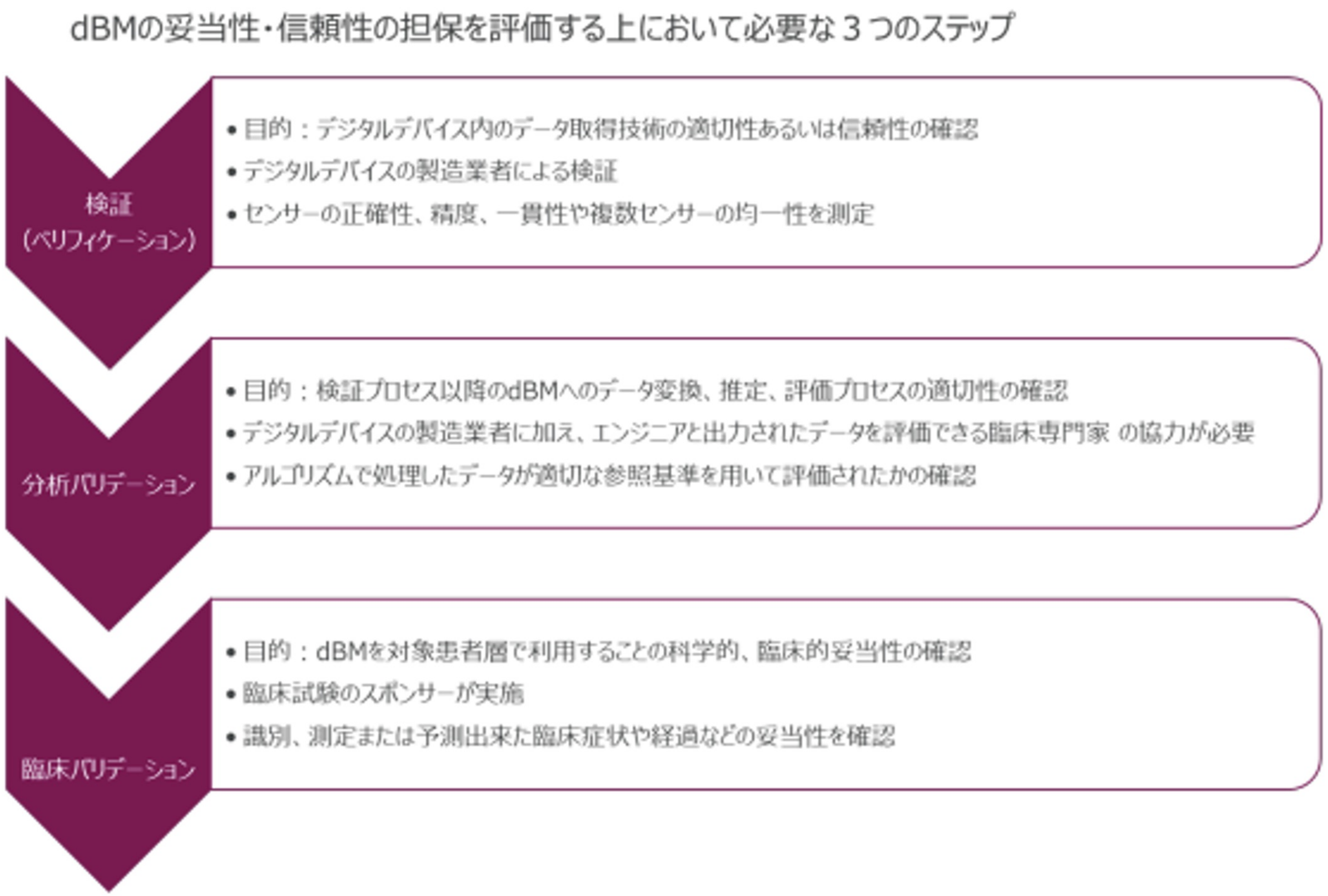


図 2-2 dBM を生成するために必要な３つのステップ（Goaldsack, et al. 2020[2] より引用）

※医薬品開発におけるデジタルバイオマーカー(dBM)の利用と要件
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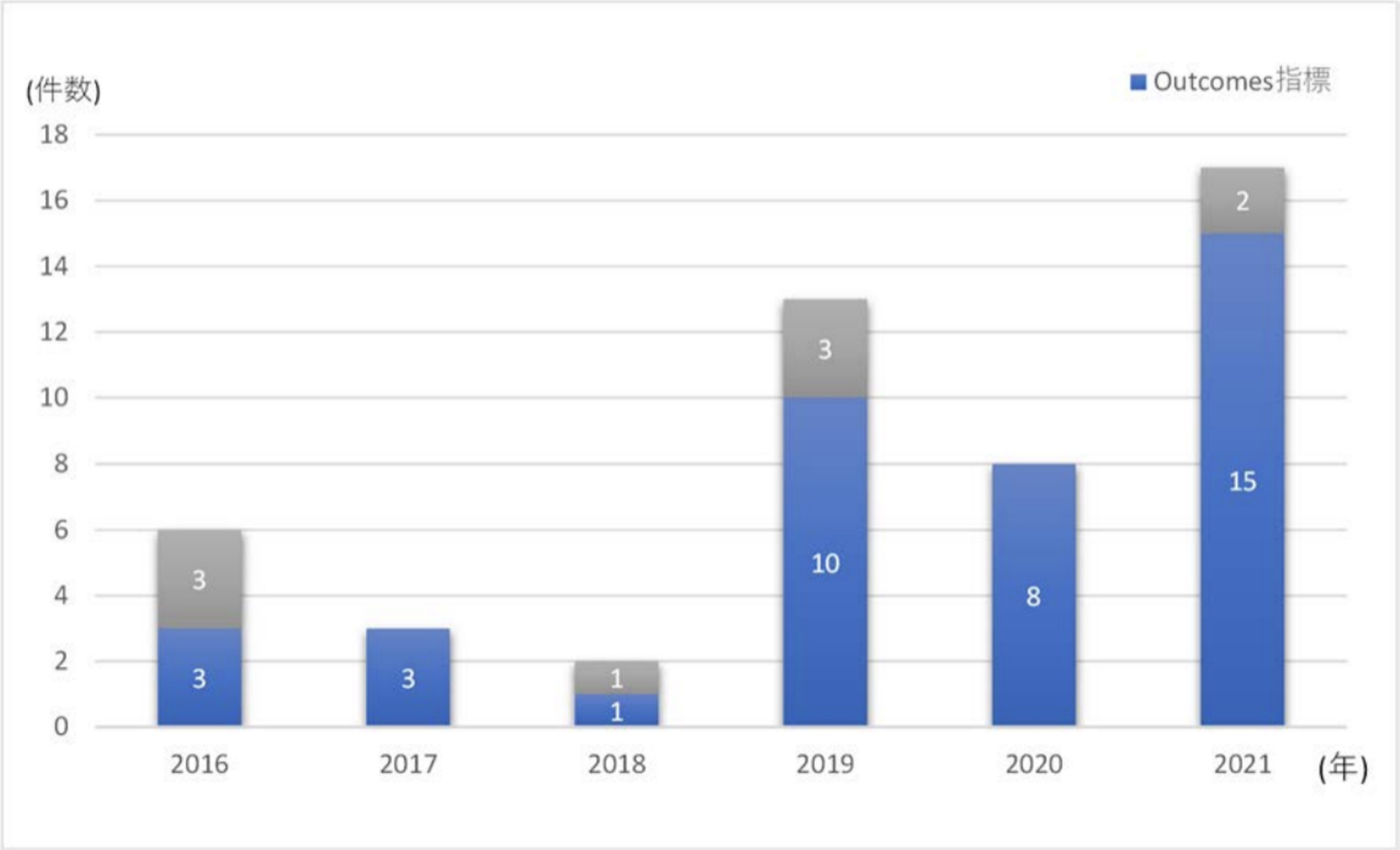
Status of Digital Device Utilization

図２　ウェアラブルデバイスを使用した臨床試験数



※2022年3月発行医療産業政策研究所リサーチペーパーシリーズNo80　中塚靖彦主任研究員
「データ駆動型研究開発を目指して—健康・医療データの活用について考える—」

Wearables in clinical trials

Experts say over the next few years, there will be a meteoric rise in the use of wearables in research. Kaiser Associates and Intel estimate that by 2025, 70% of clinical trials will incorporate sensors.

A search of ClinicalTrials.gov shows that there are already over 1,300 active or completed studies using wearables. Actigraph (1,024), Fitbit (668), Garmin (84), Apple (52), and Empatica (47) are among the most common devices used in these studies. The types of data collected include-but are not limited to- heart rate, heart rate variability, activity, sleep patterns, respiratory rate, and blood oxygen saturation level. And whenlooking at therapeutic areas using wearables, they are most frequently implemented in central nervous system, neurologic, heart, vascular, and respiratory tract trials. There are also a number of trials employing wearables for mental disorders.

1.3k

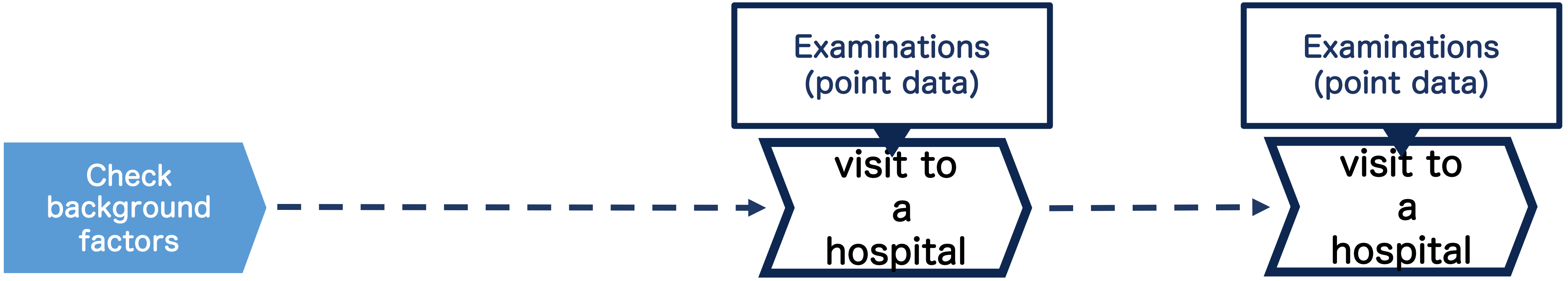
Trials with wearables

There are over 1300 active or completed trials using wearables on ClinicalTrails.gov

70%

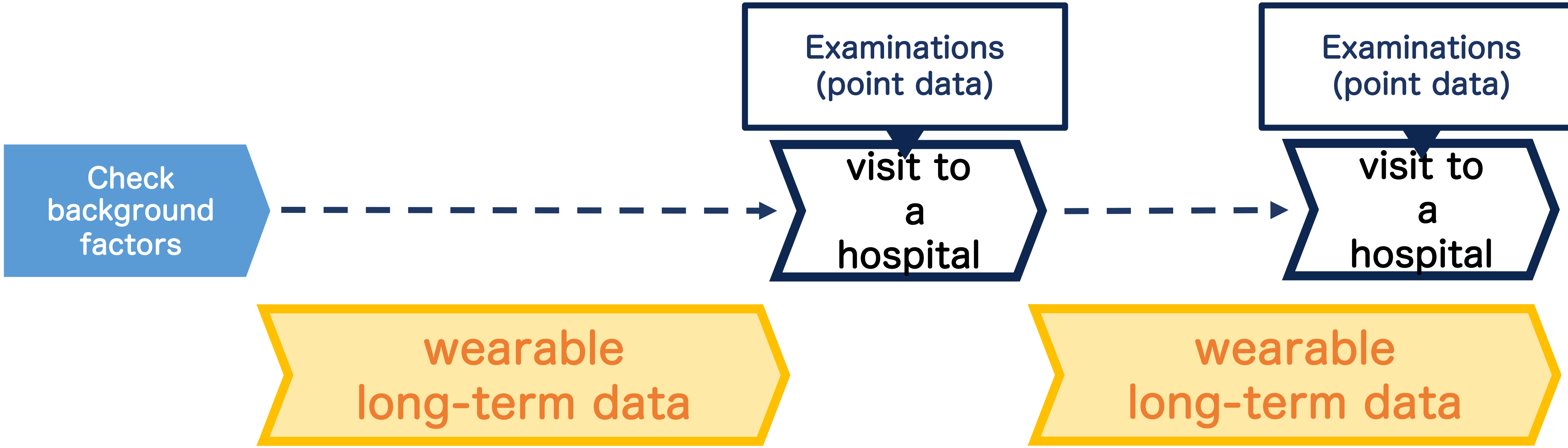
Acti	1,024
Fitbit	668
Garmin	84
Apple	52

“point data” and “long-term data” cross value



Based primarily on information collected during hospital visits It is necessary to guess the name of the disease and the course of the disease

“point data” and “long-term data” cross value



"Line data" connecting hospital visits to hospital visits
Able to track changes

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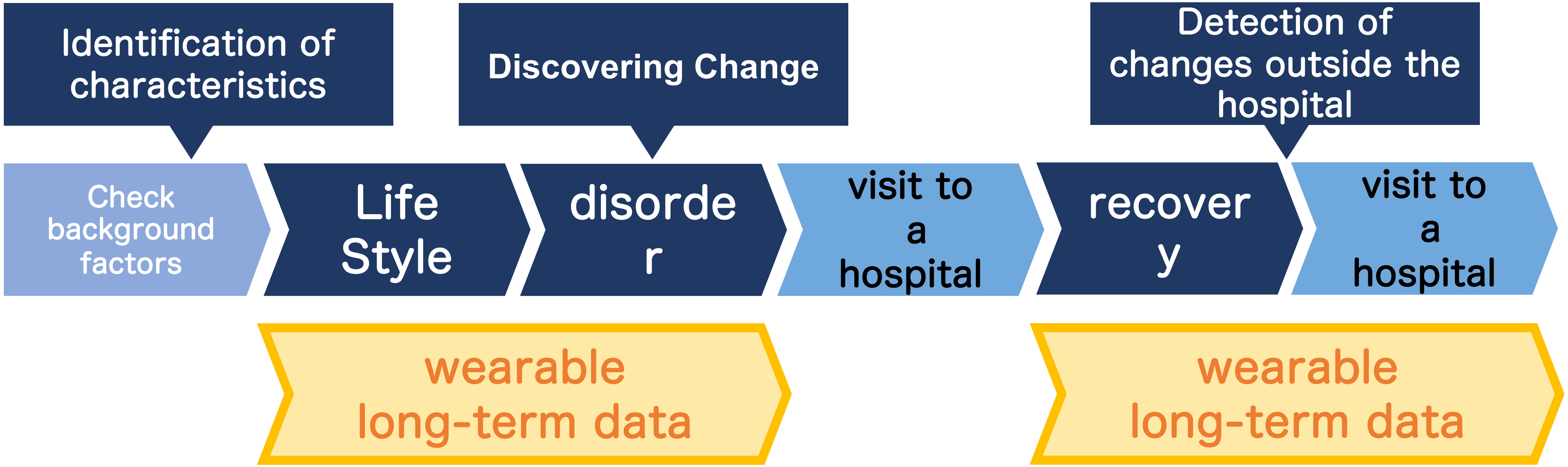
“point data” and “long-term data” cross value



Possibility to quantify change by connecting data

Examples of Utilization of Out-of-Hospital Data

patient

occupation : teacher
diagnosis : adjustment disorder
Hospital History : 7/31(1st), 8/21(2nd), 9/25(last)
Prescription drugs : -

After the hospital visit was completed, the data was used to predict the malfunction

wearable data

- data detail
- validation study
- case sutudy

data detail

Data Summary

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【heartrate】

1 : heartrate(every 5sec)
2 : hrv metrics
（RRI、CVRR、SDNN、SD1、SD2）
3 : heartrate curve type
4 : stress timing

【sleep】

5 : time in bed
6 : minutes asleep
7 : minutes awake / awake count
8 : sleep latency
9 : sleep level (awake, rem, light, deep)
10 : sleep rhythm
11 : efficiency

【activity】

12 : minutes sedentary
13 : active level
14 : heartrate
15 : steps
16 : calories
17 : time zone

【Other】

18 : Exercise time that contributed to falling asleep
19 : social jetlag
20 : resting heartrate
21 : sleep start / end time

※main items
※orange color : original value

wearable data

fitbit data sample

TECH DOCTOR

■sleep

user_id	date	startTime	endTime	deep(min)	light(min)	rem(min)	awake(min)	efficiency(%)
TD_000000001	2020-06-01	23:22:30	05:54:30	61	195	81	55	92
TD_000000001	2020-06-02	23:24:00	05:57:30	70	202	75	46	98
TD_000000001	2020-06-03	23:39:00	05:58:30	42	180	87	70	96
TD_000000001	2020-06-04	23:44:00	05:55:00	67	169	94	41	92
TD_000000001	2020-06-05	22:44:30	05:35:00	47	256	67	40	97
TD_000000001	2020-06-06	23:36:00	05:54:30	34	226	76	42	97
TD_000000001	2020-06-07	22:13:30	06:11:00	46	270	95	66	87

■activity

user_id	date	restingheartrate	peak(min)	fat burn(min)	cardio(min)
TD_000000001	2020-06-01	68	0	902	12
TD_000000001	2020-06-02	68	0	751	6
TD_000000001	2020-06-03	69	0	912	3
TD_000000001	2020-06-04	70	0	976	14
TD_000000001	2020-06-05	71	0	924	8
TD_000000001	2020-06-06	74	2	832	6
TD_000000001	2020-06-07	73	0	711	7

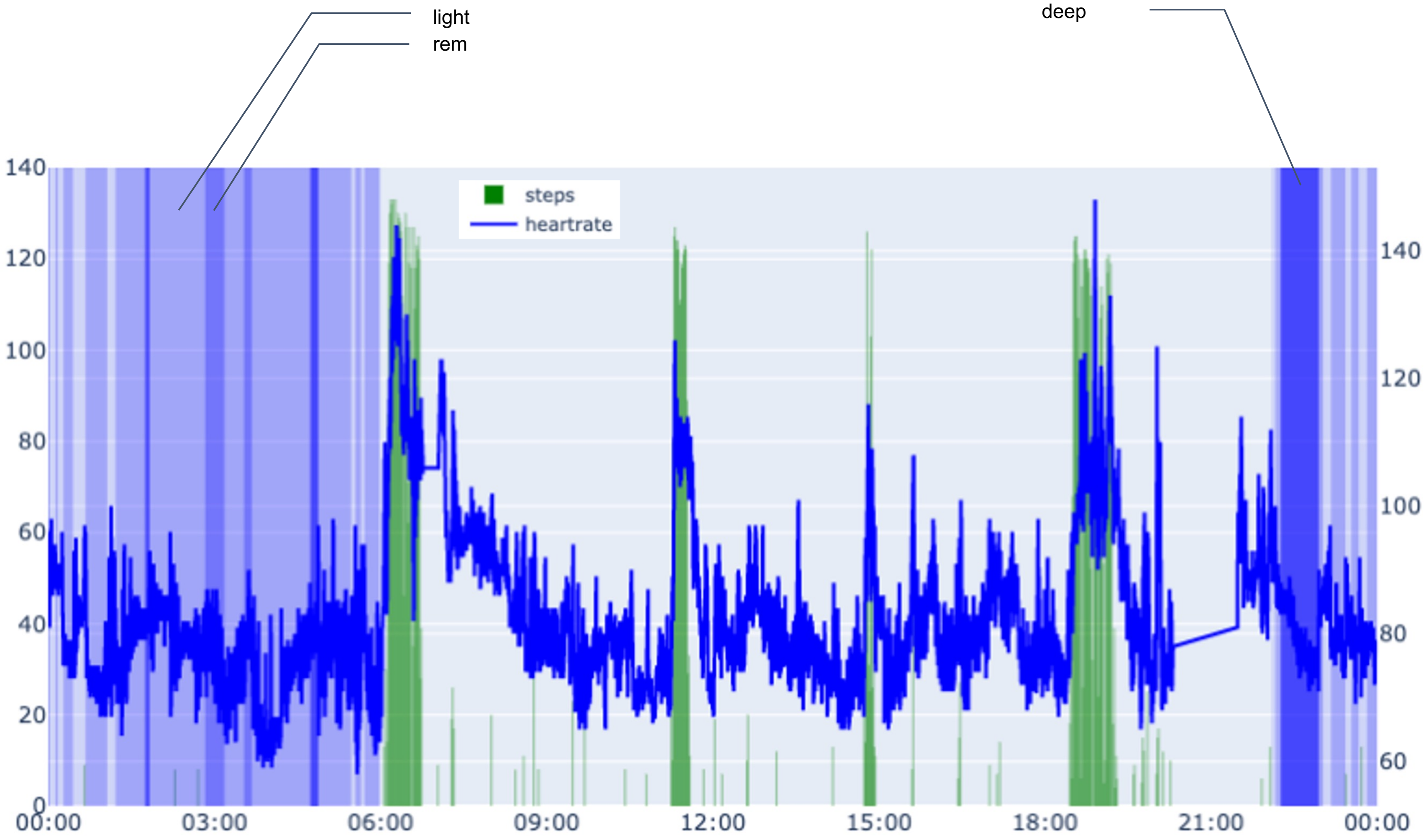
■heartrate

user_id	date	00:00:00	00:00:05	00:00:10	00:00:15	00:00:20	00:00:25	00:00:30	00:00:35	00:00:40	…	23:59:20	23:59:25	23:59:30	23:59:35	23:59:40	23:59:45	23:59:50	23:59:55
TD_000000001	2020-06-01	79	64	61	61	60	64	94	99	107	…	95	96	98	104	86	93	98	90
TD_000000001	2020-06-02	68	63	61	61	62	62	89	94	105	…	90	83	83	96	100	99	99	88
TD_000000001	2020-06-03	74	63	62	63	64	66	92	106	103	…	95	91	93	91	64	66	82	80
TD_000000001	2020-06-04	79	64	61	61	61	62	62	89	103	…	62	63	64	66	82	95	103	80
TD_000000001	2020-06-05	74	60	64	94	64	62	63	64	66	…	89	94	105	91	83	83	96	100

visualization

TECH DOCTOR

datetime	heartrate
2022-02-01 00:00:03	74
2022-02-01 00:00:08	71
2022-02-01 00:00:18	73
2022-02-01 00:00:33	73
2022-02-01 00:00:38	74
...	...
2022-02-03 23:58:24	97
2022-02-03 23:58:29	98
2022-02-03 23:58:39	99
2022-02-03 23:58:44	98
2022-02-03 23:58:49	96



quantification for confirmatory study

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【Nerve activity(stress)】

- Autonomic
- Sympathetic
- Parasympathetic

hrv metrics

【sleep】

- quantity : efficiency, latency
- quality : asleep duration

【activity】

- Mets
- steps
- sedentary time

Wearable data are broken down into three major categories
{heart rate / sleep / activity}.

In studies such as two-group, before-and-after comparisons, the basic items in each category are tabulated as representative values.

quantification for exploratory study

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【rhythm of life】

- sleep rhythm
- activity rhythm
- commuting rhythm

【long-term fluctuations】

- mom, yoy
- seasonal variation

【life event】

- before and after sleeping / waking up
- before and after an attack
- On days when you exercise more than usual

In exploratory studies, rhythms and events in everyday life are important.

Data starting from rhythmic changes and events are collected to search for representative values.

rhythm?

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Sleep and step count data alone can quantify many rhythms.

- going to bed
- getting up
- going to work
- Lunch
- Leaving work

usefulness

i. Capable of acquiring data for much longer periods of time than medical devices
   - Heart rate and other data can be obtained not only during hospital visits but also during sleep.
   - Data can be obtained for several days to several months, and both good and bad days are available.
   - A treatment-control group can be constructed that even takes into account trends in usual activity, sleep, and heart rate.

i. Long-term data can be obtained at a lower cost than medical devices

challenges

i. Accuracy
   - Strictly a pulse rate, and it is unclear if it is equivalent to the heart rate used in existing studies.
   - Heart rate includes fluctuations caused by activities such as walking, since the device is basically worn **in a free state**.

i. Granularity
   - The data is at least once every 5 seconds, so the RRI interval used in existing studies cannot be obtained.

Effect of alcohol consumption on heartrate

Targets and Methods of Collection

- Total of 24 participants (19 males, 5 females) were surveyed.
- After waking up, respondents were asked to answer an original questionnaire about last night's alcohol consumption.
- Respondents answered about the amount of alcohol consumed, time from the end of drinking to bedtime, and feeling of residual alcohol consumption.

Response Guideline

Type and amount	unit
日本酒1合	2
ビール大瓶1本	2.5
ウイスキー水割りダブル1杯	2
焼酎お湯わり1杯	1
ワイングラス1杯	1
梅酒小コップ1杯	1
酎ハイ(7%)350ml1缶	2

飲酒量アンケート

昨晩の飲酒量はどの程度でしたか。下記の飲酒量単位を参考に小数点以下を切り上げて、当てはまる選択肢を選んでください。 *

日本酒1合＝2単位、ビール大瓶1本＝2.5単位、ウイスキー水割りダブル1杯＝2単位、焼酎お湯割り1杯＝1単位、ワイングラス1杯＝1単位、梅酒小コップ1杯＝1単位、酎ハイ(7%)350mL缶1本＝2単位

- 飲酒していない。
- 1単位～2単位
- 3単位～4単位
- 5単位以上

昨晩飲酒をした場合、飲酒を終えたのは就寝時間に対して何時間前でしたか。1時間単位に切り上げて、当てはまる選択肢を選んでください。

※昨晩飲酒をしていない方は無回答にしてください。

- 1時間前
- 2時間前
- 3時間前
- 4時間以上前

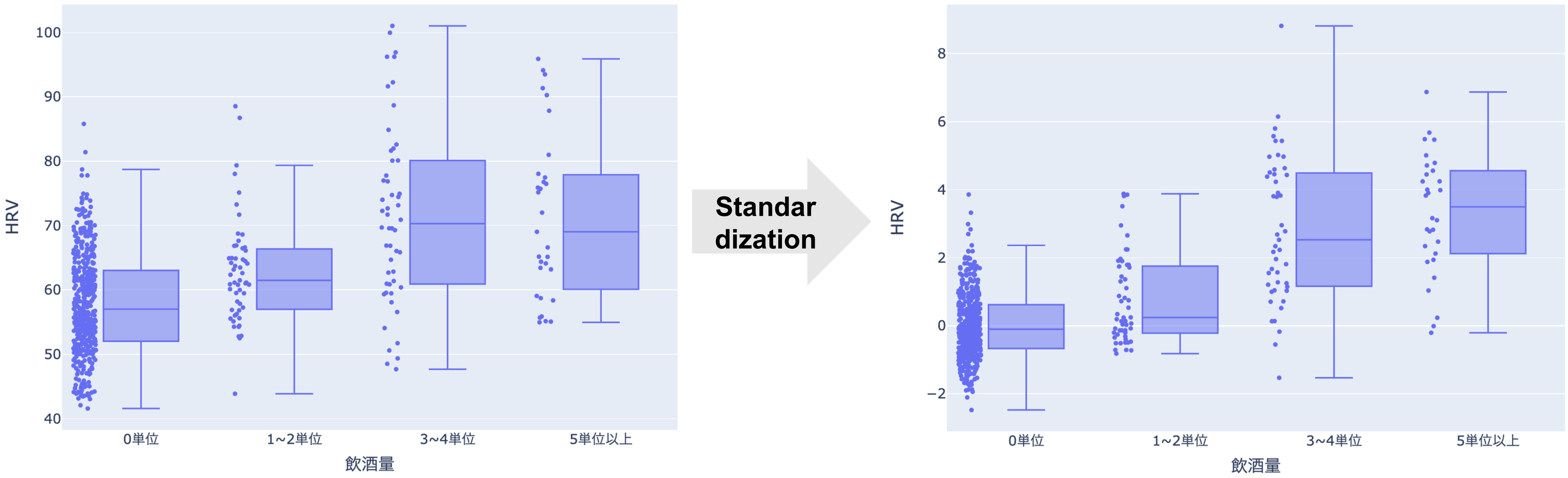
昨晩飲酒をした場合、どの程度お酒が残っていると感じましたか。

※昨晩飲酒をしていない方は無回答にしてください。

- 全く残っていない。
- 少し残っていた。
- かなり残っていた。
- 非常に残っていた。

Analysis Method Overview

- Heartrate data (excluding mid-wake) is handled if the patient went to bed within 3 hours of finishing a drink and up to 3 hours from sleep.
- To eliminate differences in values between individuals, standardize using HRV when not drinking.
- A Kruskal-Wallis test is performed for alcohol consumption (significance level of 0.05), and multiple comparisons are made for metrics for which differences are found.



results

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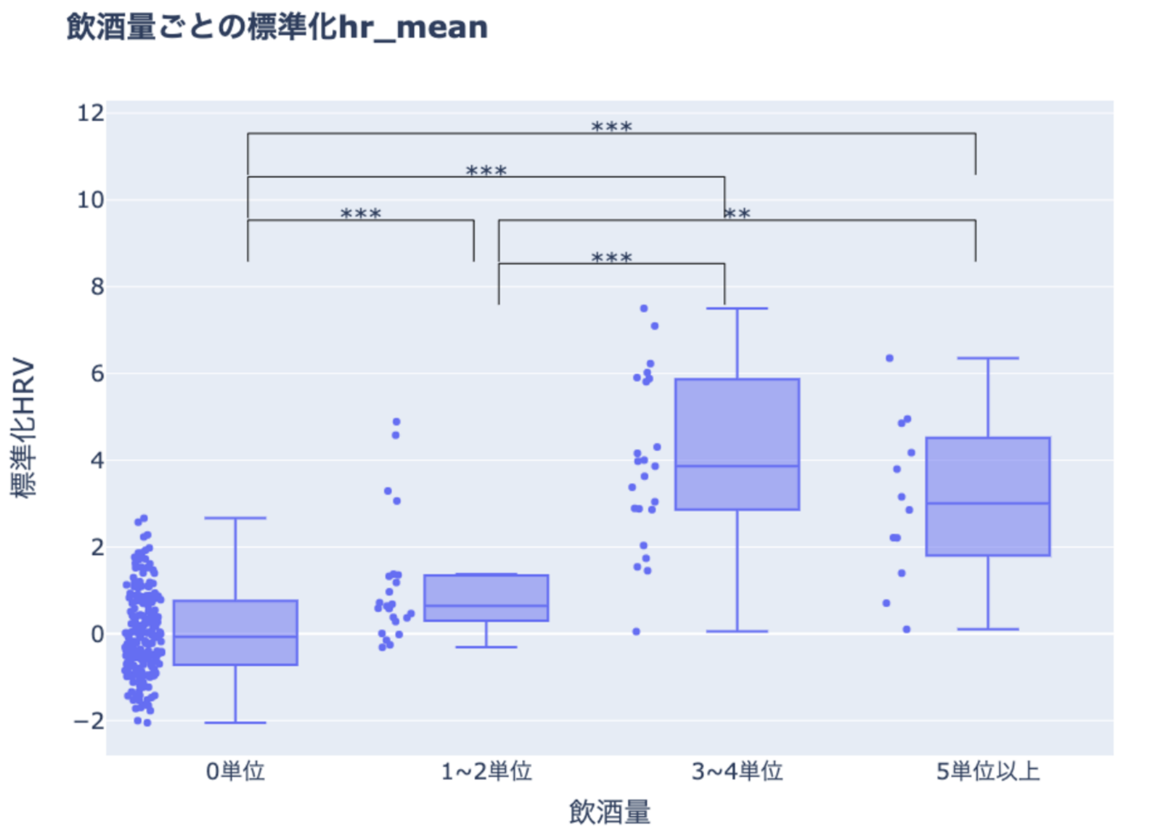
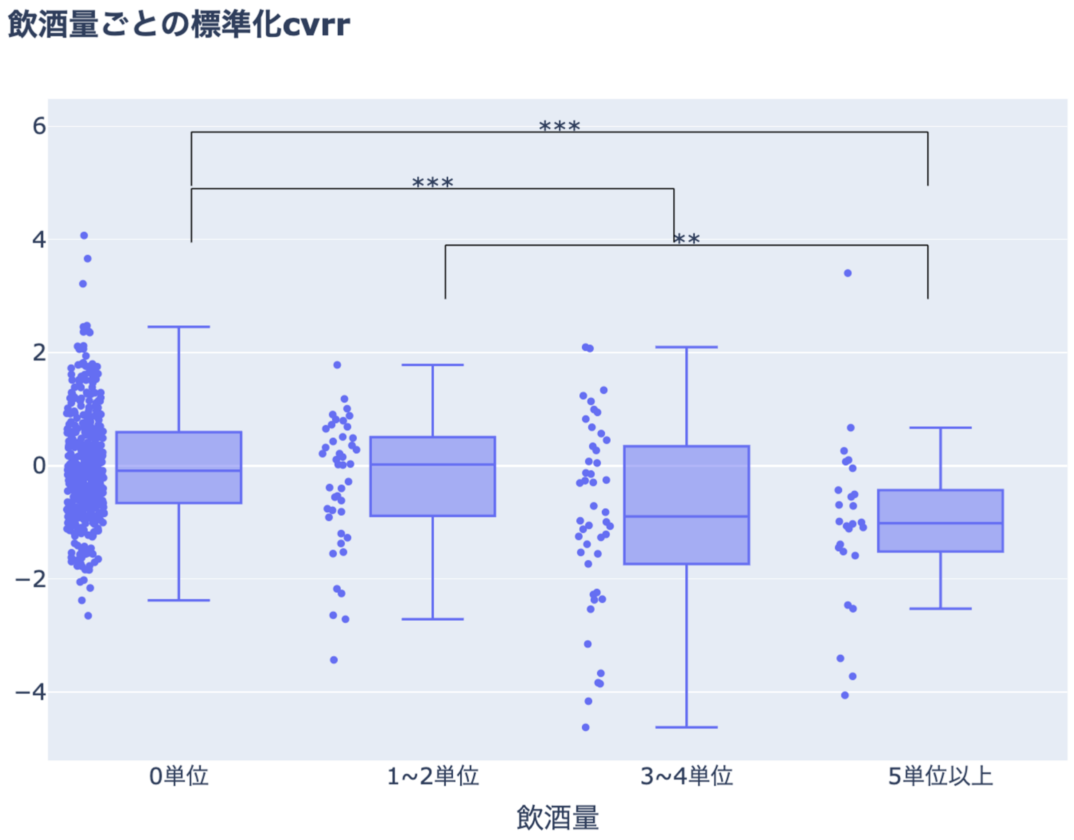
- Heart rate tends to increase with alcohol consumption, with significant differences found in all but the combination of 3~4 units and 5 or more units.
- CVRR shows a significant difference for combinations of two or more units of alcohol consumption apart, and tends to decrease with alcohol consumption.



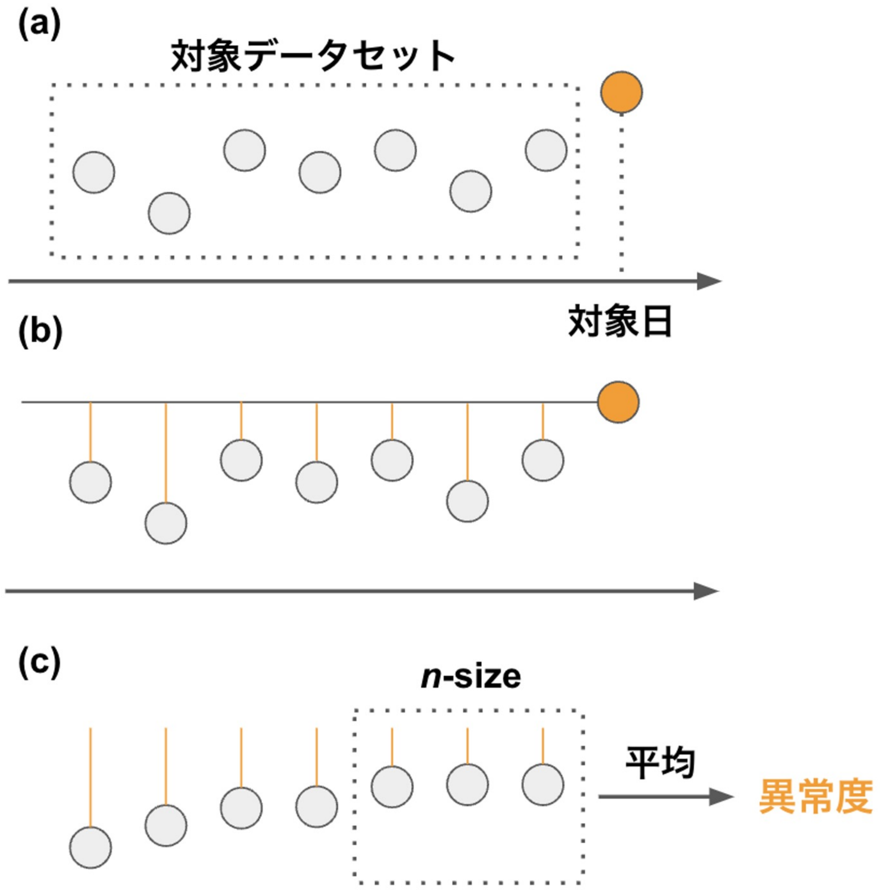


method overview

- An increase in heartrate was observed with alcohol consumption, which was found to be dependent on the amount of alcohol consumed.
- The heart rate that is markedly elevated by alcohol consumption is regarded as an abnormal value, and an abnormal value detection model is constructed.

Overview of anomaly detection algorithms based on the k-nearest neighbor method

(a) Compare the value to be evaluated with the most recent normal heartrate data set
(b) Calculate the distance between the value to be evaluated and the value in the data set
(c) Anomaly degree for the n shortest distances in the data set.
(d) Abnormality is judged as abnormal if the abnormality level is above a threshold value.
  (i) Heart rates that are not determined to be abnormal are included in the data set.



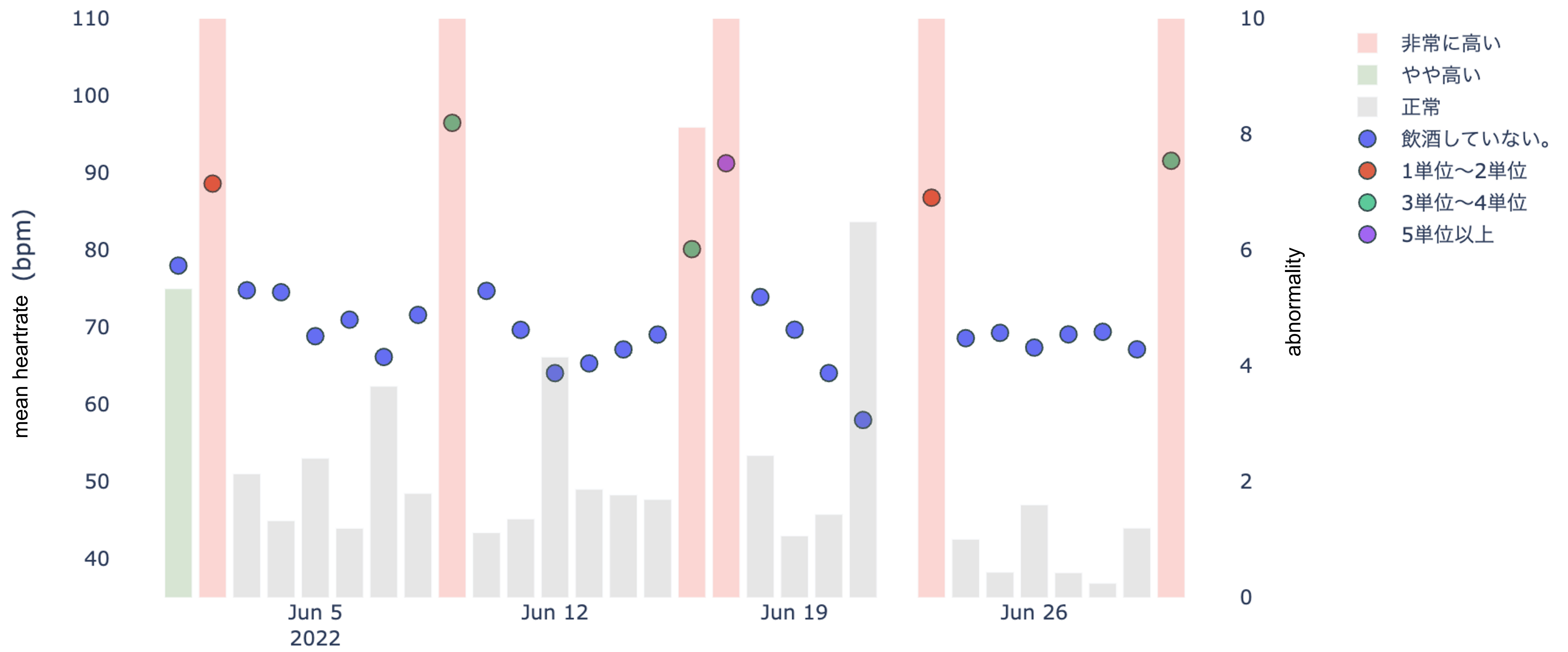
Evaluation Method

- Cross-validation with 5 partitioned groups
- Parameter tuning is performed on the training data set and evaluated on the test data set.

Fold	accuracy	precision	recall
1	0.91	1	0.38
2	0.87	0.89	0.4
3	0.79	1	0.2
4	0.76	0.95	0.48
5	0.8	0.44	0.5
avg	**0.83**	**0.86**	**0.39**

- Although the reproduction rate is low, the goodness-of-fit rate is high, averaging 0.86, making it a conservative forecasting model.
- False positives were frequently observed in some users included in Fold5 due to heart rate disturbances.

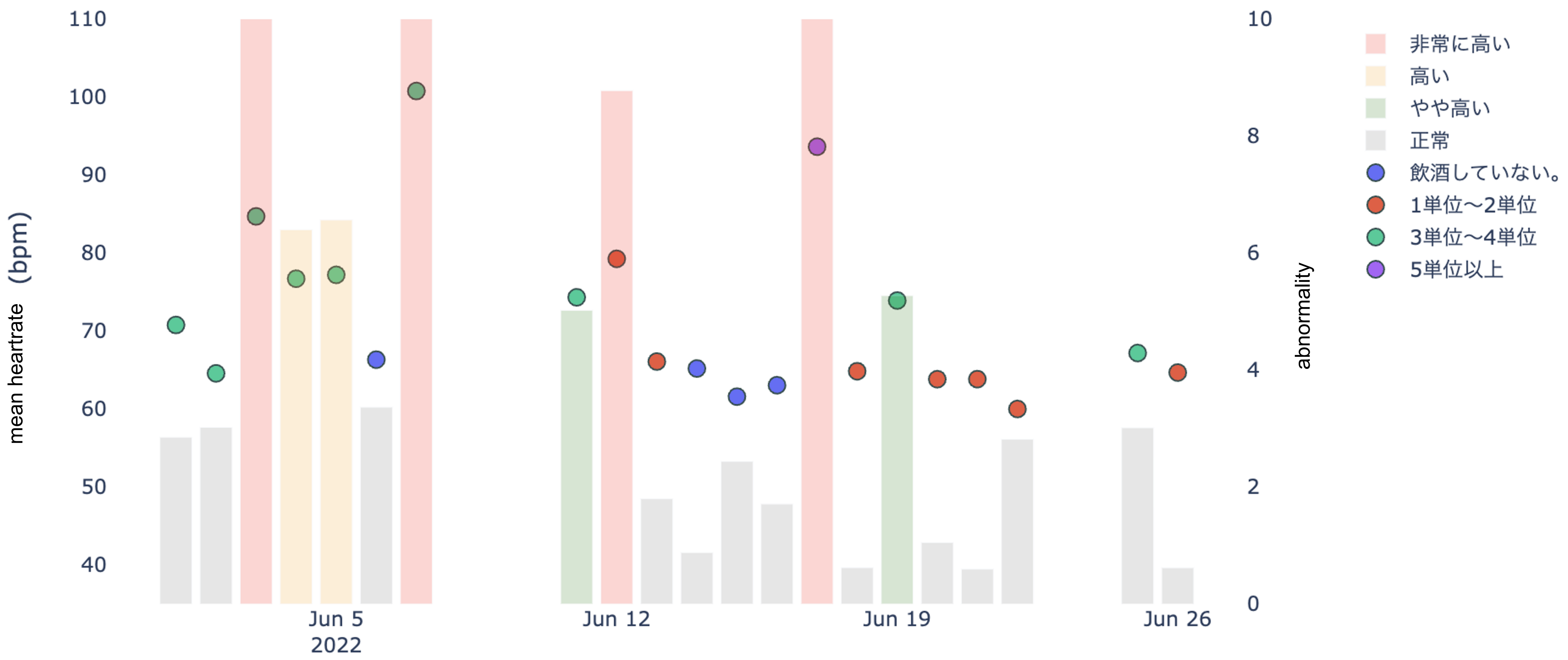
Application example 1



- Those who regularly drink alcohol
- The day of drinking (markers other than blue) is determined (red bar graph).

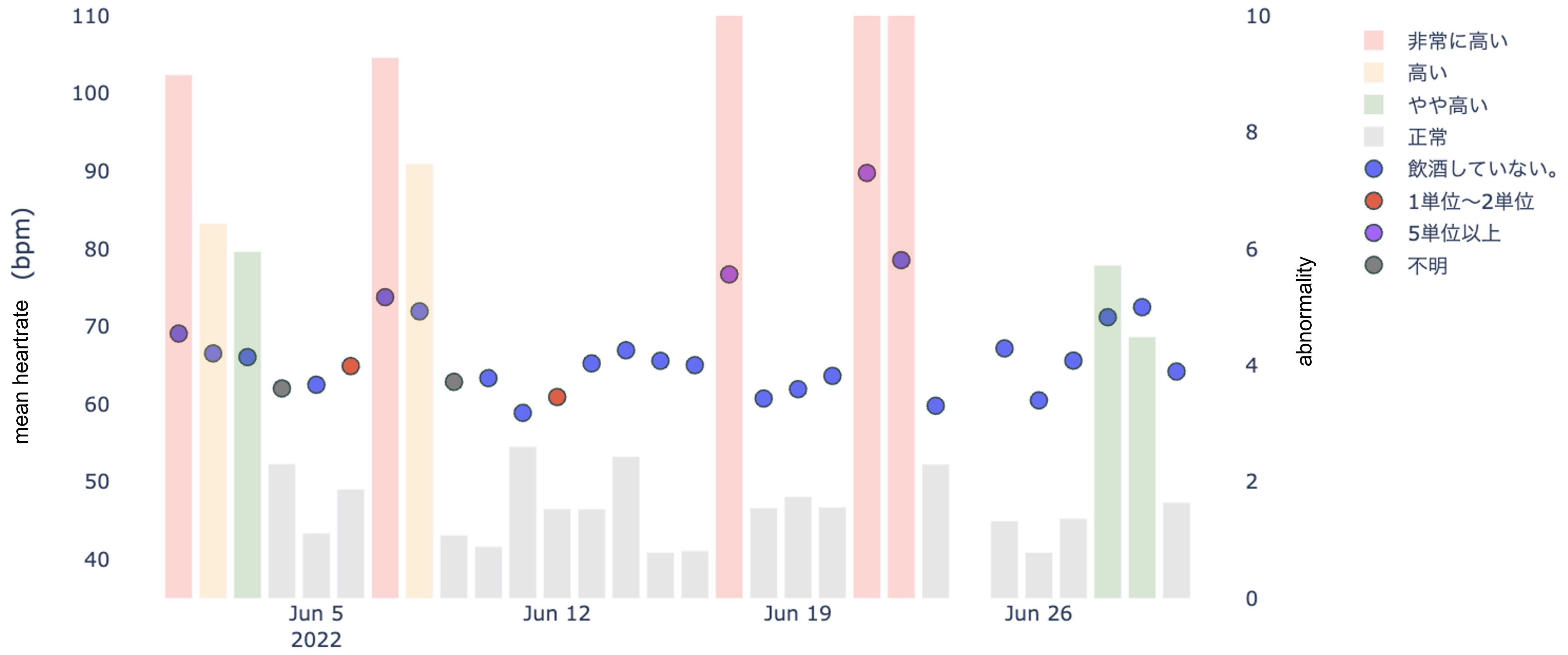
Application example 2

TECH DOCTOR



- High frequency of alcohol consumption
- Detected only on days of significantly increased heart rate

Application example 3



- Those who sometimes have a high heart rate even on days when there is no alcohol consumption
- Detected on days other than those on which the heartrate increased markedly due to alcohol consumption

Increase in personal data

+

Lifestyle quantification (custom/rhythm)

Personalization

validation study

Case1.

Validation with medical devices

validation with medical devices

Some heart rate variability metrics correlate well with medical devices

TECH DOCTOR

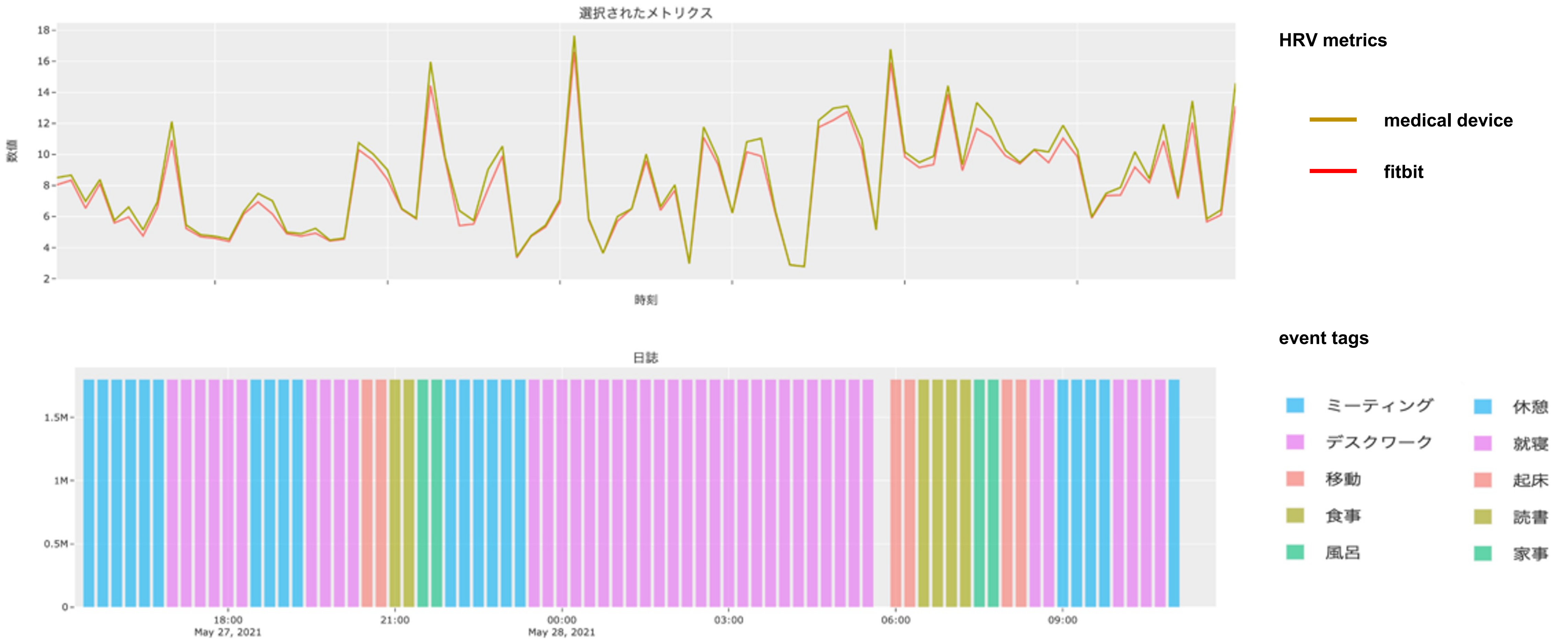
- Experiments
  - 8 subjects（2weeks）
  - Acquire heartrate data for at least one day for each subject while wearing fitbit and medical device at the same time
    - Register event tags by time, such as desk work, meals, bedtime, etc.
  - Calculation of correlation coefficients for each pair of data, taking into account the time-series nature of the data.
    - Perform tests necessary for working with time series data
    - Perform numerical transformations (logarithmic, factorial) appropriate to the state of each vector
    - Calculation of correlation coefficients
- results
  - Check correlations in the following metrics
    - Correlations were higher at bedtime than at activity

correlation	Aggregation in 15-minute increments	Aggregation in 30-minute increments
0.9 ≤ x < 1.0 : Strong	mean-HR、median-HR、mode-HR、mean-RRI、median-RRI、mode-RRI	mean-HR、median-HR、mode-HR、mean-RRI、median-RRI
0.8 ≤ x < 0.9	median-diff_RRI	mode-RRI、mean-diff_RRI、RMSSD、SDNN
0.7 ≤ x< 0.8	std-HR、CVRR	CVI（cardiovagal index）、CVRR、modified CSI（cardiac sympathetic Index）、SDSD、SD1、SD1、std-HR
0.6 ≤ x < 0.7 : weak	mean-diff_RRI、SDNN	NN50、PNN50

validation with medical devices

Some heart rate variability metrics correlate well with medical devices

Comparison plots of HRV metrics（sample）



Case2.

supplementary exam

About stress

TECH DOCTOR

Relationship between stress and HRV

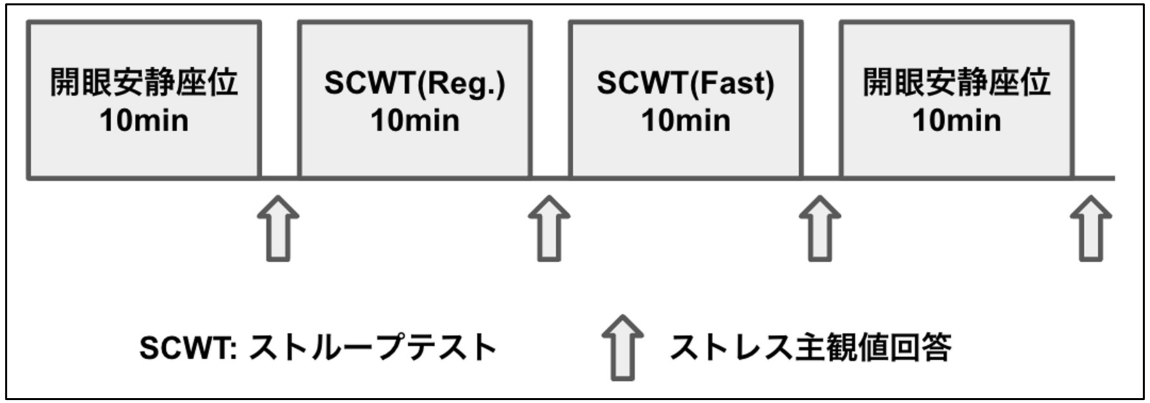
- Heart rate variability is used as an indicator of circulatory function, which is regulated by the interaction of two autonomic nervous systems, sympathetic and parasympathetic.
- There are many confounding factors other than mental stress on the autonomic nervous system (season, temperature, posture, etc.).

	acute stress	Chronic Stress
Evaluation Methods	● speech test / Cognitive test ● TSST[*1] / Stroop Test[*2]	● questionnaire[*3] ● Comparison of prevalent and healthy subjects[*4]
Relationship to HRV	● HRV (LF/HF, etc.), a sympathetic index, increases and HRV (HF, etc.), a parasympathetic index, decreases during the intervention[*5, 6] ● If respiration is not controlled during the intervention, HRV including respiratory components (e.g., SDNN and HF) may increase[*5, 7]	● HRV (SDNN) was lower under chronic stress for those with higher stress levels[*3] ● The sick had greater RRI at rest and higher LF/HF than the healthy subjects.[*4]
Case studies related to wearable devices	● Neural network was constructed using HRV (SDNN, RMSSD, average RRI, etc.) as features based on Apple Watch heart rate data(AUC=0.75)[*8]	● Analysis of Oura Ring HRV (RMSSD), sleep, acceleration data, etc. and DASS-21 showed a significant positive correlation between HRV and anxiety[*9]

*1 Kirschbaum et al. (1993), *2 Stroop(1935), *3 Seo (2016), *4 Lucini et al. (2005), *5 Rodorigues et al. (2018), *6 矢島ら (2010), *7 Schubert et al. (2009), *8 Dalmeida & Masala (2021), *9 Moshe et al. (2021)

stress test **Outline of Experiment**

- **Subject**：TechDoctor 14employees（males:11、famales:3）
- **Conditions**
  - No eating or drinking for 2 hours prior to the start
  - No caffeine or alcohol on the day of the experiment
  - No post-exercise or sleep deprivation
  - Light, quiet room, and a room temperature that is not uncomfortable
- **Protocol**
  1. After 10 minutes of rest, answer the stress value
  2. Stroop test with presentation time of 1.5 seconds (medium speed) for 10 minutes and answer the stress value
  3. Stroop test with presentation time of 1 second (fast speed) for 10 minutes and answer the stress value
  4. After 10 minutes of rest, answer the stress value
- **Stroop test**
  - Answer the color of the letters displayed on the screen within the time presented.
  - Presentation time is 1.5 seconds and 1 second
  - The letters and colors are red, blue, yellow, green, and purple, including combinations of the same color as the letters.



outline drawing

screen image

stress test　**experimental results**

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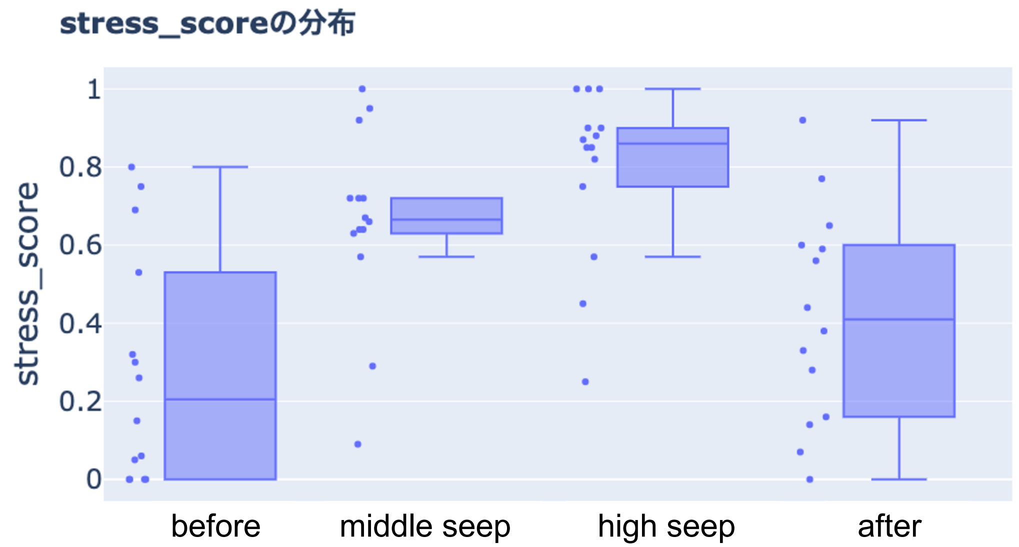
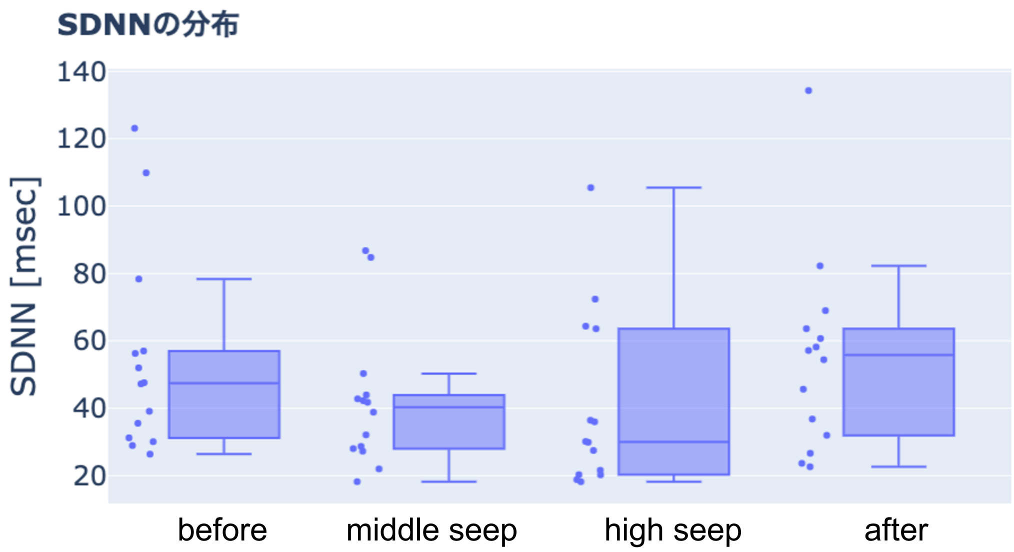
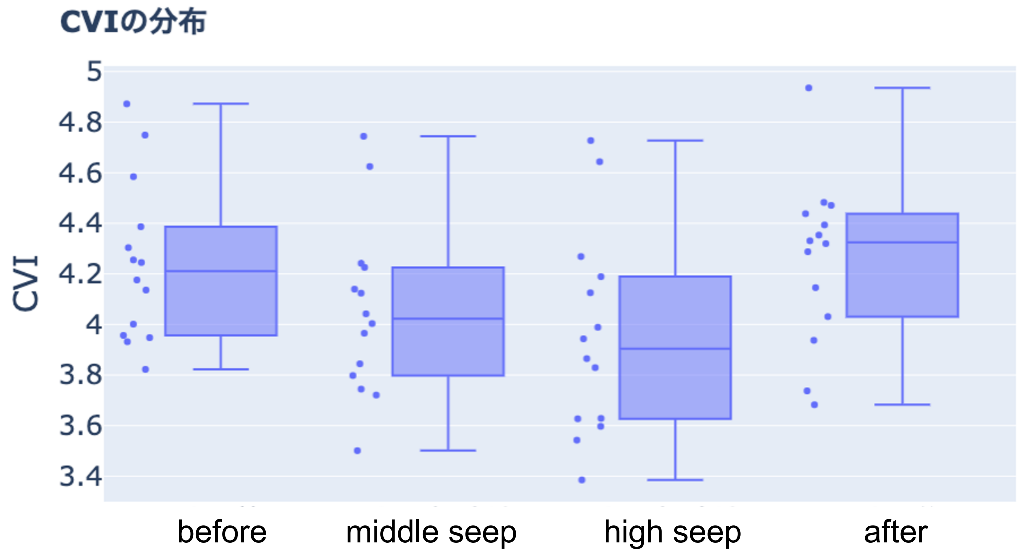




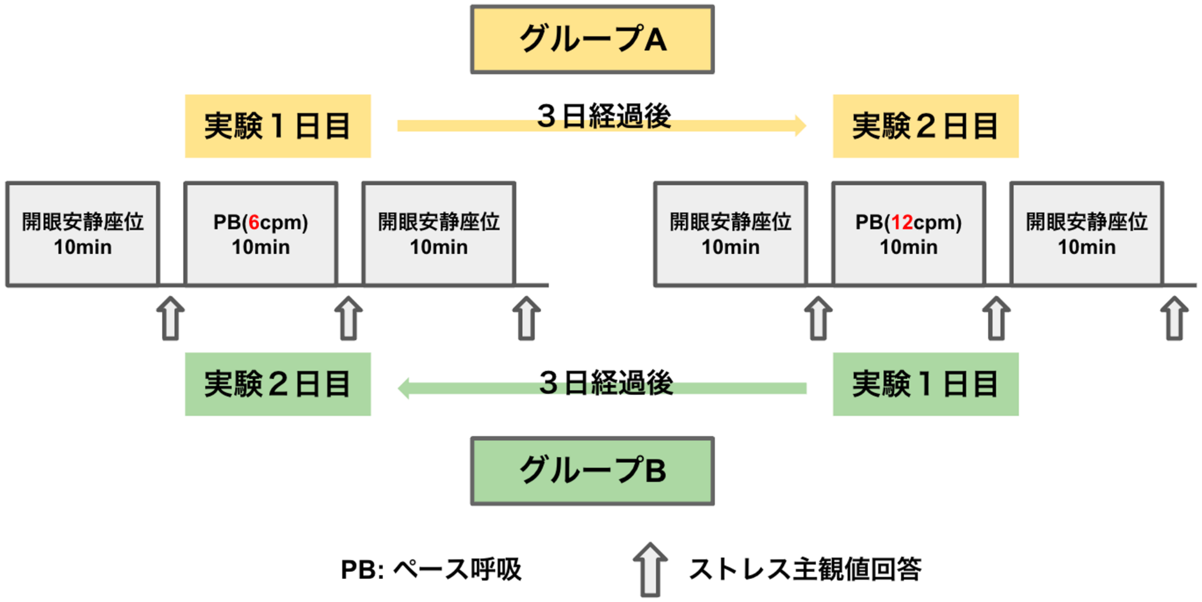


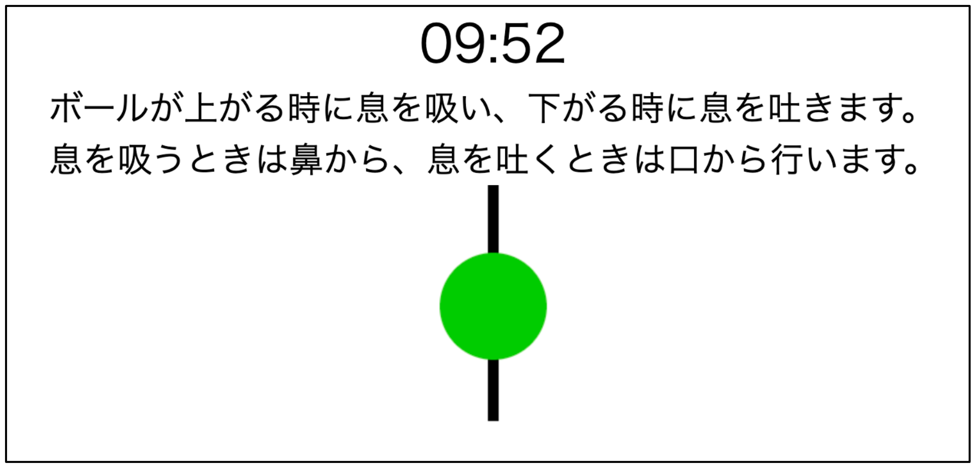
- Stress subjective values showed significant differences (5% level of significance) except for the pre- and post-intervention combinations, with the fastest presentation time condition being the most stressful.
- SDNN did not show significant differences across experiments ($p=.093$), but appears to decrease from pre-intervention toward the fast presentation condition and increase after intervention
- CVI showed significant differences across experiments ($p=.010$), and the distribution was similar to that of SDNN.

stress reduction test　**Outline of Experiment**

TECH DOCTOR

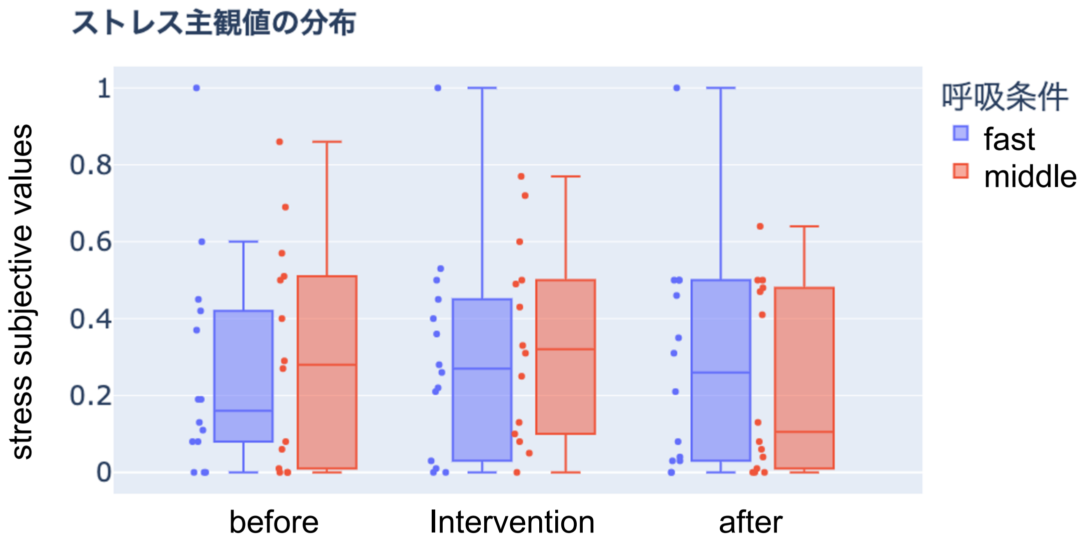
- **Subject**
  - TechDoctor 15employees（males:12、females:3）
  - 2groups (A: males:7、females:1　B: males:5、females:2)
- **Conditions:** same as stress test
- **Protcol**
  1. After 10 minutes of rest, answer the stress value
  2. Paced breathing (A: low-speed, B: medium-speed) for 10 minutes, followed by response of stress values
  3. After 10 minutes of rest, answer the value of stress
  4. After 3 days from the day of the experiment, the paced breathing conditions were changed and the same steps 1-3 were conducted.
- **Paced breathing**
  - Breathe in when the sphere on the screen rises and breathe out when it falls.
  - 6 breaths per minute (slow speed) and 12 breaths per minute (medium speed)
  - 2:3 ratio of inhalation to exhalation
  - Practice at least 5 minutes before the experiment (to prevent hyperventilation)

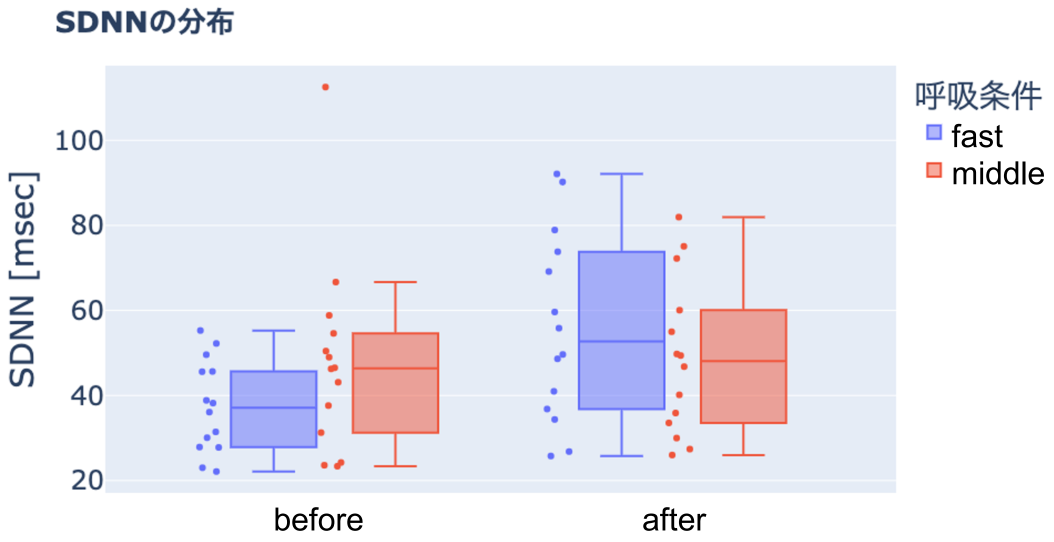


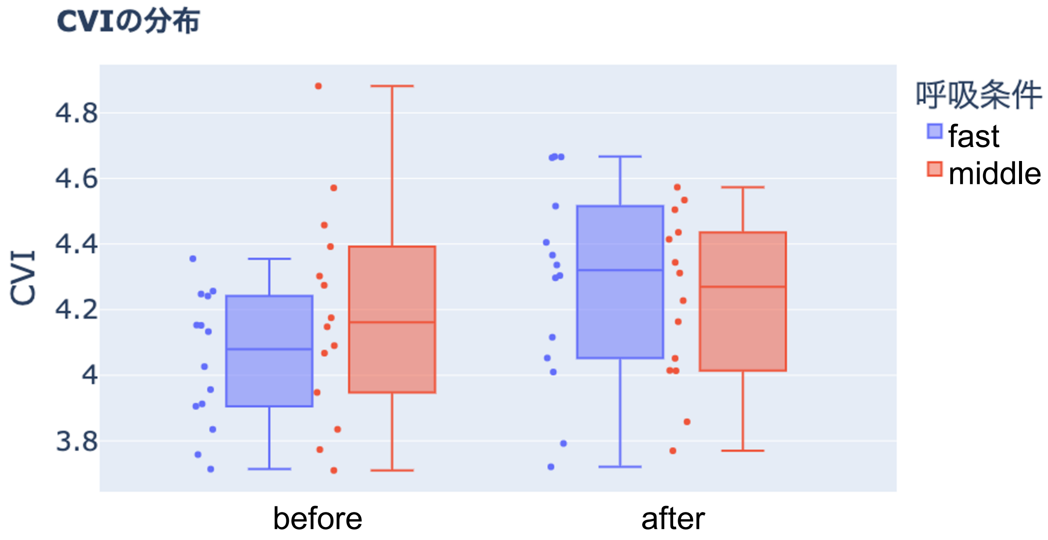


screen image

stress reduction test **experimental results**







- No significant differences in subjective stress values were found for the factors of time (before, during and after intervention) and breathing conditions (5% level of significance).
- In the SDNN, there was a significant difference in the amount of change before and after the intervention between the breathing conditions (p=.035), with the slow breathing condition showing a greater increase.
- In CVI, there was no significant difference in the amount of change between pre- and post-intervention between breathing conditions (p=.058), but the distribution showed a similar trend to that of SDNN.

Summary

TECH DOCTOR

		stress reduction			stress		
		P-value	eff-size(r)	sig-diff	P-value	eff-size(r)	sig-diff
time domain	mRRI	0.426	0.160		0.494	-	
	SDNN	0.035	0.397	*	0.093	-	
	CVRR	0.049	0.374	*	0.093	-	
	RMSSD	0.358	0.184		0.002	0.445	*
	SDNN/RMSSD	0.011	0.469	*	0.934	-	
	PNN25	0.715	0.077		0.009	0.564	*
frequency domain	LF	0.078	0.338		0.063	-	
	HF	1.000	0.006		0.027	0.362	*
	LF/HF	0.020	0.433	*	0.836	-	
	nLF	0.058	0.362		0.836	-	
	nHF	0.058	0.362		0.836	-	
non linear domain	SD1	0.358	0.184		0.002	0.445	*
	SD2	0.035	0.397	*	0.093	-	
	CSI	0.009	0.480	*	0.934	-	
	modCSI	0.058	0.362			-	
	CVI	0.058	0.368		0.010	0.433	*
	CCM	0.009	0.480	*	0.993	-	
	modCCM	0.426	0.160		0.001	0.469	*

Remarks

- P-values and effect sizes for the reduction experiment were calculated by performing a Wilcoxon signed rank sum test on the pre- and post-intervention changes between respiration conditions.
- P-values for the loading experiment were calculated using the Friedman test for time (before, during, and after the intervention).
- Multiple comparison analysis was performed only for HRVs for which significant differences were found, and effect sizes are shown for pre-intervention and fast conditions.

case study

AMED* Rheumatology Study Uses Wearable Device

公募情報

令和3年度「医療機器等における先進的研究開発・開発体制強靭化事業（健康・医療情報活用技術開発課題）」の採択課題について

採択内容

国立研究開発法人日本医療研究開発機構（AMED）は、令和3年度「医療機器等における先進的研究開発・開発体制強靭化事業（健康・医療情報活用技術開発課題）」（公募期間：令和3年4月28日から令和3年5月31日）を実施する委託研究開発先について、課題評価委員会（別紙） PDF において厳正な審査を行った結果、以下の通り、採択研究課題を決定しましたのでお知らせいたします。

公募課題1：行動変容により重症化予防等が期待できる治療分野に該当する健康データを医療現場等で活用する手法の研究開発

研究開発課題名	研究開発代表者名	所属機関	役職
経皮的冠動脈形成術術後の重症化予防を目的とする遠隔行動変容支援と外来診療との効果的連携に関する研究開発	天野 哲也	愛知医科大学	教授
食事療法の計画・実行支援AIプログラムによりPHR・EHRを糖尿病重症化予防医療に活用する仕組みの研究開発	稲垣 暢也	京都大学	教授
週次グリコアルブミン検査データの医師-患者間共有による糖尿病患者の行動変容誘発・重症化予防システムの開発	関水 康伸	株式会社PROVIGATE	代表取締役

（敬称略 五十音順）

公募課題2：神経・運動機能障害分野に該当する健康データを医療現場等で活用する手法の研究開発

研究開発課題名	研究開発代表者名	所属機関	役職
関節リウマチの遠隔診療に向けたIoTデジタルデバイスによる日々の生体データ活用法の確立	金子 祐子	慶應義塾大学	教授

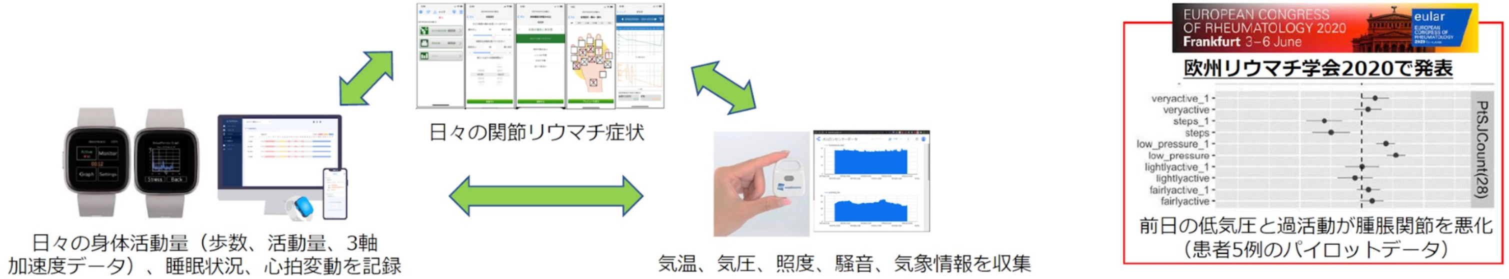
*Japan Agency for Medical Research and Development

研究開発項目1

日常の症状を簡便かつ詳細に把握する方法の開発
および診療の質向上への有用性確立

1-3
日常の症状と生活・環境要因の関連性解明

・腕時計型ウェアラブルデバイスによって日々の身体活動量、睡眠状況、心拍変動を記録
・ポータブル環境センサーで、気温、気圧、照度、騒音や気象情報を収集
・生活環境要因と日々のリウマチ症状との関連性証明と、機械学習による症状予測モデルを開発



成果：日常の症状と生活・環境要因が日常症状に与える影響を解明し、セルフモニタリング・リモートモニタリングによる身体負荷管理や薬剤使用が可能となる

- Analyze the impact of lifestyle and environmental factors on symptoms
- Development of a symptom prediction model

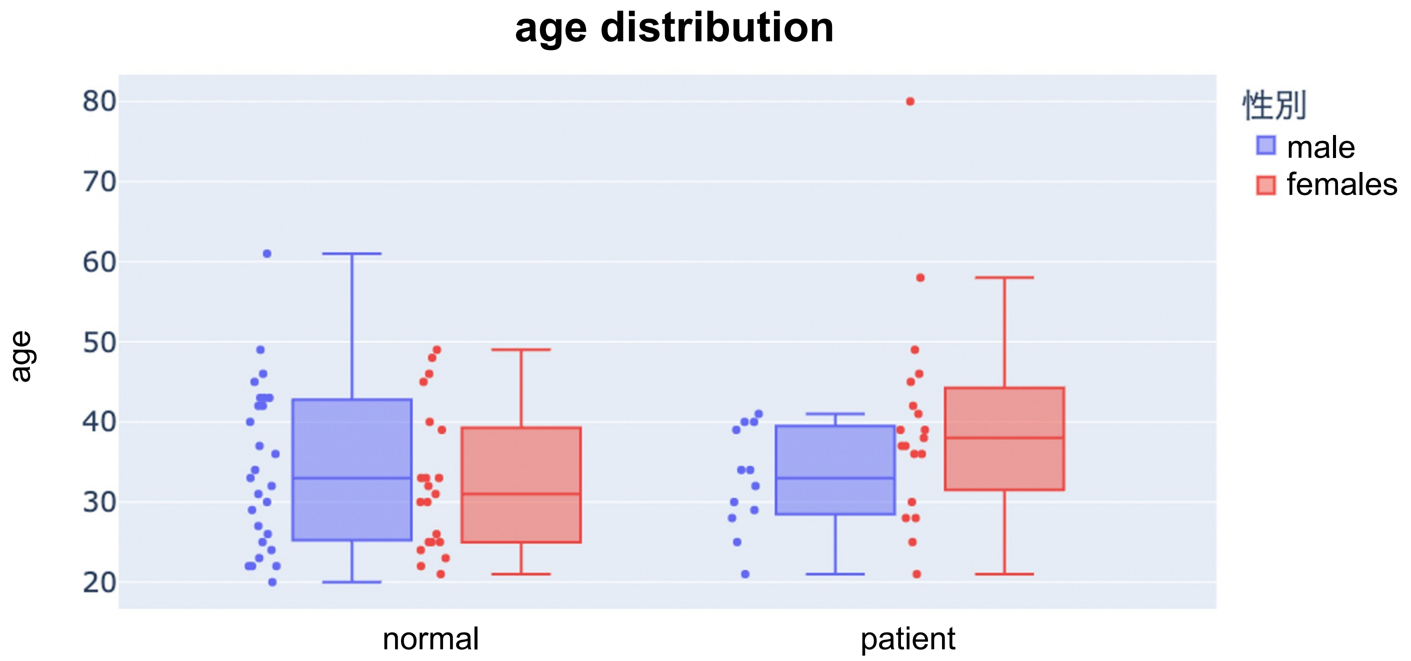
TECH DOCTOR

Cases in the area of mental illness

Machine Learning Model Building ～Classification model for mentally ill and normal subjects～

model for the mentally ill and normal subjects

- **data summary**
  - subjects : Prevalent patients with mental disorders attending clinics : 31、normal : 48
    - (Cases include depression, schizophrenia, bipolar disorder, etc.)
  - period : 2021-01-01 ~ 2022-04-12
    - Because each person wears fitbit at different times, the number of days of data acquisition for each individual is also different.



subjects info

	patient		normal	
gender	**males**	**females**	**males**	**females**
num	12	19	27	21
avg-age	32.8	39.7	34.3	32.4

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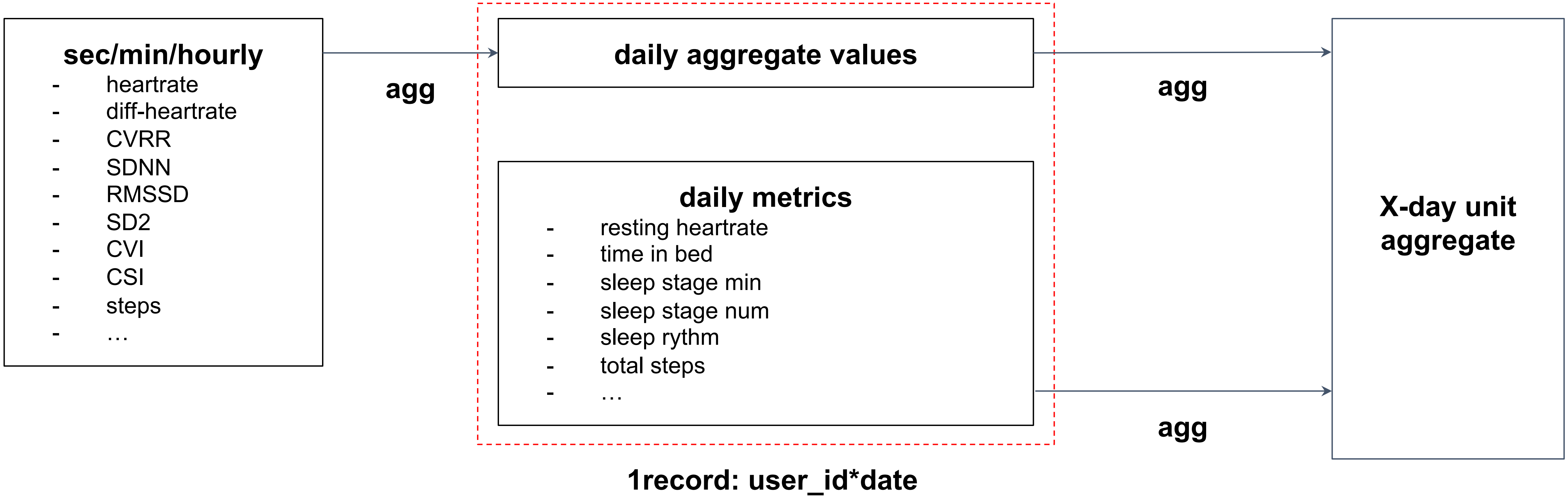
feature engineering

- **missing value**
  - Exclude records with missing records when aggregating
- **seconds, minutes, hourly metrics(heartrate/hrv/steps) → Daily aggregate values**
  - Aggregate per day（mean/max/min/std）
  - sleep・30 min before and after sleep onset/waking up・non-sleep・sleep stages : Aggregate timing is subdivided
- **daily metrics（sleep, etc）→ X-day unit aggregate values(Set arbitrarily)**
  - Aggregate in X-day increments（moving avg/moving std）
    - If 60% or more of the data is missing, remove



feature selection

- **Exclusion of low-variance variables**
  - Variables with within-item variance less than the threshold of 0.95 x (1 - 0.95) were excluded
- **Inter-item correlation coefficients**
  - If the correlation coefficient between items exceeded the threshold value of 0.9, the variable with the smaller correlation coefficient (absolute value) with the objective variable was excluded
- **Exclusion by VIF**
  - If the maximum value of VIF exceeded 10, the feature was excluded and the process was repeated until no more features were found.

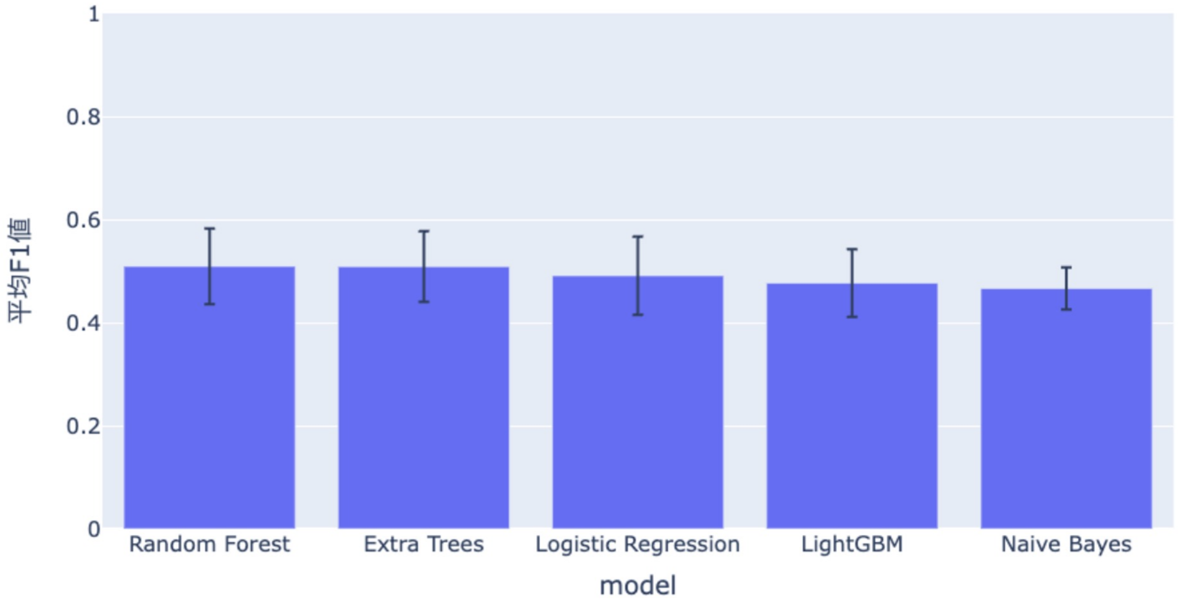
Examples of selected features

HRV	mean-PNN50 in light sleep, mean-PNN50 in rem sleep,min-PNN20 in sleep, max-modifiedCSI in daytime, min-modifiedCSI in daytime, std of min-heartrate in sleep, min-PNN50 in sleep, min-PNN20 in daytime, min-{max-min heartrate diff} in sleep, maxx-PNN50 in daytime, std-modifiedCSI in sleep
sleep	number of rem sleeps, number of deep sleeps, std-light sleep durations,min-light sleep durations, sleep latency, deep sleep duration in last sleep cycle, Mean duration of deep sleep during the sleep cycle in the second half of the sleep cycle, light sleep time in the first sleep cycle, std-REM sleep time during sleep cycle, REM sleep duration during the last sleep cycle, light sleep time during the last sleep cycle, deep sleep time in the first sleep cycle, mean deep sleep time during sleep cycle in the first half of sleep, difference between the mean value of shallow sleep time during the sleep cycle in the first and second half of the sleep cycle, min-deep sleep time during sleep cycle, difference in mean REM sleep duration during the sleep cycle before and after the sleep half, REM sleep duration during the first sleep cycle, min-REM sleep time during sleep cycle
steps	max hourly steps, min hourly steps, total steps

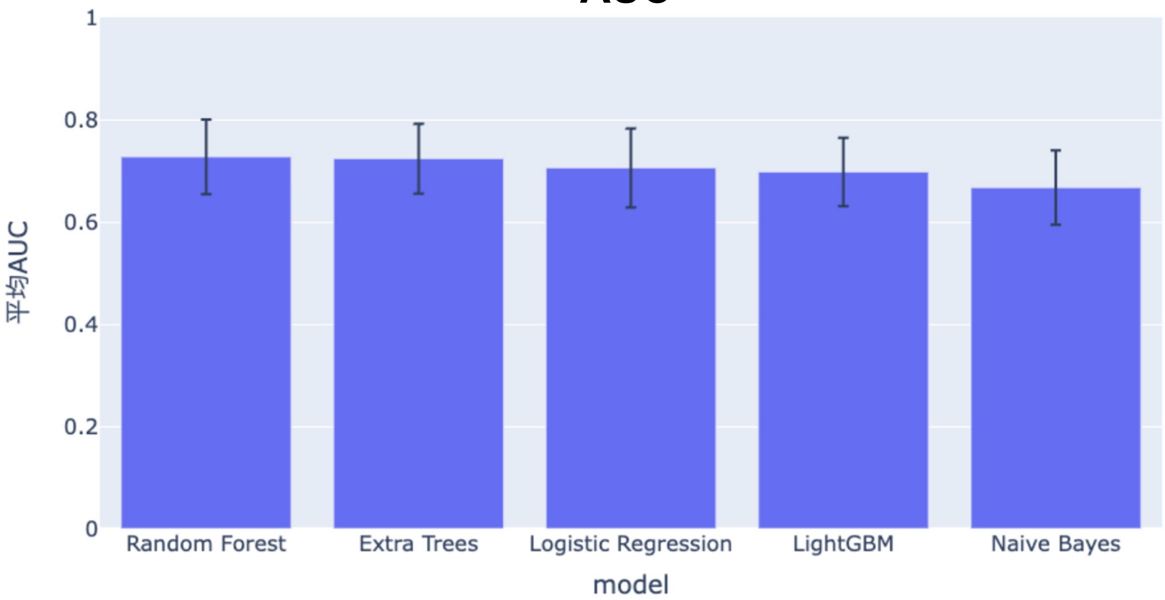
Construction and selection of classification models

- **under sampling**
  - Undersampling of data from healthy subjects in training data to equal the number of data from prevalent subjects
- **multiple model validation**
  - Validated with logistic regression, Random Forest, Extra Trees, LightGBM, NaiveBaise
- **cross validation**
  - Ensure that data for the same person exists in the same Fold when splitting, and that the ratio of prevalent data to healthy data is equal in each Fold.
  - The adopted model is determined based on the average AUC score and average F1 score for each Fold
- **hyper-parameter tuning**
  - Bayesian optimization to tune hyperparameters based on F1 scores

F1 scores



AUC



=> Random Forest

A case study of the construction of a classification model

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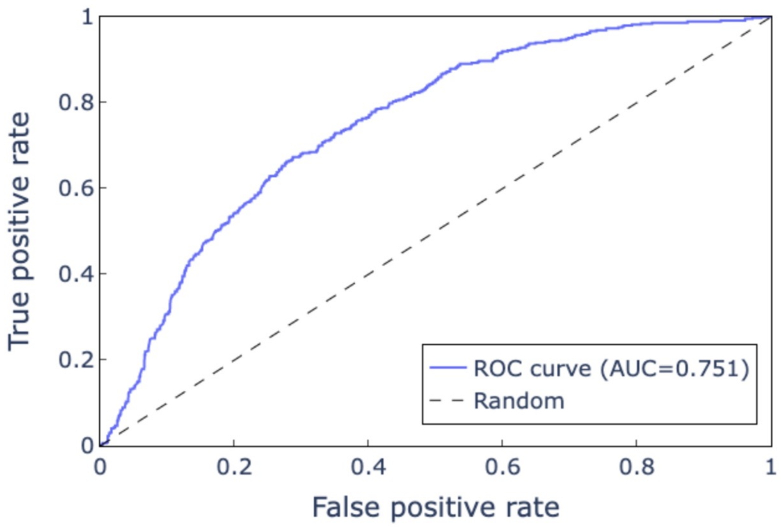
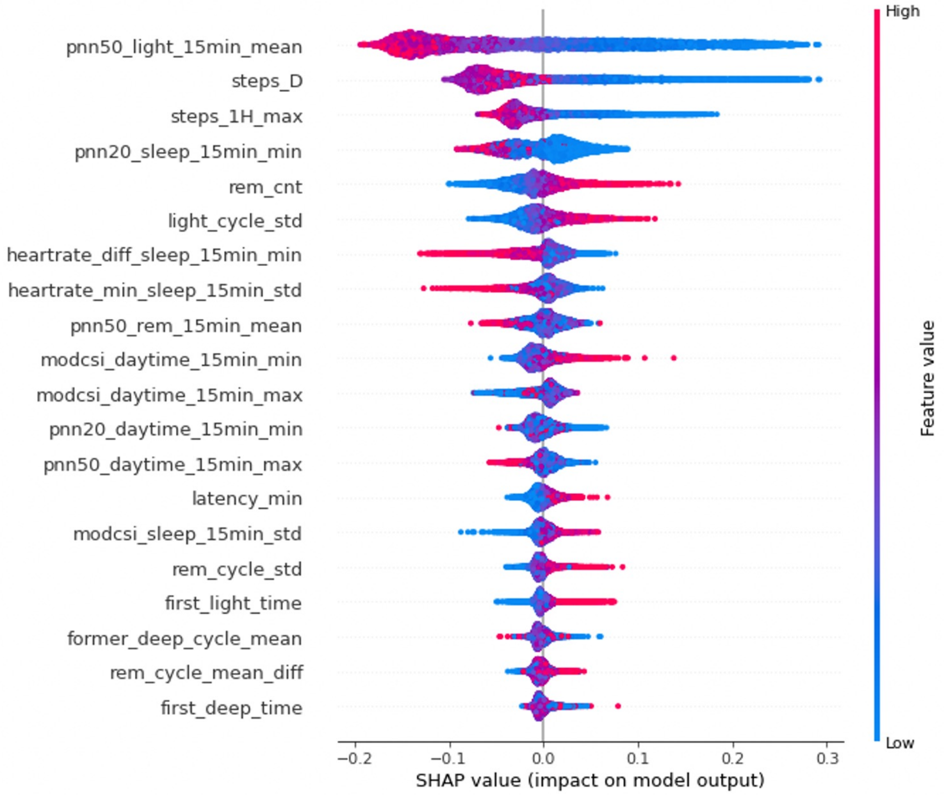
Random Forest

	accuracy	sensitivity	recall	F1score	AUC
mean	0.692	0.606	0.444	0.509	0.727

	予測健常者	予測有病者
健常者	909	344
有病者	155	292





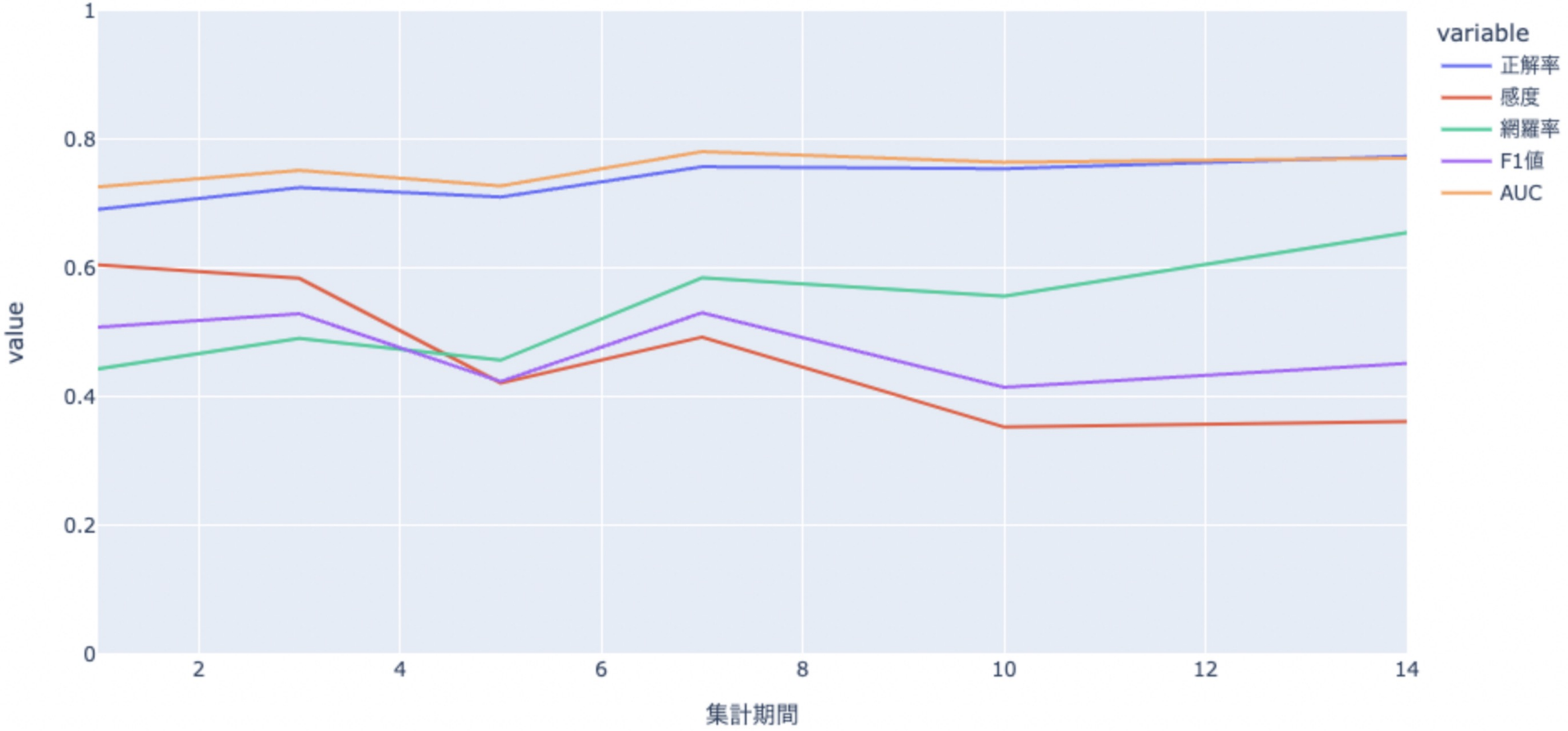
Classifies prevalent and healthy subjects with 69.2% accuracy

→ **<u>mean PNN50 during light sleep, smaller total number of steps taken in a day,</u>** higher prevalence probability

→ **<u>The prevalence probability increases with the number of occurrences of REM sleep and the std-light sleep during the sleep cycle.</u>**

Classification results for different aggregation units

- Verification of classification accuracy when the aggregation unit is 3, 5, 7, 10, or 14 days
  - Data for which the aggregation unit was 2, 3, 5, 5, and 9 days or longer, respectively, were used.
  - model : Random Forest



Increases in accuracy of AUC, correct response rate, and coverage rate are observed up to 7-day increments when the aggregation unit is changed.

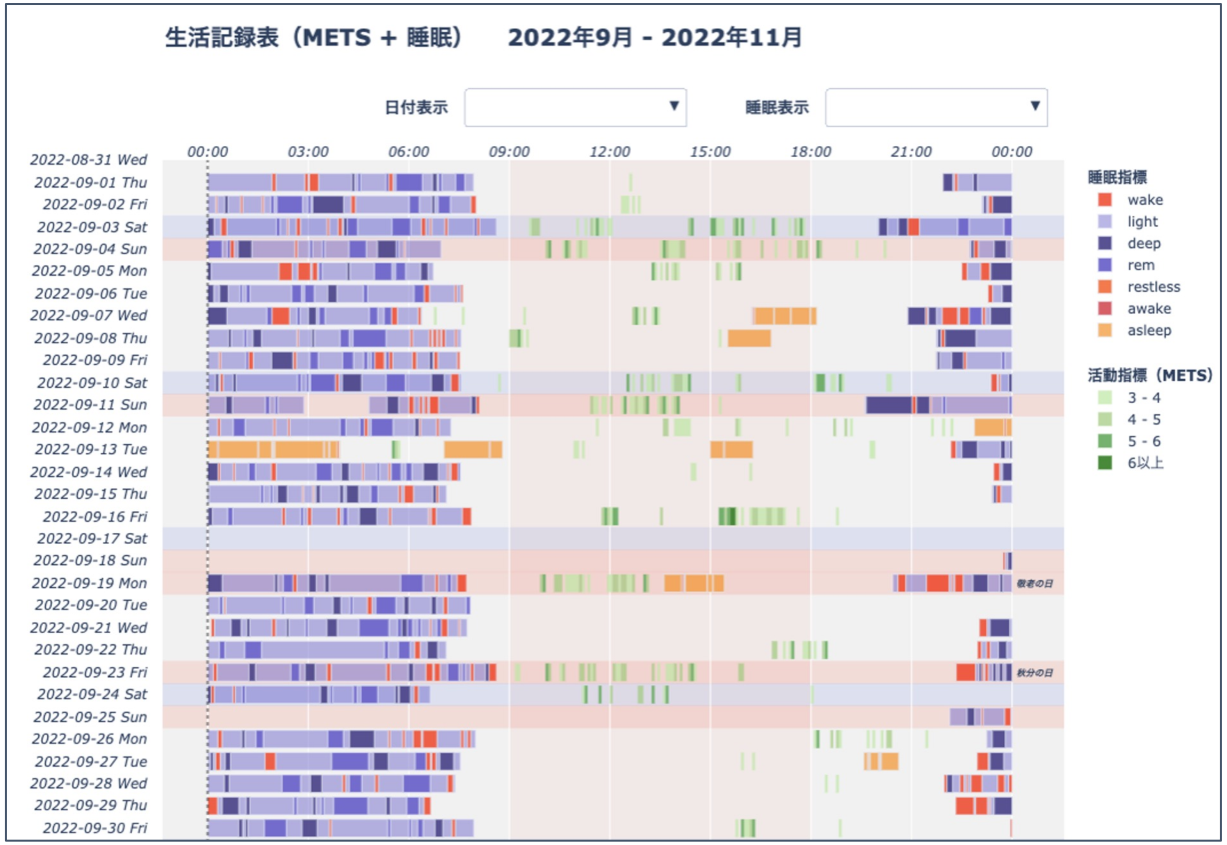
Application to Occupational Medicine

Personal Report

TECH DOCTOR

Industrial physicians and employees share data to check for disruptions in the rhythm of daily life, and search for indicators that best describe each employee's condition in collaboration with the industrial physician.

Visualization of activity and sleep data



Search for individual indicators

データで“調子”を良くする時代へ

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