



Time-Series Wearable Activity Forecasting

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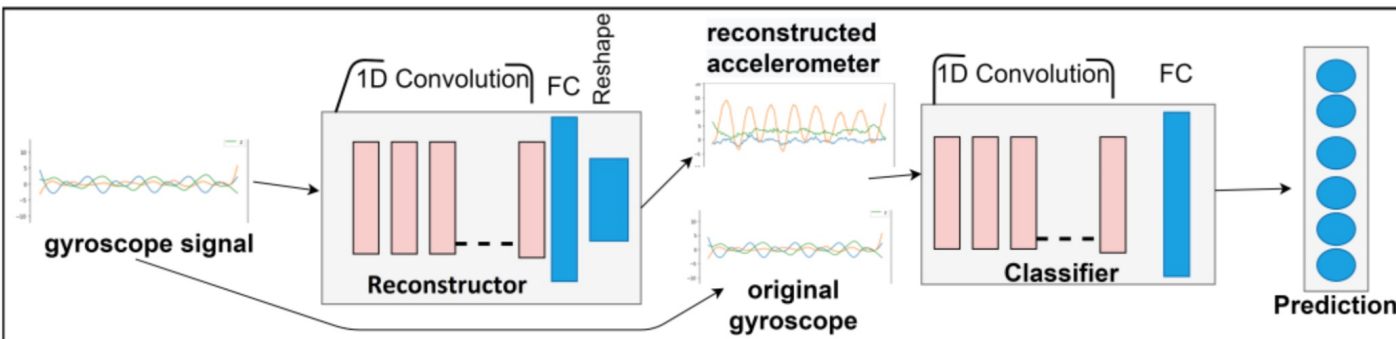
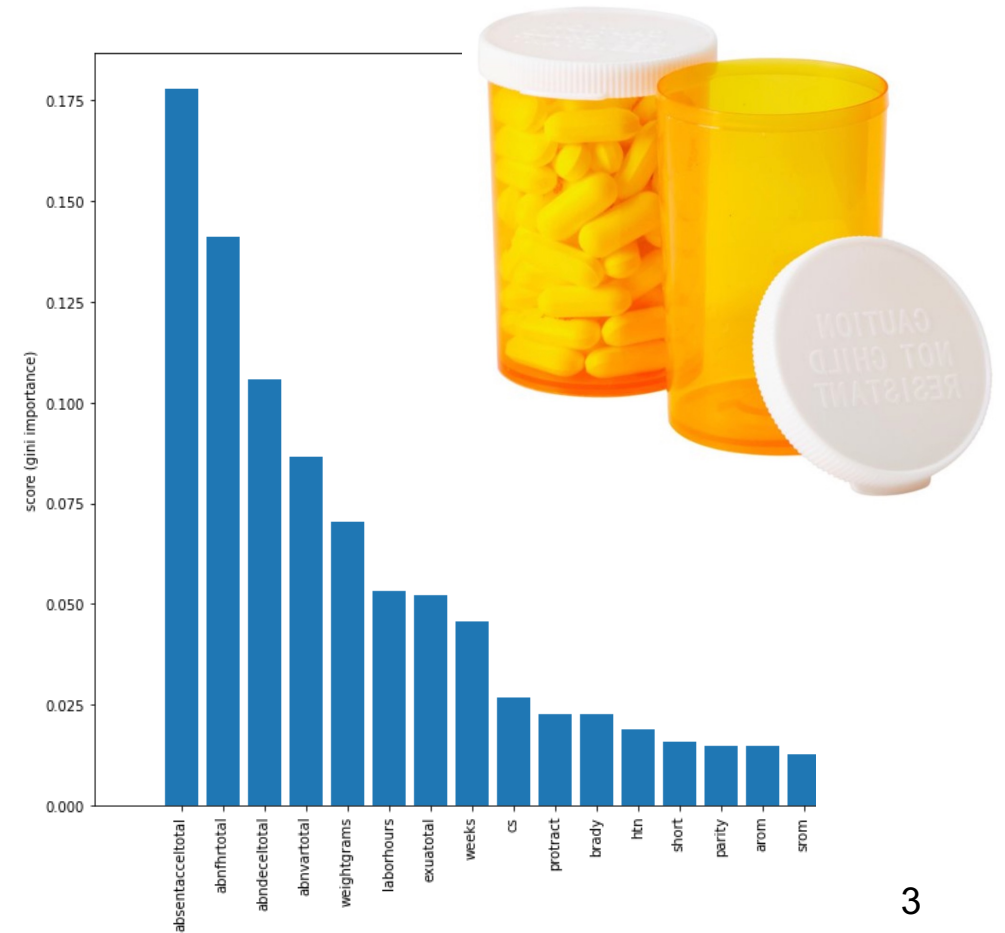
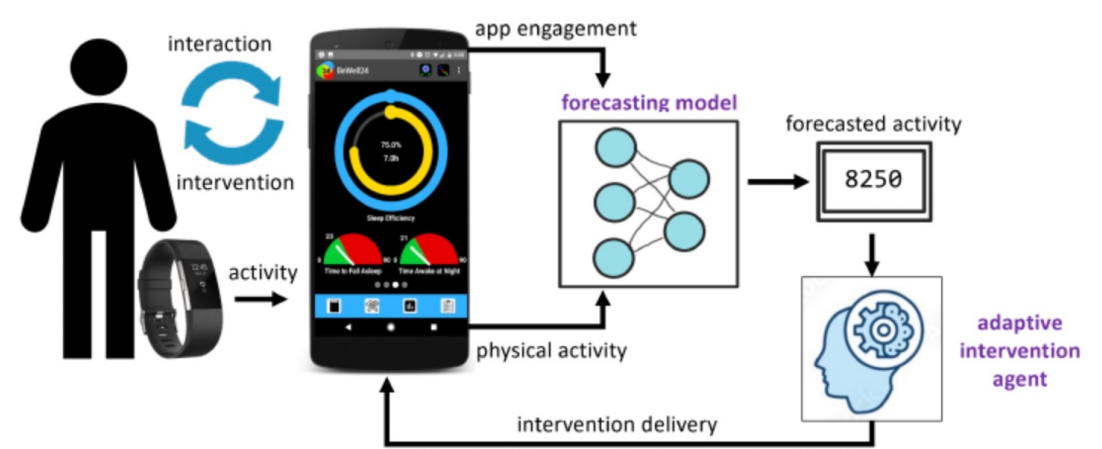
MS Students



Chia-Cheng Kuo

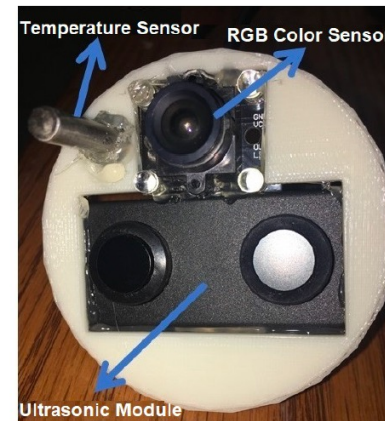
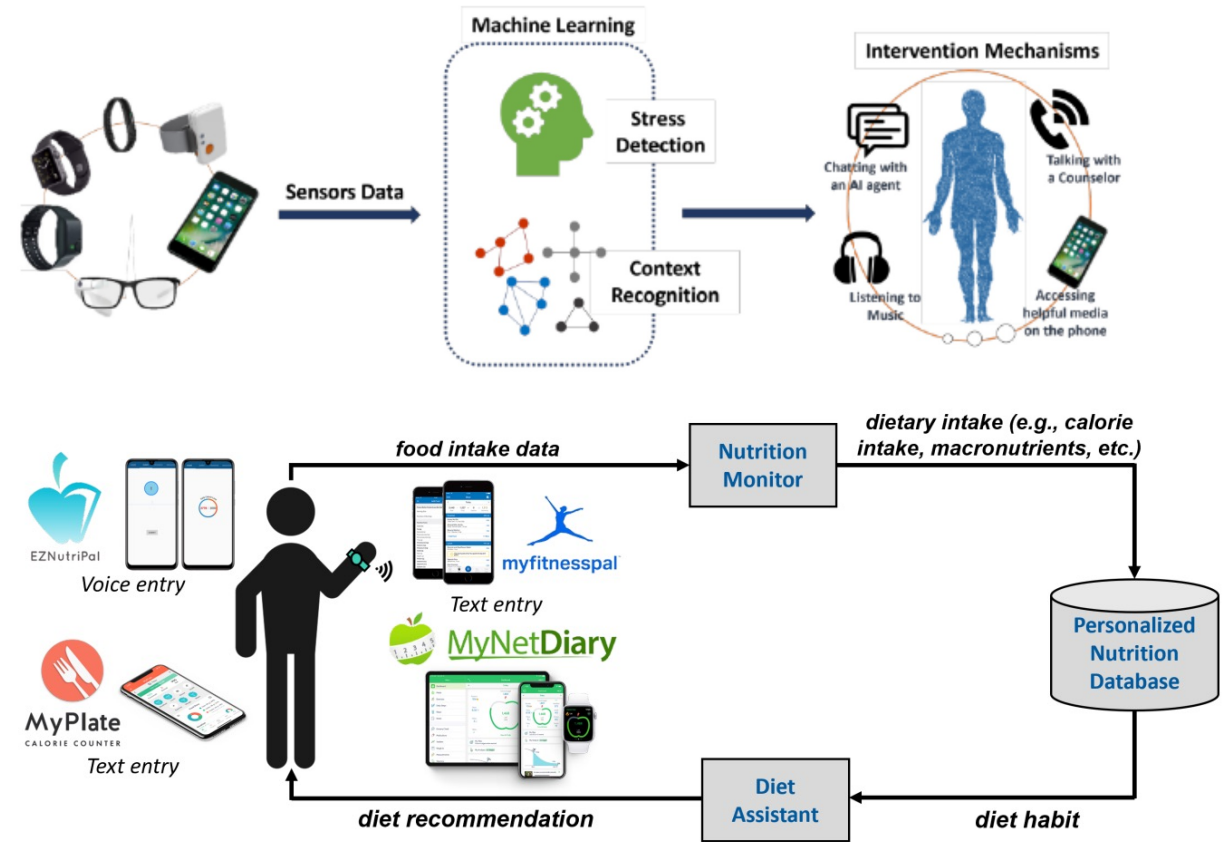
Research area of EMIL (1/2)

- Physical activity forecasting
- Treatment adherence
- Robust multi-sensor system design
- Keeping labor safe (KLS)



Research area of EMIL (2/2)

- Diet, fluid intake, and Continuous Glucose Monitoring
- Stress monitoring
- Causal discovery and causal inference
- Human-in-the-Loop Learning



(a) LIDS prototype



(b) Tested bottles for evaluation

Ongoing user studies



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ASU COLLEGE OF HEALTH SOLUTIONS RESEARCH STUDY:

HUMAN-IN-THE-LOOP DATA COLLECTION USING WEARABLE SENSORS FOR MACHINE LEARNING ALGORITHM DESIGN

We are recruiting healthy individuals to collect sensor, image, and contextual data for human activity and behavior analysis using wearable devices.



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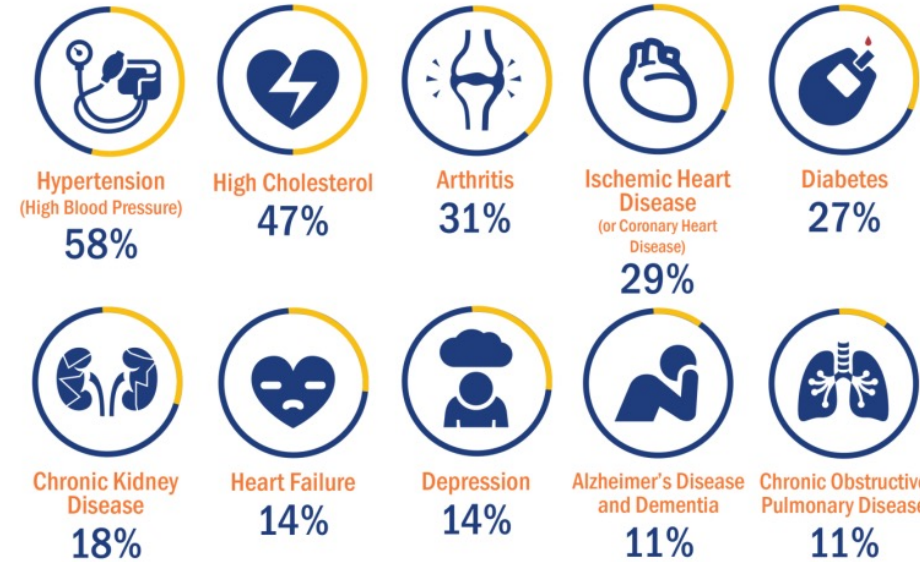
ASU COLLEGE OF HEALTH SOLUTIONS RESEARCH STUDY:

DIET & BEHAVIORAL DATA COLLECTION WITH WEARABLE SENSORS

WE ARE RECRUITING HEALTHY INDIVIDUALS TO MONITOR THE EFFECTS OF NUTRITION ON DIFFERENT PHYSIOLOGICAL PARAMETERS OF HUMAN HEALTH USING WEARABLE DEVICES.

Time-Series Wearable Activity Forecasting - Motivation

- Prevalence of chronic conditions
 - 6 in 10 adults has ≥ 1 chronic condition
 - 4 in 10 adults has ≥ 2 chronic conditions
 - 8 in 10 seniors ≥ 65 have at least 1 condition
 - 1 in 3 adults will have diabetes by 2050
- Burden of chronic conditions
 - 75% to 86% of healthcare spending
 - U.K. spends 9.9% of GDP on healthcare
 - U.S. spends 17.9% of GDP on healthcare
 - Heart disease and cancer account for 46% of all deaths



- CDS Chronic Disease Overview, 2020: <https://www.cdc.gov/chronicdisease>
- <http://dhss.alaska.gov/dph/Chronic/>
- Center for Medicare and Medicaid Services, Chronic Conditions Prevalence, 2015
- CDS Chronic Disease Overview, 2020 @ : <https://www.cdc.gov/chronicdisease>

Preventable & Manageable Diseases

- Prevent / delay
 - 80% of heart disease & stroke
 - 80% of type 2 diabetes
 - 40% of cancer
- Self-management
- By improving
 - Diet
 - **Physical activity**
 - Medication adherence
 - Symptom control
 - Healthy lifestyle



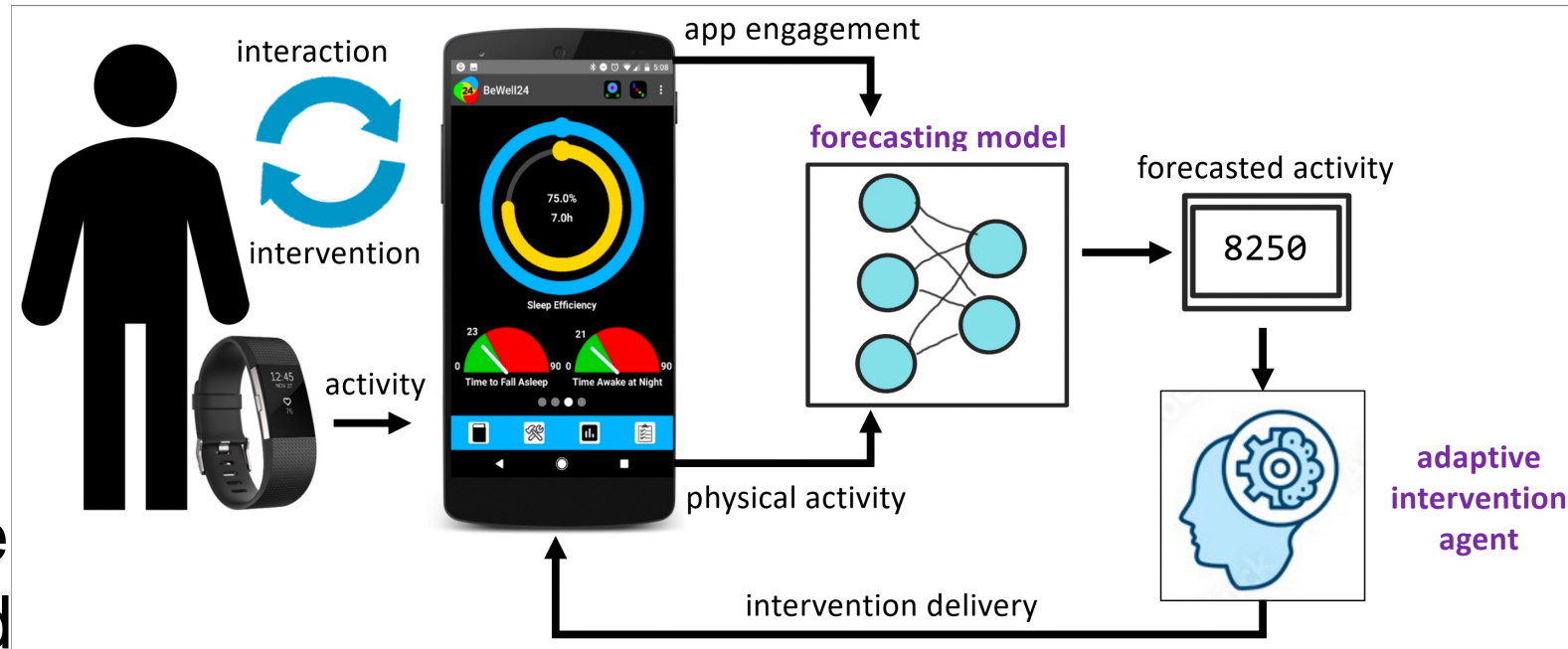
Importance of Engagement-based Interventions

- Mobile health (**mHealth**) interventions delivered through mobile apps have the potential to
 - **promote physical activity** and reduce sedentary time
 - **reduce the risk** of chronic diseases (e.g., cardiovascular disease, diabetes, and some cancers).
- There is some evidence suggesting a modest effect of these interventions in promoting healthy behaviors.



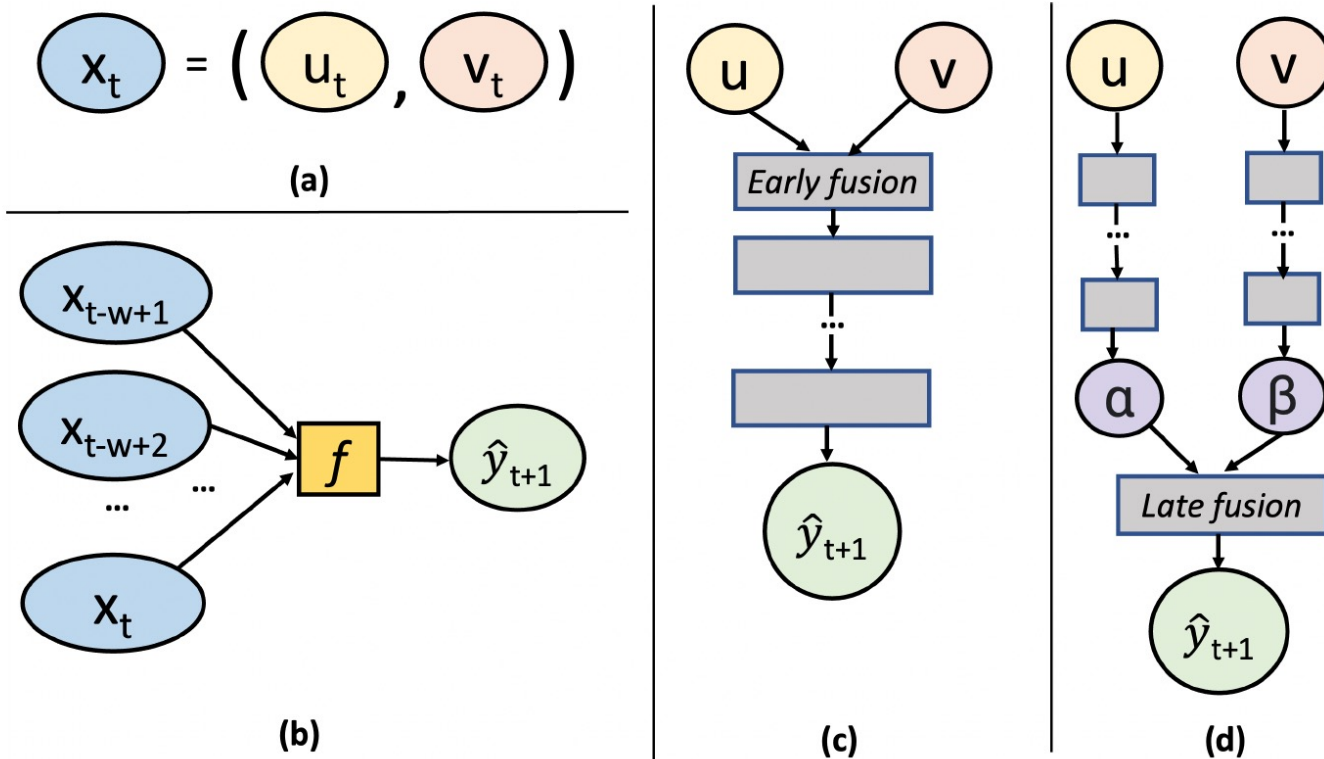
System overview

- An **adaptive** lifestyle intervention system
- A **human-in-the-loop** system with smartphone app, wearable wristband and a time-series activity forecasting model.



- Monitors **app engagement** and **physical activity** from the past and **forecast** the expected activity levels of the next day
- Based on the prediction, the system will provide recommendations and reminders (future work)

Multimodal Time-Series Activity Forecasting



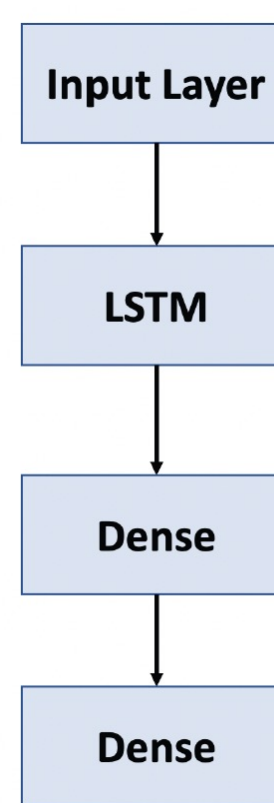
The multimodal forecasting model takes input from both modalities (activity and engagement) and forecasts the next day step count for a user.

Notations

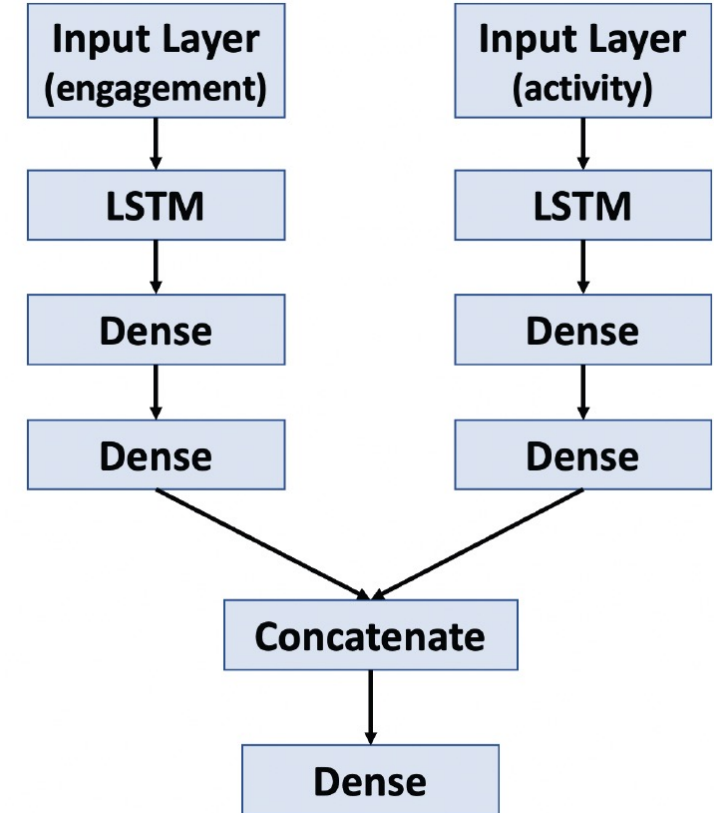
Symbol	Meaning
T	current time step
$T+1$	next time step
u_t	engagement measure for any t
v_t	physical activity measure for time t
X_t	embedding of the fusion of the two modalities, u_t and v_t
w	window size
y_{t+1}	is a physical activity outcome. The value we want to forecast
f	forecasting function
α, β	intermediate results

Implementation with machine learning

- Because of the **time-series** property of the input features, we choose **LSTM** (Long short-term memory) to capture the sequential features.
- Both single-modal and multimodal forecasting methods were implemented



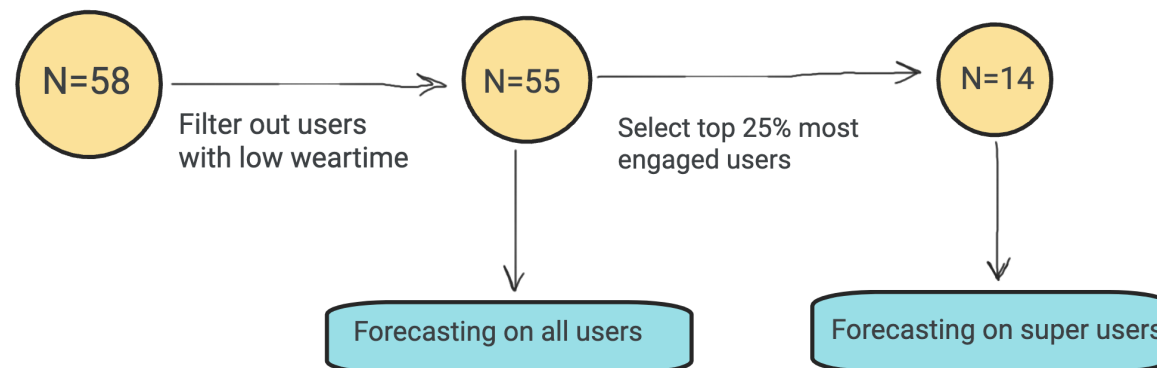
(a) *Early* fusion



(b) *Late* fusion

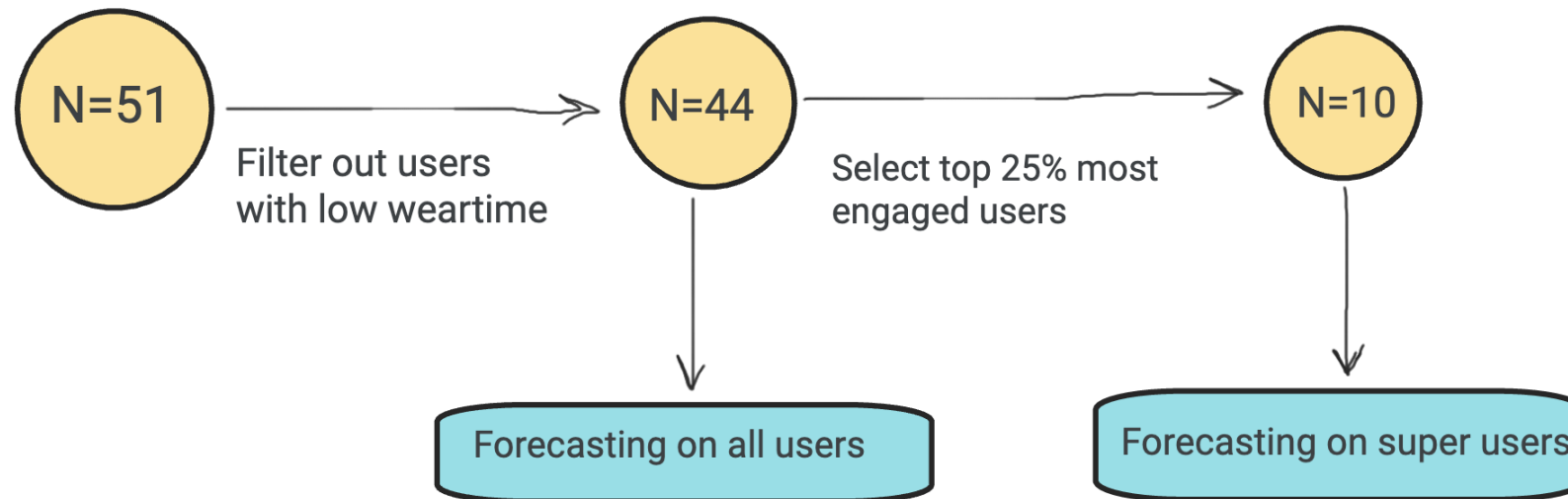
Dataset (1/2): BeWell24

- **58 veterans with prediabetes**
- Minute-level intervention app engagement (whether a user is using the app in a particular minute)
- Minute-level activity features from Fitbit, i.e., number of steps, sedentary, light physical activity (LPA), moderate-vigorous physical activity (MVPA) in seconds in a particular minute.
- We had to filter out 3 users with low wear-time (Data for less than 10 days, each of them having at least 10 hours of wear-time)
- Forecasting on super users: 14 most engaged users were selected.
- Forecasting on all users: 55 users were selected.



Dataset (2/2): SleepWell24

- **51 Mayo Clinic patients with obstructive sleep apnea (OSA)**
- Similar data as BeWell24.
- Additional data from continuous positive airway pressure (CPAP) therapy
- Similar data inclusion criteria
- Forecasting on super users: 10 most engaged users were selected.
- Forecasting on all users: 44 users were selected.



Results: Forecasting the number of steps

- Multimodal early fusion forecasting models achieve up to **22.7% and 19.1% lower mean absolute errors** than single-modal forecasting models on the prediabetes dataset and sleep dataset, respectively

TABLE IV: Performance of the LSTM model for activity forecasting on all users of the BeWell24 study.

<i>Metric</i>	<i>Multimodal (Late)</i>	<i>Multimodal (Early)</i>	<i>Single Modality (Engagement)</i>	<i>Single Modality (Activity)</i>
MAE	2620	2066	2673	2113

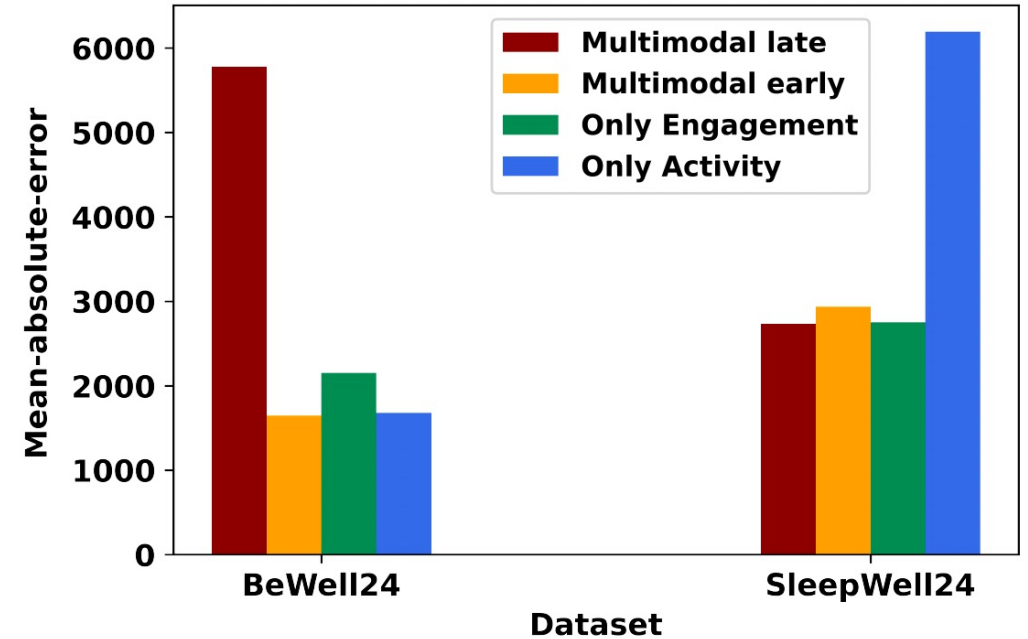
TABLE V: Performance of the LSTM model for activity forecasting on all users of the SleepWell24 study.

<i>Metric</i>	<i>Multimodal (Late)</i>	<i>Multimodal (Early)</i>	<i>Single Modality (Engagement)</i>	<i>Single Modality (Activity)</i>
MAE	7789	2900	3583	3032

Results: Forecasting the number of steps

- Multimodal early fusion forecasting models achieve up to **22.7%** and **19.1%** lower mean absolute errors than single-modal forecasting models on the prediabetes dataset and sleep dataset, respectively

Mean-absolute-error of regression forecaster - super users



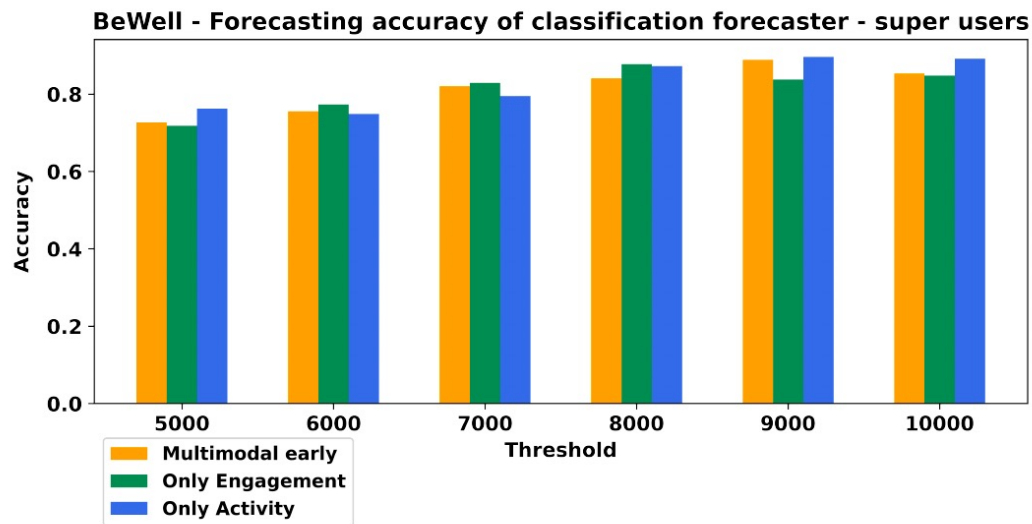
Results: Finding the window size

- How many days from the past should be considered for a forecasting a value of the future?
- We observe that a window size between 3 and 7 is ideal for these kind of data.

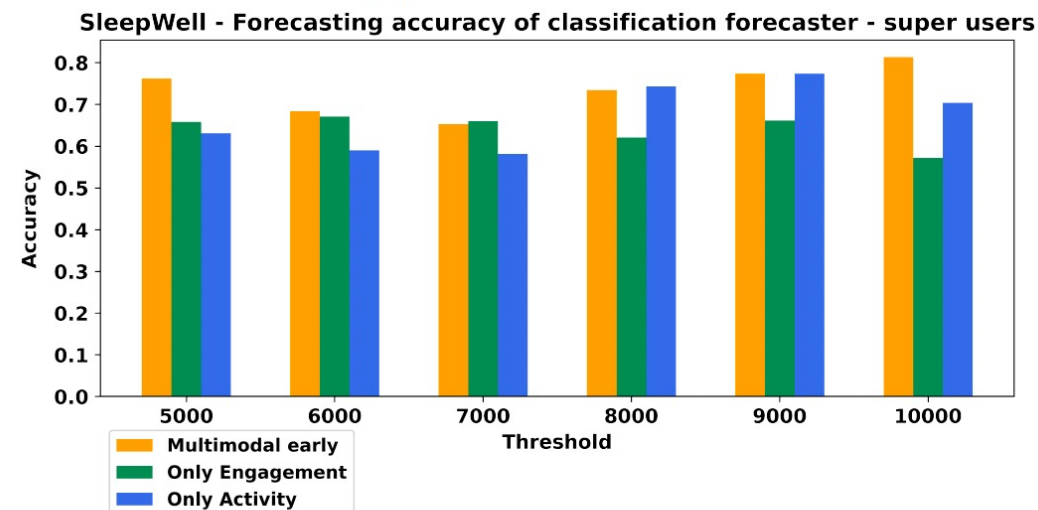
TABLE III: Mean-absolute-errors and r^2 coefficients for different window sizes with the multimodal forecasting model with early fusion.

Window size	1	3	7	14	21	28
BeWell MAE	1923	1802	1644	1701	5422	1792
BeWell r^2	0.488	0.527	0.609	0.609	0	0.57
SleepWell MAE	3485	2508	2934	3291	3411	4965
SleepWell r^2	0.151	0.251	0.074	0.04	0.001	0.066

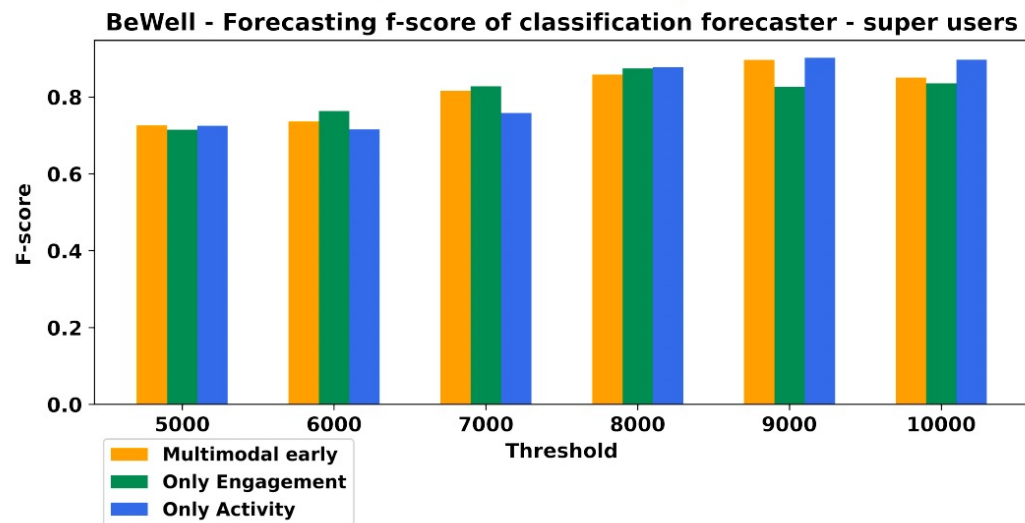
Results: Goal-based forecasting



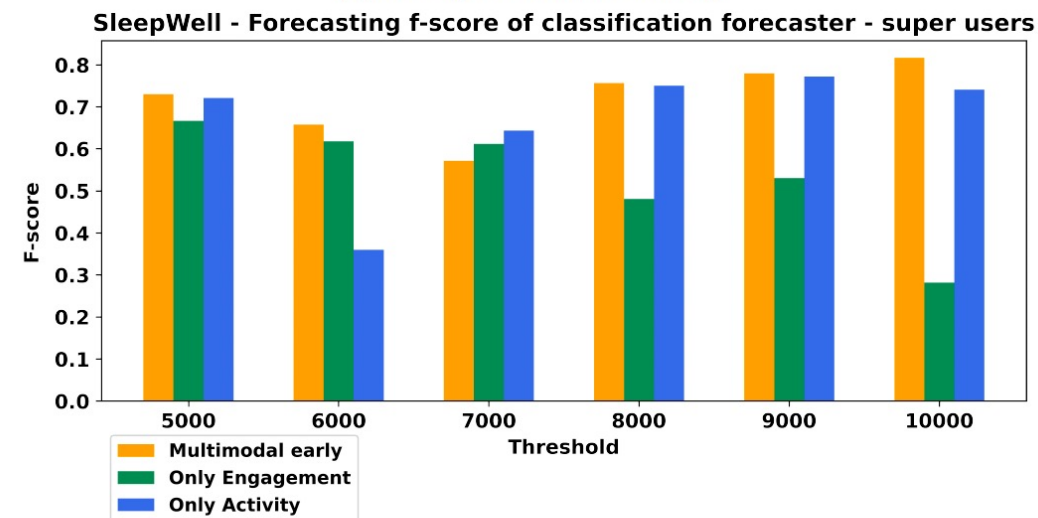
(a) BeWell24 accuracy



(c) SleepWell24 accuracy



(b) BeWell24 f-score



(d) SleepWell24 f-score

Results: Goal-based forecasting (contd.)

- On the goal-based experiments, the early fusion-based multimodal learning models can **forecast whether a person will reach their activity goal with 81% and 74% accuracies** on the prediabetes dataset and sleep dataset, respectively.

TABLE VI: Average accuracy and f-score across all different classification thresholds with their corresponding standard deviation on BeWell24 and SleepWell24 super users.

<i>Metric</i>	<i>Multimodal (Early)</i>	<i>Single Modality (Engagement)</i>	<i>Single Modality (Activity)</i>
BeWell acc	0.81 ± 0.06	0.81 ± 0.05	0.83 ± 0.06
BeWell f-score	0.81 ± 0.06	0.81 ± 0.05	0.81 ± 0.08
SleepWell acc	0.74 ± 0.05	0.64 ± 0.03	0.67 ± 0.07
SleepWell f-score	0.72 ± 0.08	0.53 ± 0.13	0.66 ± 0.14

Conclusion

- Proposed a **framework** for activity and user engagement monitoring and **adaptive intervention design**
- Modeled **activity prediction** as a multimodal **time-series forecasting problem**.
- Showed a **realization** of the forecasting problem using an **LSTM model**
- Demonstrated the **effectiveness** of our forecasting approach using data collected with **58 people with prediabetes** and **51 people with sleep apnea**
- How to improve the performance?
 - Use richer data such as **details of app engagement**
 - Design more **advanced models** such as attention-based models
- Design the **complete framework** and conduct clinical trials

Publications

- Mamun, A., Leonard, K. S., Buman, M. P., & Ghasemzadeh, H. (2022, September). [Multimodal Time-Series Activity Forecasting for Adaptive Lifestyle Intervention Design](#). In *2022 IEEE-EMBS International Conference on Wearable and Implantable Body Sensor Networks (BSN)* (pp. 1-4). IEEE.
 - Best paper (honorable mention) award winner in the BSN 2022 conference.
- Mamun, A., Leonard, K. S., Petrov, M. E., Buman, M. P., & Ghasemzadeh, H. [Time-Series Wearable Activity Forecasting](#).
 - under review at the Journal of Biomedical & Health Informatics (JBHI)





Thank You!

Questions?

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