Time-Series Wearable Activity Forecasting

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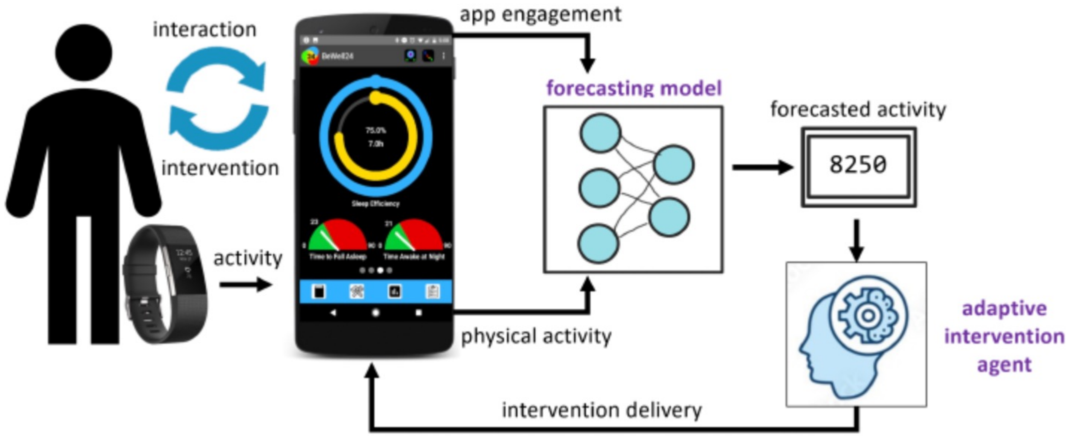
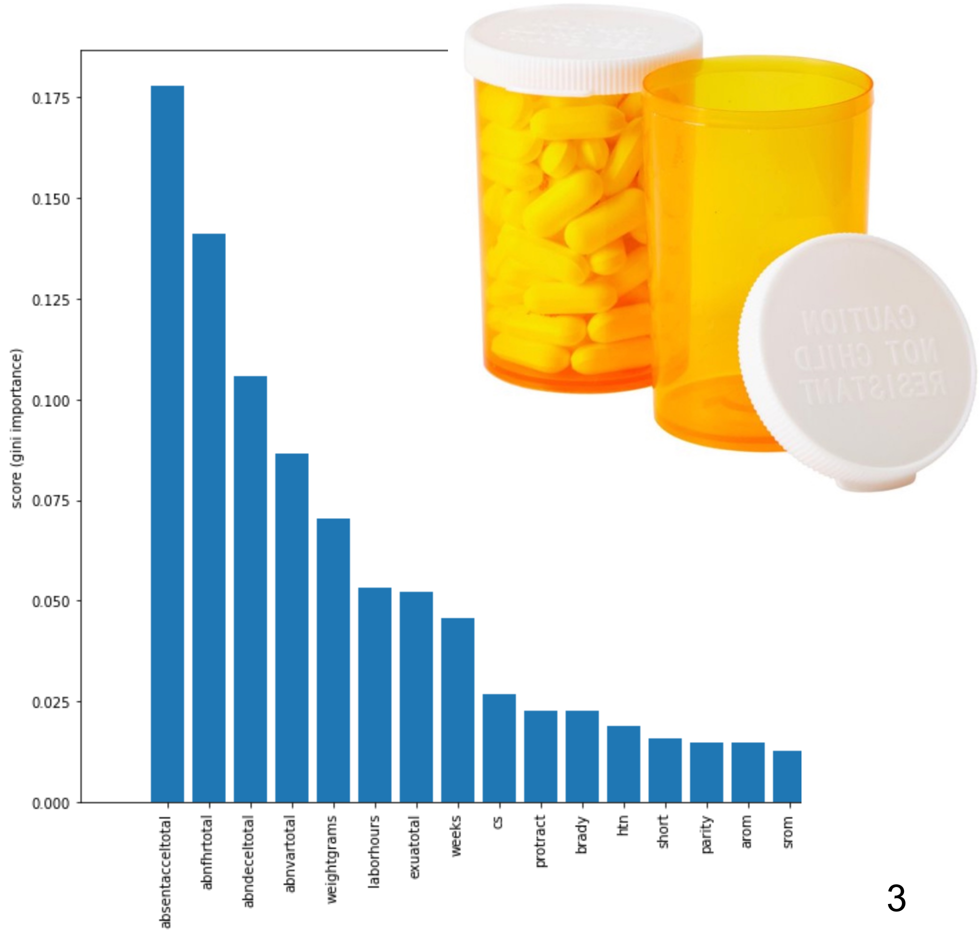
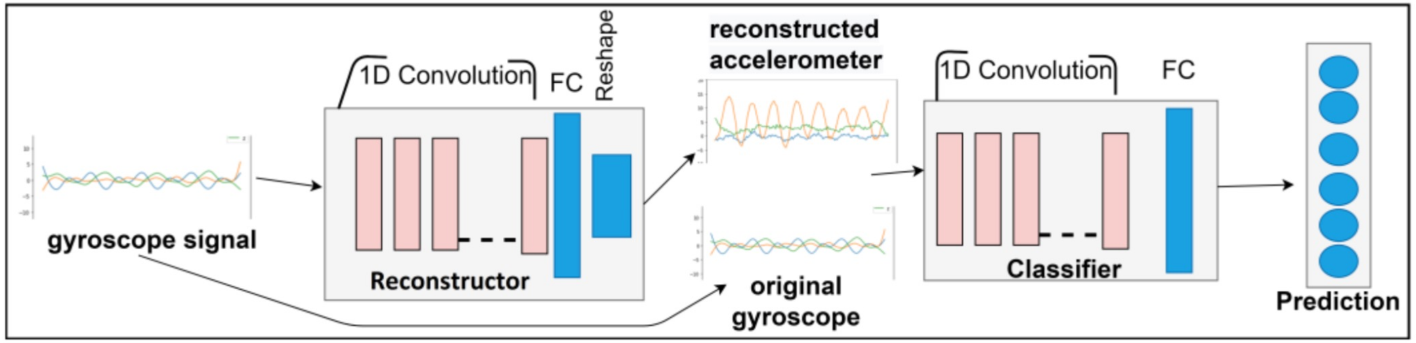
Research area of EMIL (1/2)

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

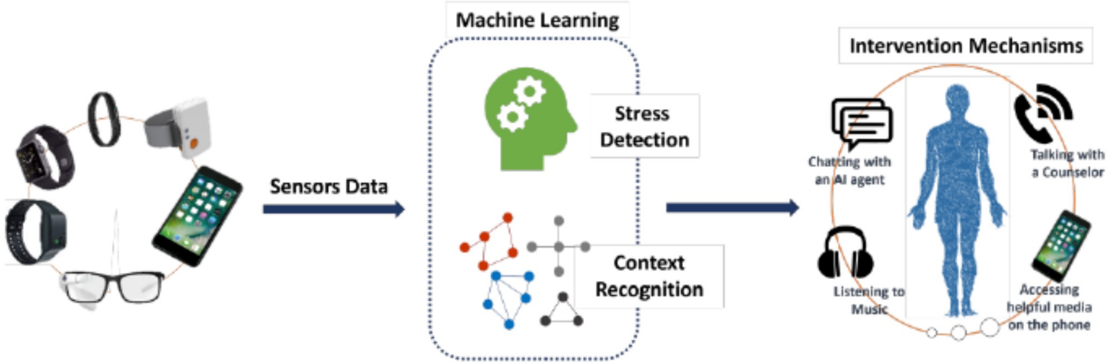


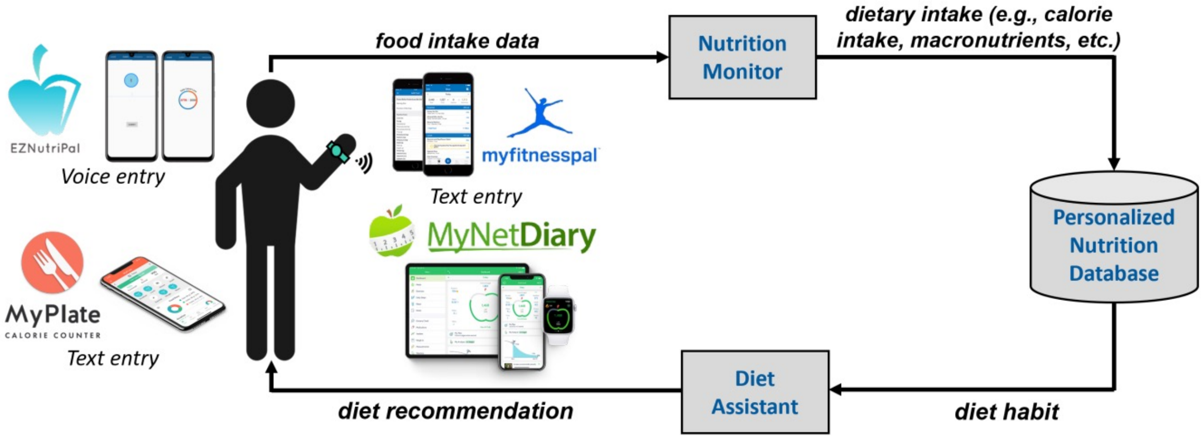




Research area of EMIL (2/2)

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



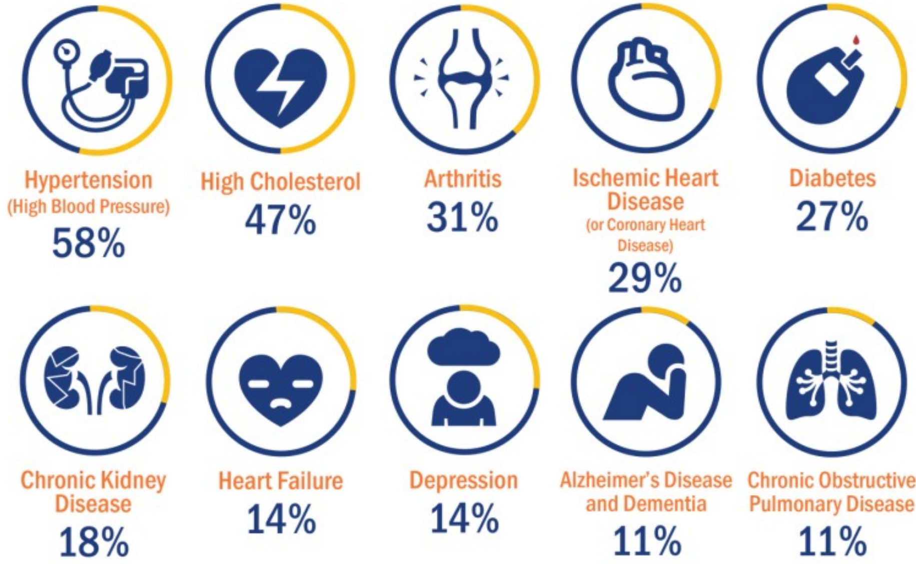


(a) LIDS prototype (b) Tested bottles for evaluation

Ongoing user studies

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



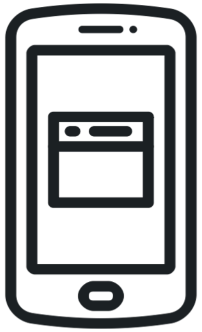
- *CDS Chronic Disease Overview, 2020: https://www.cdc.gov/chronicdisease*
- *http://dhss.alaska.gov/dph/Chronic/*
- *Center for Medicare and Medicaid Services, Chronic Conditions Prevalence, 2015*
- *CDS Chronic Disease Overview, 2020 @ : https://www.cdc.gov/chronicdisease*

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.

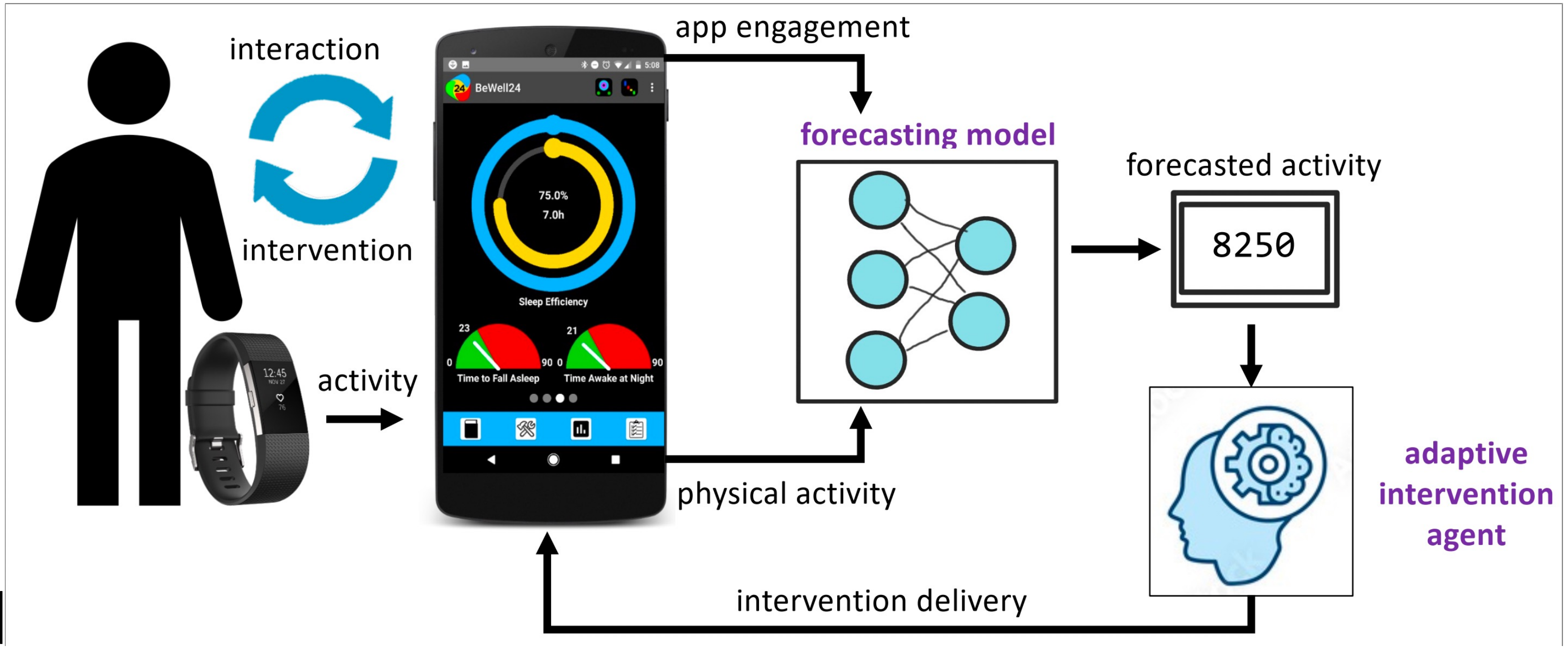


Gal et al., 2018: The effect of physical activity interventions comprising wearables and smartphone applications on physical activity: a systematic review and meta-analysis

System overview

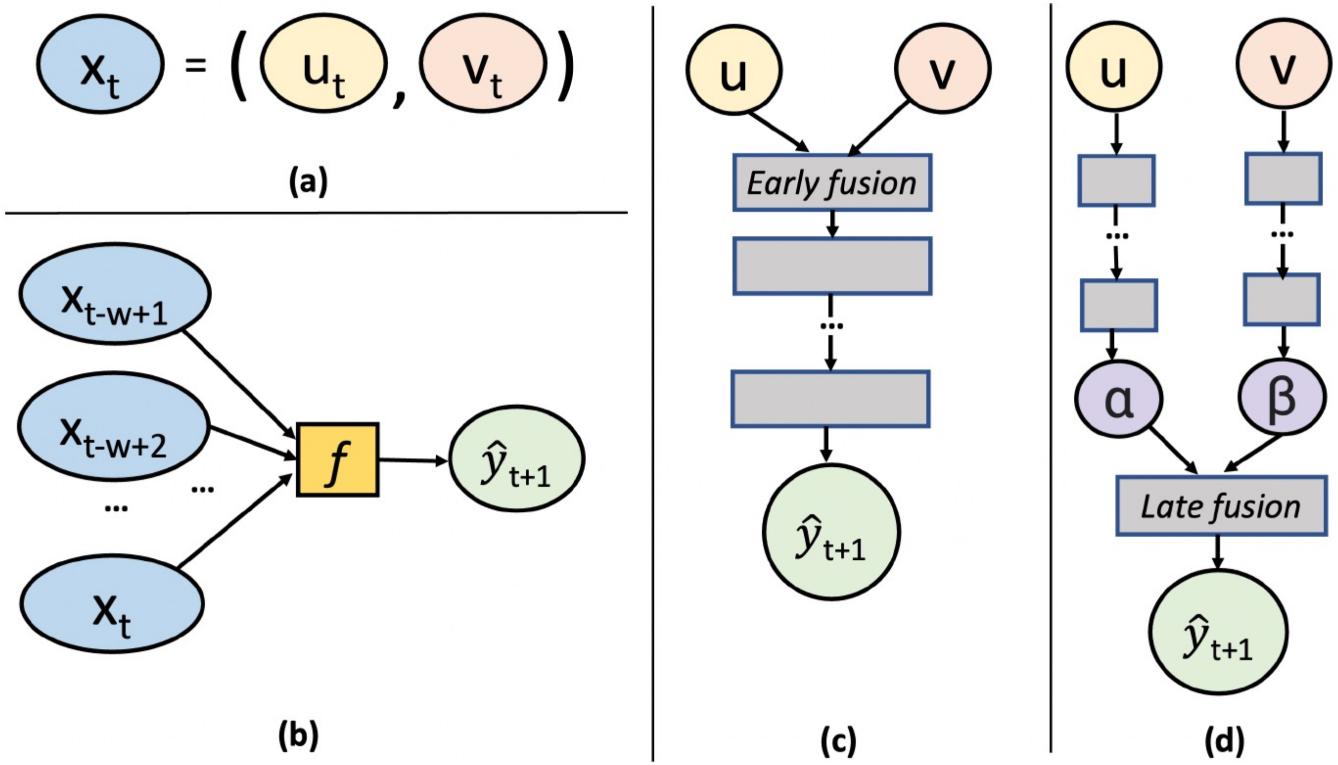
- An adaptive lifestyle intervention system

- 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



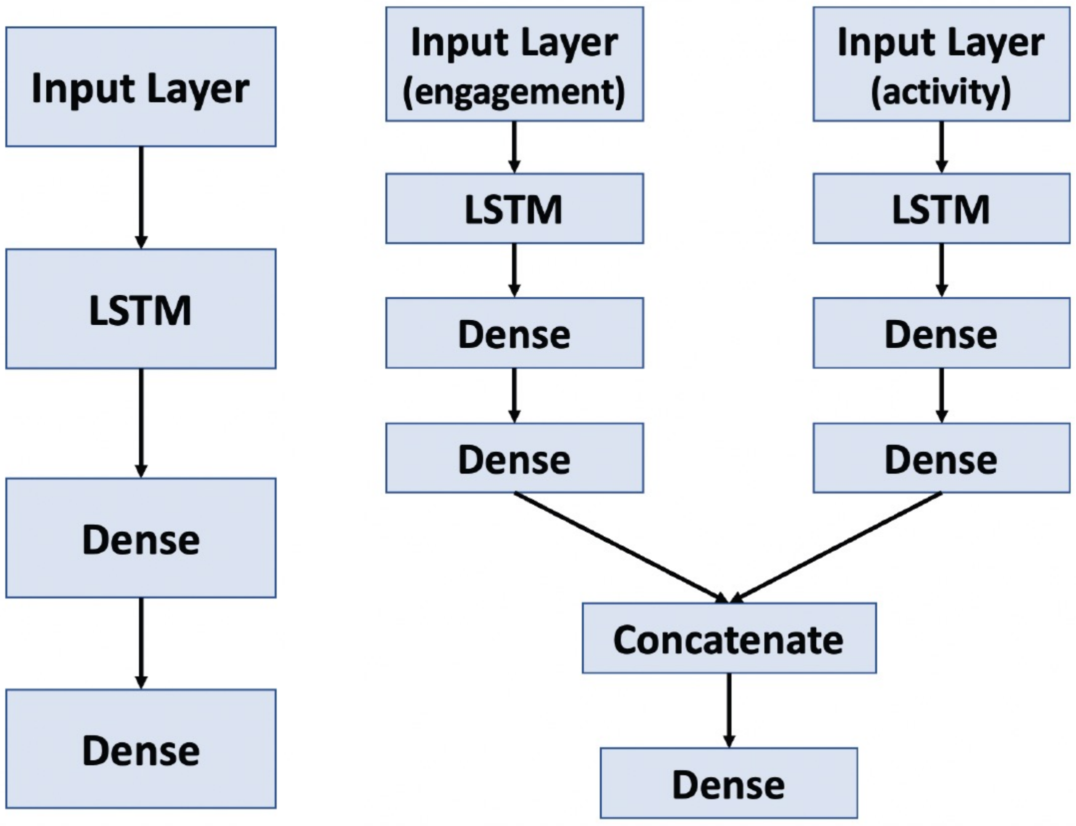
The multimodal forecasting model takes input from both modalities (activity and engagement) and forecasts the next day step count for a user.

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 funcion
α, β	intermediate results

Implementation with machine learning

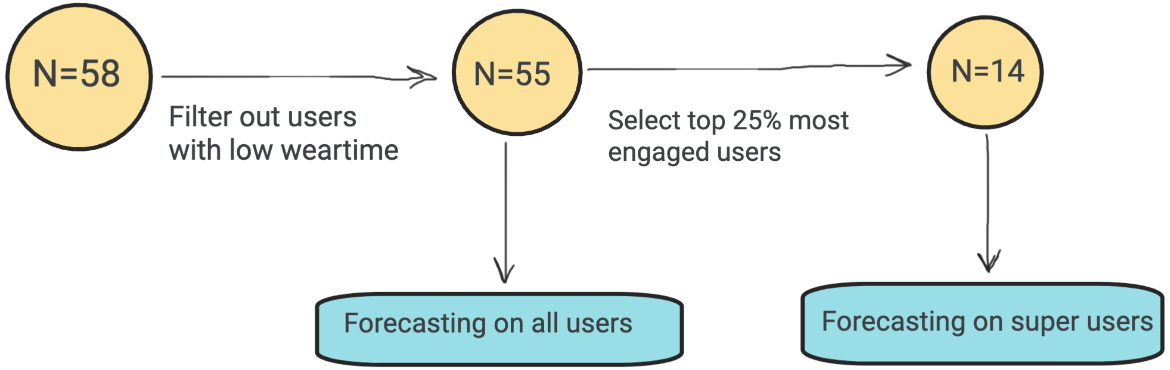
- Because of the time-series property of the input features, we choose LSTM (Long short-term memory) to capture the sequential features.
- Both single-modal and multimodal forecasting methods were implemented



(a) *Early* fusion (b) *Late* fusion

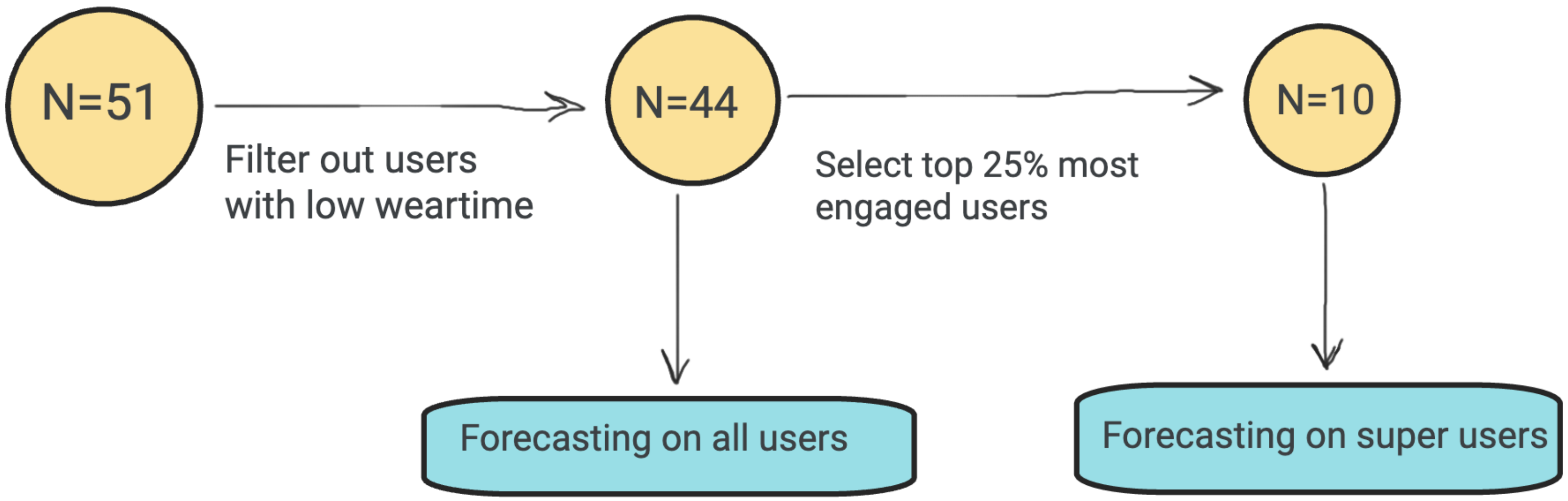
Dataset (1/2): BeWell24

- **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.

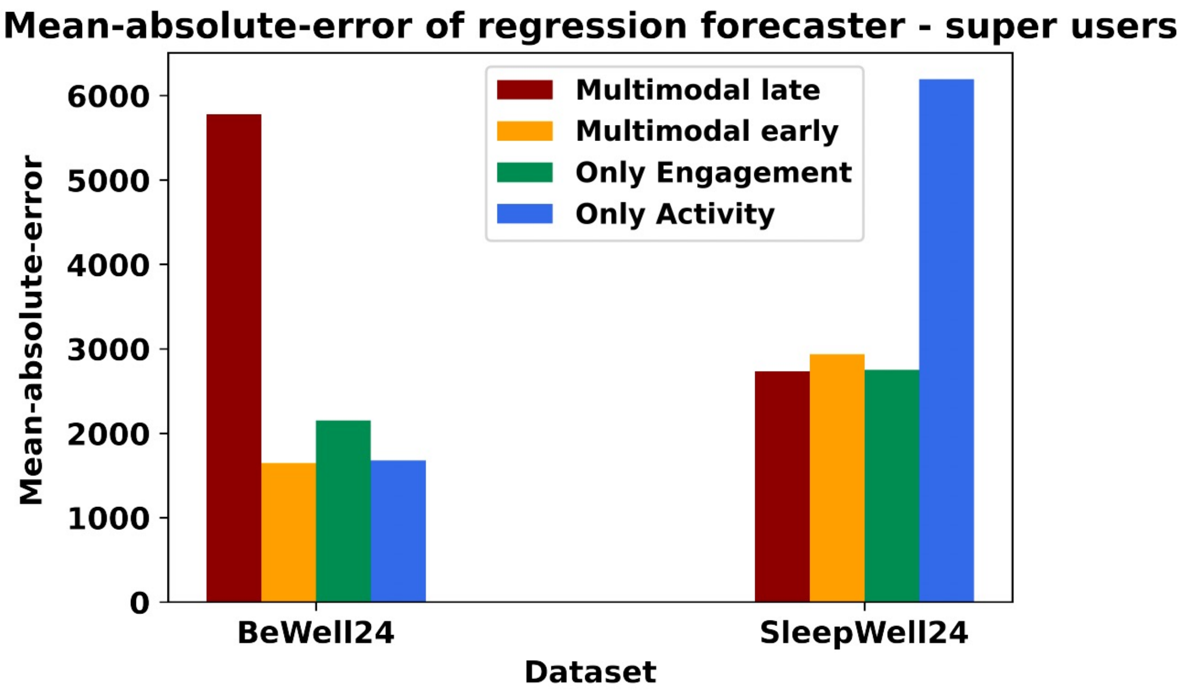
Metric	*Multimodal (Late)*	*Multimodal (Early)*	*Single Modality (Engagement)*	*Single Modality (Activity)*
MAE	2620	**2066**	2673	2113

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

Metric	*Multimodal (Late)*	*Multimodal (Early)*	*Single Modality (Engagement)*	*Single Modality (Activity)*
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



Results: Finding the window size

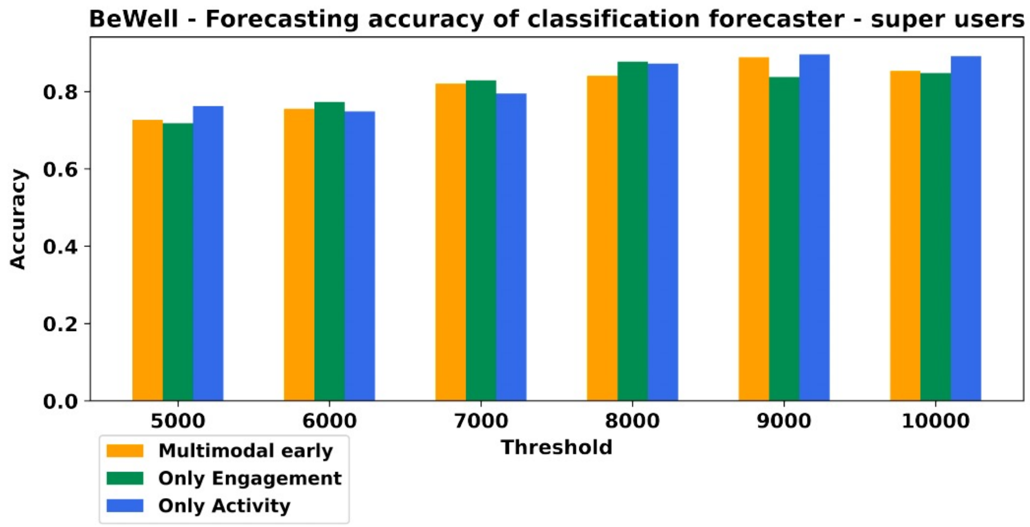
- How many days from the past should be considered for a forecasting a value of the future?

- We observe that a window size between 3 and 7 is ideal for these kind of data.

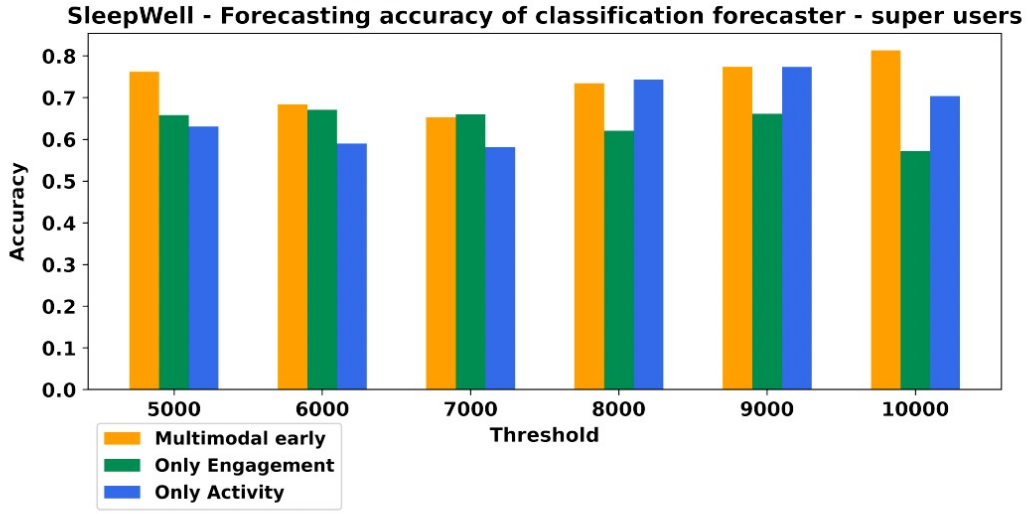
TABLE III: Mean-absolute-errors and r^2 coefficients for different window sizes with the multimodal forecasting model with early fusion.

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

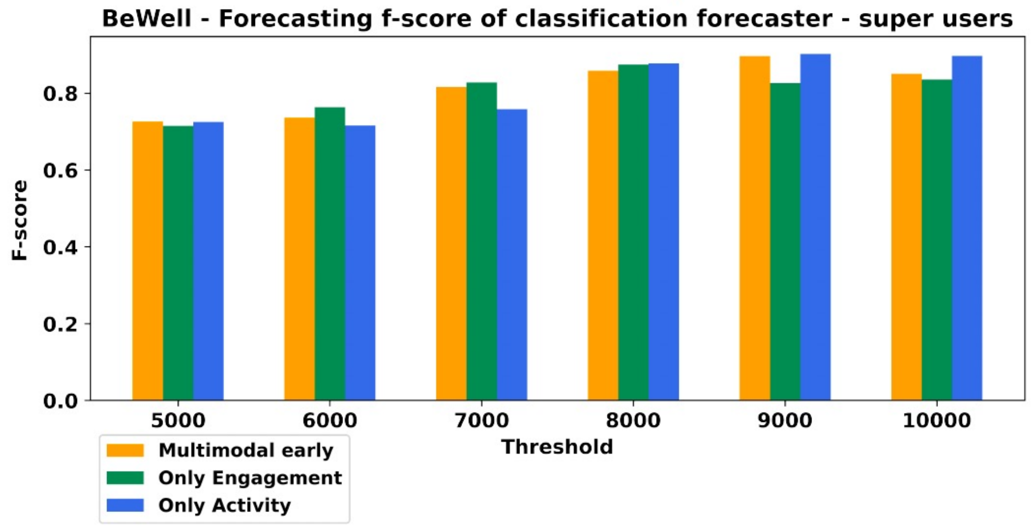
Results: Goal-based forecasting



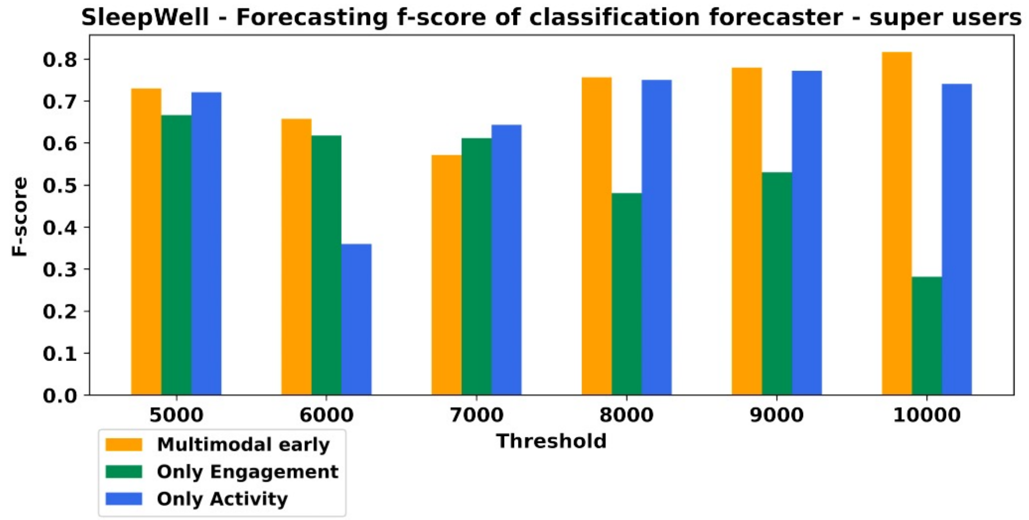
(a) BeWell24 accuracy



(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.

Metric	*Multimodal (Early)*	*Single Modality (Engagement)*	*Single Modality (Activity)*
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)





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Thank You!

Questions?

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