# Multimodal Time-Series Activity Forecasting for Adaptive Lifestyle Intervention Design

Abdullah Mamun, Krista S. Leonard, Matthew P. Buman,
Hassan Ghasemzadeh

Embedded Machine Intelligence Lab (EMIL)

College of Health Solutions

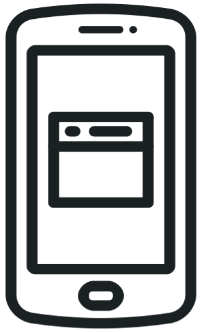
Arizona State University

# 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.

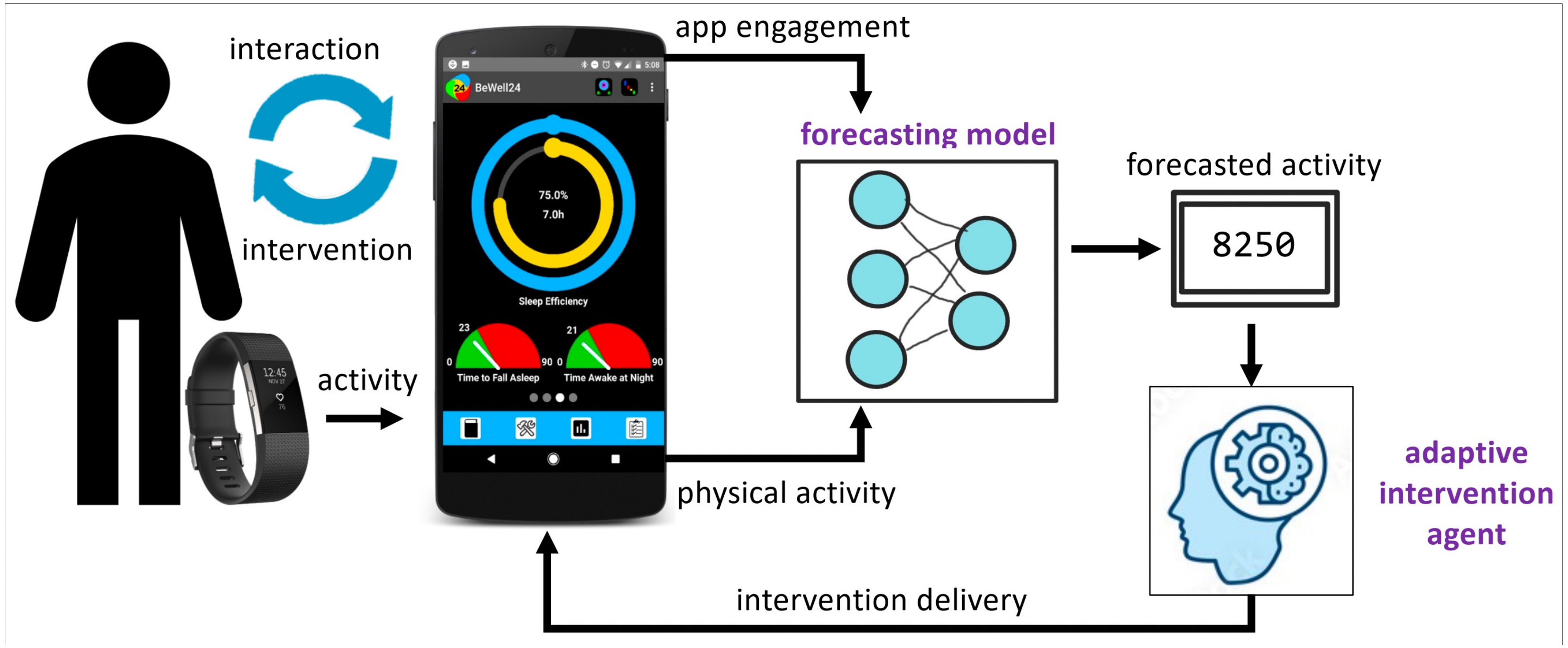



Gal et al., 2018: The effect of physical activity interventions comprising wearables and smartphone applications on physical activity: a systematic review and meta-analysis

# BeWell24Plus

- An adaptive lifestyle intervention system

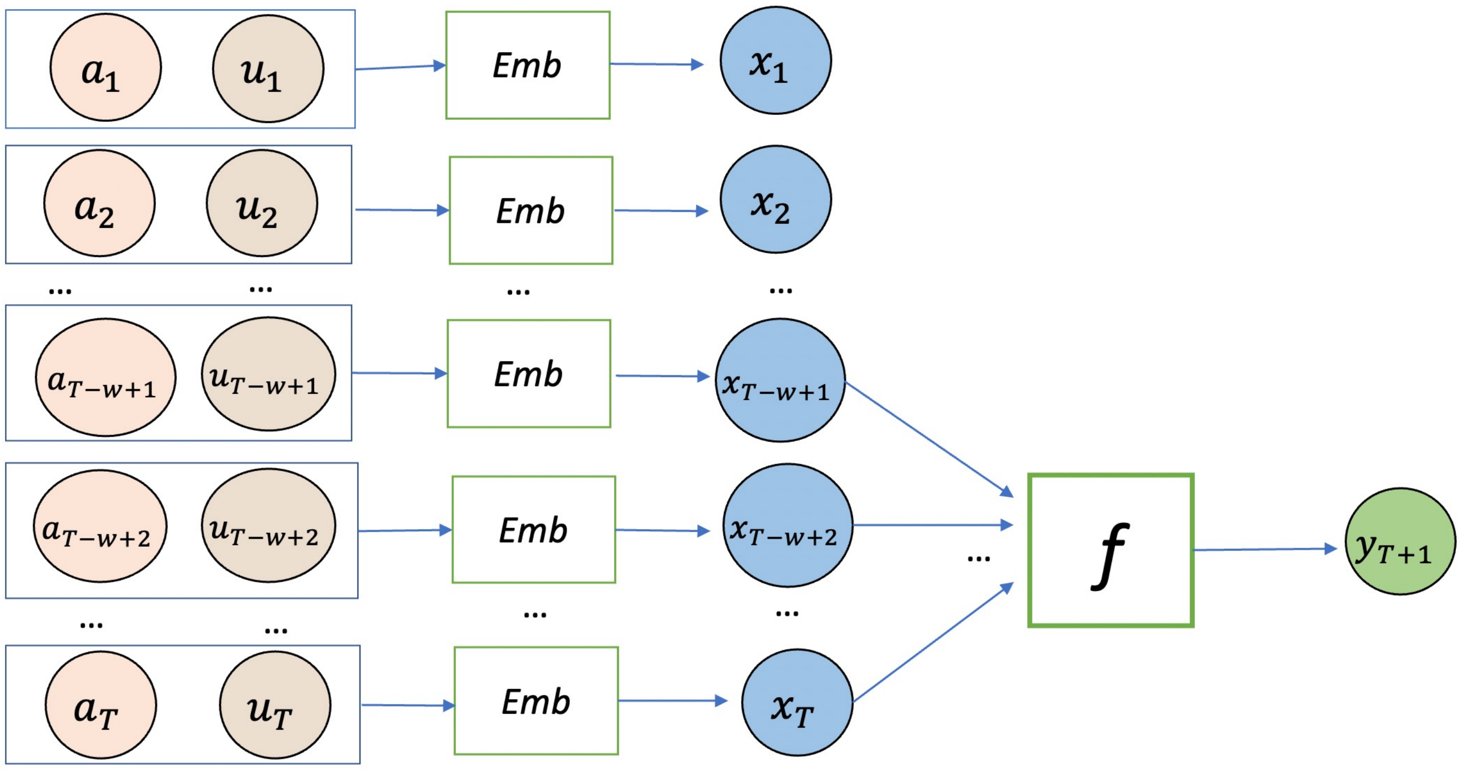
- A human-in-the-loop system with smartphone app, wearable wristband and a time-series activity forecasting model.




- 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



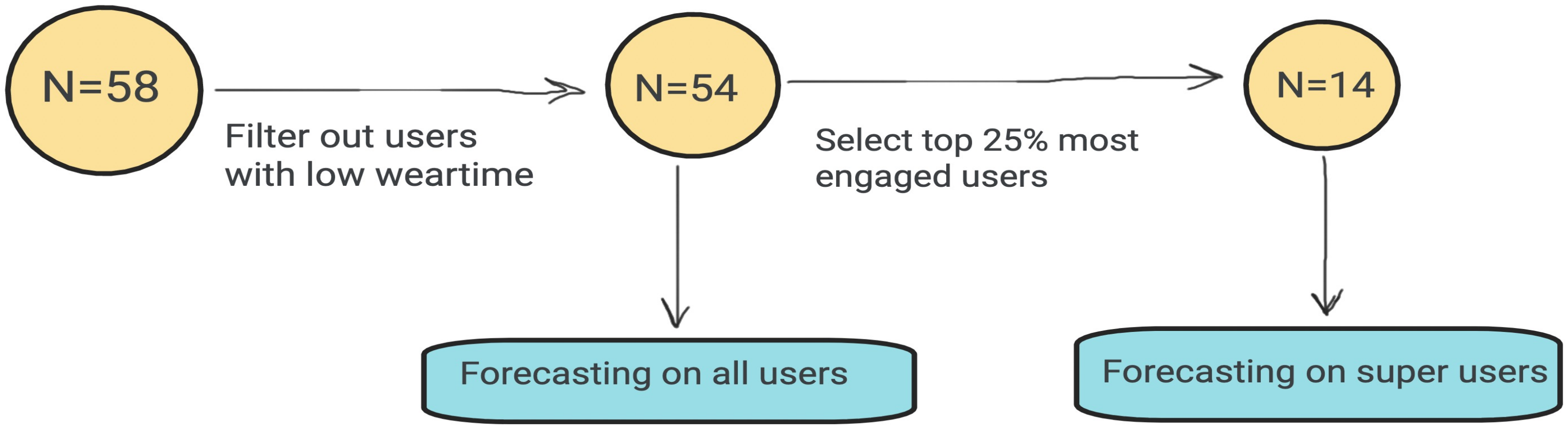

## Notations

| Symbol | Meaning |
|---|---|
| T | current time step |
| T+1 | next time step |
| $a_t$ | the physical activity measure for any t |
| $u_t$ | engagement measure for time step t |
| $x_t$ | embedding of the fusion of the two modalities, $a_t$ and $u_t$ |
| w | window size |
| $y_{T+1}$ | is a physical activity outcome. The value we want to forecast |
| f | Forecasting funcion |
| Emb | Embedding function |

# Dataset: BeWell24

- 58 prediabetic veterans
- 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-vigoros physical activity (MVPA) in seconds in a particular minute.

- We had to filter out 4 users with low weartime (Data for less than 10 days, each of them having at least 10 hours of weartime)
- Forecasting on super users: 14 most enaged users were selected.
- Forecasting on all users: 54 users were selected.



# Experimental setup

- The multimodal forecasting model takes input from both modalities (activity and engagement) and forecasts the next day step count for a user.
- Because of the time-series property of the input features, we choose LSTM to capture the sequential features.
- The outputs of the LSTM are passed through a dense layer and finally another dense unit as the final output.
- We use leave-one-subject-out cross validation method.
- We experiment and gather results for both regression and binary classification problems.

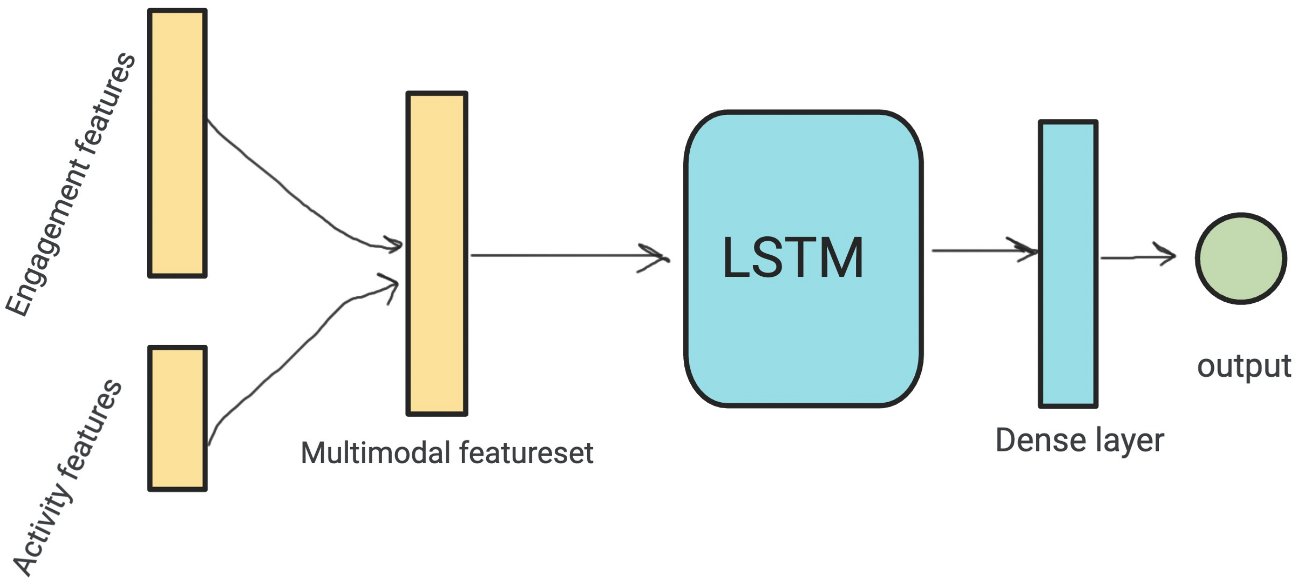
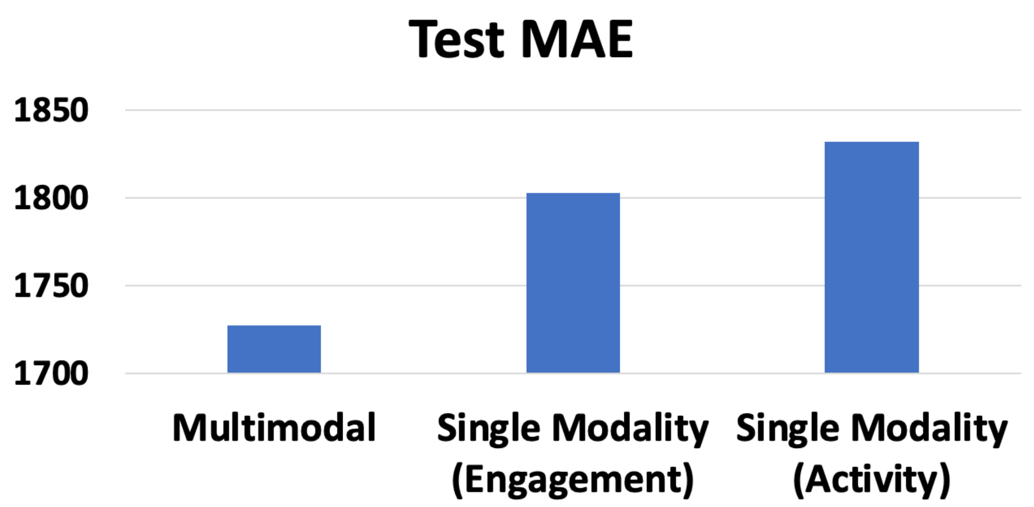
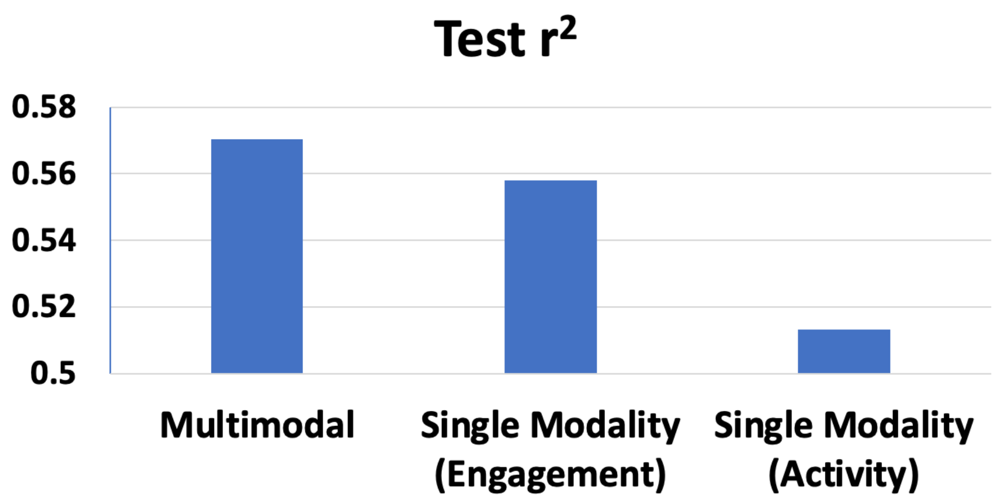



Figure: Block diagram of the regression-based multimodal forecasting model. We use early fusion for this work, which means the different modalities are combined at the feature level.

# Results: Forecasting on super users (1/2)

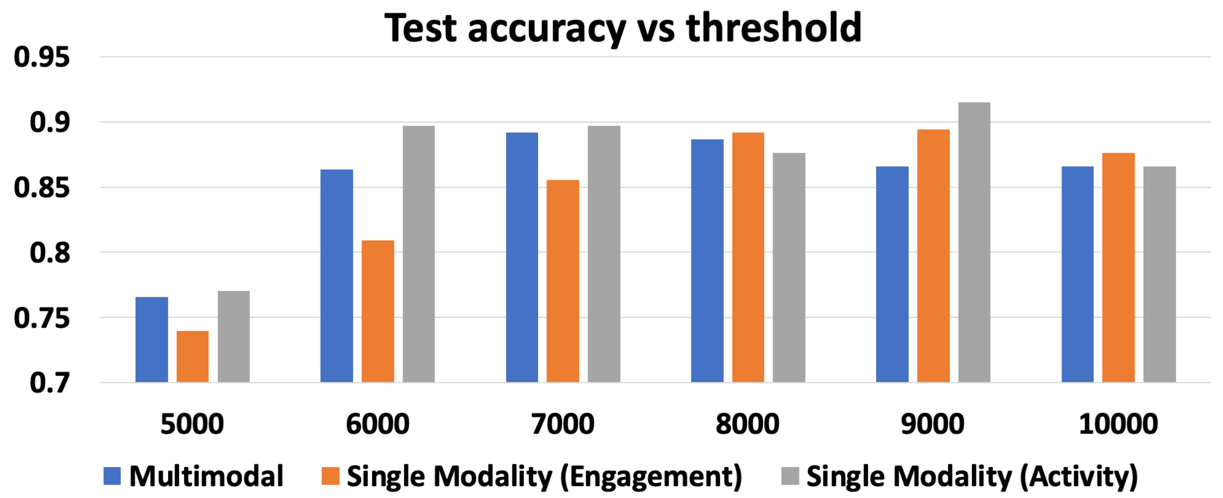
- Multimodal forecasting gets an MAE 4.2 - 5.7% lower than single modality forecasting
- Also, $r^2$ is 2.2 – 11.1% higher in multimodal forecasting compared to single modality forecasting.
- It suggests the superiority of multimodality in regression-based forecasting over single modality.

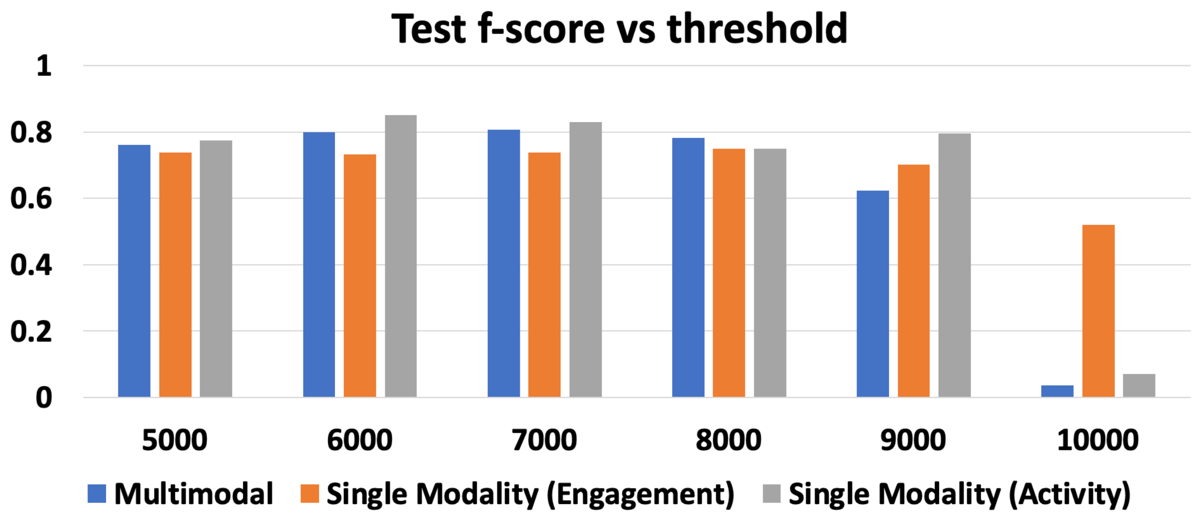


# Results: Forecasting on super users (2/2)

- Forecasting with multimodality beats the single modality f-score by a margin of 4.3% for the classification threshold 8000 steps per day.
- However, the observation is not universal for all different thresholds.
- Improvement of accuracy was also not observed in multimodality.



# Results: Forecasting on All users

- The multimodal forecasting reduces the MAE by 0.4%–12.27%.
- However, $r^2$ coefficient for multimodal method is 0.28% lower than single modality.
- It is noteworthy that $r^2$ can be adversely affected by outlier data points.

| Metric | Multimodal | Single Modality (Engagement) | Single Modality (Activity) |
|---|---|---|---|
| MAE | **2081** | 2372 | 2090 |
| $r^2$ | 0.350 | 0.267 | **0.351** |

# Conclusion

- We proposed a framework for activity and user engagement monitoring and adaptive intervention design
- We presented a formal definition of the time-series activity forecasting
- We propose an overall architecture for designing a machine learning algorithm for multimodal activity forecasting
- We showed a realization of our proposed architecture based on an LSTM model
- We demonstrated the effectiveness of our forecasting approach using data collected with 58 prediabetic people

ASU College of Health Solutions
Arizona State University

# *Thank You!*

# *Questions?*




https://ghasemzadeh.com/

hassan.ghasemzadeh@asu.edu