# Evaluating a state-of-the-art generative pre-trained transformer model to predict continuous glucose monitoring values at different time intervals

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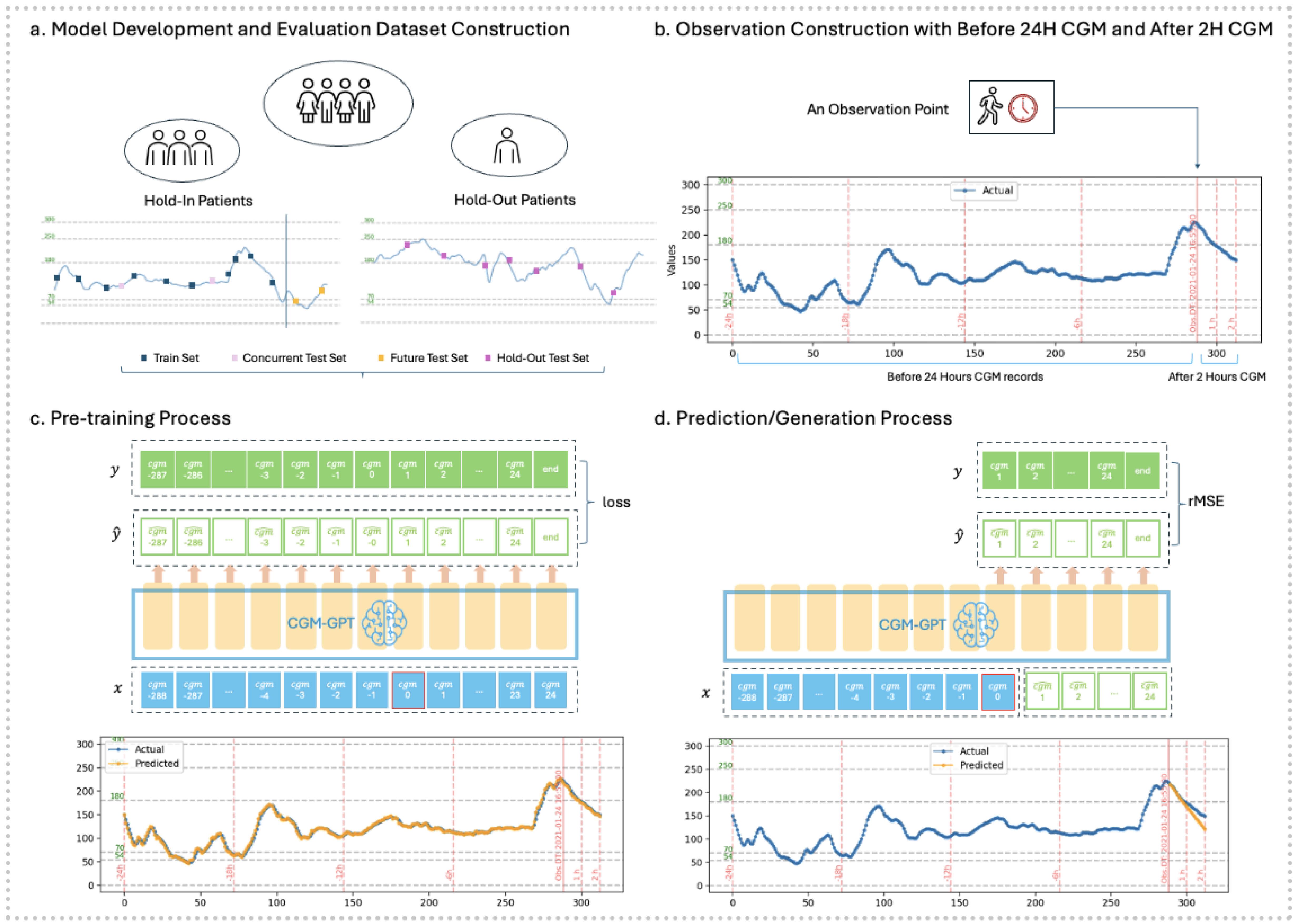
## BACKGROUND AND AIMS

Individuals living with diabetes make hundreds of decisions each day that affect their glucose levels and their overall health. Sensors like continuous glucose monitors (CGM) provide high-volume, dense glucose data that can be utilized for improved self-management. Advancements in artificial intelligence (AI) have the promise to transform the raw CGM data into more nuanced insights that can lead to better health outcomes. In this study we build and evaluate a state-of-the-art generative pre-trained transformer (GPT) model that is trained to predict CGM trajectory at different time horizons. We also introduce new evaluation metrics to further assess the accuracy of our GPT model.

### Figure 1: Model Development Workflow




## MATERIALS AND METHODS

We reviewed de-identified real-world data from 617 individuals with type 1 diabetes (T1D) and type 2 diabetes (T2D) who were enrolled in a digital health coaching platform. The dataset included 17 million CGM entries, estimated to cover 59,000 patient days or 161.7 patient years. A minimum CGM entries sufficiency criteria was established to ensure data completeness in the training and prediction periods. We used a 10% down sampled dataset to train the GPT model encompassing individuals with both T1D and T2D. Furthermore, 10% of the individuals were held-out to further evaluate the accuracy of the model. We employed 11 evaluation metrics were used to assess the accuracy of the GPT model at a 30-minute prediction interval (30min) and 60-minute prediction interval (60min).

## RESULTS

We used standard definitions of CGM glucose ranges: Very High (>13.9 mmol/L), High (10.0-13.9 mmol/L), In Range (3.9-10.0 mmol/L), Low (3.0-3.9 mmol/L), and Very Low (<3.0 mmol/L). Overall, the model achieved a 94% accuracy in predicting the next 30 minutes glucose category. The classification accuracy specifically to predict Low and Very Low glucose categories in the next 30 minutes were 52% and 54%, respectively.

### Table 1: Prediction Performance

RMSE=root mean square error; data are the mean (5% confidence interval); units are mmol/L

| Type of Diabetes | RMSE-30 min | RMSE-60 min | RMSE-2 hours |
|---|---|---|---|
| T1D | 0.50 (0.003) | 0.94 (0.006) | 1.66 (0.009) |
| T2D | 0.43 (0.003) | 0.77 (0.005) | 1.30 (0.008) |

### Table 2: Other Evaluation Metrics (T1D and T2D Combined)

| Metric | 30 min | 60 min | 2 Hours |
|---|---|---|---|
| Abs error (mmol/L) | 0.39 | 0.71 | 1.23 |
| Abs error within 5 mg/dL | 62% | 44% | 30% |
| Abs error within 10 mg/dL | 80% | 62% | 45% |

## CONCLUSIONS

- Our GPT model, trained on millions of CGM data points from individuals with T1D and T2D, achieved state-of-the-art results when predicting CGM trajectories at 30 and 60 minutes and 2 hours[1].
- Additionally, the model demonstrated high accuracy in predicting future CGM glucose categories within these intervals.
- When specifically analyzing data from those with only T1D or T2D, the GPT model performed exceptionally well in predicting CGM values for their respective conditions.
- This accurate GPT model may have significant clinical applications. The model can be utilized to further understand effects of various interactive variables like food, medication, and exercise on glucose. These insights can then be used to provide personalized automated coaching to individuals, helping them to optimally manage their health, in the moment.
- Further effort is needed to improve the accuracy in the Low and Very Low glucose ranges.

[1] Junjie Luo, Abhimanyu Kumbara, Mansur Shomali, Anand Iyer, Gordon Gao, "CGM-GPT: A Transformer Based Glucose Prediction Model to Predict Glucose Trajectories at Different Time Horizons." presented at Machine Learning Healthcare 2024, Toronto, Canada, August 17, 2024

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60th Annual Meeting
European Association for the Study of Diabetes
9 - 13 September 2024
Madrid, Spain
EASD 2024