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BACKGROUND AND AIMS

Proactive self-management of diabetes requires accurate glucose value prediction and automated, in-the-moment AI-driven coaching based on those predictions¹. With the increased adoption of continuous glucose monitoring (CGM) devices across the globe, we now have a dense glucose signal to build accurate glucose value prediction models that can be used in coaching applications to manage diabetes. Welldoc has been developing GPT models (see Figure 1) to predict CGM trajectory at different time horizons with only CGM data.^{2,3} In this study, we built a new GPT model, adding to our previous model, to include both CGM values and time series inputs to predict glucose trajectories at 30mins, 60mins and 2-hour time horizons. We also analyzed the results of the new GPT model across different population subgroups such as time of day, age group and total engagement levels within a mobile application used to manage diabetes.



MATERIALS AND METHODS

A GPT model to generate CGM trajectories at 30-minute, 60-minute, and 2-hour time intervals was created using a real-world data set from 592 CGM users. For the time-of-day subgroup analysis, root-mean-square-error (RMSE) of the predicted glucose value vs. the actual value was calculated for every hour of the day. Age group was categorized as 20-40 years, 40-60 years, and 60+ years categories. App engagement counts were characterized into 6 categories: 0, 10, 20, 30, 40, and 50+.





Figure 1: Design of the GPT Model

Methods, Analysis, and Insights from a State-Of-The-Art Large Glucose Model

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RESULTS

When comparing the average root mean square error (RMSE) in T1D and T2D populations associated with the hour of the predicted glucose values, the Large Glucose Model performed better when predicting glucose trajectories between 12am – 5am, with RMSE increasing during breakfast (6am – 10am), lunch (12pm – 3pm), and dinner (5pm – 9pm). For the T1D population, the RMSE of the model was inversely correlated with age group, and for T2D population, the RMSE of the model was positively correlated with age group. When looking at total engagement levels across medication, education, diet, activity, and labs (MEDAL) categories, engagements between 20-30 entries per month minimized the RMSE for both populations.



Figure 2: GPT Model Subgroup Analysis by Time of Day, Age Group and MEDAL Engagements

CONCLUSIONS

Analysis and insights from GPT based models like ours, enable us to understand subgroup level differences in managing diabetes. This can be used to develop smarter personalized coaching applications that can ultimately be used to improve health outcomes. Additionally, subgroup level analysis may warrant further finetuning of the models to maintain high accuracy across different subgroups. Just like how Large Language Models may need finetuning to suit specific business outcomes, Large Glucose Models may need further finetuning to address specific health outcomes of a given subpopulation.

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