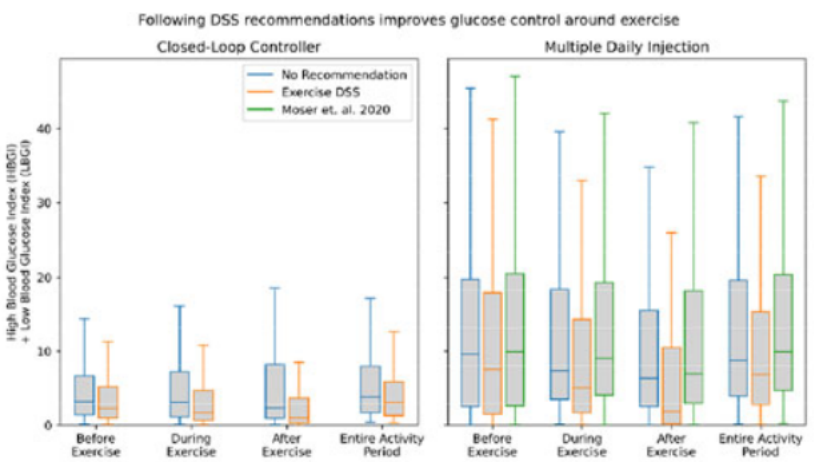
Engineering And Applied Sciences, Cambridge, United States of America, [7]Louisiana State University, Pennington Biomedical Research Center, Baton Rouge, United States of America, [8]University of Pennsylvania, Perelman School of Medicine, Rodebaugh Diabetes Center, Philadelphia, United States of America, [9]Nemours Children's Health System, Nemours Center For Healthcare Delivery Science, Jacksonville, United States of America, [10]York University, School Of Kinesiology And Health Science, Toronto, Canada

Background and Aims: People with type 1 diabetes (T1D) have difficulty managing glucose during and after exercise. A decision support system (DSS) may help.

Methods: Meal and exercise scenarios were extracted from a four-week, free-living clinical study of 33 adults with T1D from whom glucose, insulin, meal, and exercise data were collected (mean±sd: age 33 ± 13 years, BMI 26.3 ± 2.9 kg/m^2). Mean glucose changes during and after exercise were -8.7 mg/dL and -32.0 mg/dL, respectively. Digital twins from the 99-subject OHSU *in silico* simulator were matched to clinical study participants by insulin and weight to *replay* exercise scenarios from the clinical study under two interventions and a no-intervention arm under both multiple daily injection (MDI) and closed-loop therapy. One intervention was a DSS system providing recommendations during pre-exercise meals and at the start of exercise. The second intervention was to follow exercise consensus guideline (Moser et al., 2020). Recommendations included eating a snack before exercise, altering pre-exercise mealtime insulin, changing exercise duration/intensity/timing.

Results: MDI participants achieved better glucose control during and four hours post-exercise when following DSS recommendations vs. consensus guidelines vs. no intervention (during-exercise: 61.7% vs. 47.6% vs. 51.2% time-in-range (TIR), 0.7% vs. 1.1% vs. 2.5% time-in-hypoglycemia (TIH); post-exercise: 70.7% vs. 53.4% vs. 57.4% TIR, 0.3% vs. 1.7% vs. 4.3% TIH). Closed-loop participants improved glucose outcomes when following DSS recommendations vs. no intervention (during-exercise: 87.5% vs. 79.1% TIR, 0.6% vs. 2.4% TIH; post-exercise: 87.0% vs. 76.1% TIR, 0.5% vs. 1.4% TIH).

Conclusions: Exercise-specific DSS improves glucose control during and after exercise *in silico*.



EP349 / #140

Topic: ***AS17-Big data and artificial intelligence based decision support systems***

REMOTE CONTINUOUS DATA MONITORING AND PERSONALIZED DATA-DRIVEN APPROACH FOR MANAGING DIABETES IN A VIRTUAL AND PHYSICAL SETTING

M. Caccelli, Y. Said, J. Mojado, C. Palsky, A. Hashemi, I. Almarzooqi

GluCare Integrated Diabetes Center, Diabetes, DUBAI, United Arab Emirates

Background and Aims: The GluCare care model encompasses two components, a physical component and a Remote Continuous Data Monitoring (RCDM) as a standard care for patients with diabetes. Continuous monitoring and analysis of numerous parameters, under the responsibility of the primary caregiver allow for data-driven actionable insights by the care team.This report describes the RCDM approach and the associated outcomes on preliminary clinical data and patient engagement from the patient's initial visit through their 3 month follow up.Primary outcomes were glycosylated hemoglobin and interstitial glucose time in range . Secondary outcomes included reduction in cardiovascular risk,BMI, lipids, liver transaminase, uric acid and C-reactive protein.We also describe the number of CGM readings, food logs and patient interactions with the team.

Methods: Retrospective and observational analyses were performed by linking data from the GluCare app and data from other devices. Blood tests were collected and analysed inside our facility. Statistical analysis was performed by Microsoft Excel and presented as a mean. Correlations between the analysed variables were assessed by Pearson's product - moment correlation ($r > 0.5$). A paired t-test was used to compare pre and post-intervention outcomes ($p < 0.05$).

Results: Initial data ($n = 22$) indicate that patient engagement via the GluCare model lead to significant improvement in HbA1c (-2.14% point, $p = 0.00013$) and other metabolic parameters such as LDL (-17.25%, $p = 0.0071$), body mass index (-4.55%, $p = 0.0003$), triglycerides (-18.52%, $p = 0.0165$) and uric acid (-20.4%,$p = 0.0052$).

Conclusions: These initial findings suggest that management of diabetes under the GluCare model of care has the potential to significantly improve diabetes outcomes.

EP350 / #192

Topic: ***AS17-Big data and artificial intelligence based decision support systems***

RELIABILITY OF THE PROBABILITIES OF THE DIABETES RISK IN LOGISTIC REGRESSION AND GRADIENT BOOSTING DECISION TREE METHODS USING BIG HEALTH CHECKUP DATA

H. Seto[1], A. Oyama[2], S. Kitora[2], H. Toki[2], R. Yamamoto[2]

[1]Osaka University, Human Sciences, Suita City, Osaka, Japan, [2]Osaka University, Health And Counseling Center, Toyonaka City, Osaka, Japan

Background and Aims: While the accurate estimation of risk is indispensable for motivating individual lifestyle improvement, few risk prediction models for diabetes correctly evaluate their reliability, especially those made by machine learning. We aimed to develop a machine learning-based model predicting the probability of near future diabetes and to evaluate and compare its reliability to that of a regression model as accurately as possible.

Methods: We had access to Kokuho-database (KDB) in Osaka prefecture, Japan. To develop and evaluate models accurately, we focused on 16 predictors from health checkup data during 2012-2014 of 275,644 eligible participants. Diabetes was