CLOSER LOOK

MEMORANDUM

Journal of Diabetes Science and Technology publishes commentary on CGM Data Analysis 2.0, incorporating AI, ML, and LLMs – September 10, 2025

Esteemed array of authors pushes for CGM Data Analysis 2.0 to move beyond standard glycemic metrics to better analyze the scope of daily CGM data

A sweeping *Journal of Diabetes Science and Technology* commentary, "CGM Data Analysis 2.0: Functional Data Pattern Recognition and Artificial Intelligence Applications," published this week and led by the esteemed Dr. David Klonoff (Diabetes Research Institute, Mills-Peninsula Medical Center*)* et al. made the case that CGM is entering a new phase of evolution. Dubbed "CGM Data Analysis 2.0," this shift reflects a transition from traditional summary metrics – Time in Range (TIR), mean glucose, glucose management indicator (GMI), coefficient of variation (CV), glycemia risk index (GRI), and related indices — to more powerful approaches including:

- (i) functional data analysis (FDA);
- (ii) machine learning (ML);
- and (iii) artificial intelligence (AI).

These methods better analyze the full 1,440-point daily time series rather than compressing it into a handful of aggregates, helping patients and clinicians unlock insights into phenotypes, behaviors, metabolic subtypes, and risk states.

The commentary certainly brought together a "who's who" of the field — Drs. Klonoff, Richard Bergenstal (International Diabetes Center), Eda Cengiz (UCSF), Mark Clements (Children's Mercy Kansas City), Boris Kovatchev (University of Virginia), David Maahs (Stanford University), Julia Mader (University of Graz, Austria), Guillermo Umpierrez (Emory University), Michael Snyder (Stanford University), and many others — underscoring both the broad consensus behind this paradigm shift.

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Why move beyond CGM Data Analysis 1.0?

The authors noted that "CGM Data Analysis 1.0," including traditional metrics like TIR and composite indices like GRI, provided the foundation for integrating CGM into global standards of care. For example, glycemic risk index (GRI) is a composite score[1] that reflects both hypo- and hyperglycemia, with 0 representing minimal risk and 100 maximal risk. These metrics have offered simple summaries of glycemic patterns and risks. However, just as the ambulatory glucose profile (AGP) became the lingua franca of the 2010s, the next decade will demand tools that can uncover deeper patterns and translate them into personalized interventions. The hallmark metrics of CGM Data Analysis 1.0, like TIR and GMI, will continue to serve their benefits of an intuitive nature and clinical actionability. However, the authors noted that the features of CGM Data Analysis 2.o will better be able to parse through temporal granularity and differences between patients, identifying differences in postprandial responses, nocturnal variability, or behavioral drivers between two patients with identical TIR. With these added benefits, the new metrics will be able to deepen existing insights into the

individualized pathophysiology of patients' lived experience with diabetes.

Functional Data Analysis: The Statistical Bridge to AI

The authors explained that functional data analysis treats each CGM trace as a continuous curve rather than discrete points, enabling richer modeling of glucose trajectories. The commentary also positioned functional data analysis as the analytical foundation on which AI can build. Key applications highlighted include:

- **Longitudinal analyses:** Identifying and analyzing variability patterns both within and between individuals over time;
- **Phenotyping & subphenotyping:** Distinguishing groups with distinct nocturnal, postprandial, or circadian profiles;
- **Behavioral insights:** Identifying missed boluses, mistimed insulin, or exercise patterns through curve shapes;
- **Device reproducibility:** Testing precision by comparing repeated CGM trajectories within and across individuals;
- **Risk stratification:** Quantifying intra- and inter-day variability as predictors of complications; and
- **Glucodensity:** Representing an individual's entire glucose distribution as a probability density function, preserving both central tendency and fluctuations, functional data analysis can calculate this statistical approach to better characterize the full variability of glucose concentrations.

Machine learning & AI: Toward predictive and personalized CGM

The authors devoted significant attention to ML and AI, describing use cases across prediction, classification, and decision support.

- **Pattern recognition & event classification:** Algorithms validated against clinician assessments can automatically detect and label hypoglycemia, hyperglycemia, and variability events.
- **Hypoglycemia prediction:** The authors noted that several ML models have already all been applied to anticipate nocturnal hypoglycemia with high accuracy.
- **Metabolic subphenotypes:** ML models can predict insulin resistance and beta-cell function using CGM data collected during at-home OGTTs, enabling more targeted interventions and risk stratification of those with early dysglycemia.
- **Glucotypes:** The authors explained that clustering CGM responses to meals can reveal distinct subgroups within the general population — including among normoglycemic individuals — that may identify prediabetes earlier than A1c or fasting glucose.
- **Complication risk:** ML has linked CGM patterns to retinopathy, albuminuria, and other microvascular outcomes, and has been used in studies like GLAM to link CGM data with maternal and perinatal complications risk.

They also identified emerging foundation models such as *Gluformer*, which are pretrained on massive CGM datasets and capable of generalizing to diverse downstream tasks like diagnosis and risk prediction. Furthermore, the commentary explained the role of industry in moving advanced CGM data analysis from research to practice, with two examples representing early steps toward comprehensive AI-generated, user-facing insights:

- **Dexcom Stelo:** An over-the-counter CGM launched in the US in August 2024, Stelo, uses generative AI to produce weekly narrative summaries and personalized lifestyle recommendations, integrating glucose with meal logs and other wearable data streams; and
- **Roche Accu-Chek SmartGuide:** This CGM option available in the EU employs three ML models for 120-minute forecasts, 30-minute low detection, and overnight hypoglycemia prediction, with proactive bedtime alerts.

Large Language Models (LLMs) and CGM

Large language models (LLMs) will also play an increasingly important role in the shift beyond CGM Data Analysis 1.0. For example, the authors reviewed early studies of GPT-4 applied to AGP interpretation. While they concluded that the LLM had high accuracy in identifying glycemic patterns, hypoglycemia, and hyperglycemia, it generated occasional clinical misinterpretations of that data that they believed could have misled resultant treatment decisions. They also stressed the need for human oversight and better prompt design and suggested that LLMs could be optimally used in drafting natural-language CGM summaries for clinicians (especially in primary care, where time and expertise to review AGPs are limited) or propose treatment adjustments subject to clinician approval.

Barriers to Widespread Adoption

Despite the promise, the authors identified several hurdles to CGM data analysis 2.0 implementation that remain:

- **Explainability:** Clinicians must understand why an algorithm flagged a pattern, especially for safety-critical insulin dosing.
- **Model drift:** Changes in physiology, medications, or lifestyle degrade performance, requiring continuous learning and drift detection pipelines.
- **Edge cases:** AI-enabled tools must be able to identify and account for patients who are not represented by the data the model is trained on, such as those with disrupted circadian rhythms or polypharmacy.
- **Integration into workflows:** New reports must be clinician-friendly, automated, and standardized to reduce the risk of becoming unused academic tools.

Close Concerns' Questions

1. Will the FDA and EMA have to evaluate and clear AI-powered CGM reports, especially when they are tied to insulin dosing?
2. Could this lead to the convention of a "CGM 2.0" consensus group by the ADA, EASD, or DTS, similar to the 2019 Time in Range report?
3. What is the current degree to which clinicians and patients trust AI in the role layed out in 2.0?
4. Will CGM 2.0 tools demonstrate measurable improvements in glycemic outcomes, complication risk, or patient-reported outcomes, or do the authors anticipate it will primarily be serviced to facilitate clinician-patient interactions?

--by Jeremy Alkire, Kat Moon, and Kelly Close

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[1] GRI = 3*hypoglycemia component + 1.6*hyperglycemia component = 3*(% very-low glucose) + 2.4*(% low glucose) + 1.6*(% very-high glucose) + 0.8*(% high glucose).