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ORIGINAL ARTICLE

Assessing Patterns of Continuous Glucose Monitoring Use and Metrics of Glycemic Control in Type 1 Diabetes and Type 2 Diabetes Patients in the Veterans Health Care System: Integrating Continuous Glucose Monitoring Device Data with Electronic Health Records Data

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Abstract

Objective: To integrate long-term daily continuous glucose monitoring (CGM) device data with electronic health records (EHR) for patients with type 1 and type 2 diabetes (T1D and T2D) in the national Veterans Affairs Healthcare System to assess real-world patterns of CGM use and the reliability of EHR-based CGM information.

Research Design and Methods: This observational study used Dexcom CGM device data linked with EHR (from 2015 to 2020) for a large national cohort of patients with diabetes. We tracked the initiation and consistency of CGM use, assessed concordance of CGM use and measures of glucose control between CGM device data and EHR records, and examined results by age, ethnicity, and diabetes type.

Results: The time from pharmacy release of CGM to patients to initiation of uploading CGM data to Dexcom servers averaged 3 weeks but demonstrated wide variation among individuals; importantly, this delay decreased markedly over the later years. The average daily wear time of CGM exceeded 22 h over nearly 3 years of follow-up. Patterns of CGM use were generally consistent across age, race/ethnicity groups, and diabetes type. There was strong concordance between EHR-based estimates of CGM use and Dexcom CGM wear time and between estimates of glucose control from both sources.

Conclusions: The study demonstrates our ability to reliably integrate CGM devices and EHR data to provide valuable insights into CGM use patterns. The results indicate in the real-world environment that CGM is worn consistently over many years for both patients with T1D and T2D within the Veterans Affairs Healthcare System and is similar across major race/ethnic groups and age-groups.

Keywords: glycemic control, continuous glucose monitoring, electronic patient records, type 1 diabetes, type 2 diabetes.

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Highlights

- We successfully integrated glucose data from continuous glucose monitoring (CGM) devices with the national Veterans Affairs Healthcare System EHR data in each place for nearly 3000 patients with type 1 and type 2 diabetes.
- There was strong agreement between electronic health records and Dexcom device data for both estimates of CGM use and between measures of glucose control.
- Correlations between CGM-based glucose levels and HbA1c levels were lower in African Americans, suggesting greater mismatching between HbA1c and glucose levels in this group.
- Patterns of CGM use demonstrated remarkable consistency of CGM use over many years that was similar in younger and older age-groups and across major race/ethnicity groups.

Introduction

The use of continuous glucose monitoring (CGM) has seen significant recent growth, thanks to improvements in sensor accuracy, enhanced user-friendliness, and the expanded coverage of medical insurance reimbursements. Simultaneously, efforts have been dedicated to establishing the integration of CGM with other diabetes technology such as insulin pumps[1] and achieving consensus on recommendations for use and interpretation of CGM readings.[2] This latter effort has included identifying key CGM measurement standards such as time in range (70–180 mg/dL—TIR) and glycemic management index (GMI), as well as the minimum number of days (14 days) of CGM wear to obtain reliable and clinically useful metrics of CGM.[3]

CGM has demonstrated its effectiveness in improving glycemic control in both type 1 and type 2 diabetes (T1D and T2D).[4–6] However, these studies have been primarily conducted in shorter-term randomized clinical trials[7–9] and thus reflect the use of CGM in a relatively motivated subset of patients, following careful study protocols that encouraged consistent use of CGM. Thus, we know very little about the short-term and long-term patterns of CGM use in the real world and the potential value of its integration into the increasingly common systems of electronic health records (EHR). Several recent studies conducted in larger health care systems have indicated that initiation of CGM, based on insurance claims or pharmacy prescriptions, has been linked with declines in HbA1c.[10] Importantly, because of the longer-term follow-up available in the EHR used in these studies, investigators were able for the first time to compare in large samples of T1D and T2D CGM users and nonusers the effects of CGM use on common longer-term complications of diabetes and demonstrated reduced admission to emergency rooms or hospitals[10,11] and even reductions in cardiovascular events.[11] However, without the actual glucose data, EHR-based assessments of CGM have limitations as they (1) can only surmise CGM initiation by prescription refills or patterns of claims data, (2) can only estimate patterns and duration of CGM use by these same methods, and (3) cannot test the relevance of currently recommended CGM glycemic metrics (e.g., TIR) or develop improved metrics for the prediction of long-term outcomes.

To better understand the long-term patterns of CGM use in a real-world setting and to understand and improve the reliability and usefulness of EHR to study the nature and benefits of CGM use on diabetes complications, we linked CGM device data with the EHR data of users with T1D and T2D of Dexcom CGM devices in the Veterans Affairs Healthcare System. The objectives of this initial study of linking CGM device data with EHR data were to (1) describe and validate the construction of these cohorts of CGM users, (2) examine the real-world short-term and long-term patterns of use of CGM in both adult patients with T1D and T2D, (3) examine the relationships between CGM data and EHR measures of glycemic control, (4) identify the strengths and limitations of EHR-only based data to estimate CGM use, and (5) determine if these patterns of CGM use and relationships between measures of glycemic control vary by age, race/ethnicity, or diabetes type.

Research Design and Methods

This retrospective study combines CGM device data from the Dexcom, Inc., database with data extracted from EHR in the Department of Veterans Affairs (VA). CGM device data were not originally available within VA EHR, so these two datasets were manually merged for this research study using cross-walk identification. The protocol was approved by the Phoenix VA Health Care System Institutional Review Board (IRB), which provided a waiver of consent for this analysis of secondary data. Dexcom, Inc., received IRB exemption from WCG IRB (www.wcgirb.com) for the study protocol to share CGM patient data with the VA. We extracted all relevant EHR data from the VA Corporate Data Warehouse, a national repository of clinical and administrative information from VA encounters that includes both inpatient and outpatient visits, diagnoses, pharmacy and medication usage, vital signs records, laboratory measurements, and general patient demographic information.

CGM users in the VA EHR system

We identified patients with diabetes *initiating* CGM from January 1, 2015, to December 31, 2020. All available ICD-9 and ICD-10 diagnostic codes were extracted from medical encounters among Veterans aged ≥21 years or older with at least one diagnosis of diabetes (ICD-9: 250 or ICD-10: E10, E11, O24.0X, O24.1X) between 2002 and 2020. *Initiators* of CGM (also subsequently referred to as *EHR CGM users*) were identified as those with their first prescription (defined as index date) between January 1, 2015, and December 31, 2020. CGM prescriptions were identified if they matched a glucose sensor for devices available in the VA during this time period. Although some patients used more than one type of CGM during this time frame, only the periods of time reflecting the use of Dexcom devices were considered for analyses.

We also extracted longitudinal HbA1c measurements from the EHR and made use of CGM prescription data from January 2015 to January 2023, which encompass sensor release dates and run-out dates, to define the proportion of days covered (PDC) as a metric for assessing patient adherence to CGM based on EHR.

Dexcom CGM device-derived glucose metrics

CGM measures interstitial glucose concentrations and generates an estimated blood glucose value every 5 min, providing up to 288 individual readings for each day. The daily CGM data are also aggregated to compute average daily estimated glucose and the daily coefficient of variation of the glucose levels observed. Other CGM metrics calculated from daily estimated glucose values include TIR: time between 70 and 180 mg/dL; time-below-range: below 55 mg/dL and below 70 mg/dL; and time-above-range: above 180 mg/dL and above 250 mg/dL. GMI, an estimate of HbA1c, was also computed from estimated glucose values. Dexcom CGM device data were available from October 2015 to April 2023 and included records from 4585 users (also subsequently referred to as *Dexcom CGM users*). Detailed information regarding the quality control procedures applied to the Dexcom data before analysis are outlined in the Supplementary Material.

Study cohort

To identify individuals for this cohort, patients using CGM were matched between datasets (VA EHR and Dexcom CGM device glucose data) on first name, last name, and date of birth. This matching process involved two methods: an exact match using both the first and the last names along with the complete date of birth and a slightly relaxed match considering the first and last names along with the year and month of birth only (Supplementary Fig. S1). Individuals were identified as having T1D or T2D using a modified Klompas algorithm, as previously described.[12]

We excluded persons who used Dexcom CGM devices for <14 days (largely reflecting those not showing any uploaded glucose activity) during the follow-up period and those with duplicated daily CGM records (for details, see Quality Control in the Supplementary Material). We also omitted individuals without evidence of any prescription sensor refills in VA EHR encompassing periods of Dexcom CGM use (indicating non-VA sources of devices), as the CGM start, stop, and duration of use could not be defined. Furthermore, individuals who could not be identified as having T1D or T2D were removed. Our final CGM cohort (successfully matched between Dexcom records and VA EHR) included a combination of those who used Dexcom CGM devices exclusively throughout the follow-up period (Dexcom-only users) and mixed-device users who used both Dexcom and other brand device(s) at different times during the follow-up. Although we focused analyses on the large majority who were Dexcom-only users, where appropriate, we stratified the results based on user type (Dexcom-only users or Dexcom intermittent users). However, all analyses of CGM activity were based only on data from Dexcom devices.

Variable definitions

Metrics to describe patterns of CGM use. To assess the patterns of CGM use, several key indicators were defined and calculated for each individual:

1. *EHR index date, Dexcom index date, and time between EHR index date and CGM device index date*: EHR index date was the initial Dexcom CGM prescription date extracted from the EHR data. Dexcom index date was the CGM start date (reflecting the first glucose reading) using device data extracted from the Dexcom database. The time between the initial EHR index date and the start of Dexcom data was then calculated.
2. *Duration of CGM device use*, defined as the number of days between the date of the first and the last Dexcom CGM device data record.
3. *Percentage of days with CGM use*, defined as the proportion of days, wherein at least one glucose reading was uploaded.
4. *Percentage of months with CGM use*, defined as the proportion of months having at least 14 days with at least one glucose reading uploaded.
5. *Hours of CGM use per day*, averaged across the full duration of use, calculated as the total of 5-min glucose counts per day to convert into hours of CGM use, and then averaged over all days of use (disregarding days when the Dexcom device was not worn).
6. *Gaps in CGM use*, percentage of individuals who did not use their Dexcom CGM or upload data from this device for substantial periods of time (e.g., 30 or more consecutive days).

For detailed calculations and descriptions of self-reported race and ethnicity, see the Research Design Methods within Supplementary Materials.

Concordance of PDC calculated between EHR prescriptions and days of CGM use determined from Dexcom device data.

We defined PDC for each individual from both EHR and Dexcom device data.

1. *EHR-based PDC*, defined by CGM sensor refills extracted from patients' prescriptions and refills. Using EHR records, we defined continuous use of CGM if an interruption in sensor availability between prescription sensor refills was less than 28 days (as patients often have small surplus supplies that may permit continued CGM use during small periods between refills). If this interval period exceeded 28 days, this was defined as a "gap" in use of CGM. We also examined a 90-day gap in CGM use. Over *each 30-day segment*, we assigned a binary EHR-based PDC variable to denote either active CGM or gap periods. Detailed methods on the binary allocation are shown in Supplementary Figure S2.
2. *Dexcom CGM device-based PDC* reflected the proportion of days with at least 1 reading per day among each 30-day interval. For instance, if a participant wore the device for 24 out of 30 days (with at least 1 reading per day), CGM device-based PDC for that interval was 0.8 (reflecting a continuous variable).

Statistical analysis

TIR, GMI, and HbA1c. Daily TIR (%) was computed as the number of counts of glucose readings falling between 70 and 180 mg/dL divided by the total counts of readings, converting it to a percent (0%–100%). Daily GMI (%) was calculated as 3.31 plus 0.02392 times the mean glucose level (in milligrams per deciliter).[13] We quantified the relationship

between individuals' HbA1c measurements recorded in the EHR and their corresponding preceding 3 months' TIR and GMI derived from the Dexcom CGM data. Pearson correlation coefficients were calculated between HbA1c, mean GMI, and mean TIR and also between GMI and TIR, using all readings from the CGM device of each individual.

PDC concordance. The absolute value of the difference between the EHR-based PDC and Dexcom CGM device-based PDC was designated as the PDC difference, and a complementary measure, one minus the difference, was defined as the PDC concordance. The concordance was computed for each 30-day prescription/refill or gap period for each patient. A PDC concordance value of 1 (reflecting complete concordance) could occur in two scenarios. First, when a patient consistently wore a CGM throughout the covered period (in this case, both the EHR-based and the CGM device-based PDCs are 1). Second, when a participant did not have CGM, glucose values during the same EHR gap period (both PDCs are 0). "Average PDC concordance" was defined as the mean of PDC concordances for each individual across all 30-day segments. EHR-based PDCs and Dexcom CGM-based PDCs for multiple intervals during follow-up in six representative participants are shown in Supplementary Figure S3.

All statistical analyses were performed using R version 4.3.1 (https://www.r-project.org).

Results

Participants

After matching individuals using patient information from both VA EHR and Dexcom databases, we identified 3137 individuals with both EHR data and CGM device readings. Applying exclusion criteria detailed in the "study cohort" section resulted in a final cohort of 2796 participants, comprising 2168 Dexcom-only users and 628 mixed-device users (Supplementary Fig. S1). T2D CGM users tended to be older, have higher body mass index and triglycerides, and lower high-density lipoprotein cholesterol, estimated glomerular filtration rate, insulin pump, and glucagon use than T1D CGM users (Table 1). Among T1D participants, 80.0% identified as White, 15.7% African American, and 3.6% Hispanic. For patients with T2D, the corresponding percentages were 75.1%, 17.9%, and 3.9%, respectively. Supplementary Table S1 shows baseline characteristics for Dexcom-only users, which were similar to those of the overall cohort except for a slightly lower prevalence of insulin pump use.

Characterizing patterns of CGM device use

In Table 2, we characterized patterns of CGM use, making use of actual uploaded glucose data in Dexcom-only users, as there was less certainty about start and stop dates for non-Dexcom devices. We observed no substantial differences in use patterns between patients with T1D and patients with T2D. The median time from the EHR index date (first prescription release date) to the Dexcom index date (starting glucose uploading to the Dexcom servers) was 22.0 days for individuals with T1D and 21.0 days for those with T2D (Table 2 and Supplementary Fig. S4). However, the corresponding 75th quantiles were 230.5 days and 122.0 days, indicating that many patients with T1D and T2D required much longer to begin providing glucose data. Interestingly, the median and 75th quantile time decreased markedly over time and was approximately 14 days and 44 days (75th quantile) for patients with T1D and T2D by 2020. The median duration of CGM device use was approximately 3 years for patients with either T1D or T2D. CGM devices were worn for a median of ~90% of the days during this long duration of wear for both diabetes types. The proportion of participants with >90% of days with CGM use was higher among patients with T1D (52.7%) than with T2D (48.7%). Even when CGM use duration was restricted to increasingly longer minimum intervals (i.e., 180 days, 1 year, 2 years, and 3 years) during the follow-up period, as opposed to 14 days (the original exclusion criterion), the proportion with over 90% of days with CGM use was consistent for patients with T1D and T2D (see Supplementary Fig. S5). Similarly, T1D and T2D groups consistently wore CGM devices for a median duration exceeding 22 h/day (interquartile range [IQR]: 21 to ~23 h) (Table 2 and Supplementary Fig. S6). However, 44.6% of patients with T1D and 46.5% of patients with T2D experienced at least one gap of at least 30 days during follow-up. This percentage decreased to 25.1% for patients with T1D and 25.2% for patients with T2D with gaps of 120 days or longer. White, non-Hispanic users with T1D tended to have the longest duration of use, for example, 3.2 years, whereas Hispanic users with T1D had the lowest duration of use (Supplementary Table S2). Older participants tended to have longer intervals between EHR index date and CGM device index date and slightly shorter duration of use but fewer long gaps in use and a higher percentage of days with CGM use. For a more detailed breakdown of results by diabetes type, ethnicity, and age categories (<65 and ≥65 years), see Supplementary Table S2. Mixed-device users exhibited similar CGM use patterns for the percentage of days, months, gaps, and average hours per day but as expected a shorter duration of Dexcom device use (Supplementary Table S3).

Correlations between HbA1c values from EHR and mean TIR and mean GMI measured by CGM devices

The correlation between HbA1c and mean TIR exhibited a strong negative association (−0.78 for patients with T1D and −0.71 for patients with T2D) (Table 3). There was also a robust positive association between HbA1c levels and mean GMI (0.79 for patients with T1D and 0.74 for patients with T2D in Dexcom-only users). When comparing these correlations across different race/ethnicity groups (Supplementary Table S4), associations were attenuated for African Americans compared with Whites in both T1D and T2D patient groups. No notable differences were observed in correlations between younger (<65) and older (≥65) age-groups for patients with T1D and T2D. The correlations between TIR and GMI (both determined by the CGM device) were −0.89 and −0.90 for participants with T1D and T2D, respectively. These correlations were equally strong in all race/ethnic groups and age-groups.

PDC concordance

Table 4 presents PDC concordance for CGM (median [IQR]) use between EHR and Dexcom data across individuals categorized by diabetes type, ethnicity, and age-groups.

Table 1. Baseline Characteristics by Diabetes Type

	T1D	*T2D*
n (%)	970 (34.7)	1826 (65.3)
Index year, %		
2015	5.1	1.6
2016	7.7	3.7
2017	9	3.9
2018	19.7	18.5
2019	36.2	41.2
2020	22.4	31.1
Age at index (years), median [IQR]	56.0 [48.0, 66.0]	65.0 [55.0, 71.0]
Gender, % male	88.2	91.5
BMI (kg/m^2), median [IQR]	27.9 [24.8, 31.1]	31.5 [27.2, 36.4]
Ethnicity, %		
White, non-Hispanic	80.0	75.1
African American	15.7	17.9
White, Hispanic	3.6	3.9
Other	0.8	3.1
U.S. region, %		
South	37.8	39.0
Midwest	24.1	22.7
West	25.7	20.9
Northeast	12.4	17.3
LDL (mg/dL), median [IQR]	83 [66, 105]	76 [59, 98]
HDL (mg/dL), median [IQR]	51 [42, 63]	42 [34, 53]
Triglycerides (mg/dL), median [IQR]	89 [63, 132]	130 [85, 196]
Creatinine (mg/dL), median [IQR]	1.0 [0.9, 1.2]	1.1 [0.9, 1.4]
HbA1c (%), median [IQR]	8.3 [7.4, 9.3]	8.1 [7.3, 9.2]
eGFR (mL/min/1.73m2), median [IQR]	85 [67, 99]	71 [52, 89]
Insulin pump use, %	30.1	14.0
Any insulin use, %	96.4	95.2
Glucagon use, %	34.3	20.1
Statin use, %	72.0	79.7
Any non-insulin diabetes medications, %	19.9[a]	55.4
DCSI Weighted Score, %		
Score = 0	24.2	14.7
Score = 1	27.5	21.6
Score = 2	17.6	18.1
Score ≥ 3	30.6	45.6

Data are presented as median (interquartile range [IQR]) for numerical variables and *n* (%) for categorical variables.

[a]The majority of noninsulin diabetes medication used in T1D was metformin.

BMI, body mass index; DCSI, diabetes complication severity index; eGFR, estimated glomerular filtration rate; HDL, high-density lipoprotein; LDL, low-density lipoprotein; T1D, type 1 diabetes; T2D, type 2 diabetes.

Overall, concordance between the two data sources was high (≥0.80) for both the 28-day and the 90-day gap thresholds. Patients with T1D had slightly higher concordances (median [IQR]: 0.82 [0.61, 0.93]) compared with their T2D counterparts (0.80 [0.56, 0.92]). Concordance was somewhat lower for African American patients with T2D compared with the White and Hispanic patients with T2D, whereas older individuals demonstrated higher concordance compared with the younger age-group for patients with T1D and T2D (Table 4 and Supplementary Fig. S7).

The PDC concordances with 90-day gaps were about 0.05 higher than those using 28-day gaps for all subgroups with almost no difference from the PDC concordances using 60-day gaps (results are not shown), suggesting that for the majority of patients, gaps in CGM use lasted no more than 2 months.

Conclusions

In this study, we linked long-term daily CGM device data with VA EHR clinical data for large cohorts of patients with T1D and T2D. This permitted us to gain valuable insights into CGM use patterns across a large national health care setting and to clarify the reliability of EHR-based information for CGM. These findings provide novel information about how CGM is used by patients with T1D and T2D and by patient subgroups in a real-world environment. Moreover, comparing actual CGM device data with EHR CGM records helps demonstrate both the quality and the reliability of EHR CGM data.

On average, it required about 3 weeks for patients with T1D and T2D to start uploading glucose data to Dexcom servers and potentially sharing these data with providers. However, there was wide variation in this time frame, with nearly a quarter of patients with T1D and T2D taking 231 and 122 days, respectively, to generate these data. Although this did not appear to vary among race/ethnic groups, it did appear to be delayed more in older individuals. A multitude of reasons (e.g., patient concerns about revealing personal data; complexity of, and interest of providers in, viewing and using the data; insufficient experienced staff to provide the needed education to patients and providers) may help explain the longer delays in CGM device data becoming available. Whether a person used a dedicated receiver device or their smartphone to view their glucose readings likely also influenced when data were uploaded. Although data from the CGM are automatically uploaded from a smartphone, using the receiver device requires the user to connect the receiver to a personal computer to upload data. As upload delays decreased over time, alongside improvements in CGM technology and training options for patients and providers, it highlights the value of comprehensive technology support to ensure timely initiation and effective utilization of CGM.

Importantly, once the use of CGM (Dexcom users) was started, it was typically used with high levels of consistency over long periods of time. Remarkably, the average wear time per day over a median of nearly 3 years was over 22 h for patients with T1D and T2D. However, nearly 25% of patients had at least one apparent gap in CGM use of greater than 120 days. Gaps in use of CGM by patients are to be expected, just like they have gaps in their use of most medications. Although we cannot identify these reasons, they undoubtedly reflect a range of behaviors, including forgetting or being unable to refill the sensors as scheduled, taking intentional breaks away from sensors, or having problems with their devices and/or transmitters. Consistency of CGM use for both T1D and T2D trended slightly higher in White, non-Hispanics, and in individuals >65 years old. Overall, these results provide unique insights into the CGM use patterns in a real-world environment and highlight the consistent long-term

Table 2. Measures of CGM Use in Dexcom-Only Users by Diabetes Type

	T1D	*T2D*
n (%)	719 (33.2)	1449 (66.8)
Time between EHR index date and CGM device index date (days), median [IQR]	22.0 [6.0, 230.5]	21.0 [5.0, 122.0]
Duration of CGM use (years), median [IQR]	3.1 [2.2, 4.0]	2.9 [1.8, 3.7]
Percentage of days with CGM use (%), median [IQR]	91.0 [70.7, 96.5]	89.5 [71.0, 96.1]
Percentage of months with CGM use, median [IQR]	89.7 [69.2, 94.3]	88.2 [66.7, 93.8]
Hours of CGM use per day, median [IQR]	22.5 [21.4, 23.0]	22.2 [21.0, 22.9]
Gap in CGM use, %[a]		
≥30 days	44.6	46.5
≥60 days	33.0	34.6
≥120 days	25.1	25.2

[a]Users were excluded from calculations of gap thresholds if their overall duration of use was shorter than that gap period. Each day of CGM use required at least ≥1 glucose count to be present. Percentage of months with CGM use was defined as the proportion of months having at least 14 days with at least one glucose reading uploaded.

CGM, continuous glucose monitoring; EHR, electronic health record.

use of these devices with only modest differences among diabetes type, race/ethnicity, and age groups.

The use of calculated PDC based on prescription refills is a common approach to estimate medication use in EHR. Appropriately accounting for medication use is critical for a wide variety of real-world research questions pursued through EHR. However, validation of this approach is limited given the difficulty ascertaining actual medication ingestion. Although we and others have applied a similar approach to estimate CGM adherence from EHR data based on calculations of PDC,[11] confirmation of the reliability of this approach greatly enhances confidence in future investigations of CGM based on comprehensive EHR and medical claims data. Our current data demonstrate strong concordance between the estimated use of CGM using EHR PDC and more direct measures based on accumulated estimated glucose values from CGM devices. These data also suggest that CGM use identified through EHR is a reasonable proxy of the consistency of CGM use. Interestingly, the reliability of EHR for tracking use of CGM, although still quite good, appeared slightly lower in African Americans and Hispanic groups. However, the number of CGM users in these two groups was smaller compared with the White, non-Hispanic group, which may result in less stable concordance estimates. Nonetheless, our overall data indicate relatively similar degrees of EHR reliability and wear patterns among the different race/ethnic groups and support equitable use of CGMs among diverse ancestry.

Table 3. Correlations of HbA1c in VA EHR with TIR and GMI from CGM Device Data in Dexcom-Only Users by Diabetes Type

	T1D	*T2D*
n (%)[a]	652 (33.7)	1280 (66.3)
Total number of HbA1c measurements	3813	7452
Median duration of CGM use (years)[b]	2.8	2.5
Correlation between HbA1c and mean TIR	−0.774	−0.707
Correlation between HbA1c and mean GMI	0.791	0.738

[a]Users without appropriate overlapping Dexcom data and EHR HbA1c values were excluded.

[b]The duration of use reflected CGM records used to calculate the mean TIR/GMI.

GMI, glucose management indicator; TIR, time in range.

Not surprisingly, there were good correlations between Dexcom CGM data and HbA1c estimates of glycemic control within the EHR. Specifically, both TIR and GMI extracted from CGM data demonstrated correlation values of −0.7 and 0.8, respectively. The strength of these relationships between CGM metrics and HbA1c values was quite similar to those reported in randomized clinical trials of CGM that have simultaneously tracked HbA1c values.[14,15] Interestingly, these correlations with HbA1c were weaker in those identifying as African American. These findings are very consistent with reports that African Americans have HbA1c values (compared with other race/ethnic groups) that align less well with mean glucose levels whether coming from CGM data or other longitudinal measurements of glucose. Correlations between TIR and GMI (both calculated from CGM device estimated glucose values) were strong (nearly −0.9) and did not differ among race/ethnic groups.[16,17] Overall, these results provide strong internal validation of the successful integration of the two different sources of CGM users and support the reliability of the extracted data.

A novel feature of this study was the ability to integrate CGM device data with EHR data on nearly three thousand patients. This large and diverse cohort bolsters the robustness and generalizability of our results. It also allowed us to demonstrate the generally similar patterns of CGM use among different race/ethnic and age groups. As we and others have demonstrated, rates of CGM use and diabetes technology in general are lower in certain race and ethnic groups and in older individuals[11,18–22]; our findings that CGM use is similar in these groups may help change provider perceptions about who may effectively adopt this technology. The long duration of follow-up within the VA EHR also allowed us to demonstrate persistent high-level adherence to CGM with minimal drop-off in use over many years.

A potential limitation of the study is that we were limited to Dexcom CGM device data that may not reflect patterns of use of all CGM systems on the market. Although the number of women using CGM was relatively modest, the patterns of results within women seemed consistent with the whole cohort (Supplementary Table S5). Although analyses in this study were based on CGM device data aggregated to the level of daily glucose metrics, future studies will provide even more

Table 4. Average PDC Concordance in Dexcom-Only Users by Diabetes Type, Ethnicity, and Age Groups

4A.	*T1D*	*T2D*
n (%)	719 (33.2)	1449 (66.8)
PDC concordance,[a] median [IQR]		
28-day gap threshold	0.82 [0.61, 0.93]	0.80 [0.56, 0.92]
90-day gap threshold	0.89 [0.61, 0.98]	0.85 [0.55, 0.97]

	T1D (n = *719*)				
4B.	*White, Non-Hispanic*	*African American*	*White, Hispanic*	*Baseline age < 65*	*Baseline age ≥ 65*
n (%)	548 (76.2)	113 (15.7)	25 (3.5)	500 (69.5)	219 (30.5)
PDC concordance,[a] median [IQR]					
28-day gap threshold	0.83 [0.61, 0.94]	0.82 [0.64, 0.91]	0.75 [0.47, 0.92]	0.80 [0.59, 0.93]	0.88 [0.64, 0.95]
90-day gap threshold	0.90 [0.62, 0.98]	0.87 [0.64, 0.96]	0.80 [0.44, 0.98]	0.86 [0.60, 0.98]	0.94 [0.66, 0.99]

	T2D (n = *1449*)				
4C.	*White, Non-Hispanic*	*African American*	*White, Hispanic*	*Baseline age < 65*	*Baseline age ≥ 65*
n (%)	1034 (71.4)	245 (16.9)	56 (3.9)	687 (47.4)	762 (52.6)
PDC concordance,[a] median [IQR]					
28-day gap threshold	0.81 [0.53, 0.93]	0.77 [0.59, 0.88]	0.81 [0.58, 0.91]	0.78 [0.56, 0.91]	0.82 [0.55, 0.93]
90-day gap threshold	0.86 [0.54, 0.98]	0.81 [0.56, 0.94]	0.85 [0.61, 0.97]	0.81 [0.57, 0.96]	0.88 [0.54, 0.98]

Average PDC concordance in all T1D and T2D Dexcom-only users (Panel 4A) and by diabetes type across ethnicity and age groups (Panels 4B and C).

[a]PDC concordance (defined in Methods and Supplementary Fig. S2 reflects the average PDC concordance across all 30-day segments for each patient. The gap thresholds reflect the maximum EHR gap in days of CGM use allowed to link two consecutive segments of prescription-based CGM use, for example, if the gap in EHR CGM use between refills was greater than 28 days, then that period was marked as a gap in use.

PDC, proportion of days covered.

granular assessments of intraday glucose patterns and glucose fluctuations in relation to clinical outcomes in EHR data. Another limitation of the study is that EHR data may contain missing data. For example, 3.6% and 4.8% of participants with T1D and T2D, respectively, receiving CGMs, were not on insulin therapy, which may reflect the small percentage of individuals who receive one or more medications from outside the VA that are not captured in VA medication files.

In conclusion, we have successfully integrated CGM device data with long-term clinical data from patients within the Veterans Affairs national health care system. We have identified patterns of Dexcom CGM use across a large and diverse cohort and demonstrated that in a real-world environment, there is remarkably consistent and sustained use of the devices across race/ethnic groups and in young and old patients. Using Dexcom device data, we have also demonstrated high concordance with EHR estimates of CGM use and the expected relationships with HbA1c values from these records. Thus, this work lays the foundation for a myriad of future studies examining the relationships between CGM metrics of glucose control and development of short-term and long-term diabetes complications.

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Authors' Contributions

T.O. analyzed data and wrote the first draft of the article. S.A.M. extracted data from VA VINCI computing platform. G.J.N. arranged for access to Dexcom device data, provided information on the nature of this data, and contributed to discussions. P.R. conceived the idea for the project, obtained project funding, and contributed to discussions and article preparation. J.J.Z. assisted in project development, supervised the project and analyses, and assisted with article preparation. All authors reviewed, edited, and approved the article. J.J.Z. is the guarantor of this work, had full access to all the data, and takes full responsibility for the integrity of data and the accuracy of data analysis.

Disclaimer

The contents of the article do not represent the views of the VA or the U.S. government.

Author Disclosure Statement

No potential conflicts of interest relevant to this article were reported. G.J.N. is an employee of Dexcom, Inc.

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Supplementary Material

Supplementary Figure S1
Supplementary Figure S2
Supplementary Figure S3
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Supplementary Table S1

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References

1. Espinoza J, Xu NY, Nguyen KT, Klonoff DC. The need for data standards and implementation policies to integrate CGM data into the electronic health record. J Diabetes Sci Technol 2023;17(2):495–502.
2. Longo R, Sperling S. Personal versus professional continuous glucose monitoring: When to use which on whom. Diabetes Spectr 2019;32(3):183–193.
3. Battelino T, Danne T, Bergenstal RM, et al. Clinical targets for continuous glucose monitoring data interpretation: Recommendations from the international consensus on time in range. Diabetes Care 2019;42(8):1593–1603.
4. Beck RW, Riddlesworth TD, Ruedy K, et al. Continuous glucose monitoring versus usual care in patients with type 2 diabetes receiving multiple daily insulin injections: A randomized trial. Ann Intern Med 2017;167(6):365–374.
5. Park C, Le QA. The effectiveness of continuous glucose monitoring in patients with type 2 diabetes: A systematic review of literature and meta-analysis. Diabetes Technol Ther 2018;20(9):613–621.
6. Tamborlane WV, Beck RW, Bode BW, et al. Continuous glucose monitoring and intensive treatment of type 1 diabetes. N Engl J Med 2008;359(14):1464–1476.
7. Jackson MA, Ahmann A, Shah VN. Type 2 diabetes and the use of real-time continuous glucose monitoring. Diabetes Technol Ther 2021;23(S1):S27–S34.
8. Teo E, Hassan N, Tam W, Koh S. Effectiveness of continuous glucose monitoring in maintaining glycaemic control among people with type 1 diabetes mellitus: A systematic review of randomised controlled trials and meta-analysis. Diabetologia 2022;65(4):604–619.
9. Uhl S, Choure A, Rouse B, et al. Effectiveness of continuous glucose monitoring on metrics of glycemic control in type 2 diabetes mellitus: A systematic review and meta-analysis of randomized controlled trials. J Clin Endocrinol Metab 2023.
10. Karter AJ, Parker MM, Moffet HH, et al. Association of real-time continuous glucose monitoring with glycemic control and acute metabolic events among patients with insulin-treated diabetes. JAMA 2021;325(22):2273–2284.
11. Reaven PD, Newell M, Rivas S, et al. Initiation of continuous glucose monitoring is linked to improved glycemic control and fewer clinical events in type 1 and type 2 diabetes in the veterans health administration. Diabetes Care 2023;46(4):854–863.
12. Klompas M, Eggleston E, McVetta J, et al. Automated detection and classification of type 1 versus type 2 diabetes using electronic health record data. Diabetes Care 2013;36(4):914–921.
13. Bergenstal RM, Beck RW, Close KL, et al. Glucose Management Indicator (GMI): A new term for estimating A1C from continuous glucose monitoring. Diabetes Care 2018;41(11):2275–2280.
14. Vigersky RA, McMahon C. The relationship of hemoglobin A1C to time-in-range in patients with diabetes. Diabetes Technol Ther 2019;21(2):81–85.
15. Beck RW, Bergenstal RM, Cheng P, et al. The relationships between time in range, hyperglycemia metrics, and HbA1c. J Diabetes Sci Technol 2019;13(4):614–626.
16. Gonzalez A, Deng Y, Lane AN, et al. Impact of mismatches in HbA(1c) vs glucose values on the diagnostic classification of diabetes and prediabetes. Diabet Med 2020;37(4):689–696.
17. Staimez LR, Kipling LM, Nina Ham J, et al. Potential misclassification of diabetes and prediabetes in the U.S.: Mismatched HbA1c and glucose in NHANES 2005–2016. Diabetes Res Clin Pract 2022;189:109935.
18. Lai CW, Lipman TH, Willi SM, Hawkes CP. Racial and ethnic disparities in rates of continuous glucose monitor initiation and continued use in children with type 1 diabetes. Diabetes Care 2021;44(1):255–257.
19. Fantasia KL, Wirunsawanya K, Lee C, Rizo I. Racial disparities in diabetes technology use and outcomes in type 1 diabetes in a Safety-Net Hospital. J Diabetes Sci Technol 2021;15(5):1010–1017.
20. Agarwal S, Schechter C, Gonzalez J, Long JA. Racial-ethnic disparities in diabetes technology use among young adults with type 1 diabetes. Diabetes Technol Ther 2021; 23(4):306–313.
21. Toschi E, Munshi MN. Benefits and challenges of diabetes technology use in older adults. Endocrinol Metab Clin North Am 2020;49(1):57–67.
22. Auzanneau M, Eckert AJ, Meyhofer SM, et al. Area deprivation and demographic factors associated with diabetes technology use in adults with type 1 diabetes in Germany. Front Endocrinol (Lausanne) 2023;14:1191138.

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