

Impact of Real-Time Continuous Glucose Monitoring on Medication Use and Glycemic Control in Type 2 Diabetes Across Therapy Regimens

Blake C L Liu¹, Katia L Hannah¹, Poorva M Nemlekar¹, Courtney R Green², Gregory J Norman¹

¹Clinical Affairs, Dexcom, Inc., San Diego, CA, USA; ²Medical Affairs, Dexcom, Inc., San Diego, CA, USA

Correspondence: Gregory J Norman, Dexcom, Inc., 6340 Sequence Dr, San Diego, CA, 92121, Email greg.norman@dexcom.com

Purpose: This study evaluated how real-time continuous glucose monitoring (RT-CGM) use was associated with medication use patterns and A1c changes among people with type 2 diabetes (T2D) using non-insulin therapy (NIT), basal insulin therapy (BIT), or intensive insulin therapy (IIT). We hypothesized that RT-CGM use would be associated with more frequent medication class changes and reduction in polypharmacy, alongside greater improvements in A1c compared to CGM non-use.

Patients and Methods: This retrospective study analyzed US administrative claims data from the Optum Clinformatics Data Mart database between 09/01/2016 and 06/30/2024. People with T2D were divided into NIT, BIT, or IIT cohorts. Each cohort contained two groups: Dexcom RT-CGM users or CGM non-users and 1:1 propensity score matching was performed to minimize differences between the groups. We compared changes in medication use and A1c levels between RT-CGM users and CGM non-users over 12 months.

Results: Over 1.6 million people with T2D were identified prior to matching and stratified by therapy regimen as T2D-NIT, -BIT, or -IIT. After propensity score matching, the proportion of RT-CGM users taking ≥ 4 medications declined significantly and RT-CGM users had more net changes in their medications than CGM non-users. In addition, greater improvements in A1c were observed among RT-CGM users compared to CGM non-users in all cohorts (difference-in-differences of -0.4% , -0.5% , and -0.4% for T2D-NIT, T2D-BIT, and T2D-IIT, respectively, all $p < 0.0001$). More RT-CGM users also achieved a mean A1c $< 7.0\%$ or $< 8.0\%$ at follow-up overall and among those not meeting the target at baseline.

Conclusion: Higher rates of medication changes were associated with RT-CGM use. RT-CGM use was associated with significantly and meaningfully improved A1c levels among all T2D cohorts. The findings indicate that RT-CGM use could help all people with T2D improve their glycemia.

Keywords: A1c, administrative claims, anti-diabetes medication, diabetes technology, medication optimization, real-time continuous glucose monitoring

Introduction

There are a staggering number of people living with type 2 diabetes (T2D) in the United States and globally.¹ With these numbers almost certain to increase, experts advocate for increased access to diabetes technology.² This includes continuous glucose monitoring systems which last 7–15 days and report a glucose value every 1–5 minutes.

Real-time continuous glucose monitoring (RT-CGM) measures glucose levels in the interstitial fluid using a thin, transcutaneous wire. Glucose values are automatically sent to a connected display device (receiver or smartphone) where the user can check their current glucose value or perform retrospective analyses. The app or receiver connected to the RT-CGM sensor can deliver alerts related to glucose levels (hypoglycemia or hyperglycemia alerts), rapid changes in glucose, or loss of connection.

RT-CGM systems are non-adjunctive, meaning they can be used as the basis for insulin dosing decisions. Beyond its application in insulin dosing, there is increasing interest in the combined use of RT-CGM and antidiabetic medications to help inform treatment decisions. In fact, the 2025 American Diabetes Association (ADA) Standards of Care in Diabetes

included a new recommendation to consider CGM use among adults with T2D using any glucose-lowering medication to tailor therapies if A1c is above goal.³

In relation to A1c goals, previous studies have shown that the use of RT-CGM is associated with glycemic improvements among people with type 1 diabetes,⁴ type 2 diabetes using intensive insulin therapy,⁵ and, increasingly, people with T2D using only basal insulin⁶ or non-insulin therapies.^{7,8} However, real-world evidence of the benefits of RT-CGM use among people with T2D using non-insulin therapies is limited.

Therefore, this study evaluated two hypotheses: 1) RT-CGM use among people with T2D using any therapy regimen (intensive insulin, basal insulin, or non-insulin therapies) is associated with higher rates of medication class changes and reductions in polypharmacy; and 2) RT-CGM use among people with T2D using any therapy regimen is associated with greater improvements in A1c compared to CGM non-use.

Materials and Methods

Data Source

This retrospective, observational study leveraged de-identified health claims data from Optum's Clinformatics® Data Mart (CDM) database, encompassing approximately 83 million unique individuals with commercial or Medicare coverage across the United States from 01/01/2007 to 06/30/2024. The CDM contains deidentified health information consistent with the Health Insurance Portability and Accountability Act (HIPAA) and managed according to Optum customer agreements in compliance with US Code of Federal Regulations title 45, section 164.514(b)(1).⁹ CDM administrative claims submitted by healthcare providers and pharmacies are processed, validated, and anonymized prior to inclusion. This dataset captures comprehensive details on patient enrollment, healthcare service utilization, and associated costs. Access to the CDM was obtained through a license from Optum. Given that the data are fully de-identified and adhere to HIPAA standards, the study was considered exempt research from ethics committee approval under US Code of Federal Regulations title 45 section 46.104(d)(4)(ii). The study followed the ethical principles of the Declaration of Helsinki.

Study Cohorts

The study population included adults ≥ 30 years of age with T2D, identified using International Classification of Diseases, 9th and 10th Revisions (ICD-9/ICD-10) codes.¹⁰ Three cohorts were created based on therapy regimen to capture individuals at different stages of their diabetes treatment journey: non-insulin therapy (NIT), basal insulin therapy (BIT), or intensive insulin therapy (IIT). An age threshold of ≥ 30 years was used in this T2D population study to reduce sample heterogeneity.¹¹ Participants were commercially or Medicare-insured and had no prior evidence of CGM use. The identification period spanned 09/01/2017 to 06/30/2023. Continuous health plan coverage was required for 12 months pre-index (baseline) and 12 months post-index (follow-up). Individuals with evidence of pregnancy or gestational diabetes were excluded.

Each cohort (T2D-NIT, -BIT, or -IIT) was divided into RT-CGM user or CGM non-user groups. The RT-CGM group included individuals initiating Dexcom G4, G5, G6, or G7 RT-CGM systems, identified by National Drug Codes (NDCs; [Supplementary Table 1](#)), with the index date as the first RT-CGM claim. A random date was assigned as the index for the CGM non-user group. To ensure mutual exclusivity, the cohort of CGM non-users comprised individuals without CGM claims during the identification period.

For the T2D-IIT cohort, evidence of fast-acting insulin was required during the baseline period. Basal insulin use was not exclusionary in the T2D-IIT cohort. For the T2D-BIT cohort, basal insulin use was required during the baseline period with no evidence of fast-acting insulin use. For the T2D-NIT cohort, individuals with any insulin use were excluded.

To balance baseline characteristics, propensity score matching was performed at a 1:1 ratio without replacement within each cohort. Exact matching was applied to categorical variables: sex, payer type (commercial or Medicare), presence of diabetes-related (DR) emergency department or inpatient encounters at baseline, geographic region, and baseline A1c (categorized as $<7\%$, $7\text{--}8\%$, $8\text{--}9\%$, or $9\text{--}14\%$). Continuous variables including age, Charlson comorbidity score, number of unique antidiabetic medications at baseline, DR medical costs at baseline, number of DR healthcare encounters at baseline, total medical costs at baseline, and total healthcare encounters at baseline were incorporated into a logistic regression model to estimate propensity scores. Matching was constrained by a caliper of 0.02 on the

propensity score to ensure close matches, minimizing confounding and enhancing comparability between the RT-CGM user and CGM non-user groups. Lastly, valid A1c values within 12 months before and after the index date were used to assess A1c changes pre- and post-index.

Assessment of Anti-Diabetes Medications and Change in Medications

The study identification spanned nearly five years and medication availability, effectiveness, and recommendations from professional societies have evolved rapidly in that time. For example, the ADA Standards of Care in Diabetes began recommending incretin mimetics as a first-line therapy in 2020¹² due to their improved potency and favorable cardiovascular outcomes. As new medications became available, sulfonylureas and thiazolidinediones (TZD) were deprioritized due to the risks of severe hypoglycemia and weight gain.^{3,13}

To assess the number of unique anti-diabetes medications, ≥ 1 pharmacy claim for the medication was required during the 12-month baseline or follow-up period. Eleven medication classes were assessed: alpha glucosidase inhibitors, dipeptidyl peptidase-4 (DPP-4) inhibitors, dopamine agonists, incretin mimetics (glucagon-like peptide-1 receptor agonists [GLP-1 RAs] and dual glucose-dependent insulinotropic polypeptide [GIP]/GLP-1 receptor agonist), insulin, meglitinide, metformin, sodium-glucose cotransporter-2 (SGLT-2) inhibitors, sulfonylurea, TZD, and combination medicines. A complete list of medication codes is available from the corresponding author, GJN, upon reasonable request.

The change in the number of unique anti-diabetes medications, the net change in medication class count, and the relative change within each medication class were assessed for each cohort (T2D-NIT, T2D-BIT, or T2D-IIT) and stratified by group (RT-CGM user or CGM non-user) at baseline and at follow-up. Using this data, we developed a categorical variable to capture the net change in medication classes, which classified participants into one of four distinct groups similar to the categories in Garg et al¹⁴ reduction, addition, net zero change, or no change. These were defined as: reduction, a decrease in the number of unique medication classes over time; addition, an increase in the number of unique medication classes over time; Net zero change, the number of medication classes remained the same over time, but the specific medications were changed; and no change: the number and class of medications remained the same over time. Distinguishing a net zero medication change from no change indicates a change in medication therapy that did not involve simply adding new medications, which can lead to polypharmacy and increased risk of adverse effects.

Assessment of A1c Change and Proportion Reaching Target A1c

Among those with baseline and follow-up A1c data, three outcomes were evaluated: (1) Mean A1c change, calculated as the difference between mean A1c in the 12-month follow-up period and the 12-month baseline period, with negative values indicating improvement, and compared between groups using difference-in-differences (DiD); (2) Proportion achieving A1c targets of $<7.0\%$ or $<8.0\%$ during follow-up, per ADA ($<7\%$) and Healthcare Effectiveness Data and Information Set (HEDIS) ($<8.0\%$) guidelines for non-pregnant adults without significant hypoglycemia; (3) Proportion of individuals with baseline A1c $\geq 7.0\%$ or $\geq 8.0\%$ achieving A1c $<7.0\%$ or $<8.0\%$, respectively, during follow-up. Individuals with missing data were not included in this analysis.

Statistical Analyses

Descriptive statistics, including percentages, means, and standard deviations (SDs), summarized demographic characteristics and A1c outcomes by cohort (T2D-NIT, T2D-BIT, T2D-IIT) and within-cohort group (RT-CGM or CGM non-user). The difference in A1c change between RT-CGM user and CGM non-user groups was assessed using linear models with an interaction term to estimate the DiD values, which estimate the magnitude and direction of change attributable to RT-CGM use in each cohort. Analyses were performed using Instant Health Data software (Panalgo, Boston, MA) and R version 3.2.1 (R Foundation for Statistical Computing, Vienna, Austria). Figures were developed in GraphPad Prism version 10.0.1.

Results

Baseline Demographics

About 1.6 million adults ≥ 30 years of age with T2D were identified during our identification period prior to matching. This population was stratified into three cohorts by insulin use (NIT, BIT, IIT). Demographic characteristics for each cohort are summarized in [Supplementary Table 2](#) (unmatched) and [Table 1](#) (propensity-score matched). Overall, the mean age was over 60 years, the most common region was the South, and the Charlson comorbidity score was highest among people with T2D-BIT ([Table 1](#)). Only about 30% of the T2D-NIT cohort had evidence of using SMBG based on prescription fills prior to starting RT-CGM, while over 50% of the T2D-BIT and T2D-IIT cohorts used SMBG in the baseline period to monitor glucose levels ([Table 1](#)).

Medication Use Patterns

With multiple medications available for the treatment of T2D, we analyzed the number of unique non-insulin anti-diabetic medications used within each cohort stratified by RT-CGM use or CGM non-use ([Table 2](#) and [Supplementary Table 3](#)).

For people with T2D-NIT, the most common number of medication classes among RT-CGM users at baseline was 2 (28.8%), while those not using CGM were most commonly using 0 medications (36.9%; [Table 2](#)). During follow-up, the proportion of individuals on zero medications decreased in both groups (−13.5% relative change for RT-CGM users and −5.4% for CGM non-users). For those with polypharmacy, RT-CGM users saw significant reductions in the

Table 1 Demographic Characteristics of Each Cohort Stratified by CGM Use or Non-Use (Propensity-Score Matched)

Characteristic	T2D-NIT		T2D-BIT		T2D-IIT	
	RT-CGM Users	CGM non-Users	RT-CGM Users	CGM non-Users	RT-CGM Users	CGM non-Users
N	1860	1860	3092	3092	6662	6662
Female	830 (44.6%)	830 (44.6%)	1492 (48.3%)	1492 (48.3%)	3223 (48.4%)	3223 (48.4%)
Mean Age, mean (SD)	61.3 (12.5)	64.2 (12.8)	66.3 (11.1)	66.4 (11.0)	60.6 (12.2)	60.5 (12.2)
Age Groups						
30–34	20 (1.1%)	12 (0.6%)	16 (0.5%)	10 (0.3%)	97 (1.5%)	94 (1.4%)
35–44	187 (10.1%)	130 (7.0%)	144 (4.7%)	122 (3.9%)	662 (9.9%)	650 (9.8%)
45–54	353 (18.9%)	300 (16.1%)	319 (10.3%)	341 (11.0%)	1291 (19.4%)	1327 (19.9%)
55–64	465 (25.0%)	465 (25.0%)	593 (19.2%)	663 (21.4%)	1939 (29.1%)	1924 (28.9%)
≥ 65	835 (44.9%)	953 (51.2%)	2020 (65.3%)	1956 (63.3%)	2673 (40.1%)	2667 (40.0%)
Region						
Midwest	485 (26.1%)	485 (26.1%)	690 (22.3%)	690 (22.3%)	1953 (29.3%)	1953 (29.3%)
Northeast	156 (8.4%)	156 (8.4%)	291 (9.4%)	291 (9.4%)	537 (8.1%)	537 (8.1%)
South	953 (51.2%)	953 (51.2%)	1514 (49.0%)	1514 (49.0%)	3095 (46.5%)	3095 (46.5%)
West	265 (14.2%)	265 (14.2%)	596 (19.3%)	596 (19.3%)	1075 (16.1%)	1075 (16.1%)
Unknown	1 (0.05%)	1 (0.05%)	1 (0.03%)	1 (0.03%)	2 (0.03%)	2 (0.03%)
Charlson comorbidity score, mean (SD)	1.71 (1.95)	1.58 (1.94)	2.18 (1.99)	2.22 (2.10)	2.16 (2.09)	2.14 (2.11)
Payor: Commercial	938 (50.4%)	938 (50.4%)	688 (22.3%)	688 (22.3%)	3414 (51.2%)	3414 (51.2%)
Any SMBG Supplies during Baseline	638 (34.1%)	522 (28.1%)	1636 (52.9%)	1785 (57.7%)	4181 (67.7%)	3650 (54.8%)

Note: Data presented as n (%) unless noted.

Abbreviations: RT-CGM, real-time continuous glucose monitoring; SD, standard deviation; SMBG, self-monitoring of blood glucose; T2D-BIT, type 2 diabetes using basal insulin therapy; T2D-IIT, type 2 diabetes using intensive insulin therapy; T2D-NIT, type 2 diabetes using non-insulin therapy.

Table 2 Changes in the Number of Unique Non-Insulin Anti-Diabetes Medications in the Matched Cohorts Stratified by RT-CGM Use or CGM Non-Use

Medication Class Count	RT-CGM Users				CGM Non-Users			
	Baseline	Follow-Up	Relative Change	p-value	Baseline	Follow-up	Relative Change	p-value
T2D-NIT	N=1860				N=1860			
0	459 (24.7%)	397 (21.3%)	−13.5%	<0.0001	686 (36.9%)	649 (34.9%)	−5.4%	<0.0001
1	439 (23.6%)	458 (24.6%)	4.3%	0.186	578 (31.1%)	558 (30.0%)	−3.5%	0.137
2	535 (28.8%)	566 (30.4%)	5.8%	0.051	345 (18.5%)	389 (20.9%)	12.8%	<0.0001
3	285 (15.3%)	337 (18.1%)	18.2%	<0.0001	181 (9.7%)	193 (10.4%)	6.6%	0.268
4	115 (6.2%)	85 (4.6%)	−26.1%	<0.0001	61 (3.3%)	62 (3.3%)	1.6%	0.935
≥5	27 (1.5%)	17 (0.9%)	−37.0%	0.021	9 (0.5%)	9 (0.5%)	0.0%	1
T2D-BIT	N=3092				N=3092			
0	393 (12.7%)	446 (14.4%)	13.5%	<0.0001	337 (10.9%)	492 (15.9%)	46.0%	<0.0001
1	853 (27.6%)	865 (28.0%)	1.4%	0.546	915 (29.6%)	942 (30.5%)	3.0%	0.146
2	1018 (32.9%)	1059 (34.2%)	4.0%	0.055	1062 (34.3%)	958 (31.0%)	−9.8%	<0.0001
3	610 (19.7%)	557 (18.0%)	−8.7%	0.002	566 (18.3%)	511 (16.5%)	−9.7%	<0.0001
4	182 (5.9%)	144 (4.7%)	−20.9%	<0.0001	174 (5.6%)	163 (5.3%)	−6.3%	0.278
≥5	36 (1.2%)	21 (0.7%)	−41.7%	0.002	38 (1.2%)	26 (0.8%)	−31.6%	0.021
T2D-IIT	N=6662				N=6662			
0	2448 (36.7%)	2513 (37.7%)	2.7%	0.002	2006 (30.1%)	2208 (33.1%)	10.1%	<0.0001
1	1825 (27.4%)	1890 (28.4%)	3.6%	0.022	2220 (33.3%)	2061 (30.9%)	−7.2%	<0.0001
2	1491 (22.4%)	1532 (23.0%)	2.7%	0.128	1617 (24.3%)	1592 (23.9%)	−1.5%	0.336
3	675 (10.1%)	599 (9.0%)	−11.3%	<0.0001	638 (9.6%)	657 (9.9%)	3.0%	0.304
4	196 (2.9%)	118 (1.8%)	−39.8%	<0.0001	160 (2.4%)	130 (2.0%)	−18.8%	0.001
≥5	27 (0.4%)	10 (0.2%)	−63.0%	<0.0001	21 (0.3%)	14 (0.2%)	−33.3%	0.088

Note: Data presented as n (%).

Abbreviations: RT-CGM, real-time continuous glucose monitoring; T2D-BIT, type 2 diabetes using basal insulin therapy; T2D-IIT, type 2 diabetes using intensive insulin therapy; T2D-NIT, type 2 diabetes using non-insulin therapy.

proportion taking 4 (−26.1%, $p<0.0001$) or ≥ 5 (−37.0%, $p=0.021$) medications, while these 4 or ≥ 5 medication class categories in the non-user group saw no significant change.

Among people with T2D-BIT, both groups saw an increase in the proportion of individuals taking 0 non-insulin medications. These changes were +13.5% ($p<0.0001$) for RT-CGM users and +46.0% ($p<0.0001$) for CGM non-users. In terms of polypharmacy, the RT-CGM group showed significant reductions in the proportion of individuals taking 4 (−20.9%, $p<0.0001$) or ≥ 5 (−41.7%, $p=0.002$) medications. In the CGM non-user group, the proportion of individuals taking 4 (−6.3%, $p=0.278$) or ≥ 5 (−31.6%, $p=0.021$) medications also decreased, although only the latter was statistically significant.

In the T2D-IIT cohort, a similar pattern was observed. The proportion of individuals taking 4 or ≥ 5 medications decreased significantly from baseline for RT-CGM users (−39.8% [$p<0.0001$] and −63.0% [$p<0.0001$], respectively). For CGM non-users, the reductions in the proportion taking 4 or ≥ 5 medications were −18.8% ($p=0.001$) and −33.3% ($p=0.088$), respectively.

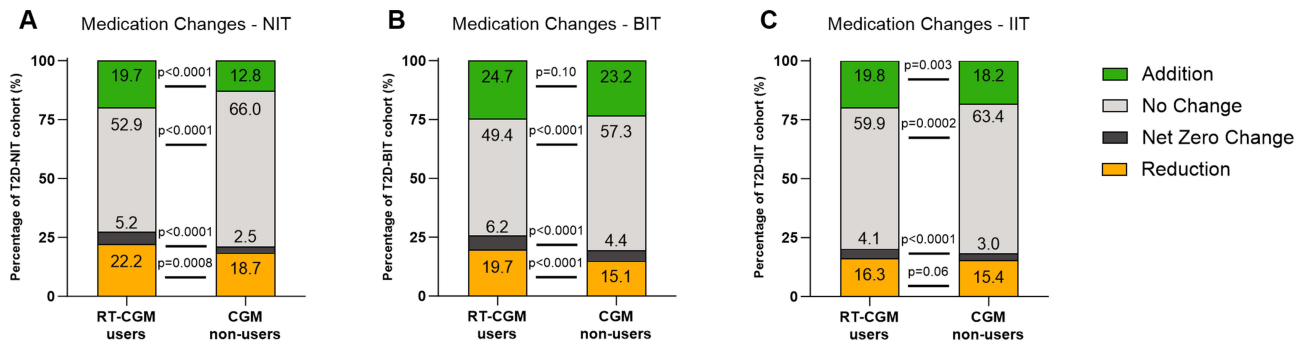


Figure 1 Net changes in non-insulin medication class count stratified by cohort and RT-CGM use or CGM non-use. “Addition” and “Reduction” categories indicate a net increase or decrease in medications at follow-up compared to baseline. “No Change” indicates the same medication classes were used at baseline and follow-up. “Net Zero Change” indicates the same number of medication classes were added as removed at follow-up compared to baseline. Cohorts are presented as (A) T2D-NIT, (B) T2D-BIT, and (C) T2D-IIT.

To further explore these medication changes, we assessed the net changes in medication class count within each cohort stratified by RT-CGM use or CGM non-use (Figure 1). Individuals fell into one of four categories: net addition of medication, net reduction of medication, no changes in medication regimen, or no net change in the number of medications. Across cohorts, the proportion of individuals with a net change in their medications (addition or reduction) was higher among RT-CGM users, although this difference was not always statistically significant. In all three cohorts, the proportion experiencing no changes in their medications was significantly higher among CGM non-users compared to RT-CGM users.

Finally, to identify the nature of these medication changes, we analyzed shifts within specific anti-diabetes medication classes from baseline to follow-up (Table 3). Significant differences were observed in insulin therapy progression at 1-year follow-up. In the T2D-NIT cohort, 23.7% of RT-CGM users initiated insulin therapy during follow-up, while only 4.2% of CGM non-users initiated insulin therapy. Among T2D-BIT users, 26.8% of RT-CGM users escalated to IIT

Table 3 Changes in Antidiabetic Medication Class Usage in Matched Cohorts Stratified by RT-CGM Use or CGM Non-Use

Medication Class	RT-CGM Users				CGM Non-Users			
	Baseline	Follow-up	Relative Change	p-value	Baseline	Follow-up	Relative Change	p-value
T2D-NIT	N=1860				N=1860			
Any insulin therapy	0 (0.0%)	441 (23.7%)	—	—	0 (0.0%)	78 (4.2%)	—	—
Basal insulin only	0 (0.0%)	184 (9.9%)	—	—	0 (0.0%)	38 (2.0%)	—	—
IIT	0 (0.0%)	257 (13.8%)	—	—	0 (0.0%)	40 (2.2%)	—	—
DPP-4 Inhibitor	151 (8.1%)	107 (5.8%)	−29.1%	<0.0001	135 (7.3%)	132 (7.1%)	−2.2%	0.65
Incretin mimetic	651 (35.0%)	863 (46.4%)	32.6%	<0.0001	200 (10.8%)	295 (15.9%)	47.5%	<0.0001
Metformin	996 (53.5%)	949 (51.0%)	−4.7%	<0.0001	933 (50.2%)	937 (50.4%)	0.4%	0.75
SGLT-2 inhibitor	406 (21.8%)	465 (25.0%)	14.5%	<0.0001	198 (10.6%)	236 (12.7%)	19.2%	<0.0001
Sulfonylurea	486 (26.1%)	416 (22.4%)	−14.4%	<0.0001	443 (23.8%)	448 (24.1%)	1.1%	0.59
TZD	123 (6.6%)	108 (5.8%)	−12.2%	0.01	91 (4.9%)	97 (5.2%)	6.6%	0.25
Combination Medicines	109 (5.9%)	109 (5.9%)	0.0%	>0.99	85 (4.6%)	81 (4.4%)	−4.7%	0.42

(Continued)

Table 3 (Continued).

Medication Class	RT-CGM Users				CGM Non-Users			
	Baseline	Follow-up	Relative Change	p-value	Baseline	Follow-up	Relative Change	p-value
T2D-BIT	N=3092				N=3092			
Any insulin therapy	3092 (100.0%)	2873 (92.9%)	−7.1%	<0.0001	3092 (100.0%)	2706 (87.5%)	−12.5%	<0.0001
Basal insulin only	3092 (100.0%)	2046 (66.2%)	−33.8%	<0.0001	3092 (100.0%)	2433 (78.7%)	−21.3%	<0.0001
IIT	0 (0.0%)	827 (26.8%)	–	–	0 (0.0%)	273 (8.8%)	–	–
DPP-4 Inhibitor	302 (9.8%)	238 (7.7%)	−21.2%	<0.0001	455 (14.7%)	359 (11.6%)	−21.1%	<0.0001
Incretin mimetic	1216 (39.3%)	1413 (45.7%)	16.2%	<0.0001	955 (30.9%)	1040 (33.6%)	8.9%	<0.0001
Metformin	1718 (55.6%)	1545 (50.0%)	−10.1%	<0.0001	1910 (61.8%)	1717 (55.5%)	−10.1%	<0.0001
SGLT-2 inhibitor	892 (28.8%)	976 (31.6%)	9.4%	<0.0001	617 (20.0%)	692 (22.4%)	12.2%	<0.0001
Sulfonylurea	963 (31.1%)	764 (24.7%)	−20.7%	<0.0001	1108 (35.8%)	941 (30.4%)	−15.5%	<0.0001
TZD	276 (8.9%)	231 (7.5%)	−16.3%	<0.0001	288 (9.3%)	268 (8.7%)	−6.9%	0.01
Combination Medicines	194 (6.3%)	164 (5.3%)	−15.5%	<0.0001	212 (6.9%)	194 (6.3%)	−8.5%	0.01
T2D-IIT	N=6662				N=6662			
Any insulin therapy	6662 (100.0%)	6429 (96.5%)	−3.5%	<0.0001	6662 (100.0%)	5467 (82.1%)	−17.9%	<0.0001
Basal insulin only	0 (0.0%)	488 (7.3%)	–	–	0 (0.0%)	728 (10.9%)	–	–
IIT	6662 (100.0%)	5941 (89.2%)	−10.8%	<0.0001	6662 (100.0%)	4739 (71.1%)	−28.9%	<0.0001
DPP-4 Inhibitor	330 (5.0%)	220 (3.3%)	−33.3%	<0.0001	496 (7.4%)	420 (6.3%)	−15.3%	<0.0001
Incretin mimetic	2034 (30.5%)	2373 (35.6%)	16.7%	<0.0001	1656 (24.9%)	1926 (28.9%)	16.3%	<0.0001
Metformin	2549 (38.3%)	2194 (32.9%)	−13.9%	<0.0001	3145 (47.2%)	2839 (42.6%)	−9.7%	<0.0001
SGLT-2 inhibitor	1386 (20.8%)	1565 (23.5%)	12.9%	<0.0001	1033 (15.5%)	1216 (18.3%)	17.7%	<0.0001
Sulfonylurea	868 (13.0%)	519 (7.8%)	−40.2%	<0.0001	1122 (16.8%)	910 (13.7%)	−18.9%	<0.0001
TZD	276 (4.1%)	221 (3.3%)	−19.9%	<0.0001	312 (4.7%)	266 (4.0%)	−14.7%	<0.0001
Combination Medicines	249 (3.7%)	197 (3.0%)	−20.9%	<0.0001	290 (4.4%)	272 (4.1%)	−6.2%	0.01

Notes: Data presented as n (%). Medications with ≥2% use at baseline or follow-up are included. Data from alpha glucosidase inhibitor, dopamine agonist, and meglitinide use are not shown due to low rates of use.

Abbreviations: DPP-4, dipeptidyl peptidase-4; RT-CGM, real-time continuous glucose monitoring; SGLT-2, sodium-glucose cotransporter-2; T2D-BIT, type 2 diabetes using basal insulin therapy; T2D-IIT, type 2 diabetes using intensive insulin therapy; T2D-NIT, type 2 diabetes using non-insulin therapy; TZD, thiazolidinediones.

compared to 8.8% of CGM non-users. Conversely, in the T2D-IIT cohort, 89.2% of RT-CGM users remained on an IIT regimen compared to 71.1% of CGM non-users. Also, in the T2D-IIT cohort, 96.5% of RT-CGM users remained on an insulin regimen, compared to 82.1% of CGM non-users.

Regarding non-insulin medications, the use of sulfonylureas decreased among all RT-CGM user groups, with the largest reduction seen in the T2D-IIT cohort (−40.2%, $p<0.0001$). Similarly, use of DPP-4 inhibitors decreased more for RT-CGM users than non-users in the T2D-NIT (−29.1% vs −2.2%) and T2D-IIT (−33.3% vs −15.3%) cohorts.

Use of incretin mimetics and SGLT-2 inhibitors increased from baseline to follow-up in both groups across all cohorts. While the relative increase for these classes was sometimes higher in the CGM non-user group due to lower baseline use, the absolute proportion of patients using these medications at follow-up was consistently higher among RT-

Table 4 Changes in A1c in the Matched Cohorts Stratified by RT-CGM Use or CGM Non-Use

A1c Value (%)	Group	N	Baseline	Follow-up	Change	Within-group p-value	DiD	p-value
T2D-NIT	RT-CGM users	789	8.0 (1.8)	7.3 (1.4)	−0.8 (1.6)	<0.0001	−0.4	<0.0001
	CGM non-users	770	7.8 (1.6)	7.5 (1.5)	−0.4 (1.3)	<0.0001		
T2D-BIT	RT-CGM users	1453	8.5 (1.5)	7.6 (1.3)	−0.8 (1.5)	<0.0001	−0.5	<0.0001
	CGM non-users	1413	8.4 (1.5)	8.1 (1.5)	−0.3 (1.3)	<0.0001		
T2D-IIT	RT-CGM users	2595	8.5 (1.6)	7.7 (1.4)	−0.8 (1.5)	<0.0001	−0.4	<0.0001
	CGM non-users	2533	8.5 (1.7)	8.1 (1.6)	−0.4 (1.4)	<0.0001		

Note: Data presented as mean (SD).

Abbreviations: CGM, continuous glucose monitoring; DiD, difference-in-differences; RT-CGM, real-time continuous glucose monitoring; T2D-BIT, type 2 diabetes using basal insulin therapy; T2D-IIT, type 2 diabetes using intensive insulin therapy; T2D-NIT, type 2 diabetes using non-insulin therapy.

CGM users. For example, the biggest differential in incretin mimetic between RT-CGM users and CGM non-users occurred in the T2D-NIT cohort (46.4% vs 15.9% incretin mimetic use at follow-up). SGLT-2 inhibitor use was also markedly different between RT-CGM users and CGM non-users with higher baseline and follow-up use rates among the former group across cohorts.

Change in Glycemia

Glycemic control as measured by A1c improved in all three cohorts between baseline and follow-up, however, larger decreases in A1c were observed among RT-CGM users compared to CGM non-users independent of therapy regimen (Table 4). A1c declined by 0.4%, 0.5%, and 0.4% more among RT-CGM users with T2D-NIT, T2D-BIT, or T2D-IIT, respectively, compared to CGM non-users (all $p < 0.0001$).

Overall, more people with T2D using RT-CGM achieved an A1c $< 7.0\%$ or $< 8.0\%$ compared to those not using CGM (Figure 2A–C). Among individuals with a baseline A1c $\geq 7.0\%$, more RT-CGM users than CGM non-users achieved an A1c $< 7.0\%$ at follow-up, independent of therapy regimen (Figure 2D). This was consistent among those with a baseline A1c $\geq 8.0\%$ who achieved a follow-up A1c $< 8.0\%$ (Figure 2E).

Discussion

In this observational, retrospective analysis of administrative claims data, more dynamic and guideline-concordant medication management³ was observed among people with T2D treated with any insulin therapy or non-insulin therapies using Dexcom RT-CGM. Medication changes were more common among RT-CGM users with larger relative changes across nearly all medication classes and cohorts. Specifically, initiation and escalation of insulin therapy, de-prescribing of higher-risk medications (eg, sulfonylurea), and a greater reduction in polypharmacy over time were more frequently observed among RT-CGM users. Finally, these changes in anti-diabetic medications were accompanied by significant and clinically meaningful reductions in A1c among RT-CGM users compared to CGM non-users. More RT-CGM users met A1c targets of $< 7.0\%$ and $< 8.0\%$ at follow-up compared to CGM non-users and, importantly, more RT-CGM users not meeting A1c targets at baseline met the target at follow-up.

Therapy Optimization

Consistent with other studies, we found high rates of polypharmacy across the T2D population.¹⁵ However, our analysis found greater decreases in the number of people taking 4 or ≥ 5 medication classes among RT-CGM users compared to CGM non-users. The analysis of net changes in the number of medication classes also revealed higher rates of net addition, net reduction, or net zero change in medication classes among RT-CGM users, although these differences were not always statistically significant. Relatedly, CGM non-users had higher rates of experiencing no change in their

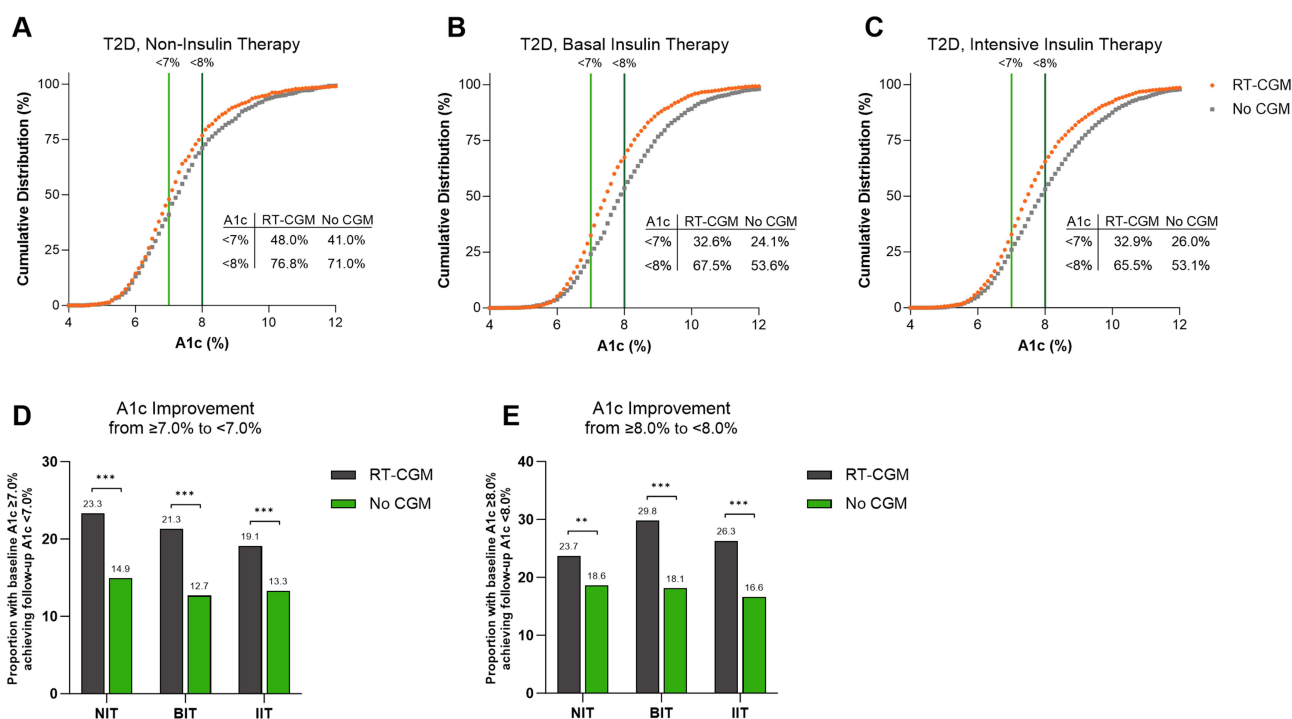


Figure 2 Proportion of each cohort achieving A1c targets stratified by RT-CGM use or CGM non-use. (A) Proportion of NIT cohort achieving A1c goals at follow-up, (B) Proportion of BIT cohort achieving A1c goals at follow-up, (C) Proportion of IIT cohort achieving A1c goals at follow-up, (D and E) Proportion of each cohort with a baseline A1c above the indicated target meeting the target at follow-up. **, $p < 0.001$; ***, $p < 0.0001$.

Abbreviations: RT-CGM, real-time continuous glucose monitoring; BIT, basal insulin therapy; IIT, intensive insulin therapy; NIT, non-insulin therapy; T2D, type 2 diabetes.

medication regimen (ie, using the same number and classes of medications at baseline and follow-up). These higher rates of medication changes among RT-CGM users may indicate more attempts at therapy optimization among patients and their healthcare providers, which likely contributed to the additional improvements in A1c observed with RT-CGM use. While we did observe some reductions in the overall rates of medication class usage, clinical trials that quantify medication burden using the medication effect score have reported significant reductions in medication burden related to RT-CGM.^{16,17}

While we observed a higher relative increase in incretin mimetic and SGLT-2 inhibitor use among certain CGM non-users (T2D-NIT: +32.6% vs +47.5% for incretin mimetics and +14.5% vs +19.2% for SGLT-2 inhibitors; T2D-BIT: +9.4% vs +12.2% for SGLT-2 inhibitors), this was likely driven by a much lower baseline rate of use. The absolute use of these guideline-recommended therapies at follow-up was consistently higher among RT-CGM users. We also observed significant de-prescribing of sulfonylureas, which aligns with ADA recommendations to reassess the need for and/or dose of medications with higher hypoglycemia risk (ie, sulfonylureas, meglitinides, and insulin) when initiating a new glucose-lowering medication to minimize the risk of hypoglycemia and treatment burden.³ Similar decreases in sulfonylurea use and increases in incretin mimetic and SGLT-2 inhibitor use were reported across T2D-NIT, -BIT, and -IIT populations in Garg et al.¹⁴

Notable changes in insulin therapy regimens occurred in all three T2D cohorts. In the T2D-NIT cohort, 23.7% of RT-CGM users initiated insulin therapy, while only 4.2% of CGM non-users began using insulin at follow-up. This rate of insulin initiation among RT-CGM users closely aligns with the rate observed in another study that assessed changes in therapy among CGM users.¹⁴ In the T2D-BIT and T2D-IIT cohorts, insulin therapy continuation among RT-CGM users was high (>90%). Notably, over one-third of the T2D-BIT cohort stopped using basal insulin as their only insulin therapy with most progressing to intensive insulin therapy. These intensifications of insulin in the T2D-NIT and T2D-BIT cohorts, in addition to the higher rates of medication optimization (ie, addition, reduction, net zero change), likely contributed to the additional glycemic improvements we observed among RT-CGM users. In the T2D-IIT cohort, about 11% of RT-CGM users stopped using fast-acting insulin with most continuing to use basal insulin. This rate of fast-acting

insulin discontinuation is about half of the rate reported in Garg et al.¹⁴ Multiple differences between our studies could have contributed to this difference, including the study observation windows and statistical analysis methods (ie, presence or absence of propensity score matching). Notably, the rates of insulin discontinuation that we observed among CGM non-users in the T2D-BIT and T2D-IIT cohorts (12.5% and 17.9%, respectively) were much lower than the 42.2% discontinuation rate reported in Wu et al, which analyzed insulin-using adults between 2010 and 2017 in a single health system.¹⁸

The significantly higher rate of medication changes among RT-CGM users could indicate a reduction in therapeutic inertia. Therapeutic inertia, or clinical inertia, is the failure to initiate or titrate a disease therapy in a timely manner and is a particular challenge for individuals with T2D treated by a primary care provider.^{19,20} The real-time availability of glucose values and the daily patterns and trends available with RT-CGM data may help HCPs see the impact of different medications and be more confident in adding or removing medications.^{21–23} Ajjan et al and Kruger et al recommend the use of CGM data rather than self-monitoring of blood glucose when performing therapy escalations, due to the extensive data available with CGM including retrospective data review and real-time information on whether glucose levels are rising or falling.^{2,7}

A1c Improvements

These results align with other studies demonstrating significant improvements in A1c with RT-CGM use among people with T2D using intensive insulin or basal insulin therapies.^{5,6,24–26} There is an increasing body of evidence reporting on the association between RT-CGM use and improvements in A1c among people with T2D-NIT. Some studies report more modest improvements in A1c^{11,27} while others report larger and more meaningful improvements^{16,24} compared to a control group. Importantly, improvements in CGM-measured time in range (TIR) 70–180 mg/dL, rather than A1c, are more consistently reported among people with T2D-NIT.^{8,24,28}

These results also align with other retrospective studies that analyzed A1c change in multiple T2D cohorts, including T2D-IIT, -BIT, and -NIT.^{14,29} These studies similarly found comparable improvements among individuals with T2D-NIT compared to those with T2D using insulin. One study found that, in addition to glycemic improvements, CGM users also experienced reductions in all-cause hospitalizations and acute diabetes-related events requiring hospitalization or emergency room visits across T2D therapy regimens.¹⁴

Greater proportions of RT-CGM users consistently achieved A1c targets of <7.0% and <8.0% across the three cohorts compared to CGM non-users. This has important clinical implications, particularly for the <7.0% goal recommended by the American Diabetes Association.³⁰ It is well established that meeting this target significantly reduces the risk diabetes complications such as retinopathy, nephropathy, neuropathy, and cardiovascular disease.³¹

These findings related to medication use are notable in combination with the greater improvements in A1c observed among RT-CGM users across cohorts and suggest that reduced therapeutic inertia and/or effective behavior modification with RT-CGM use could have contributed to the observed glycemic improvements. In fact, the analysis by Garg et al found that the greatest reductions in A1c levels after CGM initiation were observed in the T2D-NIT and T2D-BIT cohorts.¹⁴

Behavior modification with RT-CGM use is emerging as a significant element contributing to the association between RT-CGM use and glycemic improvements. A recent study among people using IIT (type 1 and type 2 diabetes) found that using CGM consistently (proportion of days covered $\geq 80\%$) was associated with greater decreases in A1c compared to using CGM less consistently.³² The real-time feedback and retrospective data review available with RT-CGM can support behavior modification by providing users with a better understanding of their diabetes and the impact of their health behaviors on their glucose levels.^{2,21,33,34} These lifestyle or behavior modifications may include dietary changes, physical activity changes, and/or taking medications as prescribed.^{7,35} The combined use of CGM and anti-diabetes medications, including GLP-1 RAs, has been shown to have a synergistic effect on glycemic outcomes.^{36–38} Other studies report that CGM users experience improved psychosocial outcomes, reduced diabetes distress, and increased knowledge about their diabetes, all of which may contribute to increased engagement with diabetes therapy.^{16,35,39,40} Given the potential role of RT-CGM in optimizing medication management and improving glycemic control for people with T2D, efforts to integrate CGM glycemic metrics with machine learning could open new avenues for personalized diabetes management.

Predictive analytics based on CGM data could enhance monitoring and provide real-time insights into metabolic progression, facilitating more precise and timely interventions for individuals with T2D.⁴¹

Strengths and Limitations

Strengths of this study include the use of a comprehensive, standardized health information database (Optum's Clinformatics® Data Mart). Limitations of our study include the all-US population, which limits generalizability outside the US. Analyses of laboratory data, including A1c, were limited to those with available data and did not include all individuals who met study cohort inclusion criteria. In addition, the analyses of medication changes only assessed medication classes, not changes in dosage or adherence, which could impact A1c outcomes. The analyses of medication changes should be interpreted cautiously given changes in clinical guidelines for anti-diabetes medications over the time span. For example, incretin mimetics became more ubiquitous and recommended as first-line standard of care for T2D in 2020.¹² While the proportion of individuals with no change to their medication regimen was slightly more common among CGM non-users, this remained the most common outcome among most individuals in the study (>49%). While our analysis differentiated between individuals with “no change” in medication classes and those with a “net zero change” (ie, simultaneous prescribing and de-prescribing of medications), the analysis was conducted at the medication class level. Therefore, it could not capture clinically meaningful changes occurring within the same medication class and the actual frequency of medication changes may be masked by the within-medication class changes. Furthermore, this analysis did not capture other critical aspects of therapy optimization, such as changes in medication dosage or improvements in adherence. Consequently, the true rate of medication adjustments among RT-CGM users may be even higher than what our findings report.

Other limitations include self-selection to RT-CGM and the potential for residual confounding. Without randomization to study groups, self-selection to RT-CGM is possible and could have contributed to A1c improvements and medication changes if the individuals were more motivated to engage in behavior change or more collaborative with their HCP. While propensity score matching was conducted on possible confounding variables to balance the groups, residual confounding from unmeasured variables between the groups cannot be ruled out. For example, we do not know to what extent individuals were compliant with RT-CGM use or lifestyle interventions in which they might be participating.

Conclusions

This retrospective, observational study of real-world administrative claims from people with T2D treated with non-insulin therapy, basal insulin therapy, or intensive insulin therapy found that Dexcom RT-CGM use was associated with higher rates of medication adjustments compared to CGM non-use, as well as reductions in polypharmacy and changes in medication use that align with clinical guidelines. This study also found that RT-CGM users achieved greater decreases in A1c compared to CGM non-users. These results add to the growing body of evidence indicating that RT-CGM use is beneficial for people with T2D on any therapy regimen and that access to the technology could improve diabetes outcomes.

Data Sharing Statement

The data that support the findings of this study are available from Optum. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from Dr. Gregory Norman with the permission of Optum.

Acknowledgments

Portions of this article were presented at the 85th Scientific Sessions of the American Diabetes Association held in Chicago, IL on June 20-23, 2025.

Author Contributions

B.C.-L.L.: conceptualization, data curation, formal analysis, investigation, methodology, project administration, writing – original draft, and writing – review & editing.

K.L.H.: conceptualization, methodology, project administration, supervision, writing – original draft, and writing – review & editing.

P.M.N.: conceptualization, methodology, and writing – review & editing.

C.R.G.: methodology, visualization, writing – original draft, and writing – review & editing.

G.J.N.: conceptualization, methodology, supervision, writing – original draft, and writing – review & editing.

In addition, all authors gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

Funding

Dexcom, Inc. funded the development of this article.

Disclosure

All authors are employees of Dexcom, Inc. The authors report no other conflicts of interest in this study.

References

1. International Diabetes Federation. IDF Diabetes Atlas, 10th edition. Report. Available from: <https://diabetesatlas.org/atlas/tenth-edition/>. Accessed January 30, 2025.
2. Kruger DF, Parkin CG, Hirsch IB, et al. Addressing the diabetes Tsunami requires expanded access to diabetes technologies. *J Diabetes Sci Technol*. 2025;19322968251332956. doi:10.1177/19322968251332956.
3. American Diabetes Association Professional Practice Committee. 9. pharmacologic approaches to glycemic treatment: standards of care in diabetes-2025. *Diabetes Care*. 2025;48(Supplement_1):S181–S206. doi:10.2337/dc25-S009.
4. Beck RW, Riddleworth T, Ruedy K, et al. Effect of continuous glucose monitoring on glycemic control in adults with type 1 diabetes using insulin injections: the DIAMOND randomized clinical trial. *JAMA*. 2017;317(4):371–378. doi:10.1001/jama.2016.19975
5. Beck RW, Riddleworth 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. doi:10.7326/M16-2855
6. Martens T, Beck RW, Bailey R, et al. Effect of continuous glucose monitoring on glycemic control in patients with type 2 diabetes treated with basal insulin: a randomized clinical trial. *JAMA*. 2021;325(22):2262–2272. doi:10.1001/jama.2021.7444
7. Ajjan RA, Battelino T, Cos X, et al. Continuous glucose monitoring for the routine care of type 2 diabetes mellitus. *Nat Rev Endocrinol*. 2024;20(7):426–440. doi:10.1038/s41574-024-00973-1
8. Layne JE, Jepson LH, Carite AM, Parkin CG, Bergenstal RM. Long-Term Improvements in glycemic control with dexcom CGM use in adults with noninsulin-treated type 2 diabetes. *Diabetes Technol Ther*. 2024;26(12):925–931. doi:10.1089/dia.2024.0197
9. U.S. Department of Health and Human Services. Guidance Regarding Methods for De-identification of Protected Health Information in Accordance with the Health Insurance Portability and Accountability Act (HIPAA) Privacy Rule. 2022. Available from: <https://www.hhs.gov/hipaa/for-professionals/privacy/special-topics/de-identification/index.html>. Accessed January 3, 2024.
10. Chronic Conditions Warehouse. 30 CCW Chronic Conditions Algorithms. Centers for Medicare & Medicaid Services. Available from: <https://www2.ccwdata.org/web/guest/condition-categories-chronic>. Accessed 27, Oct 2025.
11. Price DA, Deng Q, Kipnes M, Beck SE. Episodic real-time CGM use in adults with type 2 diabetes: results of a pilot randomized controlled trial. *Diabetes Ther*. 2021;12(7):2089–2099. doi:10.1007/s13300-021-01086-y
12. American Diabetes A. 9. pharmacologic approaches to glycemic treatment: standards of medical care in Diabetes—2020. *Diab Care*. 2020;43(Suppl Supplement_1):S98–S110. doi:10.2337/dc20-S009.
13. Apovian CM, Okemah J, O'Neil PM. Body weight considerations in the management of type 2 diabetes. *Adv Ther*. 2019;36(1):44–58. doi:10.1007/s12325-018-0824-8
14. Garg SK, Hirsch IB, Repetto E, et al. Impact of continuous glucose monitoring on hospitalizations and glucose control in people with type 2 diabetes: real-world analysis. *Diab Obes Metab*. 2024;26(11):5202–5210. doi:10.1111/dom.15866
15. Saeed ZI, Ostrominski JW, Aroda VR. Polypharmacy in type 2 diabetes: appropriate or cause for concern? *Diab Care*. 2024;47(12):2104–2106. doi:10.2337/dci24-0035
16. Cox DJ, Banton T, Moncrief M, Conaway M, Diamond A, McCall AL. Minimizing glucose excursions (GEM) with continuous glucose monitoring in type 2 diabetes: a randomized clinical trial. *J Endocr Soc*. 2020;4(11):bvaa118. doi:10.1210/jendso/bvaa118
17. Taylor PJ, Thompson CH, Luscombe-Marsh ND, Wycherley TP, Wittert G, Brinkworth GD. Efficacy of real-time continuous glucose monitoring to improve effects of a prescriptive lifestyle intervention in type 2 diabetes: a pilot study. *Diabetes Ther*. 2019;10(2):509–522. doi:10.1007/s13300-019-0572-z
18. Wu J, Morrison F, Zhao Z, et al. Reasons for discontinuing insulin and factors associated with insulin discontinuation in patients with type 2 diabetes mellitus: a real-world evidence study. *Clin Diab Endocrinol*. 2024;7(1):1. doi:10.1186/s40842-020-00115-2.
19. Martens TW, Parkin CG. How use of continuous glucose monitoring can address therapeutic inertia in primary care. *Postgrad Med*. 2022;134(6):576–588. doi:10.1080/00325481.2022.2080419
20. Almigbal TH, Alzarrah SA, Aljanoubi FA, et al. Clinical inertia in the management of type 2 diabetes mellitus: a systematic review. *Medicina*. 2023;59(1). doi:10.3390/medicina59010182
21. Marrero DG, Parkin CG, Aleppo G, et al. The role of advanced technologies in improving diabetes outcomes. *Am J Manag Care*. 2025;31(4):e102–e112. doi:10.37765/ajmc.2025.89725

22. Parsiani R, Grace T, Green CR, Castle JR, Wilson LM. Continuous glucose monitoring guides glucagon-like peptide 1-based therapy use and optimization in people with type 2 diabetes. *J Family Med Prim Care*. 2025;14(2):790–795. doi:10.4103/jfmpe.jfmpe_773_24
23. Majithia AR, Erani DM, Kusiak CM, et al. Medication optimization among people with type 2 diabetes participating in a continuous glucose monitoring-driven virtual care program: prospective study. *JMIR Form Res*. 2022;6(4):e31629. doi:10.2196/31629
24. Shields S, Thomas R, Durham J, Moran J, Clary J, Ciemins EL. Continuous glucose monitoring among adults with type 2 diabetes receiving noninsulin or basal insulin therapy in primary care. *Sci Rep*. 2024;14(1):31990. doi:10.1038/s41598-024-83548-4
25. Lever CS, Williman JA, Boucsein A, et al. Real time continuous glucose monitoring in high-risk people with insulin-requiring type 2 diabetes: a randomised controlled trial. *Diabet Med*. 2024;41(8):e15348. doi:10.1111/dme.15348
26. Lind N, Christensen MB, Hansen DL, Norgaard K. Comparing continuous glucose monitoring and blood glucose monitoring in adults with inadequately controlled, insulin-treated type 2 diabetes (Steno2tech Study): a 12-month, single-center, randomized controlled trial. *Diab Care*. 2024;47(5):881–889. doi:10.2337/dc23-2194
27. Bergenstal RM, Mullen DM, Strock E, Johnson ML, Xi MX. Randomized comparison of self-monitored blood glucose (BGM) versus continuous glucose monitoring (CGM) data to optimize glucose control in type 2 diabetes. *J Diab Compl*. 2022;36(3):108106. doi:10.1016/j.jdiacomp.2021.108106
28. Reed J, Dong T, Eaton E, et al. Continuous glucose monitoring for glycaemic control and cardiovascular risk reduction in patients with type 2 diabetes not on insulin therapy: a clinical trial. *Diab Obes Metab*. 2024;26(7):2881–2889. doi:10.1111/dom.15608
29. Norman GJ, Fernandes J, Nemlekar P, Andrade SB, Lupton L, Berk A. Initiating continuous glucose monitoring is associated with improvements in glycemic control and reduced health care resource utilization for people with diabetes in a large US-insured population: a real-world evidence study. *J Manag Care Spec Pharm*. 2025;31(1):15–24. doi:10.18553/jmcp.2024.24255
30. American Diabetes Association Professional Practice Committee for D. 6. glycemic goals, hypoglycemia, and hyperglycemic crises: standards of care in diabetes-2026. *Diab Care*. 2026;49(Supplement_1):S132–S149. doi:10.2337/dc26-S006
31. Tsushima Y, Galloway N. Glycemic targets and prevention of complications. *J Clin Endocrinol Metab*. 2025;110(Supplement_2):S100–S111. doi:10.1210/clinem/dgae776
32. Nemlekar PM, Hannah KL, Green CR, Norman GJ. Association between adherence, A1C improvement, and type of continuous glucose monitoring system in people with type 1 diabetes or type 2 diabetes treated with intensive insulin therapy. *Diab Ther*. 2024;15(3):639–648. doi:10.1007/s13300-023-01529-8
33. Farhan HA, Bukhari K, Grewal N, Devarasetty S, Munir K. Use of continuous glucose monitor as a motivational device for lifestyle modifications to improve glycaemic control in patients with type 2 diabetes treated with non-insulin therapies. *BMJ Case Rep*. 2022;15(6). doi:10.1136/bcr-2021-248579
34. Porter M, Fonda S, Swigert T, Ehrhardt N. Real-time continuous glucose monitoring to support self-care: results from a pilot study of patients with type 2 diabetes. *J Diab Sci Technol*. 2022;16(2):578–580. doi:10.1177/19322968211053886
35. Ettestad TM, Willis HJ, Johnson E, Green CR, Bergenstal RM. Continuous glucose monitoring (CGM) as a behavior modification tool: a case series on CGM-guided nutrition in people with type 2 diabetes not using insulin. *Clin Diab*. 2025;43(4):610–617. doi:10.2337/cd24-0106
36. Wright EE, Roberts GJ, Chuang JS, Nabutovsky Y, Viridi N, Miller E. Initiating GLP-1 therapy in combination with freestyle libre provides greater benefit compared with GLP-1 therapy alone. *Diab Technol Ther*. 2024;26(10):754–762. doi:10.1089/dia.2024.0015
37. Nemlekar PM, Hannah KL, Green CR, et al. Combined effect of continuous glucose monitoring and semaglutide: analysis of administrative claims. *Am J Manag Care*. 2025;31(4):183–188. doi:10.37765/ajmc.2025.89719
38. Nemlekar PM, Hannah KL, Green CR, Norman GJ. Exploring combined use of continuous glucose monitoring and anti-diabetes medications on glycaemic control for people with type 2 diabetes not using insulin. *Endocrinol Diab Metabol*. 2025;8(5):e70089. doi:10.1002/edm2.70089
39. Clark TL, Polonsky WH, Soriano EC. The potential impact of continuous glucose monitoring use on diabetes-related attitudes and behaviors in adults with type 2 diabetes: a qualitative investigation of the patient experience. *Diab Technol Ther*. 2024;26(10):700–708. doi:10.1089/dia.2023.0612
40. Soriano EC, Polonsky WH. The influence of real-time continuous glucose monitoring on psychosocial outcomes in insulin-using type 2 diabetes. *J Diab Sci Technol*. 2023;17(6):1614–1622. doi:10.1177/19322968221094831
41. Montaser E, Fabris C, Kovatchev B. Essential continuous glucose monitoring metrics: the principal dimensions of glycemic control in diabetes. *Diab Technol Ther*. 2022;24(11):797–804.

Diabetes, Metabolic Syndrome and Obesity

Publish your work in this journal

Diabetes, Metabolic Syndrome and Obesity is an international, peer-reviewed open-access journal committed to the rapid publication of the latest laboratory and clinical findings in the fields of diabetes, metabolic syndrome and obesity research. Original research, review, case reports, hypothesis formation, expert opinion and commentaries are all considered for publication. The manuscript management system is completely online and includes a very quick and fair peer-review system, which is all easy to use. Visit <http://www.dovepress.com/testimonials.php> to read real quotes from published authors.

Submit your manuscript here: <https://www.dovepress.com/diabetes-metabolic-syndrome-and-obesity-journal>

Dovepress
Taylor & Francis Group