HHS Public Access

Author manuscript

Obes Res Clin Pract. Author manuscript; available in PMC 2022 September 02.

Published in final edited form as:

Obes Res Clin Pract. 2021 ; 15(5): 431–438. doi:10.1016/j.orcp.2021.08.006.

Use of Continuous Glucose Monitoring in Obesity Research: A Scoping Review

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Ms. Hegedus, Drs. Vidmar, Salvy, Raymond, Naguib and Ms. Wee conceptualized and designed the study, drafted the initial manuscript, and reviewed and revised the manuscript. Dr. Fox reviewed and revised the manuscript. All authors approved the final manuscript as submitted and agree to be accountable for all aspects of the work.

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Conflict of Interest:

The authors have no financial relationships or conflict of interest relevant to this article to disclose.

Consent for Publication:

Not applicable.

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Abstract

Background: This scoping review provides a timely synthesis of the use of continuous glucose monitoring in obesity research with considerations to adherence to continuous glucose monitor devices and metrics most frequently reported.

Methods: This scoping review was conducted adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) checklist. Eligible studies (n=31) evaluated continuous glucose monitor use in research on participants, of all ages, with overweight or obesity.

Results: Reviewed studies varied in duration from one to 84 days (mean: 8.74 d, SD 15.2, range 1 to 84 d) with 889 participants total (range: 11-118 participants). Across all studies, the mean percent continuous glucose monitor wear time (actual/intended wear time in days) was 92% (numerator - mean: 266.1 d, SD: 452, range: 9-1596 d/denominator - mean: 271.6 d, SD: 451.5, range: 9-1596 d). Continuous glucose monitoring was utilized to provide biofeedback (n=2, 6%), monitor dietary adherence (n=2, 6%), and assess glycemic variability (n=29, 93%). The most common variability metrics reported were standard deviation (n=19, 62%), area under the curve (n=12, 39%), and glycemic range (n=12, 39%).

Conclusions: Available evidence suggests that continuous glucose monitoring is a well-tolerated and versatile tool for obesity research in pediatric and adult patients. Future investigation is needed to substantiate the feasibility and utility of continuous glucose monitors in obesity research and maximize comparability across studies.

Keywords

Continuous Glucose Monitor; Obesity; Overweight; Adherence

1. Introduction

Continuous glucose monitors (CGM) are wearable devices that track glucose levels in interstitial fluid by taking measurements at regular and frequent intervals throughout the day and night [1, 2]. These measurements generate dynamic information on the glycemic profile of the patient throughout the day [3]. CGM devices have been validated for measuring blood glucose levels and are well tolerated by children and adults with diabetes in clinical settings. Though CGM devices were initially deployed to help manage type-1 diabetes, their use is now expanding into the care of adults and children with type-2 diabetes as well [4].

More recently, researchers have considered the potential utility of CGM in obesity research with adults and children, both as an outcome measure and to supplement behavioral weight management interventions. This interest emerged in response to studies supporting the effectiveness of other mHealth devices, such as activity monitors, on intervention engagement [5-7]. Available research further suggests that the provision of real-time feedback on biological indicators of health can increase adherence, motivate behavior change and promote weight loss and physical activity in both clinical and research settings [8-12].

CGM real-time feedback and data collection will only be a useful research tool if the participants are able to utilize the devices appropriately and for the prescribed wear time. However, unlike health technology involving smartphone-based applications, CGM is not well known or understood by individuals without diabetes. The majority of CGM acceptability data comes from type-1 diabetes studies [13-16], and those patients with diabetes are usually highly motivated to adhere to CGM use to achieve euglycemia [17, 18]. It is unclear whether the perceived benefits of CGM are substantial enough to motivate adherence to continuous wear among research participants without type-I diabetes. Therefore, demonstrating adherence to prescribed wear times is essential to support the use of CGM in obesity research.

Glycemic variability refers to changes in blood glucose levels that occur throughout the day. Although mostly used in diabetes care and beta cell pathology research, glycemic variability is a physiological process involving a complex array of regulatory hormones, and also depends on variations in glucose tolerance and insulin activity [19]. There are multiple metrics commonly used to calculate glycemic variability, including percent time in range (TIR), standard deviation (SD) of glucose measurements, continuous overlapping net glycemic action (CONGA), mean amplitude of glycemic excursions (MAGE), mean of daily difference (MODD), and area under the curve (AUC) [19, 20]. Glycemic variability is a potentially useful research metric to understand the impact of obesity interventions on adiposity and glucose metabolism. Given inconsistent reports in the obesity literature regarding the utility of glycemic variability, we are cataloging the varying definitions of CGM derived glycemic variability, seeking to better delineate the potential of CGM devices in obesity research.

To date, there has been no comprehensive review of CGM use in obesity research. Furthermore, no previous review has summarized data on CGM adherence in children and

adults with obesity, nor cataloged the glycemic variability metrics used. This information is needed to appraise the utility of CGM use among individuals without diabetes and, also, to evaluate the relevance of currently used metrics to obesity research. Since CGM use in obesity research is relatively new, the overarching aim of this scoping review was to synthesize current evidence on the use of CGM in clinical trials and observational studies. The two specific aims of this review were: 1) examine participants' adherence to CGM, across studies (operationalized as actual wear time relative to prescribed wear time), and 2) catalog the metrics used to evaluate glycemic variability in obesity research.

2. Methods

2.1 Eligibility Criteria

Eligible studies included randomized controlled trials (RCT), non-RCT, and/or quasi-experimental studies (observational) involving children, adolescents, and/or adults with overweight or obesity. Research conducted in community, outpatient, inpatient, and/or primary care settings was included. CGM use was required to be part of the study, either as the main intervention, or as a tool to collect research data. Studies were excluded if they did not use human participants or enrolled participants with type-1 diabetes. Studies of participants that included groups with obesity alone and with type-2 diabetes (n=3, 9%) were included. Studies with lean participants were included, as long as they also included participants with overweight/obesity as well. Studies were excluded if specific data were not collected or reported, including demographic characteristics, Body Mass Index (BMI), intervention setting, intervention duration, or CGM metrics. Intervention duration had to be at least 24 hours. No limitations were placed on length of follow-up, or study date. All studies identified in the search that met the eligibility criteria were included in this scoping review.

2.2 Identification of Relevant Studies

This scoping review was conducted using the Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) checklist [21]. A systematic search of published articles up to April 2020 was undertaken using electronic databases: PubMed, Science, Cochrane Library, PsychINFO, CINAHL database, Google Scholar, and clinicaltrials.gov. Keywords were searched using both the National Library of Medicine's Medical Subject Headings (MeSH) and as independent search terms (e.g., *overweight* AND *continuous glucose monitor OR monitoring, obesity AND continuous glucose monitor* OR *monitoring*). A research librarian was consulted to design the most effective strategies for each database. The search terms were intentionally broad, to capture relevant studies and prevent omissions. Key journals and references cited in all systematic reviews identified during those initial searches were also manually reviewed for additional relevant studies. Initial search of articles was conducted manually by one reviewer (first author EH). The database search resulted in an initial pool of 961 articles. Deduplication was completed using Endnote online software (Clarivate, Philadelphia, PA). All records were then independently reviewed for inclusion by two reviewers (AV and EH) using the defined inclusion criteria, evaluating articles first by title and abstract, followed by full text review. Discrepancies were resolved through discussion between investigators.

2.3. Data Extraction

Data was independently extracted from eligible articles by using a data extraction form that mirrored the Joanna Briggs Institute extraction instrument for scoping reviews (Microsoft, Redmond, WA) [22]. The following information was extracted: authors, year of publication, location, study design, sample size, sample characteristics, intervention duration, CGM use duration, research outcomes, glycemic variability metrics (if reported), and CGM-relevant outcomes data. Data were collated, summarized, and reported in Table 1. Diligent efforts were made to reach out to the original authors to collect unreported data. Studies were excluded if the data required for analysis could not be obtained.

AV and EH independently appraised the methodological quality of included studies using the Johns Hopkins Nursing Evidence-Based Practice to access evidence level and quality of research [23]. Articles were classified according to their quality of evidence and rigor of study design. Classification and scores were based on the rigor of study design (level I, II, or III) and the quality of research being reported (high, medium, or low quality). Scores range from IA (RCT with high quality results) to IIIC (non-experimental with low quality results or major flaws). At each level of classification, there are specific metrics the study must reach [23]. The appraisal tool provides a systematic and standardized approach to categorizing journal articles. This methodology was selected because it integrates the scientific evidence with the best available experimental (patient and practitioner) evidence.

2.4. Measures of Adherence

Adherence was defined as the actual total CGM wear time by the research participant, divided by the prescribed wear time stated in the study protocols. This data was either calculated from quantitative data reported in the results section of the study or based on summary adherence outcomes reported by authors in their discussion section.

2.5. Categorization of Patient Cohorts

To better understand the current populations that CGM are being deployed in obesity research, the cohort of studies included in this scoping review were categorized by patient cohort. The categories were generated after the relevant studies in this scoping review were demographics. Studies were divided into adult and pediatric categories based of the age of participants, then further subdivided by glycemic dysfunction (cohort of subjects with glycemic dysfunction, for example type-2 diabetes or pre-diabetes), post-gastric bypass (cohort of patients after gastric bypass surgery), pregnancy (cohort of patients who are pregnant), and weight based (cohort of patients with no specific requirements).

2.6. Data Synthesis

Results were synthesized by AV and EH, following data extraction. Given the studies' extreme heterogeneity, no meta-analysis or other statistical tests were performed on the data set.

3. Results

3.1 Study and Participant Characteristics

The 31 studies that met criteria for data extraction are summarized in Table 1. The majority of studies were conducted in adult populations (n=24) [12, 24-46] and seven studies were conducted in children [47-53]. Most studies took place in the US (n=16) [12, 24, 25, 29, 32, 33, 36, 37, 40, 43, 45-50]. The remaining studies were conducted in Australia (n=3)[27, 35, 44], Canada (n=2) [26, 42], China (n=1) [53], Denmark (n=1) [28], France (n=1) [30], Italy (n=2) [34, 52], Mexico (n=1) [38], Poland (n=1) [31], New Zealand (n=1) [39], Turkey (n=1) [51], and the UK (n=1) [41]. Participant ages ranged from 6 to 78 years of age. The sample size ranged from 12 adult participants in a post-gastric bypass observational study [30] to 118 participants in an observational study evaluating the relationship between CGM use and hemoglobin A1C values in a pediatric population [49]. The majority of studies recruited both male and female participants; four studies recruited females only [28, 29, 32, 33]. All studies, except one, reported the BMI of participants.

3.2 Adherence

Adherence was defined as percent (%) of actual CGM wear time relative to the study protocol prescribed wear time in days. A large majority, 92% (numerator - mean: 266.1 d, SD: 452, range: 9-1596 d/denominator - mean: 271.6d, SD: 451.5, range: 9-1596 d) of participants wore their CGM for the entire prescribed duration of the research study. Common reasons for premature discontinuation or non-use included skin irritation due to the CGM adhesive, technical difficulty with the device, other concerns regarding wearing a device, and non-CGM related adherence issues. Three studies specifically surveyed patients' satisfaction regarding CGM as a tool for weight management treatment [54, 55]. In those three studies, self-report patient satisfaction with CGM, was high, further suggesting CGM use is feasible in the weight management context [54, 55].

3.3 CGM Utilization

Continuous glucose monitoring was utilized to provide biofeedback (n=2, 6%), monitor dietary adherence (n=2, 6%), and assess glycemic variability (n=29, 93%). CGM was most often deployed to characterize the glycemic variability of either a patient cohort or during the research intervention (n=29, 93%). Other applications identified for the CGM device were to provide behavioral cues (n=1,3%) [12], hunger cues (n=1, 3%) [39], and monitor adherence (n=2, 6%) [37, 45].

3.4 Glycemic Variability

Glycemic variability was reported in 29 of the 31 included studies. Eight different glycemic variability metrics were identified across all studies Figure 2. The majority of studies (n=23) used multiple metrics to capture glycemic variability. The glycemic variability metrics identified were standard deviation of the glucose measurements (SD) (n=19, 62%), area under the curve (AUC) (n=12, 39%), glycemic range (GR) (n=12, 39%), mean amplitude of glycemic excursions (MAGE) (n=11, 35%), time in range (TIR) (n=5,16%), continuous

overlapping net glycemic action (CONGA) (n=4,13%), coefficient of variability (CV) (n=2, 6%), and absolute means of daily differences (MODD) (n=1, 3%).

3.5. Categorization of Patient Cohorts

Of the adult studies, the following cohorts of patients were identified: glycemic dysfunction (n=4), post-gastric bypass (n=4), pregnancy (n=2), and weight (n=14). Of the pediatric studies, the following cohorts of patients were identified: glycemic dysfunction (n=1) and weight (n=7). These categorizations can be found in Table 1.

4. Discussion

The overarching aim of this scoping review was to synthesize the currently available evidence on uses of CGM in obesity research. We were specifically interested in examining parameters relevant to research implementation, namely participants' adherence to CGM wear time and the glycemic variability metrics most often used in obesity research. The results suggest that the feasibility of using CGM for obesity research is high, and the utility of those CGM measurements is less well established.

Regarding the feasibility of CGM use in obesity research, participants across studies seemed to tolerate the device well, as demonstrated by the high adherence across varying study protocols and research subject populations. The protocols spanned diverse research settings (community, outpatient, and/or inpatient) and both pediatric and adult populations. Many of the relatively infrequent adherence issues are well recognized and addressed in diabetes related research, including adhesive sensitivity [56, 57]. However, adherence to obesity study protocols may not perfectly capture subjective parameters of tolerability. We acknowledge that some participants may have varying degrees of intrinsic motivation to adhere to CGM protocols based on their underlying health state. For example, participants with obesity and glycemic dysfunction may be highly motivated to adhere to study protocols to prevent disease progression. Future research is necessary to investigate the feasibility across larger subgroups of patients with obesity with no glycemic dysregulation and to uncover the best ways to implement CGM use in obesity research. Additionally, future research should consider explicitly measuring participant satisfaction with CGM wear, while also identifying possible barriers or discomforts that may impede continuous wear.

This review identified multiple different applications for CGM both as an intervention tool and as an outcome measure. Across all the studies examined, CGM data was used for a variety of purposes including: 1) as a behavioral intervention by providing real-time biofeedback connected to a specific process such as identifying hunger cues, 2) as a method to monitor adherence to dietary interventions, or 3) as a method to assess glycemic variability.

In one study, as a behavioral intervention, CGM was shown to be as reliable as manual finger-checks for teaching hunger training and thus has the potential to be used alongside a behavioral intervention to increase motivation, provide real-time feedback and augment treatment effectiveness in obesity research. Verification of dietary intervention adherence in obesity research is an important factor to consider in any obesity trial. Self-report and

interviewled dietary recalls remain the gold standard strategies to evaluate dietary intake in obesity research; however, these tools have been criticized due to potential error in reporting, omission bias and suboptimal compliance. CGM data may provide an alternative to monitoring adherence in dietary interventions and improve the validity of the data collected in ensuring that intervention dosage is implemented as intended (e.g., monitoring actual fast in intermittent fasting studies). The diversity of CGM use across these studies highlights the promising potential of CGM as tool in obesity research.

This review highlights the multiplicity of glucose variability metrics reported from CGM devices. We found that measuring glycemic variability was the most frequent application of the CGM. The most commonly used glycemic variability metric was the standard deviation of the glucose measurements either in isolation or reported with AUC and MAGE. There is no current consensus regarding the most useful metric(s), possibly due to the multiplicity of intended uses. For example, the metric selected will be different if the goal is to motivate users, rather than directly assess an intervention's impact on weight loss or insulin resistance. This variability is reflected in the studies examined here. In order to advance our understanding of glycemic variability future studies should compare metrics side-by-side to standardize protocols and optimize comparability across studies.

4.4. Strengths and Limitations

Naturally, this review is not without limitations. First, by including CGM as one of our search terms, it is possible that we could have missed studies where data from CGM was reported as a secondary outcome and therefore not pick up by MESH terms. Second, the significant differences in methodology and reported data complicated any quantitative comparison across studies. In addition, few studies provided information on completers versus non-completers, or other potential confounding factors, so it is unclear to what degree selection bias affects high reported adherence. The studies reviewed also differed markedly in their terminology (e.g., 'tolerability') and how they operationalized adherence. Third, we included all eligible papers regardless of the quality and rigor of the studies featured, thus potentially introducing biases in our conclusions if study findings were misrepresented. Finally, while we strove to identify all relevant studies, unpublished null-effect studies and manuscripts published in a language other than English were omitted from this review. These omissions limit the generalizability of our conclusions regarding the use of CGM in obesity research.

5. Conclusion

The available evidence to date suggests that CGM is a well-tolerated and versatile tool for obesity research in both pediatric and adult patients. A diversity of metrics was used to report glycemic variability from studies' CGM data. In order to advance our understanding of glycemic variability as a useful outcome measure in obesity research, future studies should carefully evaluate the validity and reliability of these metrics to support standardization of protocols and comparability across studies. CGM use may also be a useful tool not only to collect glycemic data, but also to augment behavioral interventions

and monitor adherence. Realizing this potential requires further investigation to better harness the utility of CGM and strengthen both obesity research and treatment outcomes.

Funding Source:

This project was supported by eHealth International, Inc; by National Institutes of Health [grant number UL1 TR000130]; by Obesity Health Disparities Research Center [grant number U54MD000502]; and by National Institute of Child Health and Human Development [grant number R01HD092483].

Availability of Data and Material

The datasets from this study will be available from the corresponding author on written request.

Abbreviations:

BMI	Body mass index
zBMI	Body mass index Z-score
CI	Confidence Interval
CGM	Continuous glucose monitor
GV	Glycemic Variability
MeSH	Medical Subject Headings
%BMI$_{p95}$	Percent over the 95th percentile

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Highlights

- Continuous glucose monitoring is tolerated in obesity research
- Standard deviation is the most common glycemic variability metric
- Continuous glucose monitoring can provide biofeedback and monitor dietary adherence

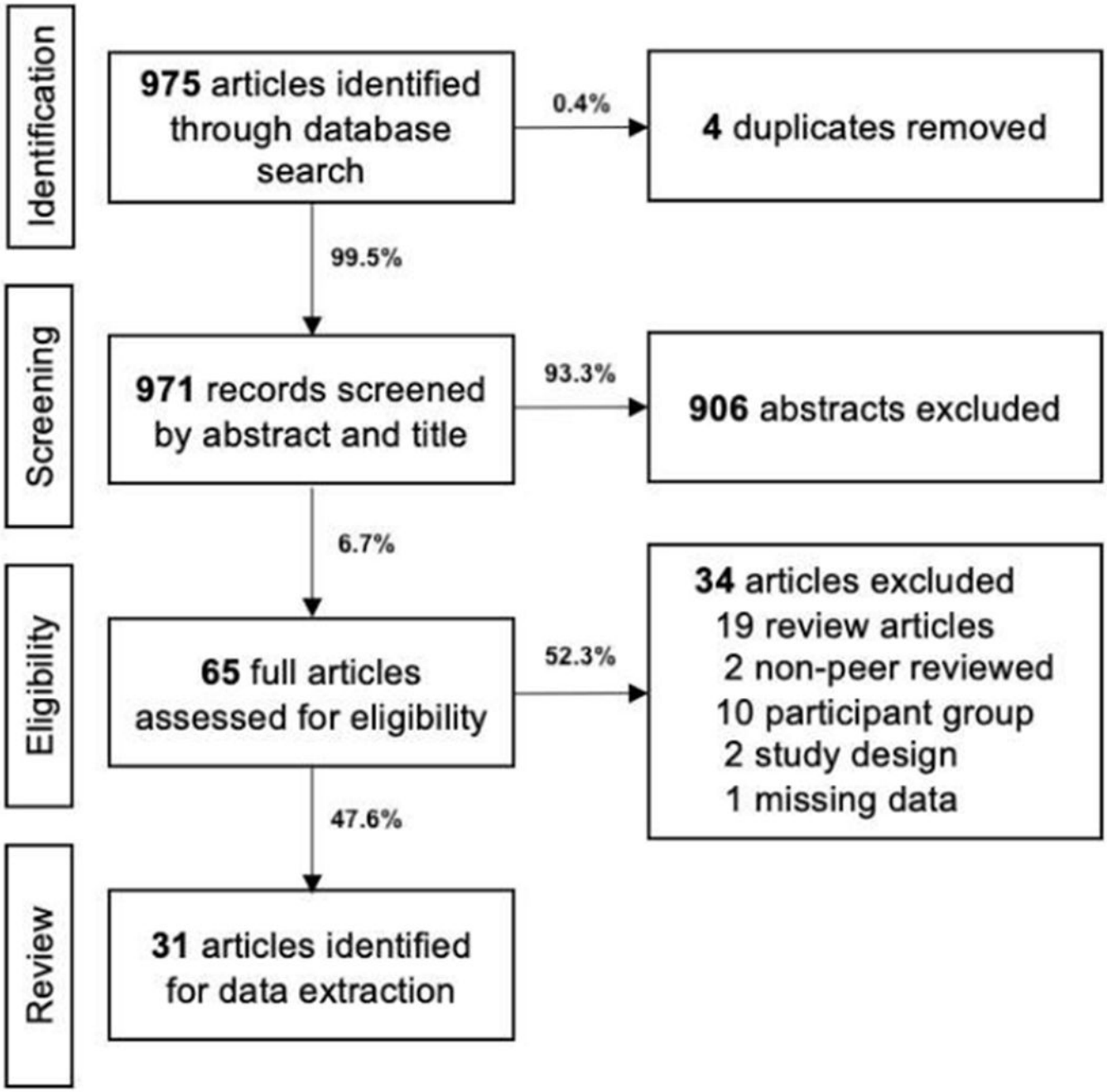

Figure 1.
Flow diagram of screening and review process.

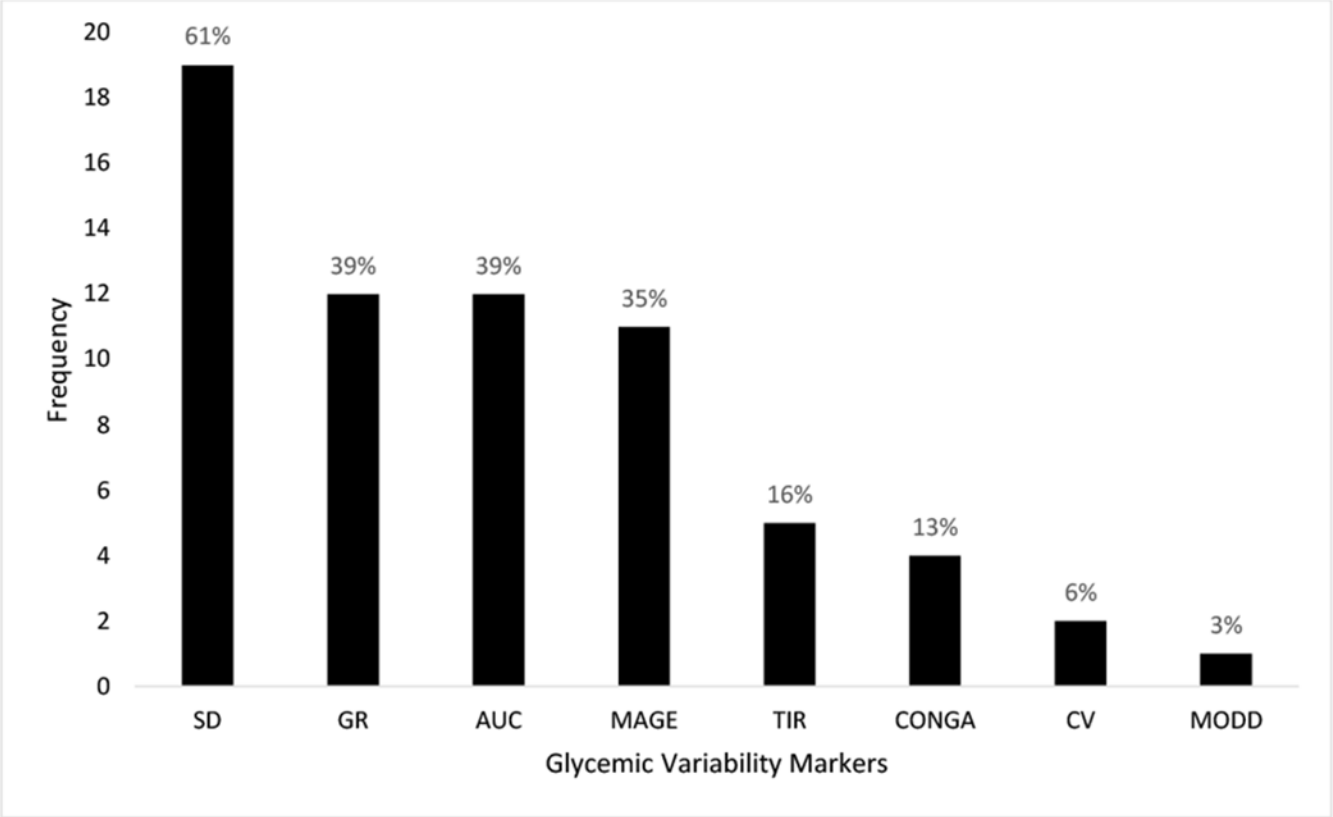

Figure 2.

Frequency of glycemic variability metrics reported across included studies. Percentage reflects metric usage across included studies (n=31).

Abbreviations: Standard deviation (SD), continuous overlapping net glycemic action (CONGA), mean amplitude of glycemic excursions (MAGE), area under the curve (AUC), absolute means of daily differences (MODD), time in range (TIR), coefficient of variability (CV), and glycemic range (GR)

Table 1.

Scoping review on the use of continuous glucose monitors in obesity research.

Author (Date,Country)	Participants	Design	Study Aims	Metrics	Wear Time	Grading
Adult Studies						
Glycemic Dysfunction						
Farabi, et al. (2015, USA)	N=38 Adults with BMI ≥30 kg/m^2 with T2D	Crossover RCT	Assess impact of single bout of exercise on diurnal and nocturnal oxidative stress and glycemic variability	SD CONGA	3 day-wear x 2	IB
Gay, et al. (2018, USA)	N=9 Adults with BMI ≥25 kg/m^2 with prediabetes	Crossover RCT	Determine the effects of 2-min and 4-min bouts of vigorous-intensity stair-climbing on glucose levels	AUC GR	1 day	IIB
Little, et al. (2014, Canada)	N=10 Adults with BMI ≥25 kg/m^2 with T2D	Crossover RCT	Examine the effect of acute high-intensity interval training compared with continuous moderate-intensity exercise on postprandial hyperglycemia	SD MAGE	3-day wear x 2	IA
Parr, et al. (2018, Australia)	N=13 Adults with BMI ≥25 kg/m^2 and prediabetes	Crossover RCT	Compare the effect of a high versus low energy intake first meal on glucose and insulin responses during prolonged sitting in individuals with prediabetes	SD CONGA MAGE AUC	1-day wear x 2	IIB
Post- Gastric Bypass						
Christfort Ø hrstrøm, et al. (2019, Denmark)	N=11 Women with BMI ≥30 kg/m^2 post Roux-en-Y gastric bypass	Crossover RCT	Investigate the effects of acarbose, sitagliptin, verapamil, liraglutide and pasireotide on post-bariatric hypoglycemia	SD TIR	6-day wear x 5	IIA
Halperin, et al. (2011, USA)	N=16 Women post-Roux-en-Y gastric bypass	Observational	Investigate if CGM is an effective tool for characterizing glycemic variability after Roux-en-Y Gastric Bypass	GR	3 days	IIB
Ritz, et al. (2012, France)	N=8 Adults s/p Gastric Bypass Surgery	Observational	Evaluate the effect of treatment with dietary counseling plus acarbose administration on the symptoms of dumping syndrome and on the characteristics of the CGM profile	SD MAGE TIR	3-day wear x 2	IIIB
Wysocki, et al. (2019, Poland)	N=32 Adults with BMI >30kg/m^2 with T2D	Observational	Compare effects of laparoscopic sleeve gastrectomy vs. gastric bypass on blood glucose using CGM	SD TIR	10 days	IIIA
Pregnancy						
Harmon, et al. (2011, USA)	N=38 Pregnant Women with BMI ≥18 kg/m^2	Observational	Define 24-h glycemia in normal-weight and pregnant women with obesity using CGM	AUC GR	4 day-wear x 2	IIA
Yogev, et al. (2004, USA)	N=57 Pregnant women with BMI ≥30kg/m^2	Observational	Evaluate the ambulatory daily glycemic profile in the second half of pregnancy in women without diabetes	GR	3 days	IIA
Weight Based						
Buscemi, et al. (2013, Italy)	N=40 Adults with BMI ≥30 kg/m^2	RCT	Determine the effects of hypocaloric diets with different glycemic indexes and glycemic loads on endothelial function and glycemic variability	SD GR CV	2-day wear x 2	IIA

Author (Date,Country)	Participants	Design	Study Aims	Metrics	Wear Time	Grading
Climie, et al. (2018, Australia)	N=9 Adults with BMI ≥25 kg/m^2	Crossover RCT	Test the effect of brief activity breaks vs. uninterrupted sitting on postprandial glucose and insulin levels	SD CONGA MAGE AUC	4 days	IIA
Crespo, et al. (2016, USA)	N=11 Adults with BMI ≥25 kg/m^2	Crossover RCT	Compare the 24-h and postprandial glucose responses to incremental intervals of standing, walking, and cycling compared to sitting	SD MAGE AUC	4 days	IIA
Jamshed, et al. (2019, USA)	N=11 Adults with BMI ≥25 kg/m^2	Crossover RCT	Investigate the impact of Time Restricted Feeding on cardiovascular disease risk	SD MAGE AUC GR	4-day wear x 2	IIB
Jiménez-Domínguez, et al. (2015, Mexico)	N=20 Adults with BMI ≥18 kg/m^2	Crossover RCT	Examine the effects of acute ingestion of native banana starch on glycemic profiles	SD MAGE AUC CV	4 days	IIB
Jospe, et al. (2020, New Zealand)	N=40 Adults with BMI >30 kg/m^2	RCT	Assess hunger training using CGM with fingerprick glucose monitoring on weight loss and adherence	NA	30 days	IIA
Kim, et al. (2019, USA)	N=31 Adults with BMI ≥30 kg/m^2	Observational	Determine the predictive effect of circulating glucose levels on eating in free-living individuals	SD MAGE	7 days	IIA
Liao, et al. (2020, USA)	N=19 Adults with BMI ≥25 kg/m^2	Observational	Determine the acceptability of a physical activity intervention that incorporated the use of CGMs in sedentary adults with overweight and obesity without diabetes and evaluate the changes in exercise motivation	NA	10 days	IIA
Philippou, et al. (2008, UK)	N=18 Adults with BMI ≥30kg/m^2	RCT	Compare the effects of two energy-restricted healthy diets on heart disease risk factors and weight loss	AUC GR	1-day wear x 2	IIIA
Rafiei, et al. (2019, Canada)	N=15 Women with BMI ≥25 kg/m^2	RCT	Compare the effects of high-intensity interval training with moderate-intensity continuous training for improvement of CGM-derived markers of glycemic variability	SD MAGE AUC	2-day wear x 2	IIA
Salkind, et al. (2014, USA)	N=36 Adults with BMI ≥30 kg/m^2	Observational	Investigate glycemic profile in adults with severe obesity	SD MAGE CONGA MODD	3 days	IIA
Wennberg, et al. (2015, Australia)	N=19 Adults with BMI ≥25 kg/m^2	Crossover RCT	Compare the acute effects of uninterrupted sitting with sitting interrupted by brief bouts of light-intensity walking on neuroendocrine biomarkers	SD AUC TIR	1-day wear x 2	IA
Wilkinson, et al. (2020, USA)	N=19 Adults with BMI ≥25 mg/m^2	Single-arm paired-sample trial	Investigate if 10-h time restricted eating intervention in patients with metabolic syndrome would result in a significant improvement in mean blood glucose, fasting insulin, and inflammatory markers	SD	12 weeks	IIA
Winn, et al. (2019, USA)	N=10 Adults with BMI ≥25 kg/m^2	Crossover RCT	Determine whether mild energy restriction preserves glycemic control during physical inactivity and whether this preservation is	GR	3-day wear x 2	IIA

Author (Date,Country)	Participants	Design	Study Aims	Metrics	Wear Time	Grading
			more effectively achieved with a higher-protein diet			
Pediatric Studies						
Glycemic Dysfunction						
Choudhary, et al. (2013, USA)	N=17 Children ages 7-18, with BMI ≥95th%ile and prediabetes	Observational	Examine daily glycemic excursions in children with prediabetes	MAGE GR	4 days	IIIC
Weight Based						
Bauer, et al. (2015, USA)	N=28 Adolescents, ages 14-18, with BMI ≤85th %ile	RCT	Examine the effect of high vs. normal protein breakfast consumption on glycemic control in youth	SD	3-day wear x 2	IIB
Chan, et al. (2015, USA)	N=118 Children ages 10-18, with BMI ≥85th%ile	Observational	Determine if HbA1c or oral glucose tolerance test is a better predictor of free-living glycemia as measured by CGM	SD AUC TIR	3 days	IIIA
Ghane, et al. (2019, USA)	N=33 Children ages 10-11 of all BMI %iles	RCT	Determine the accuracy of Freestyle Pro for estimating plasma glucose during oral glucose tolerance test in healthy children	AUC GR	1 day	IIB
Kaya, et al. (2017, Turkey)	N=50 Children ages 10-18, with BMI ≥95th %ile	Observational	Investigate the relationship between glycemic variability and inflammatory parameters in children with insulin resistance and obesity	SD AUC	1 day	IIIB
Schiaffini (2016, Italy)	N=30 Children ages 7-17, with BMI ≥120th % of the 95th %ile	Observational	Evaluate the glucose profile in children with non-alcoholic fatty liver disease	SD GR	4-day wear x 2	IA
Zou, et al. (2008, China)	N=84 Children ages 6-15, with BMI ≥95th %ile	Observational	Assess glucose metabolism disorder by CGMs in children with obesity	GR	1 day	IIA

Abbreviations: Body Mass Index (BMI), Percentile (%ile), Randomized Controlled Trial (RCT), standard deviation (SD), continuous overlapping net glycemic action (CONGA), mean amplitude of glycemic excursions (MAGE), area under the curve (AUC), absolute means of daily differences (MODD), time in range (TIR), coefficient of variability (CV), and glycemic range (GR).

Grading System: Classification and scores were based on the rigor of study design (level I, II, or II) and the quality of research being reported (high, medium, or low quality). Scores range from IA (RCT with high quality results) to IIIC (non-experimental with low quality results or major flaws) [23].