

GlyCulator: A Glycemic Variability Calculation Tool for Continuous Glucose Monitoring Data

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Abstract

Glycemic variability has become a major concern over the years as growing evidence is gathered on its detrimental impact on the risk of diabetes complications. Glycated hemoglobin, although ubiquitous in clinical practice, does not adequately summarize short-term glycemic variability. This gap may be addressed through the use of continuous glucose monitoring, which continuously estimates glycemia based on interstitial fluid glucose concentration. As the amount of collected data is substantial, variability of the glycemic pattern can be analyzed in context of its direction, periodicity, and amplitude. As freely available variability calculation tools are limited in number and complexity, the authors have devised a simple-to-use Web-based application, "GlyCulator," allowing for rapid computation of glucose variability parameters from continuous glucose monitoring data.

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Background

Glycemic variability was documented to increase metabolic stress and mortality in acute states.¹⁻⁵ An increasing number of studies show that sole use of glycated hemoglobin (HbA1c), the cornerstone of long-term monitoring of metabolic control, is not sufficient to adequately assess the metabolic status of patients with diabetes. The risk of developing diabetes-related complications is related not only to long-term glycemic variability,⁶ but may also be related to short-term glucose variability from peaks to nadirs.⁴ Oscillating glucose

concentration may exert more deleterious effects than sustained chronic hyperglycemia on endothelial function and oxidative stress, two key players in the development and progression of cardiovascular diseases in diabetes.⁷ Such short-term fluctuations, however, may be detectable by means of continuous glucose monitoring (CGM)—a method that measures glycemia continuously over a period of several days. A large amount of resulting data is, however, cumbersome to use in research studies and requires some simplification and transformation into

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Abbreviations: (%CV) percentage coefficient of variation, (CGM) continuous glucose monitoring, (CONGA) continuous overall net glycemic action, (FD) fractal dimension, (HbA1c) glycated hemoglobin, (MAGE) mean amplitude of glycemic excursions, (MODD) mean of daily differences, (SD) standard deviation

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usable parameters. To address the evident paucity of glucose variability calculation tools, the authors have devised a Web-based application for rapid computation of numerous glucose variability parameters from CGM data: "GlyCulator."

Parameters of Glycemic Variability

Percentage of glucose values above or below a given threshold measured as the percentage of hyperglycemia (levels between 126 and 180 mg/dl) and hypoglycemia (levels below 70.2 mg/dl) episodes. These are the most clinically applicable and intuitive parameters of glycemic variability, though they are difficult to use for research purposes.⁸

The standard deviation (SD) of mean glycemia of CGM data is probably the simplest tool for assessment of glycemic variability.⁹ Calculation of this parameter provides information for both minor and major fluctuations but not does distinguish them. For a more detailed assessment of day-to-day variability, several methods based on SD can be marked out, such as the average SD within corresponding time points of multiple days (SD_w), SD between multiple days within corresponding time points ($SD_{b\ hh:mm}$), SD between daily means (SD_{dm}), and SD between days within corresponding time points after including variation of daily means ($SD_{b\ hh:mm//dm}$).^{10,11}

Percentage coefficient of variation (%CV) is the ratio of SD to mean. This parameter describes the magnitude sample values and the variation within them and allows for standardized comparisons between patients with different levels of mean glycemia.

Mean amplitude of glycemic excursions (MAGE), together with mean and SD, is the most popular parameter for assessing glycemic variability and is calculated based on the arithmetic mean of differences between consecutive peaks and nadirs of differences greater than one SD of mean glycemia. It is designed to assess major glucose swings and exclude minor ones.¹²

Weighted average of glucose values (M_R) provides a measure of stability of glycemia in comparison with an arbitrary assigned "ideal" glucose value, "R," initially set to 100 mg/dl. It is obtained as mean of values transformed using the following formula: $1000 \times |\log_{10}(\text{glucose}/100)|$.^{3,13}

J index is a measure of quality of glycemic control based on the combination of information from the mean and SD calculated as $0.001 \times (\text{mean} + \text{SD})^2$.¹⁴

The mean of daily differences (MODD) index provides an estimation of interday glycemic variability. This parameter is calculated as the mean of absolute differences between glucose values at corresponding time points of consecutive days.¹⁵

Continuous overall net glycemic action (CONGA) is similar to SD but assesses glucose variability within a predetermined time window. Calculation of this parameter is based on the assessment of the differences between glucose values measured at regular time intervals, then on the SD of these differences.¹⁶

Fractal dimension (FD) is an experimental method, based on the works of Higuchi and currently adapted by the authors, that describes glucose variability of high frequency and small amplitude. The calculation is based on the changes of glucose values between subsequent measurements using the Higuchi algorithm.^{17,18}

Firmware Design and Methods

"GlyCulator" is an application designed to evaluate glycemic variability based on data collected by means of a CGM device. The application is available in two versions. A platform-independent Web-based interface is presented in **Figure 1**. This version is available online at www.pediatrics.umed.pl/team/glyculator. A more complex Windows-based tool shown in **Figure 2** can be installed on a computer running any contemporary Microsoft Windows operating system (Microsoft .Net Framework v.4.0 or above is required). This version is available on request from the authors. Both versions share the same core functionality of reading data previously exported from any CGM device.

The main requirement is that the CGM data need to be exported to a Microsoft Excel 2003 file (.xls file). The choice of this file format was based on its popularity and the fact that most CGM devices provide some "export to Excel" functionality.

After loading a data set, the user is prompted to select the sheet and columns with measurement date and time and corresponding blood glucose sensor value. Each file will be assigned with a unique identifier for collective database construction. In the Windows-based version, the following settings can be adjusted: number of readings per day/hour (default set to 288/12) and initial time point (default set to noon), which gives an option to analyze specific periods (i.e., days or nights). Moreover, the user can choose units (mmol/liter or mg/dl)



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GlyCulator

Continuous glucose monitoring (CGM) devices are gaining popularity in the daily monitoring of diabetes, for both doctors and patients. Moreover, they are being used in the scientific research, in which the data analysis is not only a daily average value of blood glucose but also its daily profile changes.

"GlyCulator" tool provides a quick conversion of the parameters of glycemic variability based on CGM report. In current version available variability parameters are: mean, median, SD, %CV, M100, J, MAGE, MODD, CONGA (for 1h, 2h, 4h and 6h time intervals), FD, percentage of hyperglycemia (levels above 7 mmol/L and 10 mmol/L) and hypoglycemia (levels below 3.9 mmol/L) episodes. They are calculated for the first complete two days from imported CGM data set. Additionally, basic variability parameters (mean, SD, median, %CV, M100, J, MAGE, hyperglycemia and hypoglycemia episodes) are calculated for the whole CGM file.



Age: months

Diabetes duration: months

Gender: Female Male

Current daily dose of insulin: U/kg

Latest HbA1c: %

CGMS data file:

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Figure 1. Graphic user interface screen image presenting the Web-based application.

and reading mode (single file or batch import). In both versions available, variability parameters are mean, median, SD, SD_{wv} , SD_b hh:mmv, SD_{dmv} , SD_b hh:mm//dmv, %CV, M100, J, MAGE, MODD, CONGA (for 1, 2, 4, 6, and 24 h time intervals), FD, and percentage of hyperglycemia (levels between 7 and 10 mmol/liter) and hypoglycemia (levels below 3.9 mmol/liter) episodes. All parameters are calculated for the first complete two days from the imported CGM data set. Additionally, basic variability parameters (mean, SD, median, %CV, M100, J, MAGE, and hyperglycemia and hypoglycemia episodes) are calculated for the whole CGM file. Optionally, GlyCulator allows the user to enter additional clinical data, such as patient's age, gender, duration of the diabetes, current daily dose of insulin, and latest HbA1c level and link them with the imported patient CGM file. The Windows-based version allows multiple file analyses of all .xls files stored in the chosen directory, provided they have the same structure of columns containing date/time stamps and corresponding sensor values. After calculation, a summary report can be saved as an excel database file for further analysis. Additionally, the Web-based version allows the user to preview results before saving to .xls.

Conclusions

Glycemic variability has become a major concern over the years as growing evidence has been gathered on its detrimental impact on oxidative stress^{1,19,20} and dysregulation of adipokine secretion.² Clinically, glycemic variability was associated with greater mortality in intensive care,^{3,5} increased rate of diabetes complications,²¹ and postprandial beta-cell dysfunction.²² However, data on the significance of glycemic variability is not as unequivocal as one could expect, with reports abolishing its importance altogether mixing with those in favor.^{6,23,24} The features discouraging use of glycemic variability as a parameter in clinical practice and trials are the difficulty of interpreting numerous parameters describing this phenomenon and a limited number of computational opportunities allowing rapid calculation of glycemic variability parameters in CGM data. Clinical benefits of using these devices have been well documented and range from reduced frequency of hypoglycemia to improved metabolic control.^{9,25,26} In order to facilitate access to glycemic variability parameters, the authors developed an application for quantifying the most popular glucose variability parameters, including a novel measurement currently tested by the group (FD). The Web-based application allows input of several clinical parameters to facilitate database construction and integration of variability data

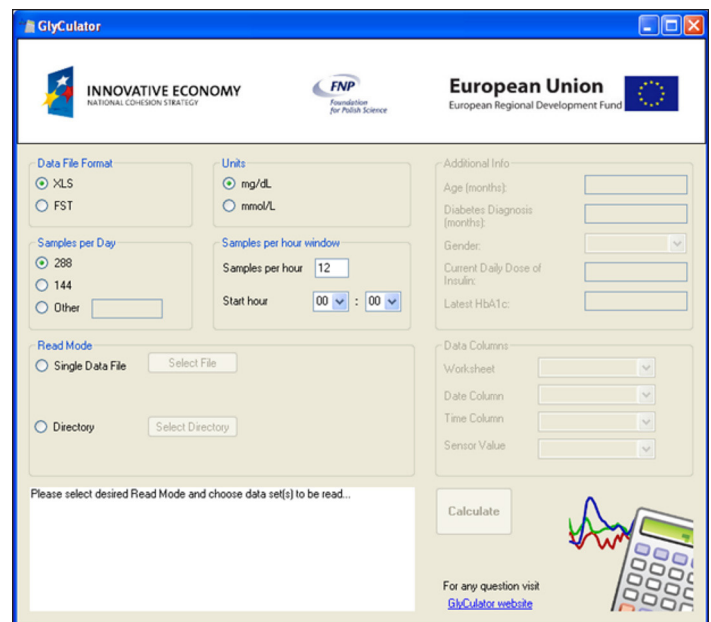


Figure 2. Graphic user interface screen image presenting the Windows-based application.

with clinical characteristics. As parameters included in the current version are by no means a conclusive list, further development, based on the suggestions of users and the development of novel glucose variability measurements, is warranted. The software was mainly intended for research purposes and use with short CGM recordings (~72 h, with two complete days), although the algorithms used allow reconfiguration and analysis of longer data traces, with a modified software version available on demand.

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