Glooko's Diabetes Management Application Improves Glycemic Outcomes Compared to Control

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INTRODUCTION

Research has shown that people with diabetes can improve their health outcomes and ultimately lower the cost of treatment with optimized self management strategies (Shetty, S., 2005). However, many studies do not disentangle the effect of a mobile application from that of clinical feedback (e.g. Wang et al., 2017, Marcolino et al., 2013) and even fewer have ever isolated the effect of simply using the mobile application. This is important because a recent meta-analysis suggested that mobile applications with a structured display (ie: organizing a patient's data in a meaningful way) can significantly improve glycemic outcomes (Wu et al., 2017).

We hypothesized that active mobile application usage will improve blood glucose (BG) control significantly better than a control group receiving regular medical care. To test this hypothesis, we conducted a retrospective study to determine if the Glooko Mobile App improves patient outcomes.

METHODS

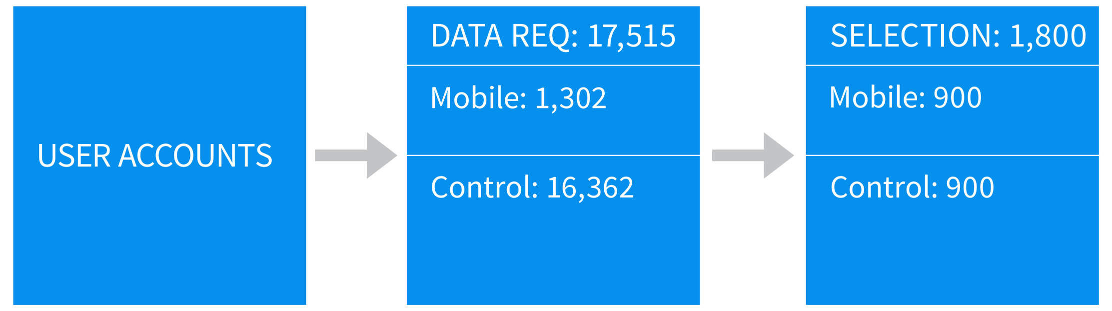

FIGURE 1: Selection of users eligible for current study, based on retrospective data.

RECRUITMENT

For this retrospective study, we focused on a subset of Glooko user accounts. We randomly selected users from our database once they met specific data requirements for the study. First usage of Glooko was designated by a person with diabetes (PWD)'s first upload. All data collected were uploaded between November 11, 2011 and March 15, 2017.

DATA COLLECTION

Groups were defined as:

- **Mobile :** PWDs who used the mobile app
- **Control:** PWDs who did not use the mobile app

All users had:

- Uploaded their data with Glooko at least twice
- Valid timestamp data
- Met specific data minimums including
- At least three months of pre-existing data
- At least three months of data after first upload

STATISTICS

To ensure integrity of the SMBG count variable, we analyzed only two months of data after their first upload, although three months were required. This allowed us to identify users who failed to test for a month or two and distinguish from those who simply stopped using the mobile application.

For each dependent variable, we used a mixed effects generalized linear model (GLM), considering subjects as a random effect and the effect of time as a linear fixed effect. We adjusted the distribution assumptions for each dependent variable. Hypoglycemia was defined as less than 70mg/dL and hyperglycemia defined as greater than 200mg/dL.

RESULTS

TABLE 1: DEMOGRAPHICS

VARIABLE		CONTROL	MOBILE
Gender	Male	0	440
	Female	2	171
	Unknown	898	288
Diabetes Type	Type I	3	375
	Type II	15	285
	Other	0	22
	Unknown	882	285

NOTE: Demographics for control and mobile groups. Unknown values occur when users decline to provide data, or are not presented with the option of filling in their profile.

TABLE 2: TESTING RATE IMPROVEMENT

	B	IRR	%Δ	T-VALUE	P-VALUE
(Intercept)	3.880	-	-	149.67	<0.001
Time	-0.016	0.984	-1.587%	-1.917	0.055
Mobile	0.143	1.154	15.373%	3.943	<0.001
Time * Mobile	0.076	1.079	7.896%	6.886	<0.001

NOTE: Summary of GLM examining change in blood glucose test rate over the course of the study period. *B* indicates the parameter estimate for each variable. IRR indicates the incidence rate ratio for each variable and is used to calculate percent delta. % Δ indicates the percent change in BG test rate.

Users in the mobile group started with a higher monthly testing rate of 15.37% (p<0.01) compared to the control group. Overall, we found a small, but non-significant decrease in testing rate for those in the control group by 1.59% per month (p=0.06). Across the study period, mobile users significantly increased their testing rate by 7.90% per month (p<0.01). These results indicate that mobile users increased their testing rates after initial use of the Glooko mobile application, compared to control.

FIGURE 2: Mean (standard error) increase in monthly SMBG test rate compared to baseline.

TABLE 3: AVERAGE BG

	B	EXP(B)	%Δ	T-VALUE	P-VALUE
(Intercept)	5.119	-	-	540.042	<0.001
Time	0.007	1.007	0.702%	2.252	0.024
Mobile	-0.047	0.954	-4.591%	-3.522	<0.001
Time * Mobile	-0.025	0.975	-2.469%	-5.791	<0.001

NOTE: Summary of GLM examining change in average BG over the course of the study period. *B* indicates the parameter estimate for each variable. Exp(B) is the exponentiated *B* estimate and is used to calculate percent delta. % Δ indicates the percent change in average BG.

Before the start of the study, mobile users demonstrated 4.59% lower average BG (p<0.01) compared to control users. Over time, the control group exhibited a significant increase of ~1% in average BG (p=0.02), while mobile users decreased 1.47% per month (p<0.01). In total, across two months, a mobile user could expect about 3.56% drop in average BG, compared to their baseline measurements. For a visual representation of these results expressed as average BG and eA1c, please refer to figure 4.

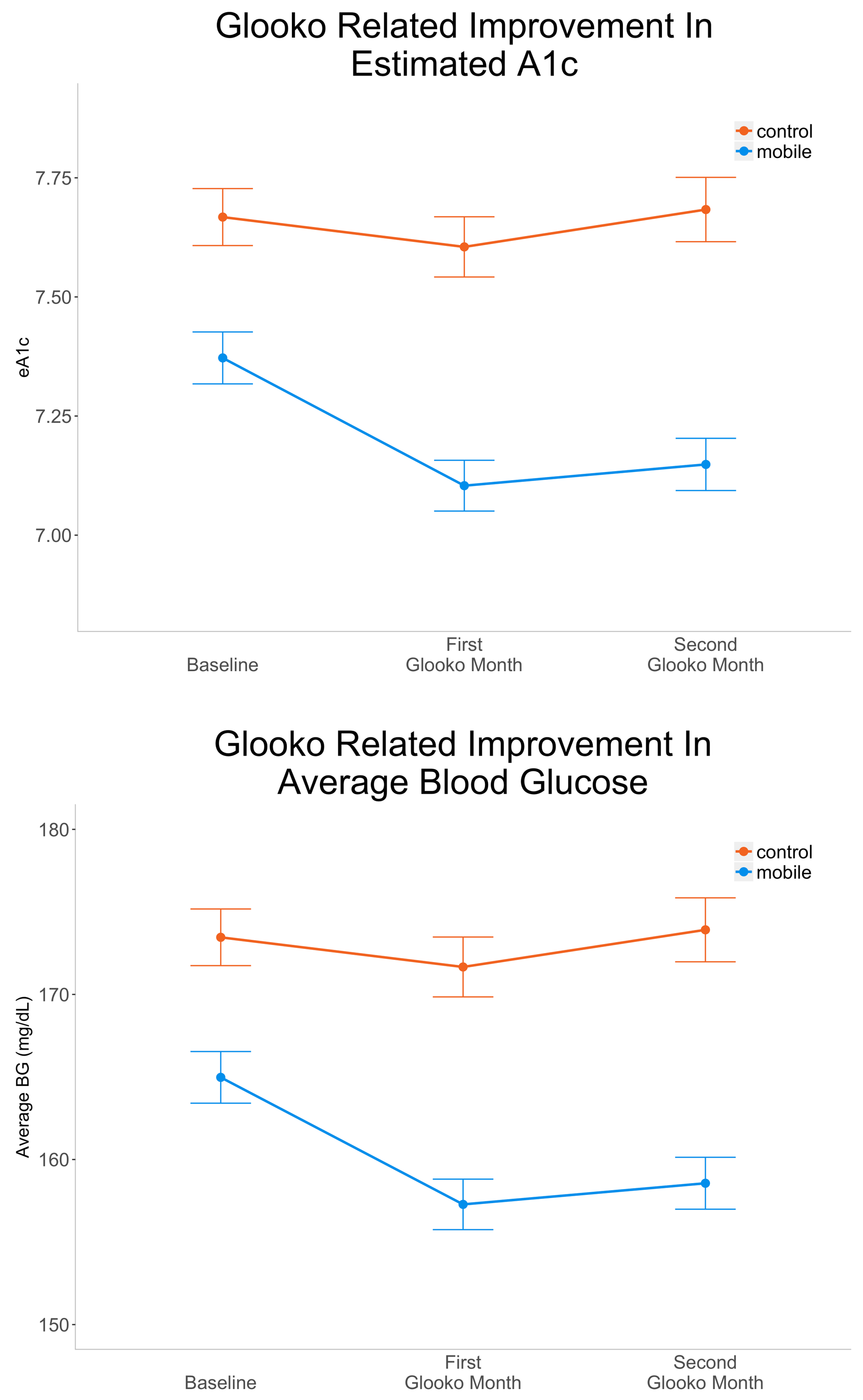

FIGURE 3: Estimated A1c (top) and average BG (bottom) with standard error at baseline and following two months.

TABLE 4: HYPERGLYCEMIA

	B	OR	%Δ	T-VALUE	P-VALUE
(Intercept)	-0.499	-	-	-16.728	<0.001
Time	-0.011	0.989	-1.094%	-1.526	0.127
Mobile	-0.169	0.845	-15.549%	-4.033	<0.001
Time * Mobile	-0.045	0.956	-4.400%	-4.425	<0.001

NOTE: Summary of GLM examining change in hyperglycemia over the course of the study period. *B* indicates the parameter estimate for each variable. OR indicates the odds ratio of experiencing a hyperglycemic reading. % Δ indicates the percent change in hyperglycemia.

Before the start of the study, mobile users exhibited a 15.55% lower probability of hyperglycemic events (p<0.01). After the start of the study, the control group did not significantly increase or decrease their probability of a hyperglycemic event (p>0.05). By comparison, mobile users exhibited an additional decrease in the probability of hyperglycemic events by 4.40% per month, compared to control group (p<0.01). Overall, a mobile user could expect a 10.70% decrease in the probability of hyperglycemic events by the end of two months.

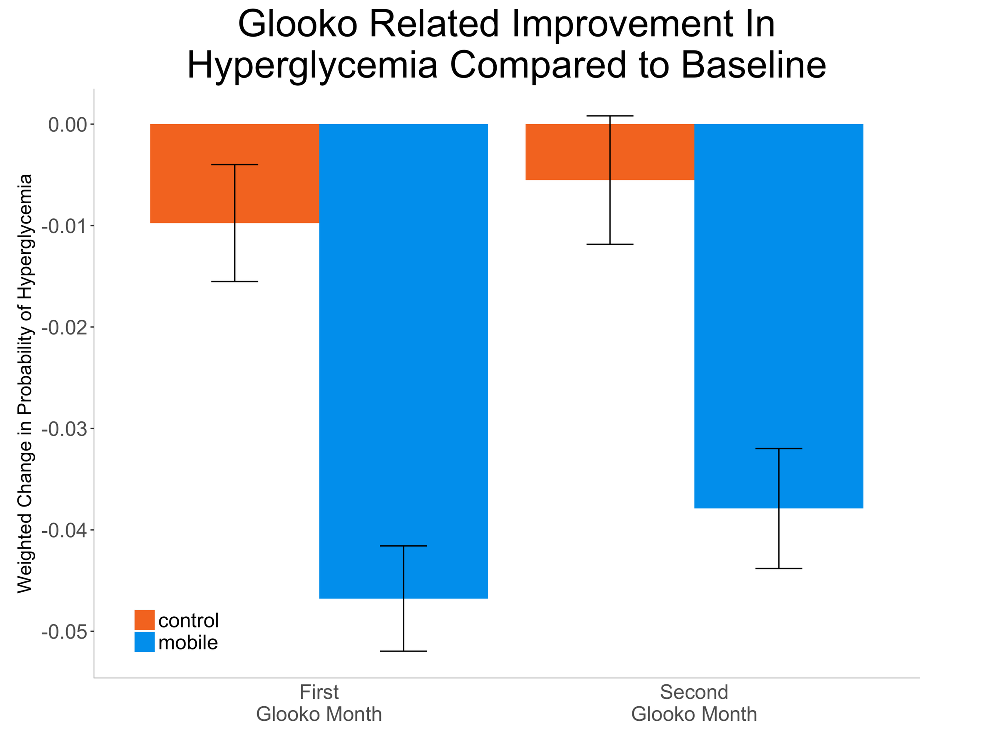

FIGURE 4: Monthly improvement in hyperglycemia over baseline. Improvement quantified by mean (standard error) decrease in proportion of hyperglycemic readings, weighted by number of readings for that month.

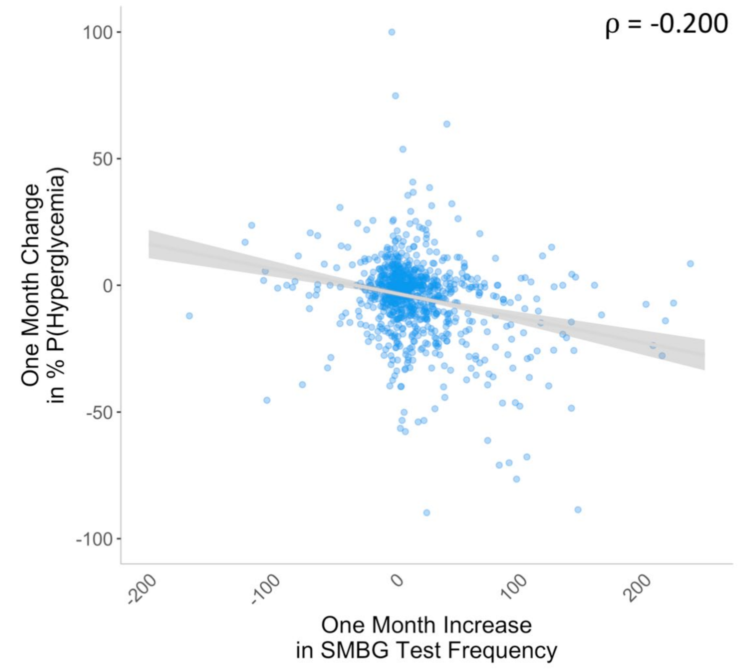

FIGURE 5: Using mobile data only. Scatter plot and spearman rho correlations between change in SMBG count and change in percent probability of Hyperglycemia.

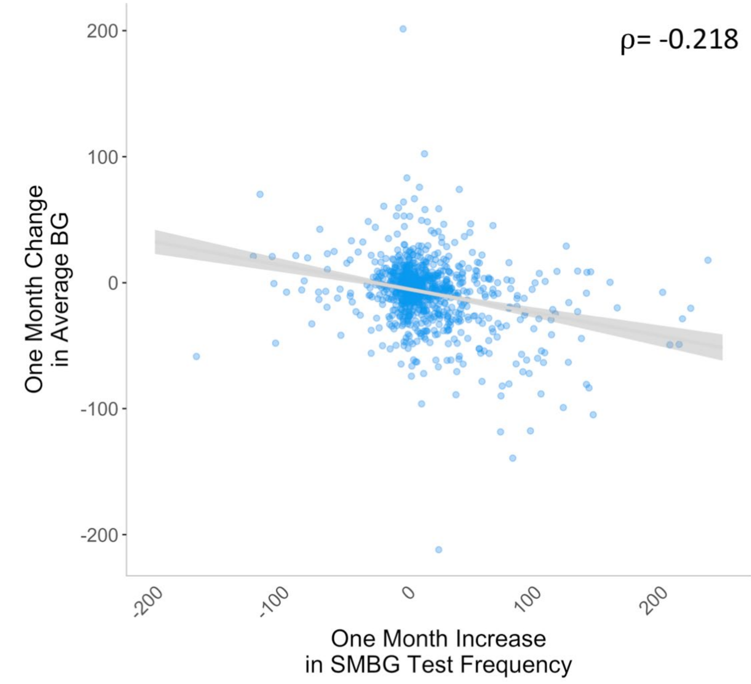

FIGURE 6: Using mobile data only. Scatter plot and spearman rho correlations between change in SMBG count and change in average blood glucose.

Previous research has shown that SMBG test rate may positively correlate with glycemic improvement (e.g. Schramm, 2012, Polonsky et al., 2012). We therefore hypothesized that the observed glycemic improvement was partially attributable to an increased test rate. To test this hypothesis, we isolated the first 30 day period for the mobile group and calculated change in probability of experiencing a hyperglycemic event, along with the change in average blood glucose. Using Spearman rho correlations, we found that the increase in SMBG test rate negatively correlated with change in the probability of experiencing a hyperglycemic event ($\rho = -0.20$, p<0.01) and change in average blood glucose ($\rho = -0.22$, p<0.01). In other words, more testing was related to lower BG and fewer hyperglycemic events.

CONCLUSION AND DISCUSSION

These results indicate that patients who used the mobile application, which allows users to more readily explore and organize their diabetes data, improved significantly more than users who did not use the mobile application. Overall, mobile users exhibited a significantly greater increase in SMBG test rates, a significantly greater drop in average blood glucose and significantly less hyperglycemia, without an increase in hypoglycemia. These findings supported a recent meta-analysis suggesting the structured display of data was the most important factor influencing diabetes outcomes (Wu et al., 2017).

We can attribute some of this improvement to an increase in SMBG testing (e.g. Schramm et al., 2012, Polonsky et al., 2012, Miller et al., 2013). Although these correlations are significant, they represent modest effect sizes and are therefore unlikely to explain all of the improvement reported above.

Overall, we found evidence to suggest that the Glooko Mobile App enhanced patient ability to manage their diabetes. These findings dovetail with Wu et al., (2017), implying that improvement could be attributable to easier access to data via structured display of data.

REFERENCES

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