Predicting Conversion from Self-Monitoring of Blood Glucose to Continuous Glucose Monitoring using clinical and demographic characteristics

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MS in Data Science
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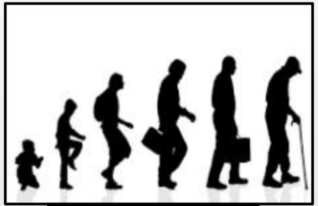
Our objective is to obtain insightful and actionable information to shape the diabetic industry

Location

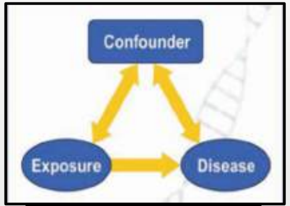
Referrals



Age

Health insurance

Gender



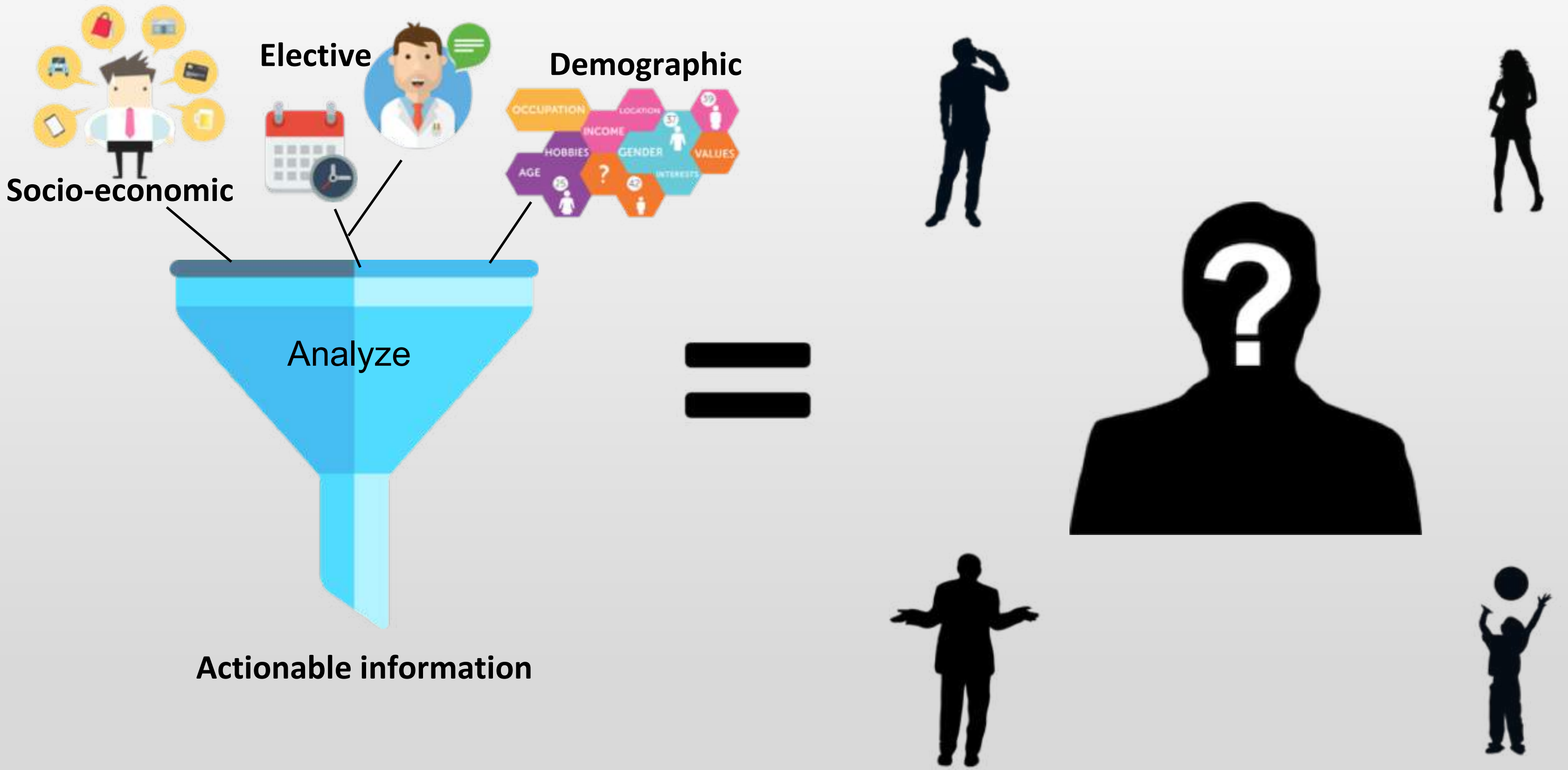
Confounders

Finger-prick method

Analysis of factors

CGM method

Our objective is to obtain insightful and actionable information to shape the diabetic industry



In the last few decades, there have been significant technological leaps in glucose monitoring

SMBG

Urine testing, 1945 - 1957

The first test strip and meter, 1964-1970

Now

CGM

The first CGM, 2006

The first CGM mobile system, 2015

Now

FGM

The first FGM product, 2014

There are pros and cons for each current method of glucose monitoring

Self-monitoring blood glucose (SMBG)

Advantages	Limitations
Familiarity	Inconvenience
Accuracy	Pain/antisocial
Relatively low cost	Sporadic nature

Continuous glucose monitoring(CGM)

Advantages	Limitations
Full glucose profile	High cost
Alarms for “hypo”	Need for calibration
IP connection	Difficulties in data interpretation

Flash glucose monitoring(FGM)

Advantages	Limitations
Full glucose profile	No alarm for “hypo”
No calibration	No IP connection
Long sensor use	
Relatively affordable	

Glossary: CGM, continuous glucose monitoring; FGM, flash glucose monitoring; IP, insulin pump; SMBG, self-monitoring of blood glucose

Majority of suggests that the CGM is superior to SMBG in many ways

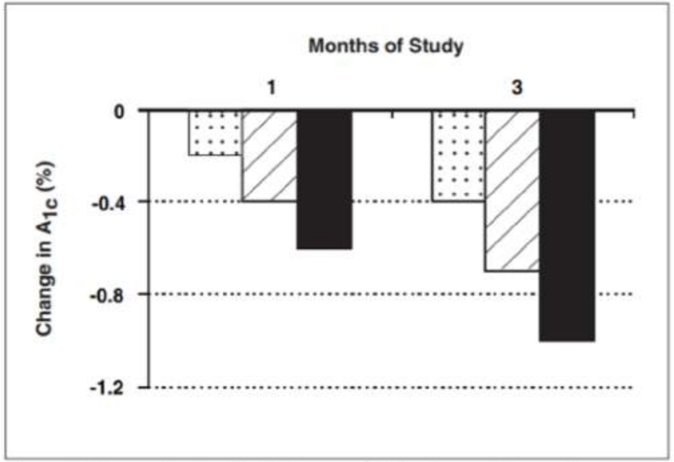
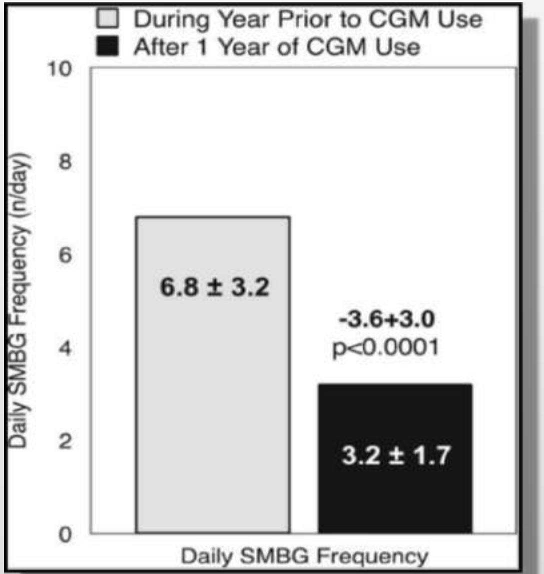
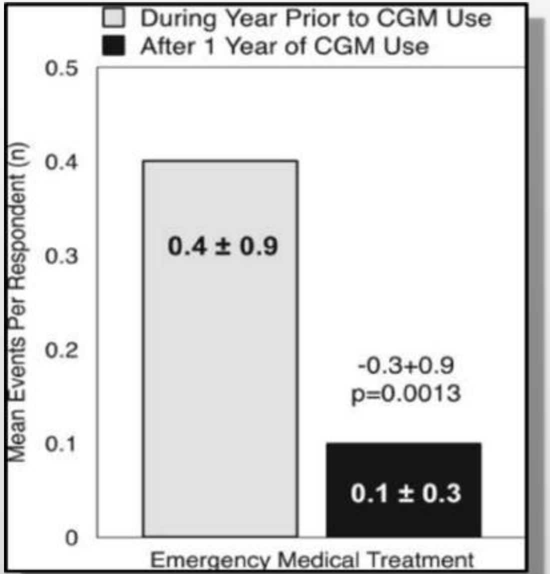


Figure 3. Mean reduction in A1C among 156 patients with poorly controlled diabetes who used no CGM (stippled bars), intermittent CGM (hatched bars), or continuous CGM (solid bars) for a 3-month period. Adapted from Ref. 15.

Source: Burge, Mitchell, Sawyer, & Schade (2008)

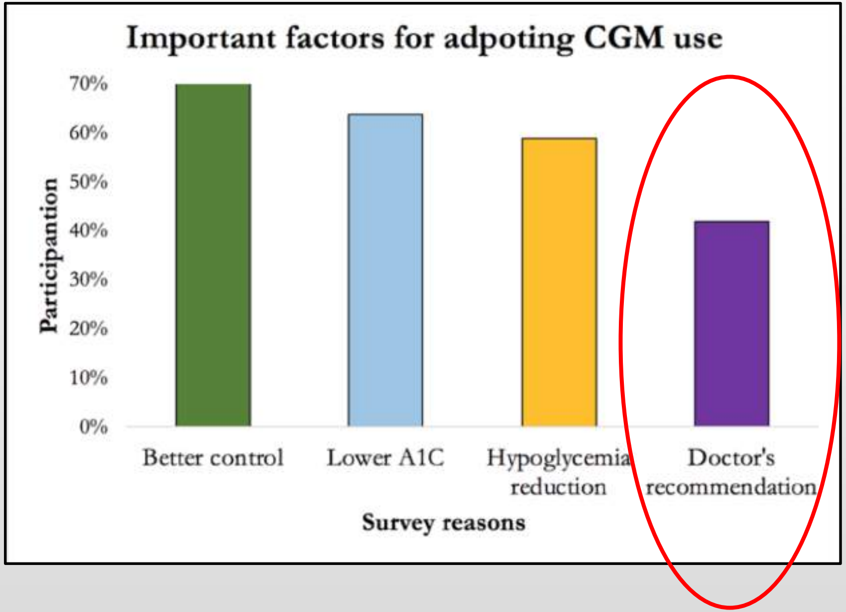


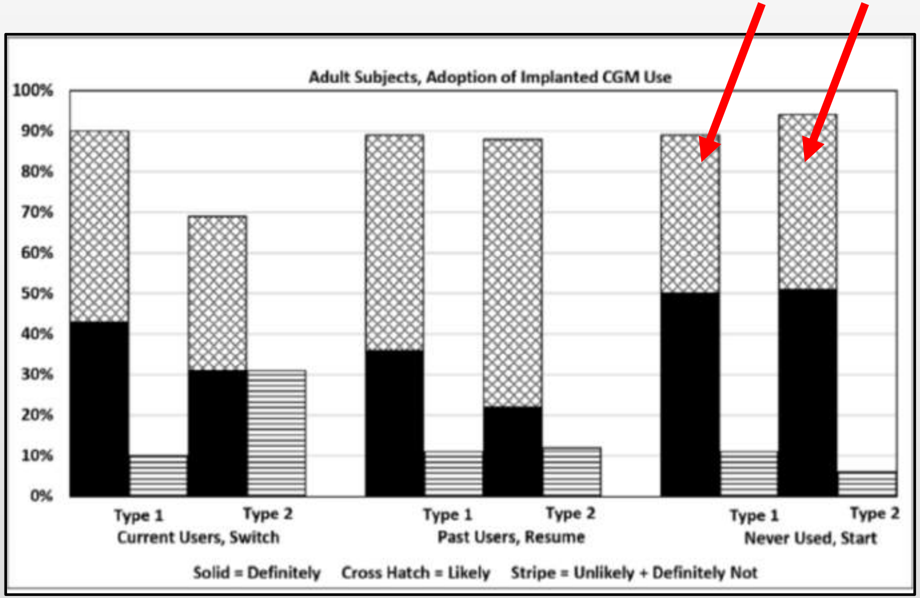


Source: Chamberlain, Dopita, Gilgen, & Neuman (2015)

There are a few crucial factors for the likelihood of adopting a CGM device

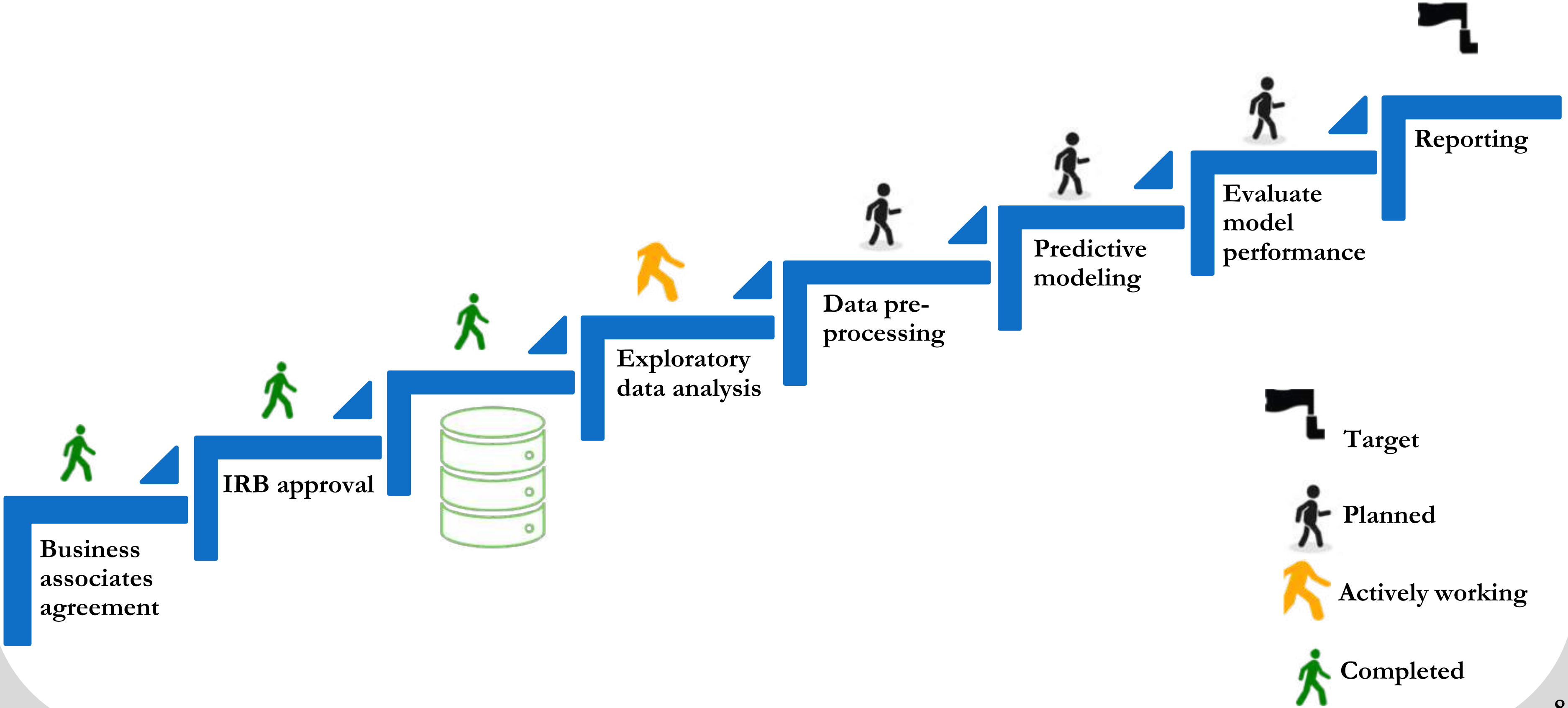
Definite or likely adoption ~90%





Source: Engler, Routh, & Lucisano (2018)

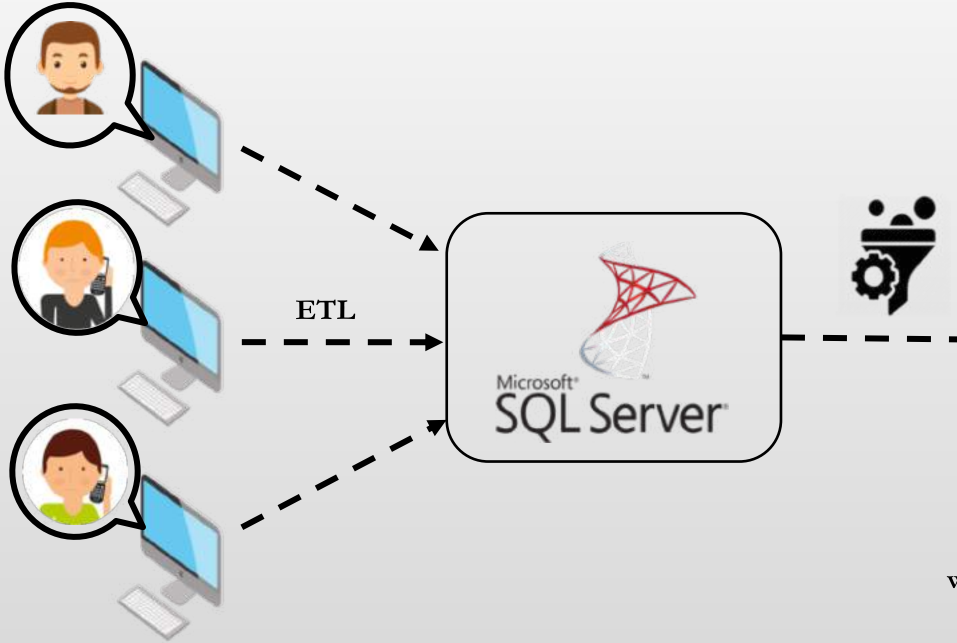
The scope of our methodology is outlined in 8 steps



Data was gathered from diabetic patients across the U.S. and will be generated for the analyses in our project

Dependent variable

Yes: switched to Libre

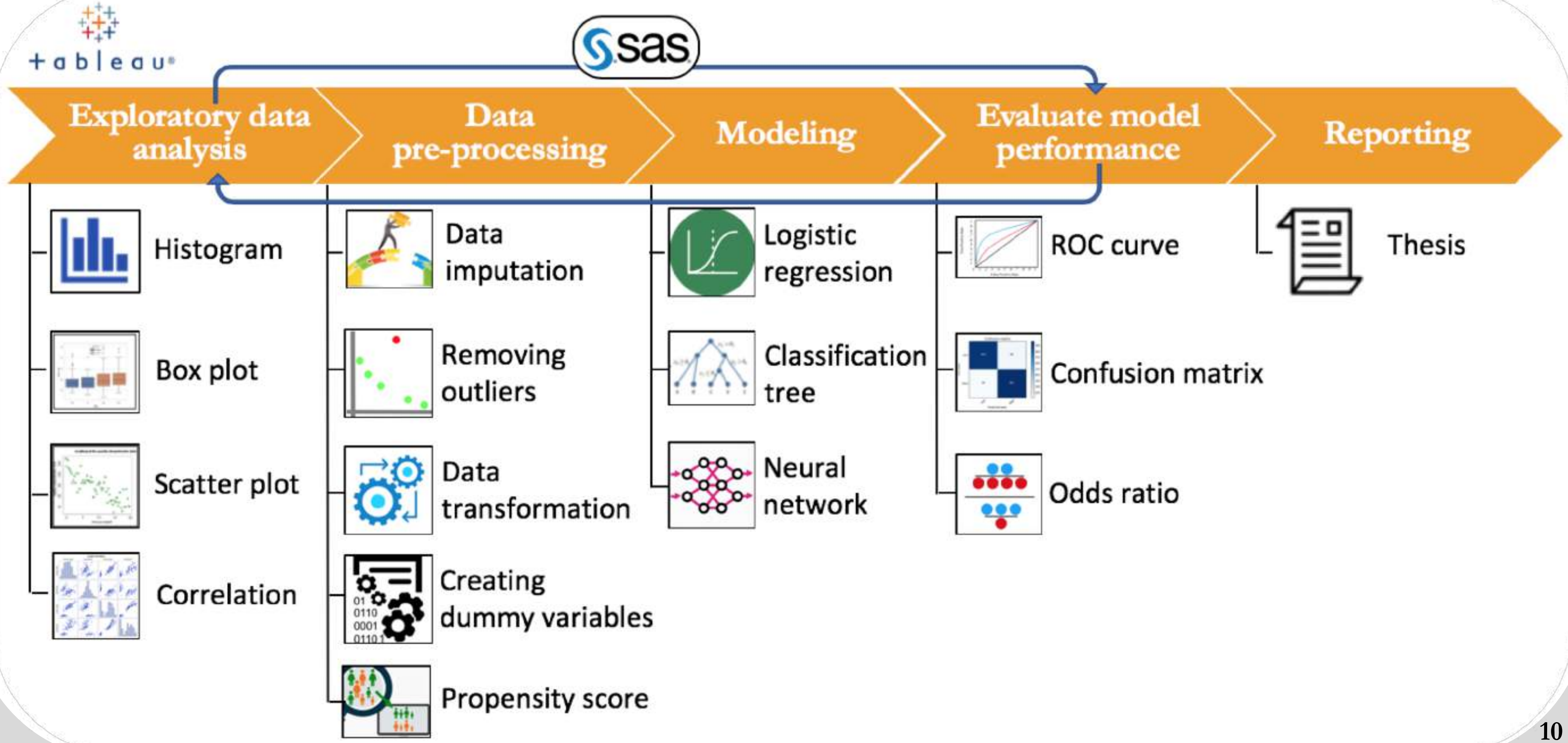


No.	Variable	Description
1	age	Age
2	gender	Gender (male and female)
3	referral	Referral source (doctor, friend, website etc..)
4	state	What state patient lives in
5	city	What city patient lives in
6	method	Traditional method or on CGM
7	conversion_date	Date that patient converted to CGM
8	npi	National Provider Identifier
9	npi_state	State of national provider
10	diabetes_type	Type I or Type II diabetes
11	elig_waiver	If patient is on eligibility waiver or not
12	pro_offer	If patient is compliant over >70% threshold when due for supplies (compliant/noncompliant)
13	brand	Diabetic brand preferred or is using
14	insurance	Health insurance that the patient has
15	start_date	Date when patient first contacted ADS
16	bill_date	Last date patient was billed for a product
17	libre_prompt_date	Date when patient was prompted to Libre offer
18	diagnosis_code	International Classification of Diseases (ICD) code
19	insulin_usage	Amount of times patient is injecting insulin
20	times_testing	Amount of times patient does finger-prick testing
21	patientid	Patient unique identifier

who

Prompt date

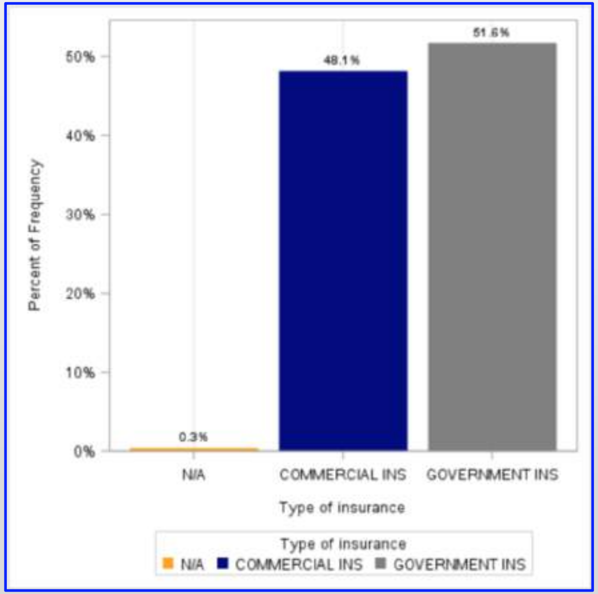
These are the essential tools and techniques we will use to analyze the factors of glucose monitoring conversion



Incomplete, noisy, and inconsistent data will be changed into quality data, which can lead to significant improvement in the model's predictive performance

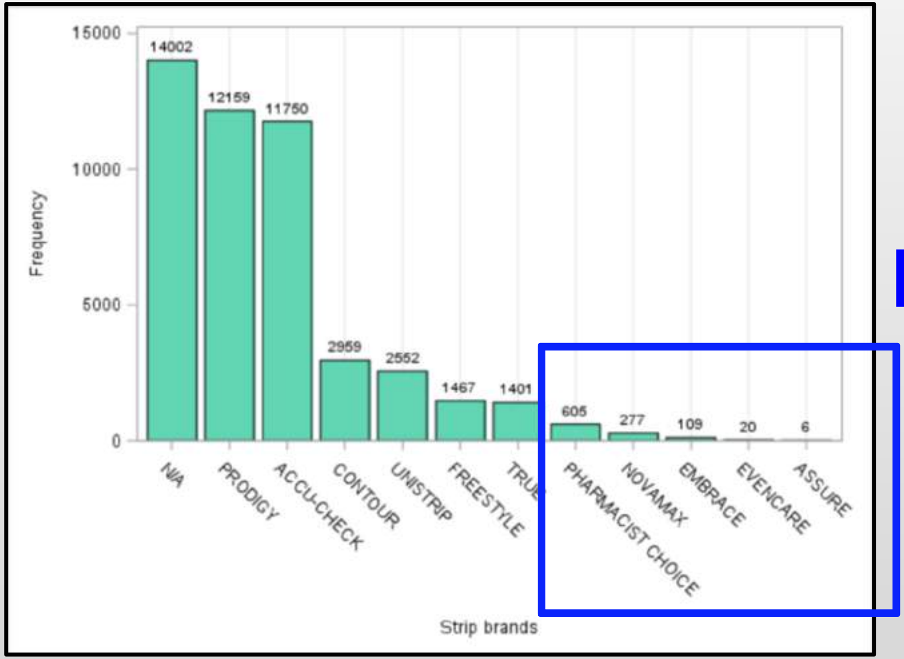
'medi-cal' 'mcal' 'medicaid ca' 'medicare' 'tricare' 'champva' 'dual' 'meridian' 'medicaid mo' 'medicaid or' 'medicaid sc'	→	Government insurance
other companies	→	Commercial insurance
unknown	→	N/A

insurance_2	Frequency	Percent	Cumulative Frequency	Cumulative Percent
GOVERNMENT INS	25235	51.64	25235	51.64
COMMERCIAL INS	23490	48.07	48725	99.71
N/A	141	0.29	48866	100.00

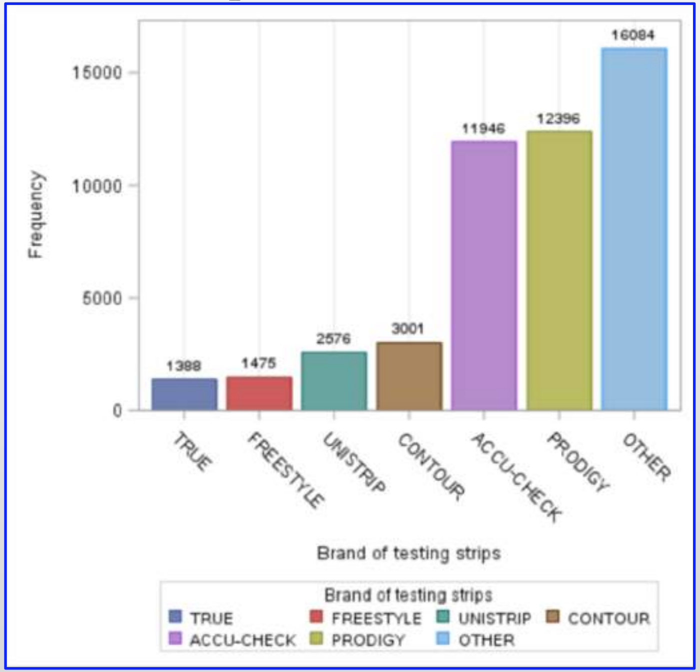


Incomplete, noisy, and inconsistent data will be changed into quality data, which can lead to significant improvement in the model's predictive performance

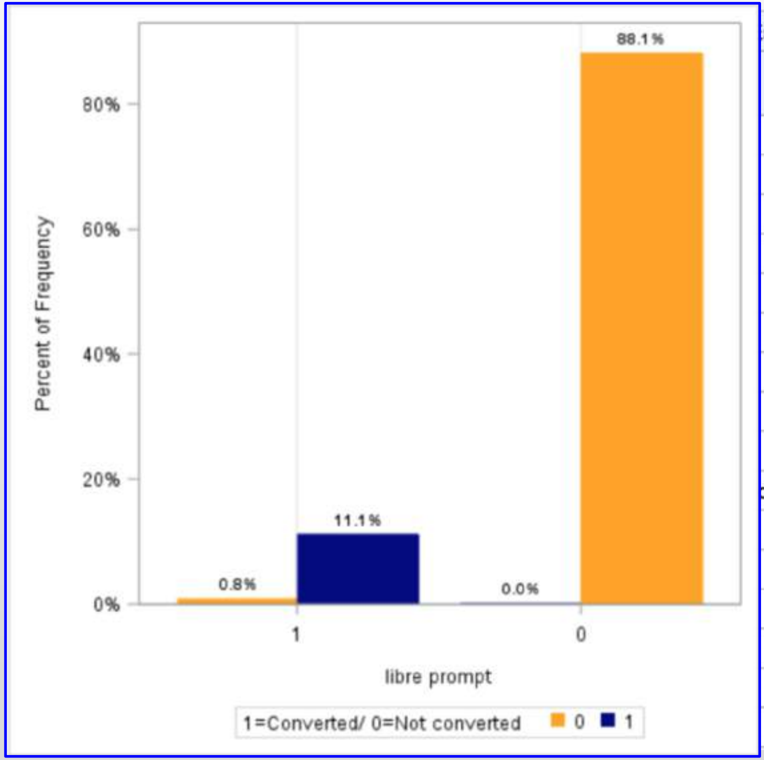
Strip brands (12 levels)

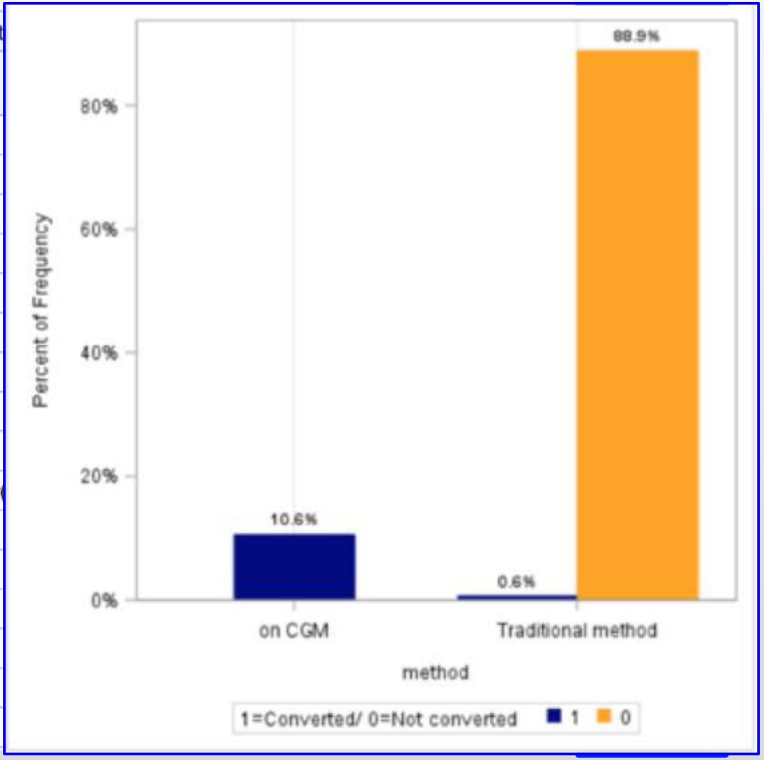


Strip brands (7 levels)



There should be minimal or no multicollinearity among the independent variables. A variance inflation factor (VIF) value of more than 4 is an alarming value that the variables may be confounding.





Chi-square analyses were performed to determine bivariate associations between categorical variables

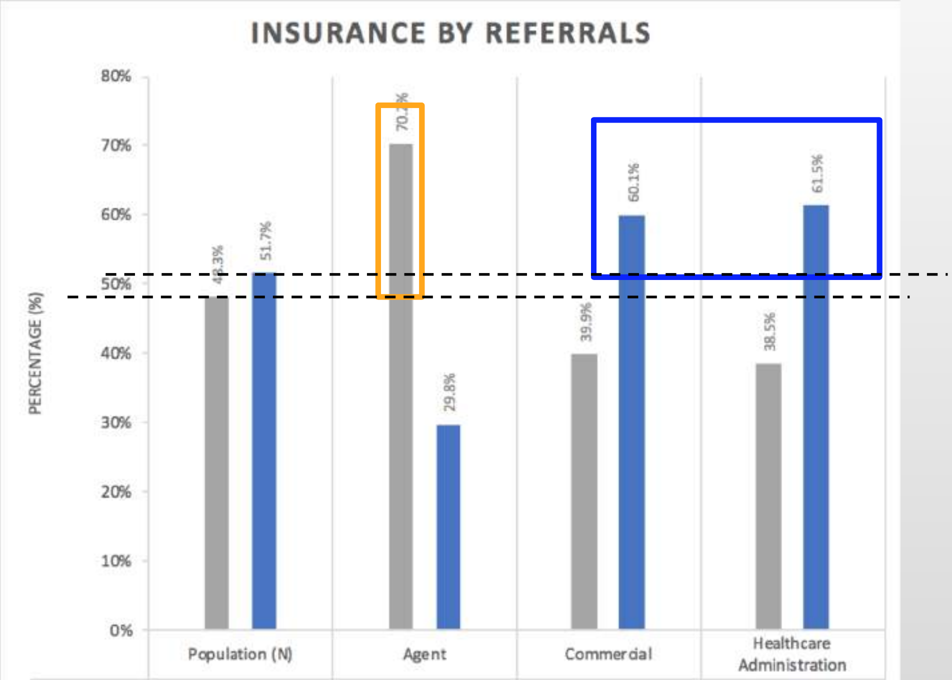
Bivariate Associations of Demographic and Clinical Characteristics of 47,968 Diabetic Patients from ADS by Referrals

Variable	Population N = 47,968[a] (100%)	Agent N=13,772 (28.71%)	Commercial N=23,312 (48.60%)	Healthcare administration N=10,884 (22.69%)	p-value[b]
Gender					
Female	26,620 (55.5%)	8,520 (61.9%)	12,136 (52.1%)	5,964 (54.8%)	
Male	21,348 (44.5%)	5,252 (38.5%)	11,176 (48.0%)	4,920 (45.2%)	<0.0001
Medicare jurisdiction					
Jurisdiction A	4,921 (10.2%)	685 (5.0%)	3,708 (15.9%)	528 (4.8%)	
Jurisdiction B	5,202 (10.9%)	1,825 (13.2%)	2,881(12.4%)	496 (4.6%)	
Jurisdiction C	19,668 (41.0%)	9,960 (72.3%)	7,996 (34.3%)	1,712 (15.7%)	
Jurisdiction D	18,177 (37.9%)	1,302 (9.4%)	8,727 (37.4%)	8,148 (74.9%)	<0.0001
Age					
Children and young adult (1-26)	4,197 (8.7%)	7 (0.1%)	4,123 (17.7%)	67 (0.6%)	
Adult (27-64)	11,867 (24.7%)	3,528 (25.6%)	6,370 (27.3%)	1,969 (18.1%)	
Senior (65+)	31,904 (66.5%)	10,237 (74.3%)	12,819 (55.0%)	8,848 (81.3%)	<0.0001
Diabetes type					
T1D	11,237 (23.4%)	536 (3.9%)	10,128 (43.5%)	573 (5.3%)	
T2D	36,731 (76.6%)	13,236 (96.1%)	13,184 (56.5%)	10,311 (94.7%)	<0.0001
Eligibility waiver					
Not on waiver	42,074 (87.7%)	10,370 (75.3%)	21,456 (92.0%)	10,248 (94.2%)	
On waiver	5,894 (12.3%)	3,402 (24.7%)	1,856 (8.0%)	636 (5.8%)	<0.0001
Patient reorder opportunity offer					
Compliant	34,420 (71.8%)	9,749 (70.8%)	17,035 (73.1%)	7,636 (70.2%)	
Non-compliant	13,548 (28.2%)	4,023 (29.2%)	6,277 (26.9%)	3,248 (29.8%)	<0.0001
Insurance					
Commercial	23166 (48.3%)	9,671 (70.2%)	9,303 (39.9%)	4,192 (38.5%)	
Government	24802 (51.7%)	4,101 (29.8%)	14,009 (60.1%)	6,692 (61.5%)	<0.0001

Bivariate Associations of Demographic and Clinical Characteristics of 47,968 Diabetic Patients from ADS by CGM Conversion

Variable	Population N = 47,968[a] (100%)	Not convert N = 42,599 (88.81%)	Converted N = 5,369 (11.19%)	p-value[b]
Referral type				
Agent	13,772 (28.7%)	13,709 (32.2%)	63 (1.2%)	
Commercial	23,312 (48.6%)	18,742 (44.0%)	4,570 (85.1%)	
HCA	10,884 (22.7%)	10,148 (23.8%)	736 (13.7%)	<0.0001
Gender				
Female	26,620 (55.5%)	23,936 (56.2%)	2,684 (50.0%)	
Male	21,348 (44.5%)	18,663 (43.8%)	2,685 (50.0%)	<0.0001
Medicare jurisdiction				
Jurisdiction A	4,921 (10.3%)	3,904 (9.2%)	1,017 (18.9%)	
Jurisdiction B	5,202 (10.8%)	4,250 (10.0%)	952 (17.7%)	
Jurisdiction C	19,668 (41.0%)	18,379 (43.1%)	1,289 (24.0%)	
Jurisdiction D	18,177 (37.9%)	16,066 (37.7%)	2,111 (39.3%)	<0.0001
Age				
Child and young adult (1-26)	4,197 (8.8%)	4,187 (9.8%)	10 (0.2%)	
Adult (27-64)	11,867 (24.7%)	10,772 (25.3%)	1,095 (20.4%)	
Senior (65+)	31,904 (66.5%)	27,640 (64.9%)	4,264 (79.4%)	<0.0001
Diabetes type				
T1D	11,237 (23.4%)	10,093 (23.7%)	1,144 (21.3%)	
T2D	36,731 (76.6%)	32,506 (76.3%)	4,225 (78.7%)	<0.0001
Eligibility waiver				
Not on waiver	42,074 (87.7%)	37,253 (87.5%)	4,821 (89.8%)	
On waiver	5,894 (12.3%)	5,346 (12.5%)	548 (10.2%)	<0.0001
Patient reorder opportunity offer				
Compliant	34,420 (71.8%)	30,130 (70.7%)	4,290 (79.9%)	
Non-compliant	13,548 (28.2%)	12,469 (29.3%)	1,079 (20.1%)	<0.0001
Insurance				
Commercial	23,166 (48.3%)	22,661 (53.2%)	505 (9.4%)	
Government	24,802 (51.7%)	19,938 (46.8%)	4,864 (90.6%)	<0.0001

Chi-square analyses were performed to determine if there is an association between the variable of interest (referrals) and each control variable



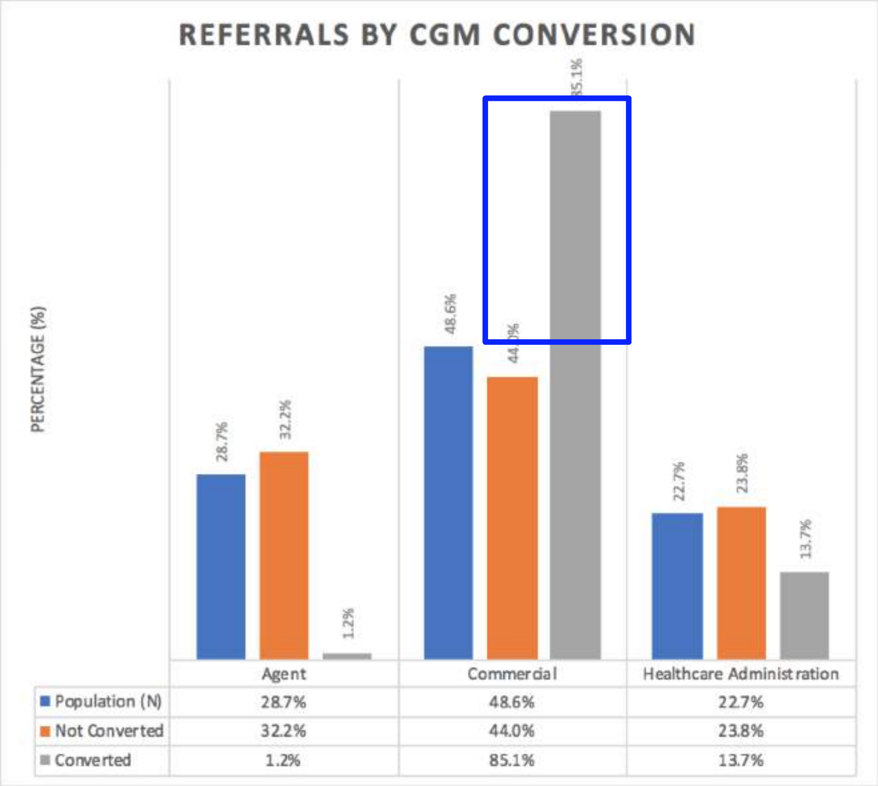
	Population (N)	Agent	Commercial	Healthcare Administration
Commercial	48.3%	70.2%	39.9%	38.5%
Government	51.7%	29.8%	60.1%	61.5%

Statistics for Table of insurance_2 by referral_type2

Statistic	DF	Value	Prob
Chi-Square	4	3741.2786	<.0001

There is an association between referrals (VOI) and insurance type

Chi-square analysis was performed to determine if there is an association between the dependent variable (CGM conversion) and referrals



Statistics for Table of referral_type2 by CGM_Conversion

Statistic	DF	Value	Prob
Chi-Square	4	4406.9150	<.0001

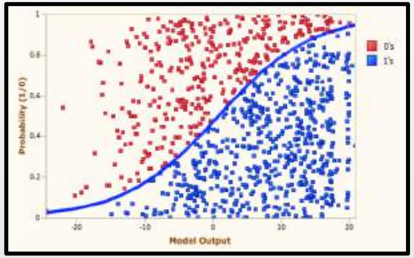
There is an association between converting patients (DV) and referrals

The train/test data split operation was done in the ratio of 3:1 to validate our results properly

% split	75%	25%	
	Train set Frequency (%)	Test set Frequency (%)	Total
Non-event	32,568 (89%)	10,856 (89%)	43,424
Event	1,360 (11%)	4,082 (11%)	5,442
Total event	35,481	11,826	48,866

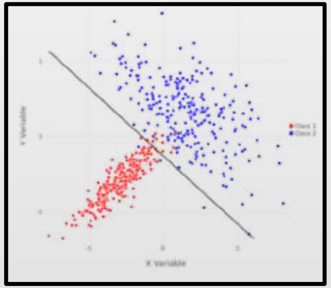
Multiple multivariate analyses account for other variables at the same time, and can be utilized for predictive modeling

Logistic regression



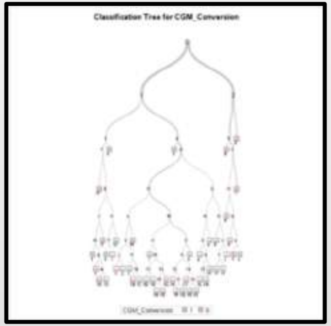
Source: (Banga, 2016)

Linear discriminant analysis

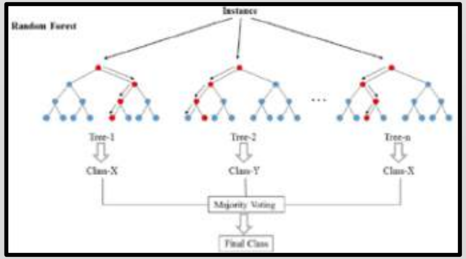


Source: Thatcher T. (2015)

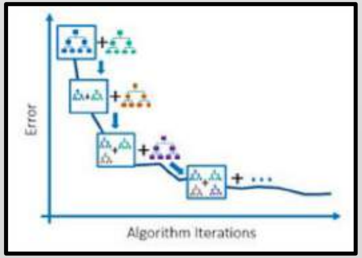
Decision tree



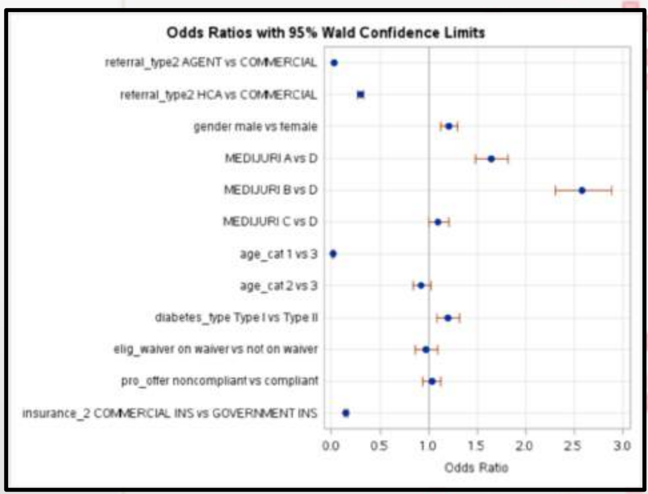
Random forest



Gradient boosting



Logistic regression

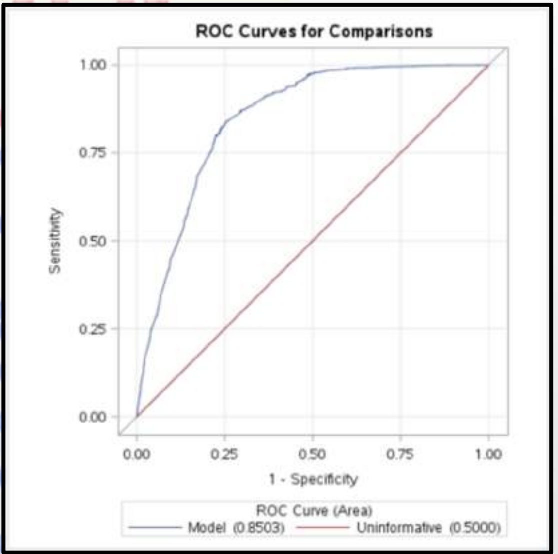


Association of Predicted Probabilities and Observed Responses

Percent Concordant	84.6	Somers' D	0.701
Percent Discordant	14.5	Gamma	0.707
Percent Tied	0.9	Tau-a	0.139
Pairs	128662650	c	0.850

Partition for the Hosmer and Lemeshow Test

		CGM_Conversion = 1		CGM_Conversion = 0	
Group	Total	Observed	Expected	Observed	Expected
1	1225	2	0.98	1223	1224.02
2	1049	3	1.52	1046	1047.48
3	1182	2	3.02	1180	1178.98
4	1303	17	14.82	1286	1288.18
5	1322	36	40.97	1286	1281.03
6	1339	96	100.75	1243	1238.25
7	1181	120	130.82	1061	1050.18
8	1340	350	326.31	990	1013.69
9	1331	409	404.44	922	926.56
10	719	306	317.37	413	401.63



Odds Ratio Estimates and Wald Confidence Intervals

Effect	Unit	Estimate	95% Confidence Limits	
referral_type2 COMMERCIAL vs AGENT	1.0000	40.347	24.437	66.616
referral_type2 HCA vs AGENT	1.0000	12.751	7.561	21.505
gender male vs female	1.0000	1.215	1.071	1.378
MEDIJURI A vs D	1.0000	1.846	1.545	2.206
MEDIJURI B vs D	1.0000	2.534	2.088	3.075
MEDIJURI C vs D	1.0000	1.169	0.989	1.382
age_cat 1 vs 3	1.0000	0.008	0.001	0.056
age_cat 2 vs 3	1.0000	0.988	0.838	1.165
insurance_2 COMMERCIAL INS vs GOVERNMENT INS	1.0000	0.156	0.127	0.192

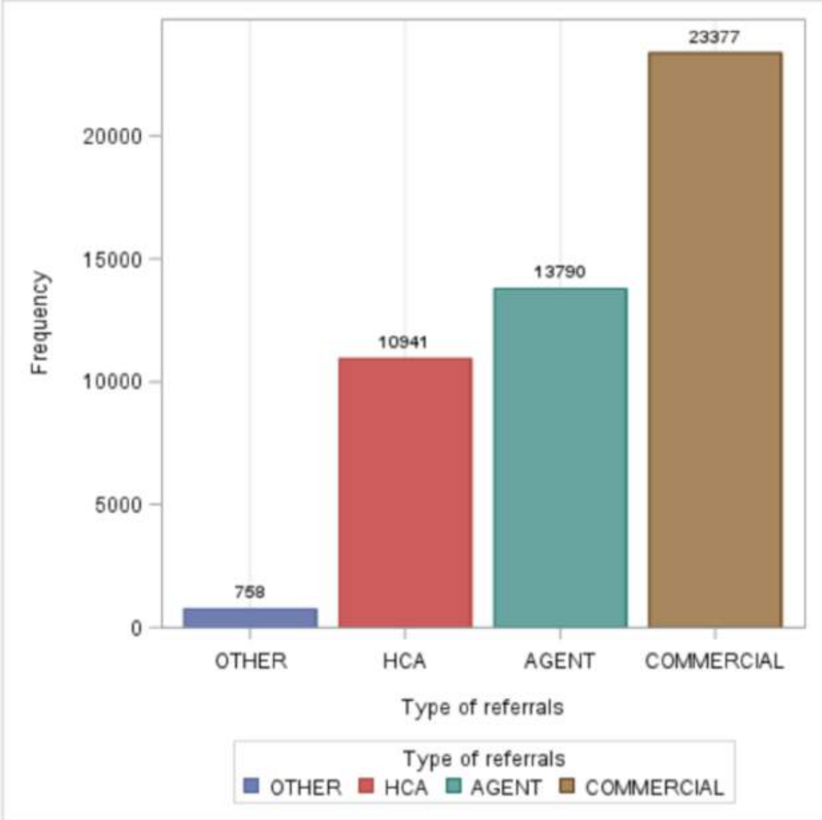
Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
8.1120	8	0.4226

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Standardized Estimate
Intercept		1	-4.8684	0.2622	344.7628	<.0001	
referral_type2	COMMERCIAL	1	3.6975	0.2558	208.8808	<.0001	1.0185
referral_type2	HCA	1	2.5456	0.2667	91.1230	<.0001	0.5918
gender	male	1	0.1946	0.0643	9.1496	0.0025	0.0533
MEDIJURI	A	1	0.6130	0.0908	45.5474	<.0001	0.1040
MEDIJURI	B	1	0.9297	0.0987	88.6579	<.0001	0.1621
MEDIJURI	C	1	0.1559	0.0853	3.3382	0.0677	0.0422
age_cat	1	1	-4.8391	1.0017	23.3361	<.0001	-0.7466
age_cat	2	1	-0.0120	0.0839	0.0206	0.8859	-0.00287
insurance_2	COMMERCIAL INS	1	-1.8577	0.1057	309.0088	<.0001	-0.5120

The referral variable did indeed have the highest impact in both the unadjusted and adjusted analyses



<u>Commercial</u>(10): ADS Marketing, ADS employee, Insurance company, DEXCOM, trade show, DME, gas card referral, manufacturer, internet, patient referral

<u>Agents</u>(5): UHC Agent, ICA Agent, EDC Agent, managed care broker, insurance broker

<u>Other</u>(3): miscellaneous, unknown, acquisition

<u>Healthcare administrations</u>(17): Home health, hospital, pharmacy, pharmacy partner, blind center, managed care, LTC, assisted living, CA Medical groups, medical group, clinic, medicaid, medi-cal, endocrinologist, health professional, physician, CDE

As expected, none of the SMBG patients converted without being prompted; but when there were prompted, almost all of them converted!

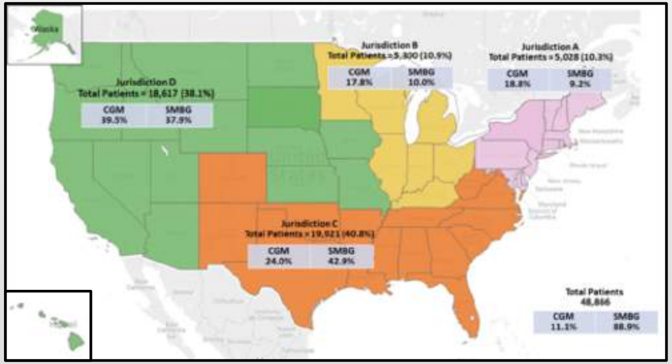
93% Chance of conversion after being prompted

Finger-prick method

CGM method

The multivariate analysis indicated that only five variables were viable for predicting CGM conversion: referral type, region, age, gender and health insurance

Referral type

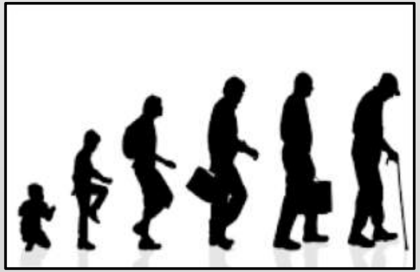


Region

Medi-Cal

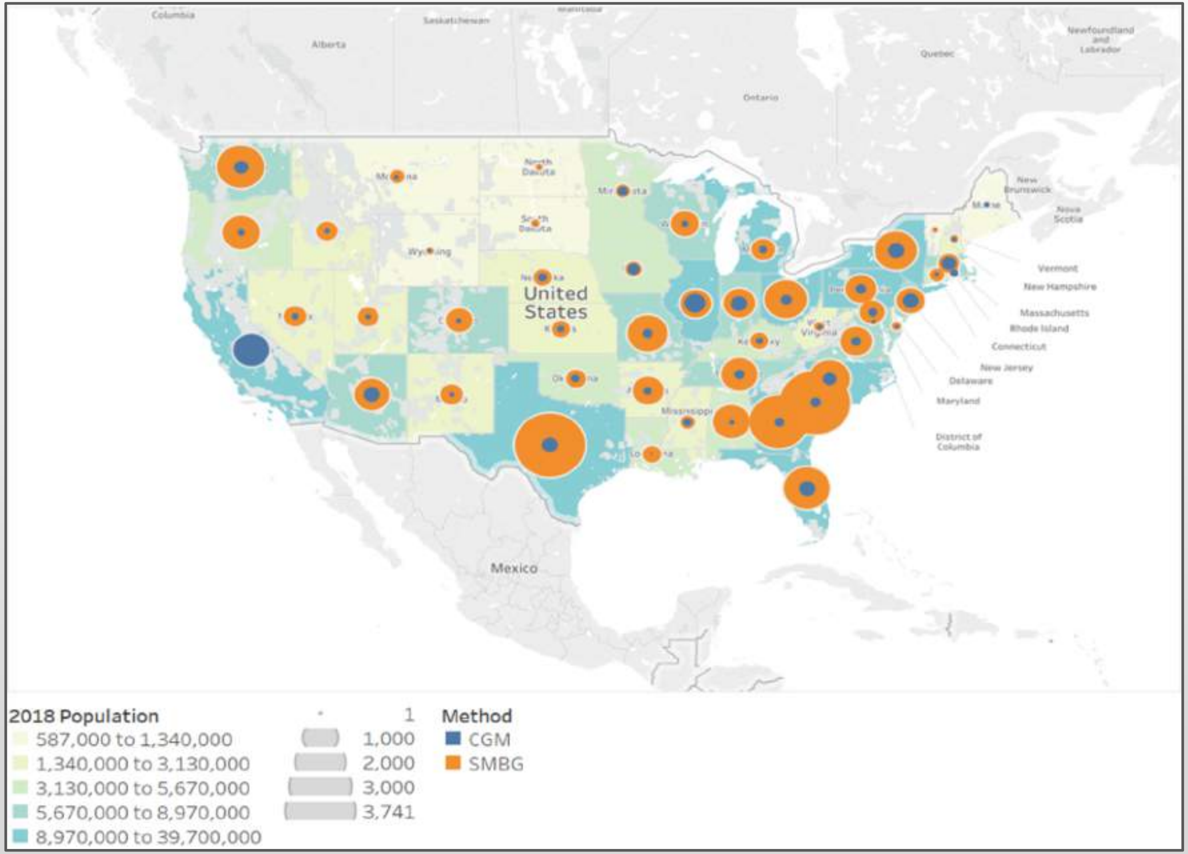
Health insurance

Gender



Age

Patients device type profile by state in United States



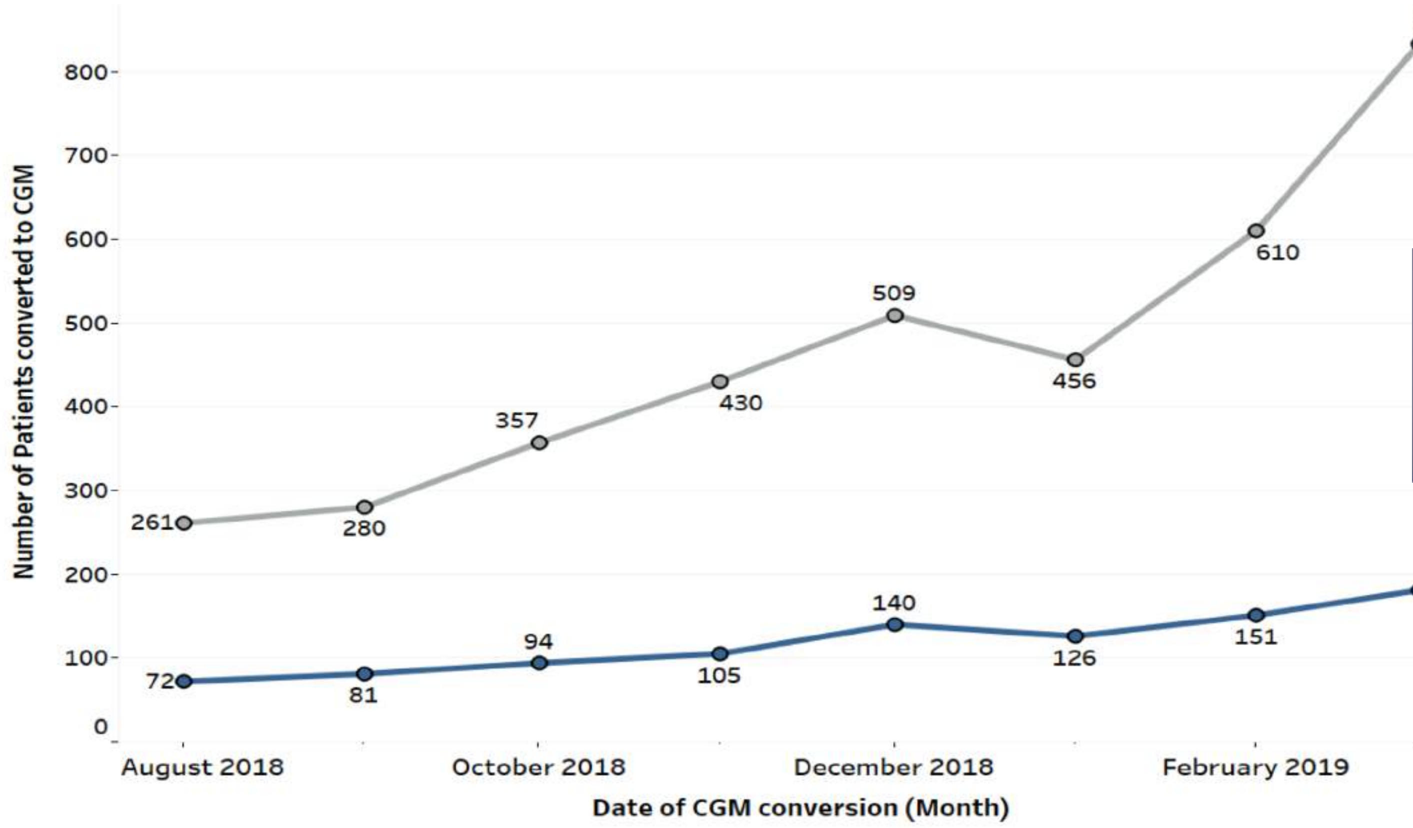
Other insights on clinical factors that had a significant impact on CGM conversion were people on eligibility waivers, if they were compliant, and their insurance

Not on eligibility waiver

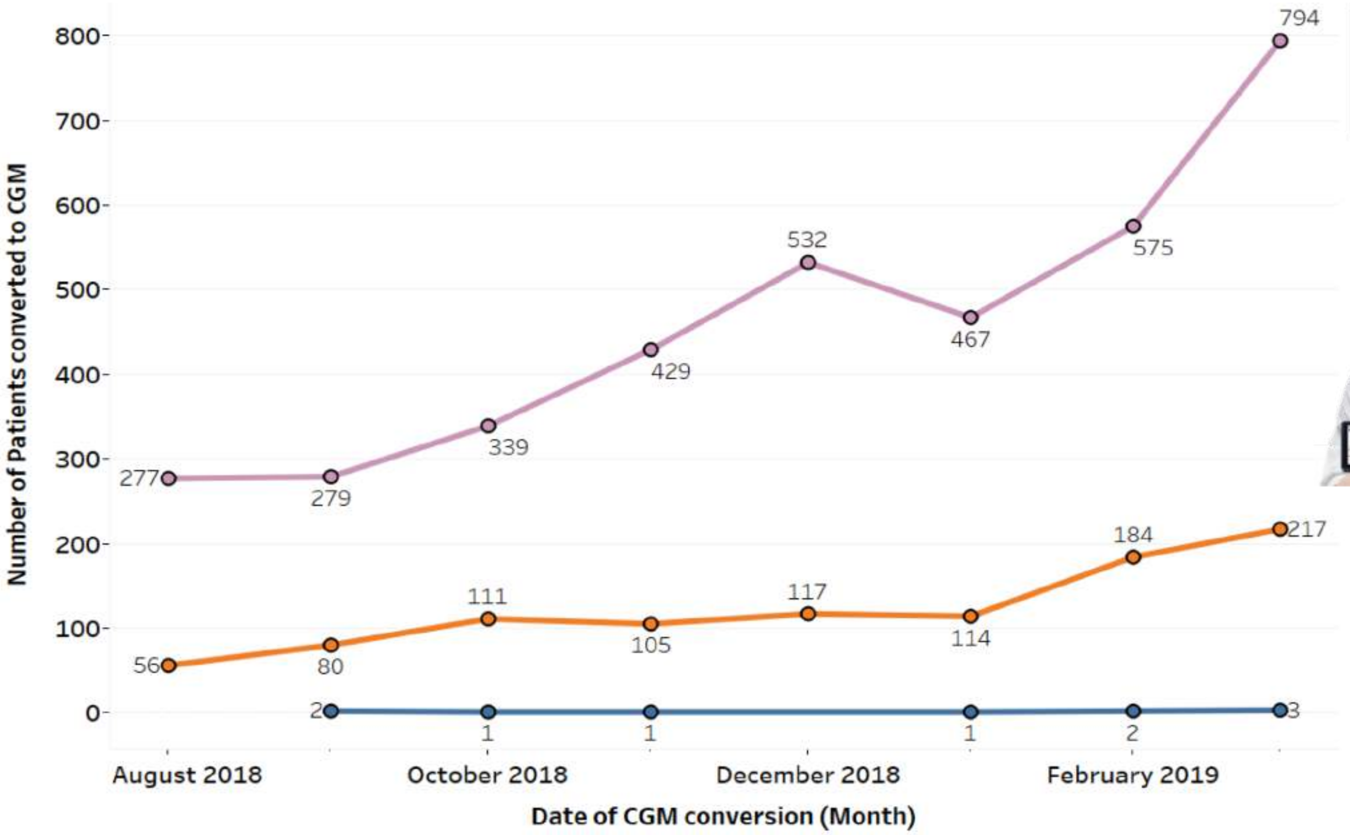
Type II patients

Compliant patients

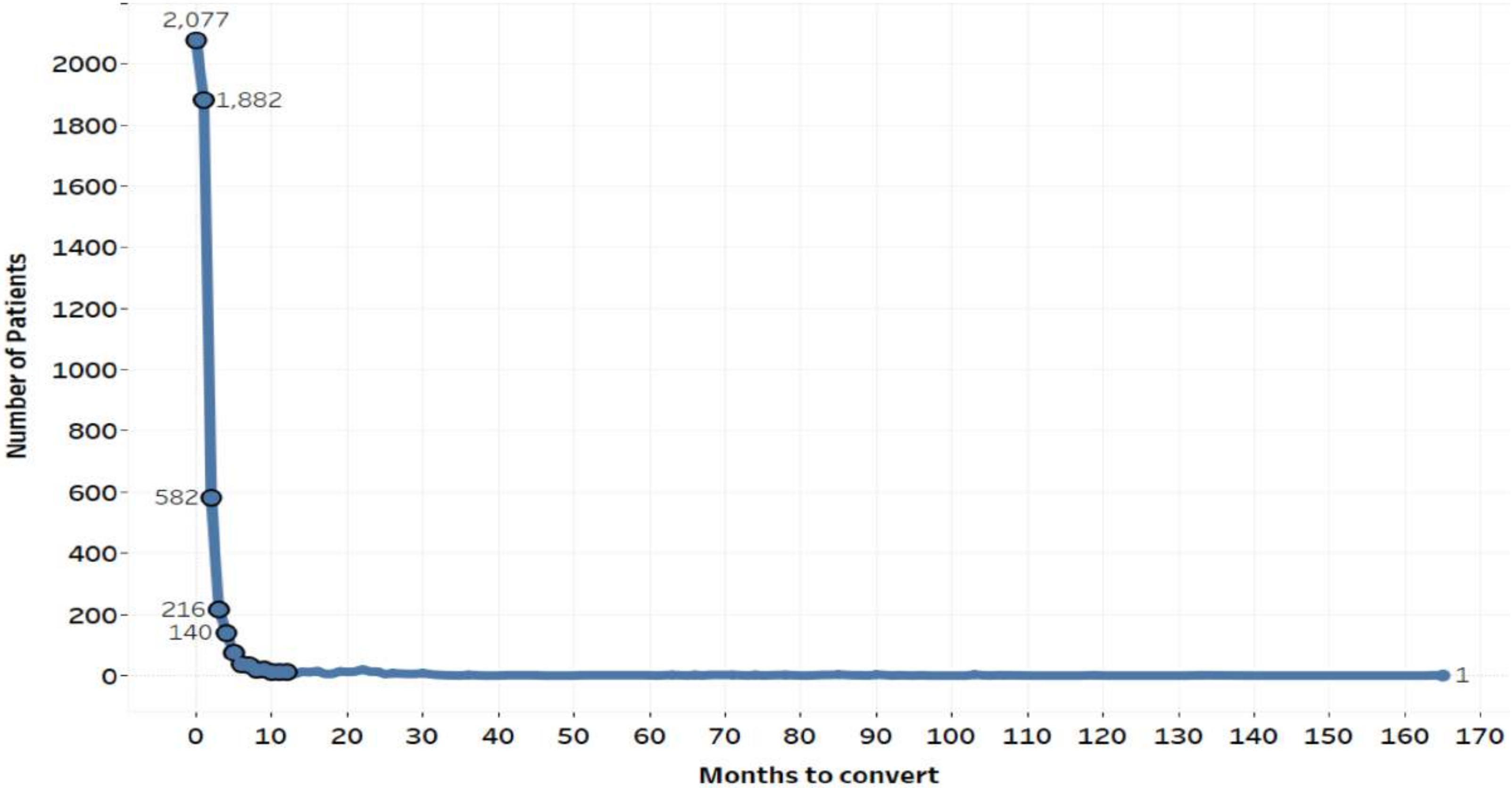
Diabetic type II patients are more likely to convert to CGM compared to diabetic type I patients



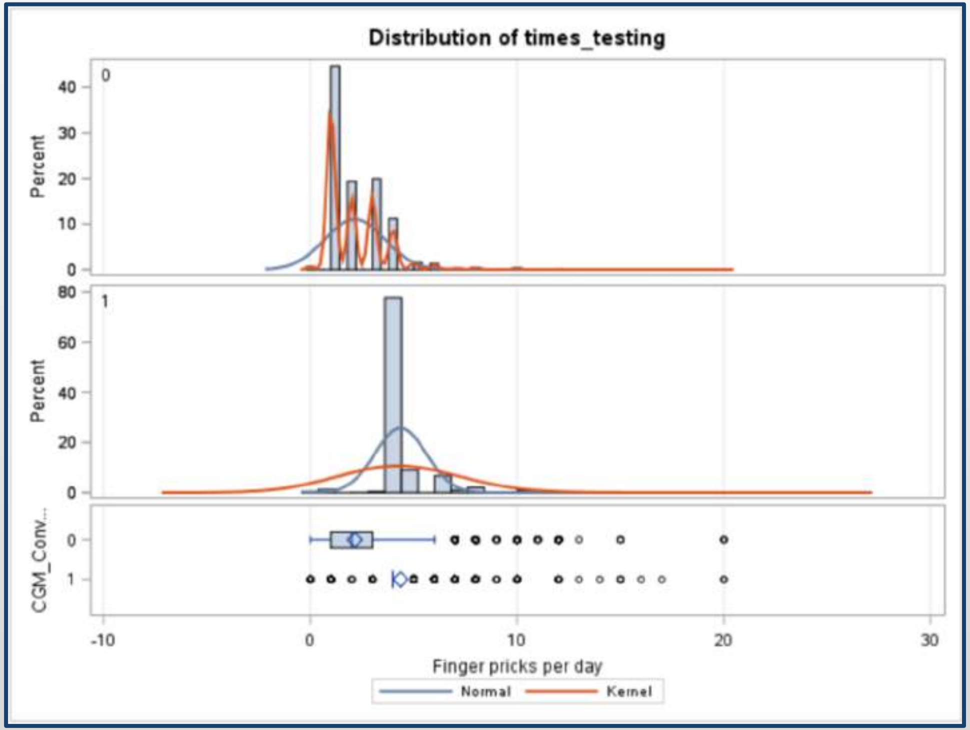
Above 65 years age group patients are more likely to convert to CGM



Patients have high probability to convert within three to four months after they become a member of ADS



T-tests for continuous variables revealed that patients on the CGM method regularly test more often than those on the SMBG method



CGM_Conversion	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0		2.1513	2.1375	2.1651	1.4414	1.4316	1.4512
1		4.3649	4.3319	4.3979	1.2384	1.2155	1.2622
Diff (1-2)	Pooled	-2.2136	-2.2538	-2.1734	1.4195	1.4105	1.4286
Diff (1-2)	Satterthwaite	-2.2136	-2.2494	-2.1778			

Finger-prick method

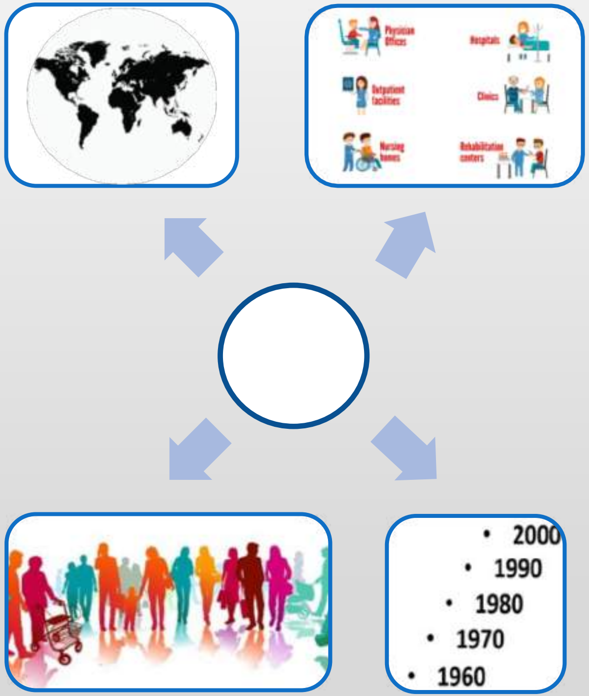
= Testing 2 times a day

CGM method

= Testing 4 times a day

Current research suggests that socio-economic and emotional factors play large roles in conversion as well

1. Generalizability



2. Socio-economic factors

Educational attainment

Income level

Occupation

3. Emotional factors

Parental Control

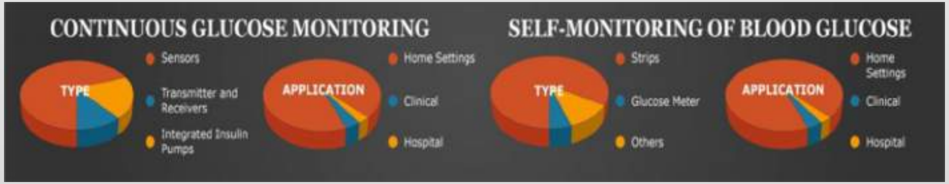
Child ostracization

Adjusted to former SMBG

Future studies will need to be conducted on emotional/social variables, expansion and financial administration with insurance coverage

Asia Pacific is the faster growing region.

North America holds the largest market share in 2016.



Source: Inkwood research (2019)

versus

Thank you for viewing our presentation!

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