

Effect of the Affordable Care Act on diabetes care at major health centers: newly detected diabetes and diabetes medication management

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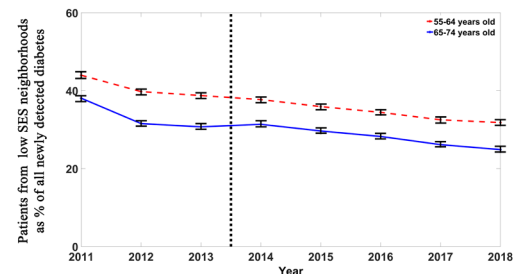
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The adoption of the Affordable Care Act (ACA)¹ in the USA expanded health insurance for low-income Americans and took two main forms: Medicaid expansion in some states and subsidized private health insurance through insurance exchanges available in all states, with deep subsidies for persons with incomes from 138% to 250% of the federal poverty limit (FPL) in Medicaid expansion states and from 100% to 250% of the FPL in non-expansion states. Prior studies found a statistically significant slightly negative² effects of the ACA on diabetes diagnoses and controversial (from insignificantly slightly positive³ to significantly positive⁴) effects on diabetes therapies at county and state levels. We examined the effect of both forms of ACA reform on the improvement of diabetes diagnostics and management in low-income patients who had access to healthcare before the ACA expansion (2011–2013).

We used electronic health records (EHR) from 11 major academic health systems in 8 states in the USA (Illinois, Iowa, Wisconsin, Kansas, Nebraska, Missouri, Texas, Indiana). The sample (see [table 1](#) for demographics) was limited to patients aged 55–74 over 2011–2018 who used care (any encounter type) at the study facilities at least once in the pre-expansion period. Due to inconsistent depiction of insurance status in EHR, patient residence in a socially deprived⁵ census tract (see online supplemental appendix for details) was used as proxy for persons who were more likely to gain insurance under the

ACA. Therefore persons aged 55–64 from the socially deprived census tracts were the treatment group. Persons aged 65–74 from socially deprived census tracts were the control group

Panel A



Panel B

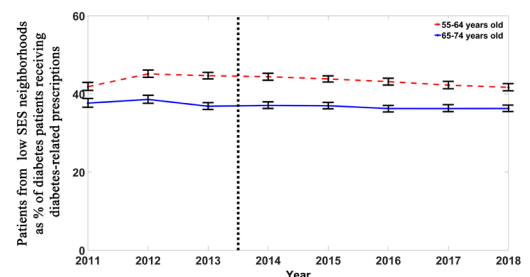


Figure 1 Annual trends in healthcare utilization outcomes before and during the Affordable Care Act Medicaid expansion (dotted vertical line). States are equally weighted. Bars are 95% CI. (A) Disadvantaged patients as per cent of all patients with newly detected diabetes. (B) Disadvantaged patients (with low socioeconomic status (SES)) as per cent of individuals with prevalent diabetes who received medical management at partnering health systems.

Table 1 Sample characteristics used to measure healthcare utilization outcomes

Sample demographic characteristics for outcome measures	2011–2013		2014–2018	
	55–64	65–74	55–64	65–74
(A) Total newly detected diabetes (305726 patients aged 55–74 years old during 2011–2018)	73479	56371	90948	84928
% from socially deprived census tracts	41.9	34.3	34.7	28.3
Sex: % female	50.2	50.2	47.6	48.0
Race: % white	65.2	71.9	69.8	75.7
Race: % black	22.0	15.7	16.9	11.4
Race: % Asian	3.2	3.3	2.6	2.8
Race: % mixed	0.0	0.0	0.0	0.0
Race: % missing	9.6	9.1	10.7	10.1
Ethnicity: % Hispanic	11.9	8.1	9.5	6.9
Ethnicity: % missing	18.1	20.3	20.8	21.7
(B) Total with prevalent diabetes and relevant medical prescriptions (67083 patients aged 55–74 years old during 2011–2018)	34831	32252		
% from socially deprived census tracts	44.1	37.6		
Sex: % female	51.0	49.9		
Race: % white	62.0	59.9		
Race: % black	15.7	11		
Race: % Asian	1.7	1.6		
Race: % mixed	0.3	0.3		
Race: % missing	6.1	5.2		
Ethnicity: % Hispanic	5.4	4.1		
Ethnicity: % missing	21.5	19.7		

The pre-ACA period is 2011–2013; the ACA period is 2014–2018. For medical management of diabetes, patients with prevalent diabetes were studied (sample is the same before and during the ACA period).
ACA, Affordable Care Act.

because they had Medicare insurance. For each age group, we studied the per cent of patients of interest with newly detected diabetes⁶ and the per cent of patients with prevalent diabetes receiving diabetes-related medications before (2011–2013) and during (2014–2018) the ACA expansion. Combined age discontinuity and difference-in-difference research design was employed.

Different from individuals who had no access to healthcare² before the ACA, our sample of patients from socially deprived tracts shows no increase in rates of newly diagnosed diabetes (figure 1). An insignificant drop of -0.72 (95% CI -3.22 to 1.77) in newly diagnosed diabetes for the treated group was detected. We have to note the identification of diabetes in the sample was not limited to ambulatory settings. This makes us conclude that the study centers may have already been using all available resources to accurately diagnose diabetes before 2014, including for low-income patients. Therefore, the ACA did not lead to an improvement in diagnostics for our sample. The decline in new diabetes cases may be a positive effect of the improved access to other preventive care⁷ services and medications during the ACA.

We also assessed whether the ACA led to low-income persons with prevalent diabetes having better access to diabetes medications. We detected an insignificant increase of 0.21 (95% CI -2.10 to 2.52) in the prescription for diabetes medications in the treatment group.

The observed trend for the prescribed diabetes medications matched the 2010–2016 dispensed medication trend detected with the Medicaid State Drug Utilization Data.³ Overall, the reported increase in diabetes medication due to the ACA tended to be modest if a ‘per enrollee’-like measure was selected as opposed to an ‘all prescriptions’⁴ one.

In summary, we would like to stress that selected health outcomes are not doing the ACA justice and, as a result, underestimating the presumed improvement in the health services for low-income patients-clients of the academic centers before the ACA implementation. Such patients would face a different level of improvement in access to care comparing with ones who were completely isolated from the healthcare system before the policy took place.

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Contributors BSB, ANK and AF conceived and designed the study. All authors interpreted the data, critically reviewed the manuscript for important intellectual content and approved the final manuscript. AF and BSB developed the analytical plan. AF performed the statistical analyses. AF and BSB drafted the initial manuscript. ANK supervised the study. AF, ML, XS, LRW, JRM, KO, AS, EC, LGC, RCS, JCM, UT, VM, ASMM, DG, FA, AP, WET, TWM and ANK contributed to data acquisition. AF and BSB contributed to analysis of data. RCS, ML, XS, JRM, KO, AS, EC, JCM, UT, ASMM, WET, TWM, LR-T, PJE and ANK contributed to interpretation of data and manuscript writing.

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Appendix for:**The Effect of the Affordable Care Act on Diabetes Care at Major Health Centers:
Newly Detected Diabetes and Diabetes Medication Management****Authors:**

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Data source

This study used electronic health record (EHR) data from 2010-2018 from 11 health systems within the CAPriCORN and GPC PCORnet Clinical Data Research Networks.¹ The GPC network was represented by the University of Kansas Medical Center, Medical College of Wisconsin, University of Nebraska Medical Center, Indiana University, University of Missouri School of Medicine, the University of Iowa Medical Center, and the University of Texas Southwestern Medical Center. The CAPRICORN network was represented by Rush University Medical Center, Northwestern Medicine, Loyola Medical Center, and Cook County Health System. We studied only patients seen two or more times during the sample period (2011-2018) since the definition of diabetes we used requires the diagnosis to be confirmed in two separate patient encounters.

Individual-level insurance status information

The EHR data source had no reliable historic information on patient insurance status. We used patient residence in a low-income Census tract as a proxy for persons who were more likely to gain insurance under the ACA. We used the Townsend Social Deprivation Index² to identify Census tracts with overall lower social-economic status (SES), which we refer to as “low-income” tracts. Tracts with higher scores on the Townsend Index have lower median incomes and a larger proportion of non-elderly adults who gained health insurance as a result of the ACA. The Townsend index was calculated using five-year average data from the American Community Survey (ACS) for 2011-2015.³ It is an aggregate measure based on the percentage of households without a car, households with more than one person per room, percent renting rather than owning housing, and percent unemployed. The value of the index is not interpretable, only relative ranking is important. We computed Townsend index values for all census tracts nationwide and assigned tracts to quintiles where the fifth quintile is representative of the most economically deprived area and the first quintile represents affluent areas. While the ACS variables used in the Townsend index are not directly related to health, the Townsend index quintiles do identify deprived neighborhoods well,⁴ and these quintiles are associated with cancer risk,⁵ poor overall health^{6,7}, and depression.⁸ We used residence in quintiles four and five as a proxy for a greater likelihood of gaining insurance due to the ACA.

Expansion status

We assessed whether trends for treated persons were different in Medicaid expansion versus non-expansion states. Our 8 states include three that implemented the ACA Medicaid expansion on 1 January 2014 (Illinois, Iowa, and Wisconsin (partial expansion, to 100% of FPL)), one state that expanded on 1 February 2015 (Indiana), and four non-expansion states (Kansas, Nebraska, Missouri, and Texas). Because Indiana expanded Medicaid in 2015 instead of 2014, we performed sensitivity analyses in which instead of treating Indiana as an expansion state, we excluded it from the sample, with similar results.

Statistical analysis

We used a combined age discontinuity and DiD design – DiD regressions, applied to persons within an age band around age 65. We compared changes in outcomes for low-income persons under age 65 to low-income persons over age 65, before and after the ACA health insurance expansion. For each outcome variable, we estimated the following regression:

$$Y_{it} = \theta_{State} + \lambda_t + \beta_0 + \beta_1 Treated + \delta(Post \cdot Treated) \quad (1)$$

where Y is the outcome of interest for each state; θ_{State} is the state fixed effects (FE); λ_t are the year FE; β_0 is a constant term; β_1 is a treatment (young) group dummy variable = 1 if, under 65, 0 if over 65; $Post$ is a dummy variable for the ACA expansion period (equal to 1 for 2014–2018; equal to 0 for 2011–2013; note that $Post$, if included in the regression, would be absorbed by the year FE); δ is the treatment effect, which captures the ACA effect on the outcome. If $\delta > 0$, this indicates an increase in the outcome for younger patients from low-income Census tracts, relative to older patients from these tracts, after ACA implementation in 2014. We use a similar model with separate annual dummy variables for the treatment and control groups to obtain the annual data for the Figures, see Appendix for details. The outcome variables are proportions, so the DiD estimate represents an after-minus-before change in the proportion.

Statistical analyses were conducted with Stata-MP 15 and figures were created using MATLAB version R2016b.

Adjustment variables

All regressions included state and year fixed effects to account for time-invariant state level and secular factors that might affect our results. We did not include other covariates because these should be similar for treated and control persons, given that we study below- versus above-65 year old persons from the same low-income Census tracts.

Definition of diabetes

We identified “detected” diabetes in adult patients using a modified version of the SUPREME-DM⁹ criterion. A patient was classified as having diabetes if the EHR contained (i) prescription of diabetes-specific medications at least once, or (ii) on two different visits one observed (a) a diabetes diagnosis code, or (b) HbA1c $\geq 6.5\%$, or (c) random glucose ≥ 200 mg/dL, or (d) fasting glucose ≥ 126 mg/dL, or (iii) prescription of a diabetes-relevant but not a diabetes-specific medication (for example, metformin) plus a single occurrence of one of the events in category (ii). Because we studied only patients age 55–74, we did not need to employ an exclusion for gestational diabetes. Newly detected diabetes was assigned to the earliest date among these events. We refer to diabetes *detection* rather than *incidence* because the true incidence is not known.

Diabetes medications

We defined diabetes-related medications to include both diabetes-specific medications (sulfonylurea, insulin, biguanide, thiazolidinedione, α -glucosidase inhibitor, incretin mimetic, meglitinide, amylin analog, or dipeptidyl peptidase inhibitor) and non-specific medications that can also be prescribed for other conditions (metformin, any thiazolidinedione, or exenatide). We used information on both prescription and dispensing, using both medication name and medication code fields (Appendix, Table S1). We note, however, that dispensing information is often incomplete because many patients have prescriptions filled at a pharmacy outside the health system, and these fills are typically not captured in the system’s EHR. We treated any instance of diabetes-related medication prescription or dispensing during a year as indicating medication access for that year. To address censoring due to patients no longer receiving care within a health system, we followed patients with diabetes from the date of diabetes detection

through the last recorded visit date in the EHR. We treat a visit anytime during a particular year as implying presence in the EHR for that year.

Table S1. Diabetes management medications. The NDC codes are normalized to PCORI CDM format prior the use in this work.

Generic name (Brand Name)	SQL-specific regular expression	RXNORM_CUI	NDC
Medications specific to diabetes			
<p>Alpha-glucosidase inhibitors: ACARBOSE (PRECOSE, GLUCOBAY) MIGLITOL (GLYSET) VOGLIBOSE (BASN)</p>	UPPER(RAW_RX_MED_NAME) like UPPER("%acarbose%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Precose%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Glucobay%") or UPPER(RAW_RX_MED_NAME) like UPPER("%miglitol%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Glyset%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Voglibose%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Basen%")		
<p>Dipeptidyl Peptidase IV Inhibitors: ALOGLIPTIN (NESINA) ANAGLIPTIN (SUIVY) LINAGLIPTIN (TRADJENTA) SAXAGLIPTIN (ONGLYZA) SITAGLIPTIN (JANUVIA) TENELIGLIPTIN (TENELIA) VILDAGLIPTIN (GALVUS, ZOMELIS)</p>	UPPER(RAW_RX_MED_NAME) like UPPER("%alogliptin%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Kazano%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Oseni%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Nesina%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Anagliptin%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Suiny%") or UPPER(RAW_RX_MED_NAME) like UPPER("%linagliptin%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Jentaducto%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Jentaducto XR%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Glyxambi%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Tradjenta%") or UPPER(RAW_RX_MED_NAME) like UPPER("%saxagliptin%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Kombiglyze XR%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Onglyza%") or UPPER(RAW_RX_MED_NAME) like UPPER("%sitagliptin%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Eucreas%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Juvisync%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Epistatin%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Synvinolin%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Zocor%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Janumet%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Janumet XR%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Januvia%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Teneligliptin%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Tenelia%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Vildagliptin%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Galvus%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Zomelis%")		
<p>Glucagon-like Peptide-1 Agonists: LIXISENATIDE (ADLYXIN, LYXUMIA) ALBIGLUTIDE (TANZEUM, EPERZAN) DULAGLUTIDE (TRULICITY)</p>	UPPER(RAW_RX_MED_NAME) like UPPER("%Lixisenatide%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Adlyxin%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Lyxumia%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Albiglutide%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Tanzeum%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Eperzan%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Dulaglutide%") or UPPER(RAW_RX_MED_NAME) like UPPER("%Trulicity%")		
<p>Sodium glucose cotransporter (SGLT) 2 inhibitors:</p>	UPPER(RAW_RX_MED_NAME) like UPPER("%dapagliflozin%") or UPPER(RAW_RX_MED_NAME) like		

<p>ASPART (NOVOLOG 50/50, NOVOLOG 70/30) INSULIN LISPRO PROTAMINE/INSULIN LISPRO (HUMALOG 50/50, HUMALOG 75/25) ACTRAPID HYPURIN ILETIN INSULATARD INSUMAN MIXTARD NOVOMIX NOVORAPID ORALIN ABASAGLAR RYZODEG V-GO</p>	<p>UPPER(%Novolin N%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin detemir%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Levemir%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin glargine%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Lantus%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Lantus SoloStar%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Toujeo%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Basaglar%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin degludec%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Tresiba%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin aspart protamine%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin aspart%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Actrapid%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Hypurin%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Iletin%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insuman%) or UPPER(%Insulatard%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insuman%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Mixtard%) or UPPER(RAW_RX_MED_NAME) like UPPER(%NovoMix%) or UPPER(RAW_RX_MED_NAME) like UPPER(%NovoRapid%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Oralin%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Abasaglar%) or UPPER(RAW_RX_MED_NAME) like UPPER(%V-go%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Ryzodeg%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin lispro protamine%) or UPPER(RAW_RX_MED_NAME) like UPPER(%insulin lispro%)</p>		
<p>Combinations: LINAGLIPTIN-EMPAGLIFLOZIN (GLYXAMBI) SITAGLIPTIN-SIMVASTATIN (JUVISYNC, EPISTATIN, SYNVINOLIN, ZOCOR) METFORMIN-ALOGLIPTIN (KAZANO) METFORMIN-CANAGLIFLOZIN (INVOKAMET) METFORMIN-DAPAGLIFLOZIN (XIGDUO XR) METFORMIN-EMPAGLIFLOZIN (SYNJARDY) METFORMIN-GLIPIZIDE (METAGLIP) METFORMIN-GLYBURIDE (GLUCOVANCE) METFORMIN-LINAGLIPTIN (JENTADUETO, JENTADUETO XR) METFORMIN-REPAGLINIDE (PRANDIMET) METFORMIN-SAXAGLIPTIN (KOMBIGLYZE XR) METFORMIN-SITAGLIPTIN (JANUMET, JANUMET XR) METFORMIN AND VILDAGLIPTIN (EUCREAS)</p>	<p>UPPER(%Novolin N%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin detemir%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Levemir%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin glargine%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Lantus%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Lantus SoloStar%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Toujeo%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Basaglar%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin degludec%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Tresiba%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin aspart protamine%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin aspart%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Actrapid%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Hypurin%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Iletin%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insuman%) or UPPER(%Insulatard%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insuman%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Mixtard%) or UPPER(RAW_RX_MED_NAME) like UPPER(%NovoMix%) or UPPER(RAW_RX_MED_NAME) like UPPER(%NovoRapid%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Oralin%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Abasaglar%) or UPPER(RAW_RX_MED_NAME) like UPPER(%V-go%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Ryzodeg%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin lispro protamine%) or UPPER(RAW_RX_MED_NAME) like UPPER(%insulin lispro%)</p>	<p>UPPER(%Novolin N%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin detemir%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Levemir%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin glargine%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Lantus%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Lantus SoloStar%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Toujeo%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Basaglar%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin degludec%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Tresiba%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin aspart protamine%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin aspart%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Actrapid%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Hypurin%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Iletin%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insuman%) or UPPER(%Insulatard%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insuman%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Mixtard%) or UPPER(RAW_RX_MED_NAME) like UPPER(%NovoMix%) or UPPER(RAW_RX_MED_NAME) like UPPER(%NovoRapid%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Oralin%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Abasaglar%) or UPPER(RAW_RX_MED_NAME) like UPPER(%V-go%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Ryzodeg%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin lispro protamine%) or UPPER(RAW_RX_MED_NAME) like UPPER(%insulin lispro%)</p>	<p>UPPER(%Novolin N%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin detemir%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Levemir%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin glargine%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Lantus%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Lantus SoloStar%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Toujeo%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Basaglar%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin degludec%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Tresiba%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin aspart protamine%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin aspart%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Actrapid%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Hypurin%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Iletin%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insuman%) or UPPER(%Insulatard%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insuman%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Mixtard%) or UPPER(RAW_RX_MED_NAME) like UPPER(%NovoMix%) or UPPER(RAW_RX_MED_NAME) like UPPER(%NovoRapid%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Oralin%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Abasaglar%) or UPPER(RAW_RX_MED_NAME) like UPPER(%V-go%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Ryzodeg%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Insulin lispro protamine%) or UPPER(RAW_RX_MED_NAME) like UPPER(%insulin lispro%)</p>

	<p>UPPER(%CHLORPROPAMIDE %) or UPPER(RAW_RX_MED_NAME) like UPPER(%TOLAZAMIDE %) or UPPER(RAW_RX_MED_NAME) like UPPER(%TOLBUTAMIDE %) or UPPER(RAW_RX_MED_NAME) like UPPER(%GLYCLOPYRAMIDE %) or UPPER(RAW_RX_MED_NAME) like UPPER(%GLIQUIDONE %) or UPPER(RAW_RX_MED_NAME) like UPPER(%GLIBORNURIDE %) or UPPER(RAW_RX_MED_NAME) like UPPER(%GLYMIDINE SODIUM %) or UPPER(RAW_RX_MED_NAME) like UPPER(%PRAMLINTIDE %) or UPPER(RAW_RX_MED_NAME) like UPPER(%NATEGLINIDE %) or UPPER(RAW_RX_MED_NAME) like UPPER(%REPAGLINIDE%) or UPPER(RAW_RX_MED_NAME) like UPPER(%GLULISINE %) or UPPER(RAW_RX_MED_NAME) like UPPER(%REGULAR INSULIN %) or UPPER(RAW_RX_MED_NAME) like UPPER(%NPH %) or UPPER(RAW_RX_MED_NAME) like UPPER(%DETEMIR %) or UPPER(RAW_RX_MED_NAME) like UPPER(%GLARGINE %) or UPPER(RAW_RX_MED_NAME) like UPPER(%DEGLUDEC %) or UPPER(RAW_RX_MED_NAME) like UPPER(%INSULIN %) or UPPER(RAW_RX_MED_NAME) like UPPER(%ASPART%) or UPPER(RAW_RX_MED_NAME) like UPPER(%LISPRO %) or UPPER(RAW_RX_MED_NAME) like UPPER(%ACTRAPID%) or UPPER(RAW_RX_MED_NAME) like UPPER(%HYPURIN%) or UPPER(RAW_RX_MED_NAME) like UPPER(%ILETIN%) or UPPER(RAW_RX_MED_NAME) like UPPER(%INSULATARD%) or UPPER(RAW_RX_MED_NAME) like UPPER(%INSUMAN%) or UPPER(RAW_RX_MED_NAME) like UPPER(%MIXTARD%) or UPPER(RAW_RX_MED_NAME) like UPPER(%NOVOMIX%) or UPPER(RAW_RX_MED_NAME) like UPPER(%NOVORAPID%) or UPPER(RAW_RX_MED_NAME) like UPPER(%ORALIN %) or UPPER(RAW_RX_MED_NAME) like UPPER(%ABASAGLAR%) or UPPER(RAW_RX_MED_NAME) like UPPER(%RYZODEG%) or UPPER(RAW_RX_MED_NAME) like UPPER(%V-GO%)))</p>		
<p>Glucagon-like Peptide-1 Agonists: EXENATIDE (BYETTA, BYDUREON) LIRAGLUTIDE (VICTOZA, SAXENDA)</p>	<p>UPPER(RAW_RX_MED_NAME) like UPPER(%Exenatide%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Byetta%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Bydureon%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Liraglutide%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Victoza%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Saxenda%)</p>		
<p>Thiazolidinediones: ROSIGLITAZONE (AVANDIA) PIOGLITAZONE (ACTOS)</p>	<p>(UPPER(RAW_RX_MED_NAME) like UPPER(%Avandia%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Actos%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Noscal%)</p>		

<p>TROGLITAZONE (NOSCAL, RESULIN, REZULIN, ROMOZIN)</p>	<p>or UPPER(RAW_RX_MED_NAME) like UPPER(%Re(zs)ulin%) or UPPER(RAW_RX_MED_NAME) like UPPER(%Romozin%) or ((UPPER(RAW_RX_MED_NAME) like UPPER(%ROSIGLITAZONE%) or UPPER(RAW_RX_MED_NAME) like UPPER(%PIOGLITAZONE%) or UPPER(RAW_RX_MED_NAME) like UPPER(%TROGLITAZONE%)) and not (UPPER(RAW_RX_MED_NAME) like UPPER(%ACARBOSE %) or UPPER(RAW_RX_MED_NAME) like UPPER(%MIGLITOL%) or UPPER(%VOGLIBOSE%) or UPPER(RAW_RX_MED_NAME) like UPPER(%ALOGLIPTIN%) or UPPER(RAW_RX_MED_NAME) like UPPER(%ANAGLIPTIN%) or UPPER(RAW_RX_MED_NAME) like UPPER(%LINAGLIPTIN%) or UPPER(RAW_RX_MED_NAME) like UPPER(%SAXAGLIPTIN%) or UPPER(RAW_RX_MED_NAME) like UPPER(%SITAGLIPTIN%) or UPPER(RAW_RX_MED_NAME) like UPPER(%TENELIGLIPTIN%) or UPPER(RAW_RX_MED_NAME) like UPPER(%VILDAGLIPTIN%) or UPPER(RAW_RX_MED_NAME) like UPPER(%LIXISENATIDE%) or UPPER(RAW_RX_MED_NAME) like UPPER(%ALBIGLUTIDE%) or UPPER(RAW_RX_MED_NAME) like UPPER(%DULAGLUTIDE%) or UPPER(RAW_RX_MED_NAME) like UPPER(%DAPAGLIFLOZIN%) or UPPER(RAW_RX_MED_NAME) like UPPER(%CANAGLIFLOZIN%) or UPPER(RAW_RX_MED_NAME) like UPPER(%EMPAGLIFLOZIN%) or UPPER(RAW_RX_MED_NAME) like UPPER(%ACETOHEXAMIDE%) or UPPER(RAW_RX_MED_NAME) like UPPER(%GLIMEPIRIDE%) or UPPER(RAW_RX_MED_NAME) like UPPER(%GLICLAZIDE%) or UPPER(RAW_RX_MED_NAME) like UPPER(%GLIPIZIDE%) or UPPER(RAW_RX_MED_NAME) like UPPER(%GLYBURIDE%) or UPPER(RAW_RX_MED_NAME) like UPPER(%GLIBENCLAMIDE%) or UPPER(RAW_RX_MED_NAME) like UPPER(%CHLORPROPAMIDE %) or UPPER(RAW_RX_MED_NAME) like UPPER(%TOLAZAMIDE %) or UPPER(RAW_RX_MED_NAME) like UPPER(%TOLBUTAMIDE %) or UPPER(RAW_RX_MED_NAME) like UPPER(%GLYCLOPYRAMIDE %) or UPPER(RAW_RX_MED_NAME) like UPPER(%GLIQUIDONE %) or UPPER(RAW_RX_MED_NAME) like UPPER(%GLIBORNURIDE %) or UPPER(RAW_RX_MED_NAME) like</p>		<p>UPPER(%TROGLITAZONE%) or UPPER(%PIOGLITAZONE%) or UPPER(%ROSIGLITAZONE%) or UPPER(%ACARBOSE %) or UPPER(%MIGLITOL%) or UPPER(%VOGLIBOSE%) or UPPER(%ALOGLIPTIN%) or UPPER(%ANAGLIPTIN%) or UPPER(%LINAGLIPTIN%) or UPPER(%SAXAGLIPTIN%) or UPPER(%SITAGLIPTIN%) or UPPER(%TENELIGLIPTIN%) or UPPER(%VILDAGLIPTIN%) or UPPER(%LIXISENATIDE%) or UPPER(%ALBIGLUTIDE%) or UPPER(%DULAGLUTIDE%) or UPPER(%DAPAGLIFLOZIN%) or UPPER(%CANAGLIFLOZIN%) or UPPER(%EMPAGLIFLOZIN%) or UPPER(%ACETOHEXAMIDE%) or UPPER(%GLIMEPIRIDE%) or UPPER(%GLICLAZIDE%) or UPPER(%GLIPIZIDE%) or UPPER(%GLYBURIDE%) or UPPER(%GLIBENCLAMIDE%) or UPPER(%CHLORPROPAMIDE %) or UPPER(%TOLAZAMIDE %) or UPPER(%TOLBUTAMIDE %) or UPPER(%GLYCLOPYRAMIDE %) or UPPER(%GLIQUIDONE %) or UPPER(%GLIBORNURIDE %) or</p>
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