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| **Observational Health Data Sciences and Informatics (OHDSI) Research Network\*** |
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| **Evaluating Reliability of Observational Research Findings via Assessment of Repeatability, Reproducibility, Replicability, Generalizability, Robustness, and Calibration.** |
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| 9 July, 2021  (Revised 9 August, 2021)  **Protocol** |

\* The Observational Health Data Sciences and Informatics (OHDSI) Research Network is a multi-stakeholder, interdisciplinary collaborative to bring out the value of health data through large-scale analytics, via open-source research and analytic tools. OHDSI has established an international network of researchers and observational health databases committed to generating reliable evidence with a central coordinating center housed at Columbia University.

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# LIST OF ABBREVIATIONS

|  |  |
| --- | --- |
| **Abbreviation** | **Description** |
| ATC | Anatomical Therapeutic Chemical Classification System |
| CC | Comparative cohort |
| CCAE | IBM Watson Commercial Claims and Encounters® |
| CDM | Common data model |
| CEM | Common Evidence Model |
| CLRD | Chronic lower respiratory disease |
| DPP-4I | Dipeptidyl peptidase-4 inhibitors |
| EHR | Electronic health record |
| GLP-1RA | Glucagon-like peptide 1 receptor agonists |
| HR | Hazard ratio |
| IPCW | Inverse probability of censoring weighting |
| IRB | Institutional Review Board |
| IRR | Incidence rate ratio |
| JMDC | Japan Medical Data Center |
| MDCD | IBM Watson MarketScan® Multi-State Medicaid Database |
| MDCR | IBM Watson MarketScan® Medicare Supplemental and Coordination of Benefits Database |
| OHDSI | Observational Health Data Sciences and Informatics |
| Optum | Optum’s ClinformaticsTM Data Mart – Socio-Economic Status |
| OptumEHR | Optum Pan-Therapeutic Electronic Health Records (Panther EHR) |
| SCC | Self-controlled cohort design |
| SCCS | Self-controlled case series design |
| SES | Socio-economic status |
| sIPTW | Stabilized inverse-probability of treatment weighting |
| T2DM | Type 2 diabetes mellitus |

# RESPONSIBLE PARTIES

## Investigator(s) and Authors

Patrick R Ryan1, Mitchell M. Conover1

1 Observational Health Data Analytics, Janssen Research and Development

## Sponsor

Observational Health Data Sciences and Informatics (OHDSI) Research Network\*

# PROTOCOL ABSTRACT

A high-quality observational comparative cohort study conducted using a nation-wide sample of U.S. administrative claims was recently published demonstrating a protective effect of Glucagon-like peptide 1 receptor agonists (GLP-1RA) medications on the risk of chronic lower respiratory disease (CLRD) exacerbations.

As a methodologic experiment intended to address what has been described as a “replication/reproducibility” crisis in health research, we propose to independently reproduce the original study according to its description in the recent publication and supplemental materials, using the same database as was used in the original study. In addition to reproducing the study, we plan to evaluate the robustness of the study findings by conducting sensitivity analyses, assessing: 1) changes to definitions of exposure and outcome phenotypes, 2) use of alternate study designs, including the self-controlled cohort and self-controlled case series designs, 3) calibration of effect estimates using empirical null distributions, and 3) observable study diagnostics that inform the validity of a given analysis. Finally, we plan to explore the generalizability of the findings by executing the analysis on several study databases that vary with respect to the populations they include (e.g. U.S. and non-U.S.) and their mechanisms of data capture (e.g. administrative claims, electronic health records data).

We propose to conduct this study within the Observational Health Data Sciences and Informatics (OHDSI) research network. The OHDSI research network is an international collaboration of researchers seeking to advance observational data research in healthcare. OHDSI is an open network, inviting healthcare institutions across the globe with patient-level data to join the network by converting data to the OMOP CDM and participating in network research studies. Each site voluntarily opts-in to each respective network study. In each study, data remains at the site behind a firewall. No patient-level data pooling occurs across network sites; only aggregate results are shared.

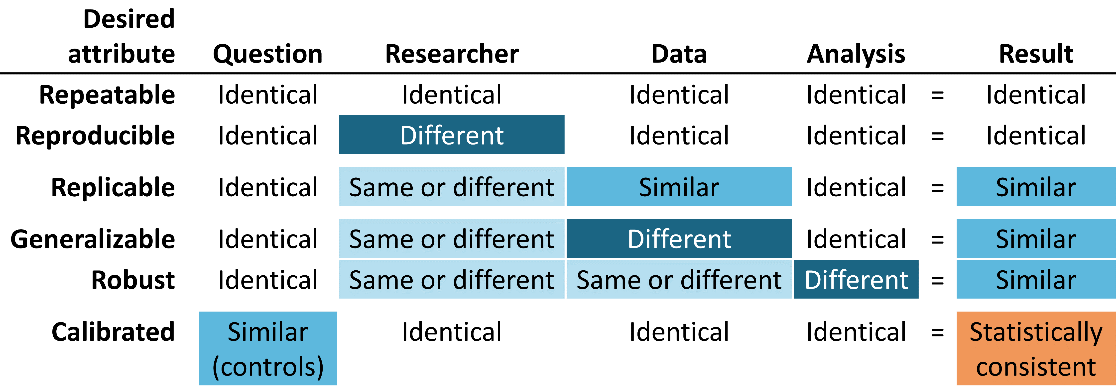
# RATIONALE AND BACKGROUND

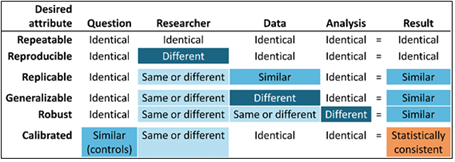
Observational research using real-world data provides an opportunity to observe how medications are used in a real-world setting and to assess the risks and benefits associated with medications in actual practice. Ongoing development of study designs and analytic methods have equipped observational researchers with a powerful toolkit to reduce and/or mitigate sources of bias. For example, developments in propensity score analysis have enabled control for large, highly-dimensional sets of confounders and developments in negative control outcome experiments allow for the assessment of residual systematic bias, which can be used to calibrate effect estimates and confidence intervals. When proper study designs and analytic methods are used to address the right study questions, observational research using real-world data can provide valuable and reliable evidence on the effectiveness and safety of medical products, as they are used in real-world clinical practice.1

Despite substantial improvements in methods and data resources used in observational causal inference research, a large number of published observational studies still conclude with the statement “Randomized trials are warranted to confirm our findings,” even in cases where the recommended randomized trial is highly unlikely to be conducted in a timely manner (e.g. due to challenges with feasibility and/or cost). Implicit in this trend is the assumption that observational research cannot provide reliable evidence absent confirmation with experimental/randomized research. Given that many of-interest health research questions simply cannot be realistically assessed using experimental methods, it is critical that systems of evidence evaluation are developed to more meaningfully apply the findings of observational research studies.Despite commonplace concerns about the reliability of evidence generated by observational research, established practices to improve the reliability of empirical evidence (e.g. reproduction and replication) are severely underutilized, an issue which has received widespread attention over the last decade.2-8

## A framework describing desirable attributes of reliable evidence

Figure 1 below presents a general framework for evaluating six desirable attributes of reliable evidence: repeatable, reproducible, replicable, generalizable, robust, and calibrated. A brief description of the framework is provided below; however more detailed discussion of the framework can be found in [Section 14.1 of the Book of OHDSI (Attributes of Reliable Evidence)](https://ohdsi.github.io/TheBookOfOhdsi/EvidenceQuality.html).9





**Figure 1**. Desired attributes of reliable evidence (*source: Book of OHDSI*)

Evidence is considered repeatable when the same researcher applying the same analytic strategy to address the same study question with the same data would get the identical result. Generating repeatable evidence requires a clear process absent of subjective judgement or interpretation. Evidence is considered reproducible when a different researcher is able to perfectly reproduce that analysis and, using the same data, is able to generate the identical result. In the case of research relying on retrospective data analysis, reproducible evidence requires the complete specification of the study protocols in human-readable and computer-executable form. Ensuring that findings from a given study are repeatable and reproducible is one of the most important principals for providing reliable evidence of causal relationships.

Evidence replicability, which relates to the Bradford-Hill consistency criterion10, implies that the identical analysis applied to a similar but different data resource / population, generates a similar finding. In other words, has the association been observed in multiple contexts (e.g. across multiple different insurance claims databases)? Generalizable evidence represents findings that can be reproduced across multiple different sources of data (e.g. administrative claims databases, large electronic health records [EHR] databases, single-facility EHR systems) which vary with respect to the populations they include and their mechanisms of data capture.

Expanding on repeatability, reproducibility, replicability, and generalizability, evidence is further strengthened when it can be shown to be robust to variation in analytic choices. Sensitivity analyses commonly included in observational research studies typically seek to explore the robustness of findings to variation in potentially important analytic choices (e.g. definition of exposures and outcomes). However, observational evidence should be considered even more robust if it can be consistently observed using broad range of study designs which have orthogonal analytic assumptions and complementary strengths and limitations. For example, a comprehensive evaluation of robustness for a comparative cohort study may also include an assessment of whether similar study findings can be consistently generated using alternate study self-controlled designs.

Lastly, reliable evidence must be calibrated, meaning the findings must be inspected for residual systematic error. Statistical artifacts should be able to be empirically demonstrated to have well-defined properties, such as a 95% confidence interval having 95% coverage probability (which can be discerned from negative control outcome experiments). Negative controls have been shown to be a powerful tool for identifying and mitigating systematic error in observational studies.11-14

## A target study for replication: glucagon-like peptide 1 receptor agonists and chronic lower respiratory disease

Preliminary evidence from animal models15-17 and small human studies18, 19 have suggested a potential beneficial effect of glucagon-like peptide 1 receptor agonists (GLP-1RAs) on lung function. To expand on this preliminary evidence, Albogami et al recently published an observational research study to explore the relationship between treatment with GLP-1RA and chronic lower respiratory disease (CLRD) exacerbations among patients with type 2 diabetes mellitus (T2DM) and pre-existing CLRD.20 Separate analyses of time-to-first CLRD inpatient admission and the count of CLRD exacerbations associated with inpatient or outpatient visits both suggested strong protective effects (HR: 0.52 [95% CI: 0.32-0.85]; IRR: 0.70 [95% CI: 0.57-0.87], respectively). In their conclusions the authors interpret these findings with two key statements: “potential beneficial effects of GLP-1RA should be considered in selection of an antidiabetes treatment regimen” and “randomized clinical trials are warranted to confirm our findings.” The authors’ conclusions do not include recommendations to revise treatment guidelines to incorporate their findings.

The embedded PDF files below include the full study manuscript and its supplemental materials, which represents the study protocol that our study designs, analyses and evaluation will be based around. A brief summary of their study approach is included below.

Albogami et al. conducted their study within IBM’s Commercial Claims and Encounters (CCAE) database, which is a nation-wide sample of adjudicated administrative claims from patients with commercial, employer-sponsored health insurance. Using data from 2005 to 2015, the authors conducted a retrospective new-user cohort study which compared GLP-1RA initiators (N=4,150) to an active comparator (dipeptidyl peptidase-4 inhibitors [DPP-4Is], N= 12,540) to assess the risk of a primary and a secondary outcome: 1) time-to-first CLRD hospitalization and 2) count of any CLRD exacerbation associated with an emergency room visit, inpatient admission, or an outpatient visit that was followed by oral steroid initiation. To identify patients with documented T2DM and CLRD, they required patients have at least one inpatient or two outpatient encounters with T2DM and CLRD, based on the presence of diagnosis codes or dispensing of relevant medications in the year before the index date.

The analysis balanced on a list of 45 potential confounders (which was compiled based on literature review and/or the input of clinical experts), using stabilized inverse-probability of treatment weighting (sIPTW), which is an extension of propensity score methods. To remove extreme values from the tails of the propensity score distribution, authors also excluded patients with the lowest and highest 1% of propensity scores. After sIPTW was implemented, none of the 45 potential confounders showed standardized differences exceeding 0.05, indicating a well-balanced cohort, with respect to those 45 confounders. The authors also sought to account for informative loss-to-follow-up (i.e. right-censoring) using inverse probability of censoring weights (IPCW).

After re-weighting to address confounding and informative loss-to-follow-up, the authors generated adjusted effect estimates using Cox proportional hazards regression to estimate the hazard ratio (HR) for the primary (time-to-event) outcome and Poisson regression to estimate the incidence rate ratio (IRR) for the secondary (count) outcome. For both estimates, they also produced 95% confidence intervals to quantify uncertainty. The authors findings appeared to be robust to a several sensitivity analyses, including one which tested the use of an alternate comparator (sulfonylurea) instead of DPP-4I. The authors also explored the use of a negative control outcome analysis (skin infection), which did not indicate the presence of residual confounding or healthy user bias.

Generally speaking, this study represents a high-quality analysis relative to the majority of retrospective observational causal inference research published using secondary data. The analysis seeks to address threats to validity and evaluate robustness with respect to several analytical assumptions, within the context of a comparative cohort design. However, additional work is needed to further examine the study’s reliability, specifically: reproducibility, replicability, generalizability, robustness, and calibration.

# STUDY Objectives

**Objective 1.** Attempt to independently reproduce the Albogami et al. study as closely as possible in the original study database (IBM CCAE), according to its description in the recent publication and supplemental materials.20

**Objective 2**. Evaluate the robustness of the Albogami et al. study findings by conducting sensitivity analyses in the IBM CCAE database, assessing:

* Sensitivity to changes in definitions of exposure and outcome phenotypes,
* Sensitivity to alternate choice of study design beyond comparative cohort (e.g. self-controlled case series, self-controlled cohort),
* Sensitivity to empirical calibration11-14 of effect estimates using negative and positive control outcomes, and
* Using observational study diagnostics to assess the robustness of their findings and risk of systematic bias before and after calibration.

**Objective 3**: Evaluate the generalizability of findings produced by the original Albogami et al. protocol across different study databases, including U.S. and non-U.S. populations.

# Research METHODs

## Overview

The general approach for this study is to sequentially build a body of evidence which seeks to examine the reliability of the original Albogami et al. finding. As the first building-block of this reliability assessment, we plan to address Objective 1 by reproducing the original analysis as closely as possible using OHDSI tools, within data formatted to the OHDSI CDM, based on direct inspection of the original study’s code and published manuscript. Assuming the study findings can be reproduced, we will proceed to Objective 2, where we evaluate whether the study findings are robust to plausible variations in study design choices, including alternate definitions of target/comparator cohorts, outcome phenotypes, and study design. To do so, we plan to conduct sensitivity analyses that vary one design choice/parameter at a time (as opposed to exploring the combination of several parameters). Furthermore, we will assess robustness by assessing whether study findings are consistent after empirical calibration of effect estimates using negative and positive control outcomes. We will also use standard OHDSI study diagnostics to assess whether the data and design are fit-for-purpose and can be expected to generate inferences with minimal systematic error. Finally, to address Objective 3, we will assess the generalizability of findings by deploying the original Albogami et al. protocol across different databases in the OHDSI Research Network (including U.S. and non-U.S. populations). Doing so allows us to evaluate whether the findings are consistent when applied to data which include different study populations and exhibit different mechanisms of data capture.

Uncertainty regarding the reliability of findings generated by observational studies limits the impact of observational research findings on real-world clinical practice. Collectively, we believe the body of evidence generated by these analyses will provide a comprehensive and holistic assessment of evidence reliability, which could either strengthen confidence in the original study finding or identify important gaps in the evidence which can be addressed by further research using alternate study designs and data resources. We believe that either result will improve the field’s understanding of this evidence and, if appropriate, enable changes in patient-care / treatment decision-making.

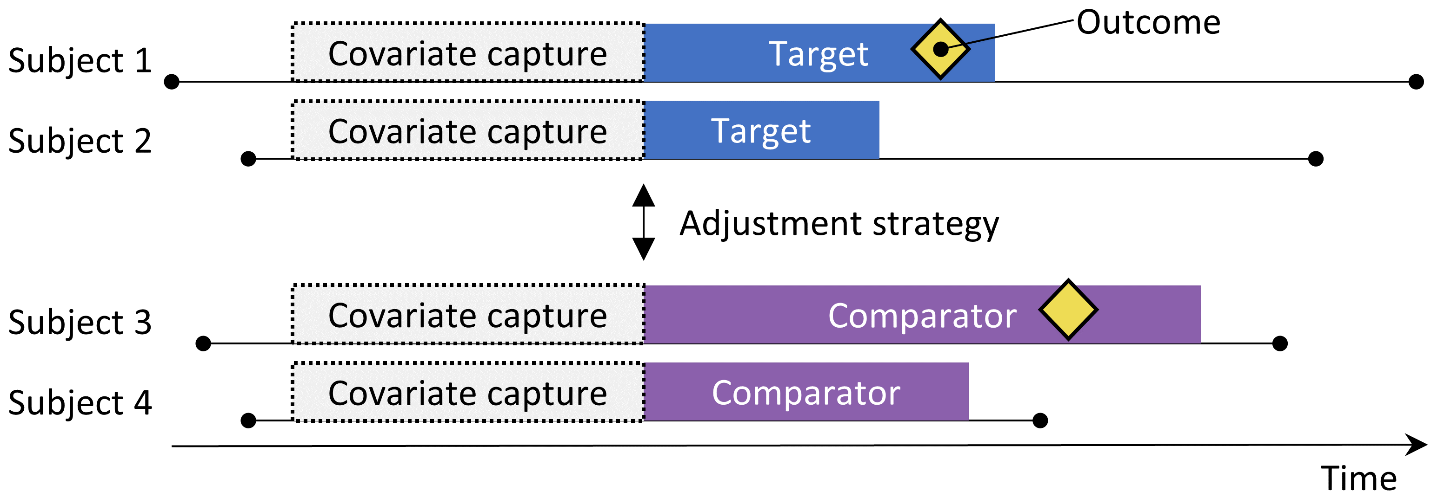
## Study design and setting

### Proposed study designs to examine evidence reliability

Three study designs will be used as part of this evaluation: a new user cohort comparison (CC), a self-controlled cohort (SCC), and a self-controlled case series (SCCS). We intend to examine the robustness of Albogami et al.’s findings with respect to these study design alternatives, which have orthogonal assumptions and complementary strengths and limitations (described in Section 10 of this protocol and in Table S1 in Appendix 1). If we are able to generate similar findings across several different study designs, we will substantially strengthen the reliability of the evidence Albogami et al. have provided in their original study. A more detailed discussion of the assumptions, strengths, and limitations of these study designs is provided in Section 10 of this protocol. A description of each study design are included below.

New-user comparative-cohort (CC) design

In the CC design (Figure 2, below), subjects observed to initiate the target treatment are compared to those initiating the comparator treatment. To adjust for differences between the two treatment groups, several adjustment strategies are available, which include stratification, matching, or weighting by the propensity score, or by adding baseline characteristics to the outcome model. In order to delineate clear temporality between exposure, outcome and baseline confounders, the characteristics included in the propensity model or outcome model only include those captured prior to treatment initiation. The CC design can be employed using several different outcome models, allowing for the estimation of various effect estimates including: logistic regression to estimate the risk ratio, Cox proportional hazards models (time-to-event analysis) to estimate the hazard ratio, and Poisson regression to estimate the incidence rate ratio. Additional description of the CC design and related analytic approaches is provided in [Section 12.1 of the Book of OHDSI](https://ohdsi.github.io/TheBookOfOhdsi/PopulationLevelEstimation.html#CohortMethod).



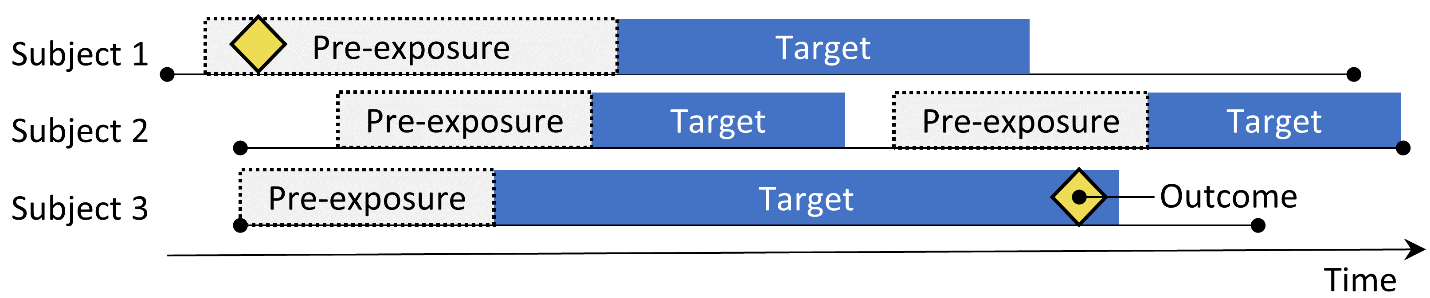
**Figure 2.** Schematic illustrating the new-user cohort comparison (CC) design

Initially, we will use the new user CC design in order to as closely as possible reproduce the analysis described in the recent publication by Albogami et al in the original study data source (CCAE). After evaluations of reproducibility, we will employ the CC design to assess the replicability when the same analysis is applied across multiple similar study data sources, including databases with similar mechanisms of data capture as the CCAE database (e.g. other commercial claims databases that capture similar patient populations). We will also use the CC design to assess generalizability by applying the same analysis to data with meaningful differences in the patients and/or data captured (e.g. EHR databases, administrative billing databases outside of the U.S. health system).

In addition to evaluating reproducibility, replicability, and generalizability, we also plan to evaluate the robustness of the findings to alternate choices in analytic choices, including 1) alternate definitions of exposure and/or outcome phenotypes, sensitivity to empirical calibration of effect estimates using negative and positive control outcomes. As a further perspective on the robustness of study findings, we plan to employ observational study diagnostics in order to inform our understanding of whether findings are systematically biased. Additional descriptions of proposed diagnostic procedures and empirical calibration methods are provided in Section 7.4 and Section 8.5 of this protocol, respectively.Furthermore, we plan to explore whether the study question addressed by Albogami et al. generates findings that are robust to alternate study designs choices, which are described below.

**Self-controlled cohort (SCC) design**

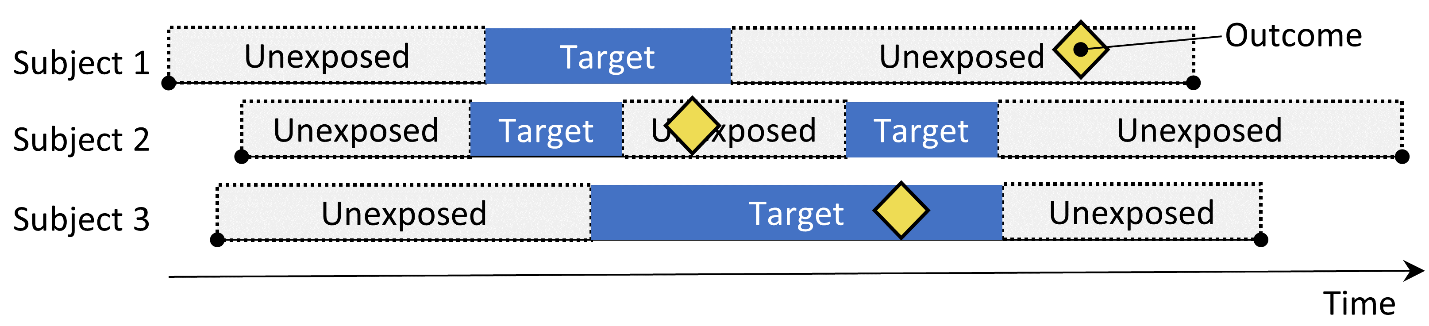
The SCC design21 (Figure 3, below) compares the rate of outcomes during exposure to the rate of outcomes in the time just prior to the exposure. Because the same subject that make up the exposed group are also used as the control group, no adjustment for between-person differences need to be made. However, the method is vulnerable to other differences, such as differences in the baseline risk of the outcome between different time periods. Typically, the SCC design employs the use of a Poisson regression outcome model which can be used to estimate the incidence rate ratio. Additional description of the SCC study design and related analytic approaches is provided in [Section 12.2 of the Book of OHDSI](https://ohdsi.github.io/TheBookOfOhdsi/PopulationLevelEstimation.html#the-self-controlled-cohort-design).



**Figure 3.** Schematic illustrating the self-controlled cohort (SCC) design

**The self-controlled case series (SCCS) design**

In the SCCS design22, 23 (Figure 4, below), longitudinal data is used to compare the rate of outcomes during periods of “at-risk” exposure time to the rate of outcomes unexposed “control” time. The SCCS design only evaluates patients who experienced the outcome and is typically used to study acute outcomes.24 This design is appropriate for the study question of interest since the primary and secondary outcomes defined by Albogami et al (CLRD hospitalizations and CLRD exacerbations) are both acute events. The CLRD exacerbation does include patients who receive a prescription for systemic corticosteroids that is accompanied by a CLRD diagnosis, however the prescription for systemic corticosteroids is restricted to Rx w/ 1-14 day supply, which should omit long-term (chronic) corticosteroid treatments. The SCCS design employs the use of a Poisson regression outcome model which can be used to estimate the incidence rate ratio. Additional description of the SCCS study design and related analytic approaches is provided in [Section 12.5 of the Book of OHDSI](https://ohdsi.github.io/TheBookOfOhdsi/PopulationLevelEstimation.html#the-self-controlled-case-series-design).



**Figure 4.** Schematic illustrating the self-controlled case series (SCCS) design

### Target population and comparators

In this study, we will seek to assess patients using glucagon-like peptide 1 receptor agonists (GLP-1RAs). In analyses employing the CC design, we explicitly plan to reproduce the comparator group from Albogami et al which includes patients initiating dipeptidyl peptidase-4 inhibitors (DPP-4Is). In order to examine the robustness of the findings from the CC design analysis, we may also explore alternate comparators, including sulfonylureas and potentially sodium-glucose transport protein 2 (SGLT2) inhibitors, since SGLT2s are indicated for a similar patient population where there is a compelling need to minimize weight gain. Beyond the original definition of target populations in the Albogami et al. protocol (i.e. patients who use these medications in conjunction with another diabetes treatment), we will conduct sensitivity analyses that vary the target and comparator populations of interest. Medication information is available at the level of the RxNorm ingredient.

### Time-at-risk

Time exposed will be considered the time-on-treatment, in accordance the original Albogami et al. protocol, which will be defined using the days supply data that accompany prescribing events. If an otherwise feasible data set is available that does not contain reliable information on days supply, on-treatment time may be inferred using product labels to inform dosing schedules. tables will be created using products labels to infer dosing schedules. Beyond the original definition of time-at-risk described in the Albogami et al. protocol, we will explore sensitivity analyses that vary the time-at-risk definition for all three study designs. A priori, we know that we want to pursue a longer at-risk period extending to 730 days (instead of the original 365) for the CC analysis.

### Outcome(s) of interest

We plan to reproduce the primary and secondary outcomes as defined by Albogami et al. Both outcomes reflect different approaches to capturing chronic lower respiratory disease (CLRD) exacerbation: 1) time-to-first-observed CLRD hospitalization and 2) count of any CLRD exacerbation associated with an emergency room visit, inpatient admission, or an outpatient visit that was followed by oral steroid initiation. In order to examine the robustness of findings with respect to changes in the outcome definition, we plan to explore alternate outcome phenotypes / approaches to defining and quantifying acute CLRD exacerbations. Clinical input from OHDSI members with clinical expertise in the relevant disease areas (type 2 diabetes and CLRD) will be included during the process of identifying alternate outcome phenotypes. Alternate outcome phenotypes will be developed and evaluated using OHDSI’s CohortDiagnostic tool which provides a suite of analyses including syntax-/vocabulary-based concept-set diagnostics, cohort incidence rates over time, gender, and age, index event breakdowns, cohort overlap statistics, baseline and temporal characterizations, cohort comparison, and patient profiles. These tools allow for a data-driven, substantive inspection of phenotypes which, when interfaced with clinical knowledge, can ably identify problems in cohort definitions including the populations they do and do not capture and the timing of the events they identify. The CohortDiagnostic tool can be used to instantiate and evaluate cohorts in any dataset formatted to the OMOP CDM. This will enable us to understand outcome performance in all study databases.

### Negative control outcome experiments

Negative controls will be used to evaluate the potential impact of residual systematic error in the study designs, and to perform the empirical calibration of confidence intervals around effect estimates.11-14 An outcome is considered a good candidate for a negative control if it is believed to have no causal relationship with the outcome or exposure (i.e. that a hypothetical, well-designed randomized trial would find no relationship between exposure and the negative control outcome). As part of the reproducability evaluation, where we produce Albogami et al's analysis as closely as possible, we may reproduce the original negative control sensitivity analysis. However, for the purposes of our evaluation of robustness, we plan to conduct an evaluation of a much broader set of negative controls. Because we believe that confounding structures are unknowable, it is our view that using a large number of negative controls provides a more meaningful assessment of uncertainty than assessing a single negative control analysis, since it provides a distribution of potential systematic error rather than a single number. The set of negative control outcomes we propose using for this assessing is provided in Table S2 in Appendix 2. Additional description of empirical calibration methods is provided in Section 8.5 of this document.

### Positive control outcome experiments

To understand the behavior of a method when the true relative risk is smaller or greater than one requires the use of positive controls where the null is believed to not be true. In OHDSI we therefore use synthetic positive controls, (Schuemie, Hripcsak, et al. 2018) created by modifying a negative control through injection of additional, simulated occurrences of the outcome during the time at risk of the exposure. For example, assume that, during exposure to ACEi, n occurrences of our negative control outcome “ingrowing nail” were observed. If we now add an additional n simulated occurrences during exposure, we have doubled the risk. Since this was a negative control, the relative risk compared to the counterfactual was one, but after injection, it becomes two.

To preserve confounding, we want the new outcomes to show similar associations with baseline subject-specific covariates as the original outcomes. To achieve this, for each outcome we train a model to predict the survival rate with respect to the outcome during exposure using covariates captured prior to exposure. These covariates include demographics, as well as all recorded diagnoses, drug exposures, measurements, and medical procedures. An L1-regularized Poisson regression (Suchard et al. 2013) using 10-fold cross-validation to select the regularization hyperparameter fits the prediction model. We then use the predicted rates to sample simulated outcomes during exposure to increase the true effect size to the desired magnitude. The resulting positive control thus contains both real and simulated outcomes.

Our process for creating positive controls synthesizes outcomes with a constant incidence rate ratio over time and between patients, using a model conditioned on the patient where this ratio is held constant, up to the point where the marginal effect is achieved. The true effect size is thus guaranteed to hold as the marginal incidence rate ratio in the treated. Under the assumption that our outcome model used during synthesis is correct, this also holds for the conditional effect size and the ATE. Since all outcomes are rare, odds ratios are all but identical to the relative risk. Additional description of positive control methods is provided in [Section 18.2.2 of the Book of OHDSI](https://ohdsi.github.io/TheBookOfOhdsi/MethodValidity.html#PositiveControls).

### Additional variables of interest (demographic characteristics, confounders)

For all designs, we will describe patient characteristics (prevalence) for each cohort and data source including but not limited to: gender, age, index month, conditions (SNOMED concepts and descendants) drugs (ATC classes and RxNorm ingredients), procedures, devices, measurements, the CHADS2Vasc score, the Diabetes Comorbidity Severity Index, and the Charlson Comorbidity Index.

## Data sources

This study will be conducted within the OHDSI research network. The OHDSI community has authored standards and tools to facilitate high-quality, reproducible research, including OMOP Standardized Vocabularies, the Common Data Model (CDM) and analytical methods packages. OHDSI network studies represent the culmination of a transparent, consistent and reproducible way to conduct research across a large number of geographically dispersed data. The OHDSI Research network is an international collaboration of researchers seeking to advance observational data research in healthcare. OHDSI is an open network, inviting healthcare institutions across the globe with patient-level data to join the network by converting data to the OMOP CDM and participating in network research studies. Each site voluntarily opts-in to each respective network study. In each study, data remains at the site behind a firewall. No patient-level data pooling occurs across network sites. Only aggregate results are shared.

The results of an observational study can be influenced by many factors that vary by the location of the data source such as patterns of treatment discontinuation/switching, genetic diversity, or environmental factors, overall health status: factors that may not have been possible to vary in the context of a clinical trial even if one exists for your same study question. A typical motivation to run an observational study in a network is therefore to increase diversity with respect to data sources, study populations, and patterns of clinical practice to inform how well the results generalize to the many types of people they will eventually be applied to. In other words, can the study findings be replicated across multiple sites or do they differ and if they differ, can any insights be gleaned as to why?

OHDSI network data sources will be used as they are made available by data partners in the OHDSI research network. We will conduct feasibility assessments with volunteered data sources to determine if they have adequate sample and sufficient data to meaningfully inform the study (e.g. through calculation of the minimally-detectable risk ratio). All data sources will receive institutional review board approval or exemption for their participation before executing the study. Specifically, the IBM CCAE database will be used to evaluate reproducibility, since that was the original database used in the study published by Albogami et al. Additional study resources will be used to evaluate the generalizability of the Albogami et al. findings.

Table 1 (below) describes 8 data sources that are currently available to be used in this study, pending assessment of feasibility. These sources encompass a variety of practice types, data capture, and populations. The embedded hyperlinks can be used to access more detailed descriptions of each data source. For each, we report a brief description and size of the population it represents as well as the calendar years and data that it captures.

**Table 1.** Already-available data sources that can be used to replicate/generalize findings from Albogami et al.

| **Data source** | **Population** | **Patients** | **History** | **Data capture and short description** |
| --- | --- | --- | --- | --- |
| IBM MarketScan Commercial Claims and Encounters ([CCAE](https://catalog.rwe.jnj.com/index#jnjsearches?dataSetUri=%2Fdataset%2F74ee6310-2b1f-43a3-8c82-4799c584ea86.xml)) | Commercially insured, < 65 years (U.S.) | 142M | 2000 – | Adjudicated health insurance claims (e.g. inpatient, outpatient, and outpatient pharmacy) from large employers and health plans who provide private healthcare coverage to employees, their spouses and dependents. |
| IBM MarketScan Medicare Supplemental Database ([MDCR](https://catalog.rwe.jnj.com/index#jnjsearches?dataSetUri=%2Fdataset%2F87883da0-c84d-4315-ae1c-b3e4f51cfe1d.xml)) | Commercially insured, 65 years (U.S.) | 10M | 2000 – | Adjudicated health insurance claims of retirees with primary or Medicare supplemental coverage through privately insured fee-for-service, point-of-service or capitated health plans. |
| IBM MarketScan Multi-State Medicaid Database ([MDCD](https://catalog.rwe.jnj.com/index#jnjsearches?dataSetUri=%2Fdataset%2F4136471c-0662-4ca7-b091-4d6120358f74.xml)) | Medicaid enrollees, racially diverse (U.S.) | 26M | 2006 – | Adjudicated health insurance claims for Medicaid enrollees from multiple states and includes hospital discharge diagnoses, outpatient diagnoses and procedures, and outpatient pharmacy claims. |
| Optum Clinformatics Data Mart ([Optum](https://catalog.rwe.jnj.com/index#jnjsearches?dataSetUri=%2Fdataset%2Fd27742b7-6a17-4a6c-96f4-a4c5a486155a.xml)) | Commercially or Medicare insured (U.S.) | 85M | 2000 – | Inpatient and outpatient healthcare insurance claims. |
| Optum Electronic Health Records ([OptumEHR](https://catalog.rwe.jnj.com/index#jnjexplore?dataSetUri=%2Fdataset%2F14462aa5-4c8d-4d20-8314-47fe170d47b1.xml)) | General population (U.S.) | 93M | 2006 – | Clinical information, prescriptions, lab results, vital signs, body measurements, diagnoses and procedures derived from clinical notes using natural language processing. |
| IQVIA Adjudicated Health Plan Claims ([PharMetrics Plus](https://catalog.rwe.jnj.com/index#jnjsearches?dataSetUri=%2Fdataset%2F4fcfbe6d-bb08-4f15-8842-f7478277204a.xml)) | Commercially or Medicare insured (U.S.) | 102M | 2015 – | Inpatient and outpatient insurance claims, prescription and office/outpatient administered drugs, costs and enrollment information. |
| Japan Medical Data Center ([JMDC](https://catalog.rwe.jnj.com/index#jnjexplore?dataSetUri=%2Fdataset%2F06d7e4d1-6000-4779-bdc9-16ace880912a.xml)) | Society-managed health insurance enrollees (18-65) (Japan) | 11M | 2005 – | Patient-level demographic information, inpatient and outpatient data inclusive of diagnosis and procedures, and prescriptions as dispensed claims information |
| IQVIA [Germany](https://catalog.rwe.jnj.com/index#jnjsearches?dataSetUri=%2Fdataset%2Fcb9e96f4-db84-4610-8d62-c32d54bba9cd.xml) | Patients treated at physician practices and medical centers (Germany) | 30M | 2010 – | Office visits, prescribed medications and vaccinations, test results, procedures and diagnosis (ICD10). Data is mostly collected from primary care physicians however captures some specialty practices. |

## Fit-for-purpose evaluation

In order to assess the diagnostics that inform the robustness of estimates generated by a single analysis within a single data source, the following additional evaluations will be performed: power calculations estimating minimum detectable relative risk; and negative-control calibration plots to assess residual systematic bias. For the CC design, we will also calculate the following: preference score (a transformation of propensity score that adjusts for prevalence differences between populations) distributions to evaluate empirical equipoise and population generalizability; patient characteristics to evaluate cohort balance before and after propensity score adjustment, and Kaplan-Meier plots to examine proportionality assumptions in the analyses estimating the hazard ratio. Given the possibility that CLRD-related outcomes vary by season, we plan to assess whether initiations of the study drugs also vary by season. These findings may inform design choices for the SCC and SCCS designs. However, the original CC study by Albogami et al does adjust for season (as will our reproduced CC analysis), so we expect that the CC analysis will be robust to seasonality of exposures and outcomes. In cases where a specific analysis produces study diagnostics that indicate potentially biased findings, we will note that when sharing the results of that analysis. Further description and justification for this approach is provided in Section 8.3 of this protocol. In Section 7.2.4 of this protocol, we also describe tools that are used to build and validate target/comparator/outcome phenotypes within study data sources.

# DATA ANALYSIS PLAN AND MODEL SPECIFICATION

## Descriptive statistics

In descriptive analyses, we will summarize patient characteristics at the point of entry into the study cohort, using proportions to describe dichotomous covariates and using the mean and standard deviation to describe continuous covariates (e.g. the Charlson Comorbidity Index). For the comparative cohort design, we will describe characteristics for each treatment group and will calculate the absolute standardized mean difference between the two.24 For the SCC design, we will contrast patient’s baseline characteristics at the start of their control period and the start of their exposure period, in order to inform the risk of time-varying, within-person confounding.

## Propensity score adjustment

To adjust for between-person confounding when using the CC design, propensity score models for each class pair and data source will be created using a data-driven process using regularized logistic regression. This process allows the data to inform which combinations of baseline patient characteristics, including demographics and previous conditions, drug exposures, procedures, and health-service-use behaviors are most predictive of treatment assignment. The propensity score model used in the comparative cohort design will include the following potential confounding variables: age, gender, the year and month of the exposure, presence of medical conditions, medications, medical procedures, and the number of distinct conditions, procedures, measurements (e.g., lab test results), and visit counts. For the reproducibility objective, where we attempt to reproduce the finding using the same approach used by Albogami et al., we plan to assess baseline covariates within a 365 day look-back window. However, for other analyses (in the replication, generalizability evaluations) we plan to use large-scale regression to empirically select covariates captured in a range of baseline windows.

The original study by Albogami et al. used stabilized inverse-probability-of-treatment (sIPTW) methods to balance the study populations being compared. We may also choose to conduct sensitivity analyses exploring the use of propensity score matching and/or propensity-score stratification. Because sIPTW can produce extreme weights and can be difficult to deploy in multiple data settings without hands-on inspections of weights, we may choose to use matching or stratification when exploring the generalizability of findings across databases. It is important to note that these treatments appear to be highly comparable so we do not anticipate that the chosen method of confounding control will meaningfully impact findings.

## Evidence evaluation and synthesis

In Section 7.4 of this protocol, we describe the diagnostics that will be used to assess fit-for-purpose evaluations for each analysis within each database. Since the explicit intention of this study is to explore the reliability of an already-published analysis, we plan to present effect estimates from all analyses, regardless of whether they pass diagnostics. Doing so provides needed information about the scale/magnitude of various sources of bias that may inform the reliability of the original finding by Albogami et al. In cases where failing diagnostics indicate potentially spurious effect estimates, we will specifically highlight that when presenting results. If appropriate, effect estimates generated by analyses that do satisfy diagnostic inspections will be aggregated across data sources using a random-effects model to produce meta-analytic estimates. Before combining into a meta-analytic estimate, we will inspect effect estimates for cross-database heterogeneity, as indicated by the I2 score, which quantifies the proportion of total variation across studies that is due to heterogeneity rather than chance.25

## Outcome models and corresponding effect estimates

The CC design can be employed using several different outcome models, allowing for the estimation of various effect estimates including: logistic regression to estimate risk ratio, Cox proportional hazards models (time-to-event analysis) to estimate the hazard ratio, and Poisson regression to estimate the incidence rate ratio. For both the SCC and the SCCS design, we will use Poisson regression outcome models, which can be used to estimate the incidence rate ratio.

## Calibration of effect estimates using the empirical null distribution

The distribution of effect estimates across all negative control outcome experiments will be used to fit an empirical null distribution, which collectively reflects both random and residual systematic error. The empirical null distribution is particularly well equipped to demonstrate systematic sources of selection bias and confounding bias and, to some degree, misclassification bias. The empirical null distribution will then be applied to the outcome of interest to calibrate the p-value and confidence interval. Empirical calibration serves as an important diagnostic tool to evaluate if the residual systematic error is sufficient to cast doubt on the accuracy of the unknown effect estimate.11-14 The calibration effect plot will be generated and included alongside results in order to inform interpretation of the results. We will report the traditional and empirically calibrated effect estimates and confidence interval for each analysis.

# SAMPLE SIZE AND STUDY POWER

This is a retrospective cohort study all available observations will be included, and thus no a priori sample size or power calculations will be performed. For each distinct analysis, we will estimate the minimally detectable relative risk, which provides an estimate of the point at which the true effect size would be too small to detect using a 95% confidence interval.

# STRENGTHS AND LIMITATIONS OF THE RESEARCH METHODS

We intend to use multiple study designs to examine the robustness of Albogami et al.’s findings with respect to various study design alternatives, which have orthogonal assumptions and complementary strengths and limitations. While the limitations of these study designs are important to consider, assess, and understand, the consolidated body of evidence provided by using all three designs to address the same question will be highly informative. Specifically, producing the same finding using all three designs would substantially weaken the argument that the result is an artifact of systematic bias due to study design.

There are several important strengths, limitations, and assumptions that inform the use of the CC design. Perhaps most importantly, the CC design emulates a randomized clinical trial and, as such, is desirable with respect to the ease of interpretability and also its clear delineation of the temporality of confounder-exposure-outcome relationships. However, in order to clearly delineate temporality, the CC design requires relative accuracy ascertaining exposure initiation status and timing. Furthermore, the CC design is susceptible to unmeasured confounders (including time-variant and time invariant confounders), specifically but not limited to confounding by indication. Finally, the CC design can be biased if loss-to-follow-up is related to both exposure and disease status.

In contrast to the CC design, self-controlled designs, such as the SCC and the SCCS designs, are not susceptible to between-person confounding, since each included patient serves as their own control. Thus, no adjustment is needed to account for between-person differences or time-invariant confounders. However, time-varying confounders that systematically differ between the exposed and unexposed windows assessed (e.g. seasonality) may still confound estimates.26 In the case of the SCC design, the control period always precedes exposure and thus cases where outcome occurrence has a strong relationship with the probability of subsequent exposure may produced biased findings. Furthermore, both the SCC and SCCS designs are vulnerable to reverse causality bias since the temporality of confounder-exposure-outcome is not as cleanly parsed as the CC design.26 Given that the SCC anchors at-risk and control windows on exposure initiation, the SCC design is strongest when we have a clear ascertainment of the timing of exposure initiation in the data.9 Lastly, an assumption of the SCCS design is that there is no meaningful competing risk or, in other words, the end of observation is mostly independent of outcome occurrence.9

From its inception, the declared goal of the OHDSI community has been to establish an international collaborative by building on open-science values.9 This work intending to interrogate the reliability of the Albogami et al. study directly aligns with OHDSI’s open-science strategy and its commitment to enable more meaningful collaboration in the health research community. OHDSI has developed a broad toolkit to make such work possible, including the use of open-source software, public availability of all conference proceedings and materials, and transparent, open-access publication of generated medical evidence. These developments enable the OHDSI community to not just conduct high-impact observational health research, but to further our understanding of the reliability of existing health research. In keeping with this philosophy, the work conducted on this project and the generated results will also be shared in such a way (i.e. including open-source, executable code) that enables other researchers, both within and outside the OHDSI community, to re-run analyses and understand the reliability of our findings. It is our hope that this work represents an early step toward a more robust system of evaluating evidence quality.

# PROTECTION OF HUMAN SUBJECTS

Confidentiality of patient records will be maintained always. All study reports will contain aggregate data only and will not identify individual patients or physicians. At no time during the study will the sponsor receive patient identifying information except when it is required by regulations in case of reporting adverse events. The use of the Optum and IBM MarketScan was reviewed by the New England Institutional Review Board (IRB) and was determined to be exempt from broad IRB approval, as this research project did not involve human subjects research. We will seek approval from all other data sources in accordance to our data use agreements as applicable.

# MANAGEMENT AND REPORTING OF ADVERSE EVENTS AND ADVERSE REACTIONS

This study uses coded data that already exist in electronic databases. In this type of database, it is not possible to link (i.e., identify a potential causal association between) a particular product and medical event for any individual. Thus, the minimum criteria for reporting an adverse event (i.e., identifiable patient, identifiable reporter, a suspect product, and event) are not available and adverse events (AEs) are not reportable as individual AE reports. The study results will be assessed for medically important results.

# PLANS FOR DISSEMINATING AND COMMUNICATING STUDY RESULTS

In accordance with OHDSI’s open-science approach, all aspects of this research will be publicly shared. From an open-science perspective, one of the most important resources to share is the code for the actual execution of studies, such as studies from the OHDSI Research Network. In turn, these programs leverage the fully open source OHDSI stack, which can be inspected, reviewed and contributed to via GitHub. Furthermore, by providing executable code, we enable other researchers to reproduce the analyses we conduct as part of this evaluation of evidence reliability. Because of the privacy-sensitive nature of healthcare data, fully open, comprehensive patient-level datasets are typically not available. However, it is possible to leverage OMOP mapped datasets to publish important aggregated data and results sets to <http://data.ohdsi.org>.

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# Appendix 1: Description of considered study designs

**Table S1. Overview of selected study designs including strengths and limitations of selected study design**

| **Study Design** |  | **Population** | **Example of Data Being Compared** | **Strengths** | **Weaknesses** | **Examples of Test Statistics or Regression Models** |
| --- | --- | --- | --- | --- | --- | --- |
| New user comparative cohort (CC) design |  | Exposed persons Persons exposed to an active comparator (often matched on potential confounders) | Incidence or incidence rates of those vaccinated vs. incidence or incidence rates of those unvaccinated | Standard design Easily implemented large observational data sources Propensity score methods control for potential confounders Accounts for seasonality; index date aligns risk period for target-exposed and comparator-exposed | Confounding by indication, other unmeasured confounders Susceptible to misclassification of exposure Unvaccinated control population may be limited Biased incidence rate ratio if loss to follow-up is affected by both exposure and disease status | Linear and logistic regression Cox regression Poisson regression (conditional logistic regression or Poisson regression if matched analysis) |
| Self-controlled case series (SCCS) design |  | Cases | Incidence rates of exposed time periods vs incidence rates of self-matched unexposed time periods | Self-controlled, adjusts for time-invariant confounders Multiple occurrences of independent events within an individual can be assessed | Time-varying confounding Reverse causality bias | Conditional Poisson regression |
| Self-controlled cohort (SCC) design |  | Exposed persons, but only cases informative | Incidence rates of exposed time periods vs. incidence rates of self-matched unexposed time periods | Self-controlled, adjusts for time-invariant confounders Less susceptible to misclassification of exposure | Time-varying confounding (less susceptible than SCCS because of less variation in periods under observation) Possible bias due to differences in baseline risk of outcome between time-periods. | Conditional Poisson regression |

\* Table contents partially informed by: Baker MA, Lieu TA, Li L, Hua W, Qiang Y, Kawai AT, et al. A vaccine study design selection framework for the postlicensure rapid immunization safety monitoring program. American journal of epidemiology. 2015;181(8):608-18.

# ApPEndix 2: list of candidate negative control outcomes

**Table S2.** Candidate negative control outcomes (N=51) to use in comparisons of antidiabetes treatments

|  | **Concept ID** | **Concept Code** | **Concept Name** |
| --- | --- | --- | --- |
| 1 | 4056591 | 212454006 | Traumatic rupture of lumbar intervertebral disc |
| 2 | 45757682 | 323351000119108 | Anomaly of jaw size |
| 3 | 4058388 | 19843006 | Hypertrophic scar |
| 4 | 439907 | 268002004 | Non-traumatic tendon rupture |
| 5 | 40481897 | 443483005 | Inadequate sleep hygiene |
| 6 | 374919 | 24700007 | Multiple sclerosis |
| 7 | 4090205 | 187251001 | Sequelae of tuberculosis |
| 8 | 438021 | 23123006 | Disorder due to and following fracture of upper limb |
| 9 | 4166231 | 47708004 | Genetic predisposition |
| 10 | 440933 | 77968000 | Effects of accidental exposure to external cause |
| 11 | 374013 | 230292008 | Secondary parkinsonism |
| 12 | 141667 | 27911000 | Laxity of ligament |
| 13 | 4216670 | 81302005 | Worried well |
| 14 | 77139 | 2630008 | Open wound of finger without complication |
| 15 | 132736 | 5758002 | Bacteremia |
| 16 | 374358 | 246815009 | Excess skin of eyelid |
| 17 | 4344500 | 239960007 | Impingement syndrome of shoulder region |
| 18 | 4128329 | 289903006 | Menopause present |
| 19 | 439438 | 162213003 | Crying, excessive |
| 20 | 4168681 | 274646000 | Irritability and anger |
| 21 | 4051630 | 23268009 | Malingering |
| 22 | 4310082 | 216551003 | Accidental poisoning by cannabis derivatives |
| 23 | 440858 | 32106001 | Cortex contusion without open intracranial wound |
| 24 | 439216 | 216545008 | Accidental poisoning by antidepressants |
| 25 | 440612 | 212899006 | Toxic effect of tobacco and nicotine |
| 26 | 373764 | 28394000 | Toxic encephalopathy |
| 27 | 432798 | 5285008 | Mechanical complication of internal orthopedic device, implant AND/OR graft |
| 28 | 374801 | 75441006 | Foreign body in ear |
| 29 | 440905 | 44400004 | Toxic effect of venom |
| 30 | 440053 | 71571008 | Infestation by insect |
| 31 | 441487 | 370977006 | Frostbite |
| 32 | 30234 | 209557005 | Neck sprain |
| 33 | 4019836 | 105412007 | Social exclusion |
| 34 | 381877 | 56713002 | Dysfunction of eustachian tube |
| 35 | 433577 | 122481008 | Hammer toe |
| 36 | 373478 | 41256004 | Presbyopia |
| 37 | 381295 | 39450006 | Senile cataract |
| 38 | 137016 | 66569006 | Retained dental root |
| 39 | 4213540 | 417347005 | Cervical somatic dysfunction |
| 40 | 4067069 | 201040000 | Callosity |
| 41 | 4209423 | 56294008 | Nicotine dependence |
| 42 | 80242 | 307945003 | Current tear of medial cartilage AND/OR meniscus of knee |
| 43 | 138384 | 111566002 | Acquired hypothyroidism |
| 44 | 4079750 | 239873007 | Osteoarthritis of knee |
| 45 | 261880 | 46621007 | Atelectasis |
| 46 | 378427 | 46152009 | Tear film insufficiency |
| 47 | 374375 | 18070006 | Impacted cerumen |
| 48 | 40479573 | 441527004 | Stimulant abuse |
| 49 | 4170260 | 419145002 | Nightmares |
| 50 | 46286594 | 987891000000105 | Problem related to lifestyle |
| 51 | 443274 | 275471001 | Psychostimulant dependence |