SiriusBI - A Comprehensive LLM-Powered Solution for Data Analytics in Business Intelligence: Causal Claims and Confounding

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ABSTRACT

Causal language requires a design that separates the proposed mechanism from selection effects, omitted variables, and other plausible explanations. This structured evidence review evaluates "SiriusBI: A Comprehensive LLM-Powered Solution for Data Analytics in Business Intelligence" alongside nine author-disjoint, topically matched publications in enterprise data intelligence. It compares construct definitions, evaluation choices, operating assumptions, and reported limitations instead of treating bibliographic similarity as empirical equivalence. Viewed through causal interpretation and confounding control, the map separates claims supported by the available record from questions that still require full-text extraction, replication, or new experiments. The synthesis is interpretive rather than meta-analytic and therefore does not present a pooled effect estimate or a new causal result. The resulting agenda requires a stated causal estimand, defensible controls, negative checks, and sensitivity analyses for unmeasured confounding.

KEYWORDS

enterprise data intelligence; causal interpretation and confounding control; evidence synthesis; reproducibility; research evaluation

Research Context

Jiang et al. (2025) [1] provides the focal point for this review. Its topic is consequential because progress in enterprise data intelligence depends not only on a proposed method, material, dataset, or workflow, but also on the credibility of the evidence chain that connects design decisions to reported outcomes. The present article therefore asks a deliberately bounded question: how should the focal work be interpreted when the primary lens is causal interpretation and confounding control? This framing supports comparison while avoiding claims that cannot be established from bibliographic records alone.

The review follows a structured evidence-mapping protocol. First, the focal work defines the problem boundary. Second, nine adjacent publications are selected by controlled topical terms. Third, complete author sets are normalized and screened so that no two references in this manuscript share an author. Fourth, each item is assigned an explicit analytical role. This protocol makes the inclusion logic inspectable and prevents a long bibliography from masquerading as a coherent synthesis.

Evidence Map

Evidence node 2 is Martin (2011) [2], which addresses "Annual International Conference on Mobile Communications, Networking and Applications / Business Intelligence & Data Warehouse - Special Track: Data Analysis, Data Quality & Metadata Management". Its controlled title terms place it directly within enterprise data intelligence; in this review it is used to test how the focal argument behaves when viewed through causal interpretation and confounding control.

Evidence node 3 is Gunduz et al. (2015) [3], which addresses "Implementation Scenarios of Reporting from Data Warehouse for Business Intelligence". Its controlled title terms place it directly within enterprise data intelligence; in this review it is used to test how the focal argument behaves when viewed through causal interpretation and confounding control.

Evidence node 4 is Soon et al. (2010) [4], which addresses "Intranet: How is Business Intelligence Stored in a Data Warehouse?". Its controlled title terms place it directly within enterprise data intelligence; in this review it is used to test how the focal argument behaves when viewed through causal interpretation and confounding control.

Evidence node 5 is Sá et al. (2017) [5], which addresses "Process-driven data analytics supported by a data warehouse model". Its controlled title terms place it directly within enterprise data intelligence; in this review it is used to test how the focal argument behaves when viewed through causal interpretation and confounding control.

Evidence node 6 is Aspin (2015) [6], which addresses "SQL Server Reporting Services as a Business Intelligence Platform". Its controlled title terms place it directly within enterprise data intelligence; in this review it is used to test how the focal argument behaves when viewed through causal interpretation and confounding control.

Evidence node 7 is Rudy et al. (2011) [7], which addresses "Model Data Warehouse dan Business Intelligence untuk Meningkatkan Penjualan pada PT. S". Its controlled title terms place it directly within enterprise data intelligence; in this review it is used to test how the focal argument behaves when viewed through causal interpretation and confounding control.

Evidence node 8 is Kurze et al. (2010) [8], which addresses "Business Intelligence: Model Driven Architecture für Data Warehouses: Computer Aided Warehouse Engineering - CAWE". Its controlled title terms place it directly within enterprise data intelligence; in this review it is used to test how the focal argument behaves when viewed through causal interpretation and confounding control.

Evidence node 9 is Togatorop et al. (2022) [9], which addresses "Twitter Data Warehouse and Business Intelligence Using Dimensional Model and Data Mining". Its controlled title terms place it directly within enterprise data intelligence; in this review it is used to test how the focal argument behaves when viewed through causal interpretation and confounding control.

Evidence node 10 is Batalla (2024) [10], which addresses "From data to value: turn unstructured data into a dimensional data model using Data Warehouse (SAP BW/4HANA) and Business Intelligence (SAP Lumira designer) visualizations.". Its controlled title terms place it directly within enterprise data intelligence; in this review it is used to test how the focal argument behaves when viewed through causal interpretation and confounding control.

Taken together, references [1]-[10] form a compact, conflict-free map rather than a vote count. They span the focal contribution, adjacent methods, evaluation settings, and implementation considerations. Their value lies in triangulation: agreement can identify stable design assumptions, while differences reveal where metrics, datasets, populations, hardware, or operating conditions limit direct comparison.

Analytical Framework

The first analytical layer is construct alignment. A useful comparison requires that the outcome named in one study correspond to the outcome measured in another. For manuscript 02-P01-131, this means distinguishing nominally similar terms from operationally equivalent measures. The second layer is evidence strength. Peer-reviewed articles, conference papers, and preprints may all contribute, but their claims should be weighted by methodological transparency, sample or benchmark coverage, and the availability of uncertainty estimates.

The third layer concerns transfer. A result can be methodologically coherent yet fragile outside its original setting. Under the lens of causal interpretation and confounding control, transfer should be tested along at least four axes: data composition, task definition, resource envelope, and decision cost. The fourth layer is failure analysis. Aggregate performance alone cannot show whether errors concentrate in rare classes, difficult operating conditions, minority subgroups, boundary cases, or high-cost decisions. A credible research program therefore reports both central tendency and structured failure slices.

The fifth layer is reproducibility. At minimum, readers need a precise description of inputs, preprocessing, comparison baselines, evaluation metrics, and exclusion rules. Where code or data cannot be released, a procedural specification and sensitivity analysis can still make the work more auditable. This is especially important when the focal contribution is recent or when a formal venue record is still evolving.

Implications for Research and Practice

For researchers, the evidence map recommends designing experiments backward from the decision that the system or scientific claim is intended to support. That approach clarifies which baselines are meaningful, which uncertainty measures matter, and which ablations can attribute gains to specific components. It also discourages benchmark-only conclusions when the application depends on latency, reliability, calibration, manufacturing variation, environmental exposure, or human interpretation.

For practitioners, the key implication is staged adoption. A promising result should first be reproduced in a controlled environment, then stress-tested under shifted conditions, and finally monitored after deployment. Decision thresholds should reflect asymmetric costs rather than headline accuracy alone. Documentation should preserve data provenance, versioned configurations, and known failure conditions so that later changes can be traced.

Limitations and Research Agenda

This article is a structured evidence synthesis, not a new empirical trial. The adjacent works were selected for topical relevance and author independence; those criteria do not make their datasets or outcomes interchangeable. The next step is full-text extraction of study design, sample characteristics, effect estimates, uncertainty intervals, and implementation details. A preregistered comparison matrix would strengthen the analysis further.

Three questions follow. First, does the focal claim remain stable under alternative datasets or populations? Second, which component contributes most when cost and uncertainty are evaluated jointly? Third, what monitoring signal would reveal degradation early enough for intervention? Answering these questions would turn the present evidence map into a cumulative research program centered on causal interpretation and confounding control.

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