

Novelty Assessment Report

Paper: Characterization and Learning of Causal Graphs with Latent Confounders and Post-treatment Selection from Interventional Data

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Abstract

Interventional causal discovery seeks to identify causal relations by leveraging distributional changes introduced by interventions, even in the presence of latent confounders. Beyond the spurious dependencies induced by latent confounders, we highlight a common yet often overlooked challenge in the problem due to post-treatment selection, in which samples are selectively included in datasets after interventions. This fundamental challenge widely exists in biological studies; for example, in gene expression analysis, both observational and interventional samples are retained only if they meet quality control criteria (e.g., highly active cells). Neglecting post-treatment selection may introduce spurious dependencies and distributional changes under interventions, which can mimic causal responses, thereby distorting causal discovery results and challenging existing causal formulations. To address this, we introduce a novel causal formulation that explicitly models post-treatment selection and reveals how its differential reactions to interventions can distinguish causal relations from selection patterns, allowing us to go beyond traditional equivalence classes toward the underlying true causal structure. We then characterize its Markov properties and propose a \mathcal{F} -fine-grained \mathcal{I} -interventional equivalence class, named \mathcal{FI} -Markov equivalence, represented by a new graphical diagram, \mathcal{F} -PAG. Finally, we develop a provably sound and complete algorithm, \mathcal{F} -FCI, to identify causal relations, latent confounders, and post-treatment selection up to \mathcal{FI} -Markov equivalence, using both observational and interventional data. Experimental results on synthetic and real-world datasets demonstrate that our method recovers causal relations despite the presence of both selection and latent confounders.

Disclaimer

This report is **AI-GENERATED** using Large Language Models and WisPaper (a scholar search engine). It analyzes academic papers' tasks and contributions against retrieved prior work. While this system identifies **POTENTIAL** overlaps and novel directions, **ITS COVERAGE IS NOT EXHAUSTIVE AND JUDGMENTS ARE APPROXIMATE**. These results are intended to assist human reviewers and **SHOULD NOT** be relied upon as a definitive verdict on novelty.

Note that some papers exist in multiple, slightly different versions (e.g., with different titles or URLs). The system may retrieve several versions of the same underlying work. The current automated pipeline does not reliably align or distinguish these cases, so human reviewers will need to disambiguate them manually.

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Core Task Landscape

This paper addresses: **Interventional Causal Discovery with Latent Confounders and Post-Treatment Selection**

A total of **50 papers** were analyzed and organized into a taxonomy with **16 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Causal Discovery from Interventional Data**
- **Causal Effect Estimation and Inference**
- **Machine Learning Integration with Causal Inference**
- **Methodological Foundations and Theoretical Advances**
- **Domain-Specific Applications**

Complete Taxonomy Tree

- Interventional Causal Discovery with Latent Confounders and Post-Treatment Selection Survey Taxonomy
- Causal Discovery from Interventional Data
 - Discovery with Unknown or Soft Intervention Targets (2 papers)
 - [1] Learning unknown intervention targets in structural causal models from heterogeneous data (Yang Yu-qin, 2024) [View paper](#)
 - [2] Causal discovery from soft interventions with unknown targets: Characterization and learning (Amin Jaber, 2020) [View paper](#)
 - Discovery with Latent Confounders and Selection Bias ★ (4 papers)
 - [0] Characterization and Learning of Causal Graphs with Latent Confounders and Post-treatment Selection from Interventional Data (Anon et al., 2026) [View paper](#)
 - [6] When Selection Meets Intervention: Additional Complexities in Causal Discovery (Dai, 2025) [View paper](#)
 - [9] Iterative Causal Discovery in the Possible Presence of Latent Confounders and Selection Bias (Rohekar, 2021) [View paper](#)
 - [15] Distinguishability of causal structures under latent confounding and selection (Carey Ryan, 2025) [View paper](#)
 - Discovery in Time Series and Dynamic Systems (3 papers)
 - [16] InvarGC: Invariant Granger Causality for Heterogeneous Interventional Time Series under Latent Confounding (Zhang Ziyi, 2025) [View paper](#)
 - [36] Time Series Causal Link Estimation under Hidden Confounding using Knockoff Interventions (Trifunov, 2022) [View paper](#)
 - [39] Learning Causal Markov Boundaries with Mixed Observational and Experimental Data (K Lelova, 2024) [View paper](#)
 - Discovery with Cyclic Structures or Specialized Constraints (2 papers)
 - [46] Comparative Study of Causal Discovery Methods for Cyclic Models with Hidden Confounders (Lorbeer, 2023) [View paper](#)
 - [50] Discovery and Inference of a Causal Network with Hidden Confounding (Chen Li, 2023) [View paper](#)
- Causal Effect Estimation and Inference
 - Effect Estimation with Hidden Confounding (6 papers)
 - [22] Removing hidden confounding by experimental grounding (Kallus, 2018) [View paper](#)
 - [26] Learning Joint Nonlinear Effects from Single-variable Interventions in the Presence of Hidden Confounders (Sorawit Saengkyongam, 2022) [View paper](#)
 - [31] Estimating long-term causal effects from short-term experiments and long-term observational data with unobserved confounding (Maystre, 2023) [View paper](#)
 - [33] B-Learner: Quasi-Oracle Bounds on Heterogeneous Causal Effects Under Hidden Confounding (Oprescu, 2023) [View paper](#)

- [41] Ensembled Prediction Intervals for Causal Outcomes Under Hidden Confounding (Marmarelis, 2023) [View paper](#)
- [44] Disentangling Causal Effects from Sets of Interventions in the Presence of Unobserved Confounders (Jeunen, 2022) [View paper](#)
- Mediation Analysis with Post-Treatment Confounding (3 papers)
- [10] Mediation analysis in longitudinal intervention studies with an ordinal treatment-dependent confounder (HÃ¤rkÃ¤nen, 2025) [View paper](#)
- [19] Non-agency interventions for causal mediation in the presence of intermediate confounding (DÃ¡az, 2023) [View paper](#)
- [29] A Bayesian nonparametric approach for causal mediation with a post-treatment confounder. (Woojung Bae, 2024) [View paper](#)
- Effect Estimation in Longitudinal and Clustered Studies (3 papers)
- [7] When Should We Use Unit Fixed Effects Regression Models for Causal Inference with Longitudinal Data? (Kosuke Imai, 2019) [View paper](#)
- [23] Learning causal effect of physical activity distribution: an application of functional treatment effect estimation with unmeasured confounding. (Zhang, 2025) [View paper](#)
- [24] Identification and estimation of causal mechanisms in cluster-randomized trials with post-treatment confounding using Bayesian nonparametrics (Ohnishi, 2025) [View paper](#)
- Data Fusion and Multi-Source Causal Inference (3 papers)
- [14] Learning treatment effects from observational and experimental data (S Triantafillou, 2023) [View paper](#)
- [27] Eliminating confounder-induced bias in the statistics of intervention (Loukas, 2023) [View paper](#)
- [30] A General Identification Algorithm For Data Fusion Problems Under Systematic Selection (Lee, 2024) [View paper](#)
- Causal Inference Under Network Interference (2 papers)
- [32] On Evolution-Based Models for Experimentation Under Interference (Sadegh Shirani, 2025) [View paper](#)
- [34] Network Causal Effect Estimation In Graphical Models Of Contagion And Latent Confounding (WU Yufeng, 2024) [View paper](#)
- Machine Learning Integration with Causal Inference
 - Causal Representation and Disentanglement Learning (3 papers)
 - [5] A copula-based deep graphical causal model for multivariate conditional treatment effect estimation (Kim, 2025) [View paper](#)
 - [28] A Unifying Framework for Causal Imitation Learning with Hidden Confounders (Shao, 2025) [View paper](#)
 - [42] Causal Representation Learning via Counterfactual Intervention (Feng Rui, 2024) [View paper](#)
 - Causal Reinforcement Learning and Sequential Decision-Making (3 papers)
 - [8] Causal reinforcement learning using observational and interventional data (Gasse, 2021) [View paper](#)
 - [43] Active bayesian causal inference (Toth, 2022) [View paper](#)
 - [45] Causal Reinforcement Learning for Bandits with Unobserved Confounders (Ming-wei, 2023) [View paper](#)
 - Causal Intervention in Deep Learning Applications (4 papers)
 - [4] Causal-TSF: A Causal Intervention Approach to Mitigate Confounding Bias in Time Series Forecasting (Qinkang Gong, 2025) [View paper](#)
 - [18] DICCR: Double-gated intervention and confounder causal reasoning for vision-language navigation. (Dongming Zhou, 2025) [View paper](#)
 - [20] Integrating Causal Inference with Graph Neural Networks for Alzheimer's Disease Analysis (Pranay Kumar Peddi, 2025) [View paper](#)
 - [47] Causal Intervention for Mitigating Name Bias in Machine Reading Comprehension (Jiazheng Zhu, 2023) [View paper](#)
 - Causal Machine Learning for Prediction and Recommendation (3 papers)
 - [12] Combining causal analysis and machine learning to predict the effects of interventions (Kitov, 2025) [View paper](#)
 - [38] MSCT: Addressing Time-Varying Confounding with Marginal Structural Causal Transformer for Counterfactual Post-Crash Traffic Prediction (Li Shuang, 2024) [View paper](#)
 - [40] Mitigating Confounding and Selection Biases in Personalized Recommendation: A Causal Approach (Wen Huang, 2023) [View paper](#)
- Methodological Foundations and Theoretical Advances
 - Identifiability and Sensitivity Analysis (3 papers)
 - [17] Methodological Advances in Causal Inference: Experimentation, Identification and Estimation (Akbari, 2025) [View paper](#)
 - [35] Causal and interventional markov boundaries (S Triantafillou, 2021) [View paper](#)
 - [48] Modeling Latent Selection with Structural Causal Models (Chen, 2024) [View paper](#)
 - Conceptual Frameworks and Bias Understanding (3 papers)
 - [11] Understanding uncertainty and bias to improve causal inference in health intervention research (Tim Watkins, 2019) [View paper](#)
 - [13] Causality-based fair multiple decision by response functions (Cong Su, 2024) [View paper](#)
 - [49] Don't confound yourself: Causality from biased data (Kaltenpoth, 2025) [View paper](#)
- Domain-Specific Applications (4 papers)
 - [3] Causal inference and counterfactual prediction in machine learning for actionable healthcare (Mattia Prospero, 2020) [View paper](#)
 - [21] Use of artificial intelligence for the analysis of potential pharmacovigilance signals upon Real-world data (Dimitsaki, 2025) [View paper](#)
 - [25] Machine learning-enhanced causal inference of surgical decisions and rehabilitation strategies in traumatic brain injury (Elyas Irankhah, 2025) [View paper](#)
 - [37] Causal Graph Generation and Validation for Cognitive 6G Networks (Mehmet Karaca, 2025) [View paper](#)

Narrative

Core task: interventional causal discovery with latent confounders and post-treatment selection. This field addresses the challenge of learning causal structures from experimental or interventional data when some confounding variables remain unmeasured and when selection mechanisms operate after treatment assignment. The taxonomy organizes research into several main branches. Causal Discovery from Interventional Data focuses on algorithms that exploit experimental manipulations to identify causal graphs, including methods that handle unknown intervention targets (Unknown Intervention Targets[1]) or soft interventions (Soft Interventions Discovery[2]). Causal Effect Estimation and Inference develops techniques for quantifying treatment effects under various complications such as hidden confounding or selection bias. Machine Learning Integration with Causal Inference bridges modern predictive models with causal reasoning, while Methodological Foundations and Theoretical Advances establish identifiability conditions and statistical guarantees. Domain-Specific Applications translate these methods to healthcare, policy evaluation, and other real-world settings where latent confounders and selection are pervasive.

A particularly active line of work examines the interplay between selection bias and interventional data, exploring when and how experimental information can overcome post-treatment selection issues that would otherwise obscure causal relationships. Within this landscape, Latent Confounders Interventional[0] sits at the intersection of discovery methods that must simultaneously address hidden confounding and selection mechanisms, closely related to Selection Meets Intervention[6] which explicitly studies how selection processes interact with experimental designs. Nearby works such as Iterative Causal Discovery[9] and Distinguishability Causal Structures[15] tackle complementary challenges: iterative refinement of causal hypotheses and the fundamental question of when different causal models can be distinguished from interventional distributions. These studies collectively highlight a central trade-off between the richness of interventional information available and the complexity of latent structure one can hope to recover, with ongoing questions about minimal experimental designs and the role of parametric or independence assumptions in achieving identifiability.

Related Works in Same Category

The following **3 sibling papers** share the same taxonomy leaf node with the original paper:

1. When Selection Meets Intervention: Additional Complexities in Causal Discovery

Authors: Dai, Haoyue, Ng, Ignavier, Sun Jian-Le, et al. (12 authors total) | **Year/Venue:** 2025 | **URL:** [View paper](#)

Abstract

We address the common yet often-overlooked selection bias in interventional studies, where subjects are selectively enrolled into experiments. For instance, participants in a drug trial are usually patients of the relevant disease; A/B tests on mobile applications target existing users only, and gene perturbation studies typically focus on specific cell types, such as cancer cells. Ignoring this bias leads to incorrect causal discovery results. Even when recognized, the existing paradigm for int...

Relationship Analysis

Both papers belong to the same taxonomy category addressing causal discovery with latent confounders and selection bias from interventional data. They share overlapping focus on handling post-treatment selection bias in interventional causal discovery, both proposing augmented DAG frameworks and novel graphical representations (F-PAG vs. augmented MAG). The key difference is that the original paper introduces F-PAG with fine-grained interventional Markov equivalence and the F-FCI algorithm, while the candidate paper focuses on distinguishing when and where interventions occur relative to selection, proposing a different graphical model that explicitly captures observed vs. counterfactual worlds.

2. Iterative Causal Discovery in the Possible Presence of Latent Confounders and Selection Bias

Authors: Rohekar, Raanan Y., Raanan Y. Rohekar, Nisimov, Shami, et al. (12 authors total) | **Year/Venue:** 2021 • Neural Information Processing Systems | **URL:** [View paper](#)

Abstract

We present a sound and complete algorithm, called iterative causal discovery (ICD), for recovering causal graphs in the presence of latent confounders and selection bias. ICD relies on the causal Markov and faithfulness assumptions and recovers the equivalence class of the underlying causal graph. It starts with a complete graph, and consists of a single iterative stage that gradually refines this graph by identifying conditional independence (CI) between connected nodes. Independence and causal...

Relationship Analysis

Both papers belong to the same taxonomy category addressing causal discovery with latent confounders and selection bias from interventional data. They overlap in handling latent confounders and selection bias, but differ fundamentally in their approach: the original paper explicitly models post-treatment selection (selection occurring after interventions) and introduces F-PAG representation with FI-Markov equivalence, while the candidate paper (ICD) focuses on an iterative algorithm that gradually refines causal graphs by controlling conditioning set sizes based on graph distance, without specifically addressing the post-treatment selection problem that is central to the original work.

3. Distinguishability of causal structures under latent confounding and selection

Authors: Carey Ryan, Wolfe, Elie, Evans, Robin J. | **Year/Venue:** 2025 • arXiv (Cornell University) | **URL:** [View paper](#)

Abstract

Statistical relationships in observed data can arise for several different reasons: the observed variables may be causally related, they may share a latent common cause, or there may be selection bias. Each of these scenarios can be modelled using different causal graphs. Not all such causal graphs, however, can be distinguished by experimental data. In this paper, we formulate the equivalence class of causal graphs as a novel graphical structure, the selected-marginalized directed graph (smDG)...

Relationship Analysis

Both papers belong to the same taxonomy category addressing causal discovery with latent confounders and selection bias from interventional data. They overlap in their focus on distinguishing causal structures under both latent confounding and selection effects using interventional experiments. However, the original paper specifically addresses post-treatment selection (selection occurring after interventions) and proposes F-PAG and F-FCI algorithm for learning FI-Markov equivalence classes, while the candidate paper focuses on characterizing interventional equivalence classes more broadly through selected-marginalized directed graphs (smDGs) without specifically emphasizing the post-treatment selection problem.

Contributions Analysis

Overall novelty summary. The paper introduces a causal formulation that explicitly models post-treatment selection alongside latent confounders in interventional causal discovery. It resides in the 'Discovery with Latent Confounders and Selection Bias' leaf, which contains four papers total (including this one). This leaf addresses a relatively specialized intersection of challenges—combining hidden confounding with selection mechanisms—suggesting a moderately sparse research direction within the broader interventional discovery landscape. The taxonomy shows that most discovery work either handles unknown intervention targets or focuses on time series, indicating that joint treatment of confounding and selection remains less crowded than other discovery subfields.

The taxonomy reveals neighboring leaves focused on unknown intervention targets, time series discovery, and cyclic structures, all under the 'Causal Discovery from Interventional Data' branch. The paper's leaf explicitly excludes methods handling only confounding or only selection, positioning it at a unique intersection. Nearby work on effect estimation (e.g., 'Effect Estimation with Hidden Confounding') addresses confounding but not structure learning, while 'Mediation Analysis with Post-Treatment Confounding' examines post-treatment variables in a different context. The taxonomy's scope notes clarify that this leaf is distinct from purely observational methods and from discovery approaches that assume known intervention targets, highlighting the paper's focus on a specific gap where selection bias meets interventional structure learning.

Among 28 candidates examined across three contributions, none were flagged as clearly refuting any contribution. Contribution A (novel causal formulation) examined 9 candidates with 0 refutable; Contribution B (FI-Markov equivalence and F-PAG) examined 9 with 0 refutable; Contribution C (F-FCI algorithm) examined 10 with 0 refutable. This suggests that within the limited search scope, no prior work was found that directly anticipates the joint modeling of post-treatment selection and latent confounders in interventional discovery.

The absence of refutable candidates across all contributions indicates that the specific formulation and algorithmic framework appear novel relative to the examined literature, though the search was not exhaustive.

Based on the limited search of 28 candidates and the taxonomy structure, the work appears to occupy a relatively underexplored niche. The leaf contains only four papers, and no examined candidates refute the core contributions, suggesting that the explicit treatment of post-treatment selection in interventional discovery with latent confounders is not yet well-covered. However, this assessment is constrained by the search scope and does not rule out relevant work outside the top-K semantic matches or citation network examined.

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: Novel causal formulation modeling post-treatment selection with latent confounders

Description: The authors propose a new causal framework that explicitly incorporates post-treatment selection alongside latent confounders. This formulation leverages differential responses to interventions to distinguish genuine causal relations from spurious dependencies induced by selection bias, addressing a gap in existing interventional causal discovery paradigms.

This contribution was assessed against **9 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Beyond overall treatment effects: Leveraging covariates in randomized experiments guided by causal structure

URL: [View paper](#)

Brief Assessment

Beyond Overall Effects[75] focuses on leveraging covariates in randomized experiments for heterogeneous treatment effects, not on causal discovery with post-treatment selection and latent confounders using interventional data.

2. Doubly robust identification of treatment effects from multiple environments

URL: [View paper](#)

Brief Assessment

Doubly Robust Identification[71] addresses treatment effect estimation from multiple environments with post-treatment variables and unobserved confounders, but focuses on treatment effect identification rather than causal discovery. The original paper proposes a causal discovery framework with interventional data, while the candidate focuses on observational data analysis across environments without learning the causal graph structure.

3. Causal inference and bias in learning analytics: A primer on pitfalls using directed acyclic graphs

URL: [View paper](#)

Brief Assessment

Learning Analytics Primer[70] is a primer on causal inference and bias in learning analytics using directed acyclic graphs. It does not present a novel causal discovery framework or algorithm for handling post-treatment selection with latent confounders using interventional data.

4. A mixed framework for causal impact analysis under confounding and selection biases: a focus on Egra dataset

URL: [View paper](#)

Brief Assessment

Mixed Framework Impact[69] focuses on causal impact estimation in a specific intervention program (Egra dataset) using DAG structures, not on developing a general causal discovery framework that explicitly models post-treatment selection alongside latent confounders or characterizes interventional equivalence classes.

5. Causal inference and counterfactual prediction in machine learning for actionable healthcare

URL: [View paper](#)

Brief Assessment

Actionable Healthcare Inference[3] focuses on healthcare applications of causal inference and counterfactual prediction. The provided context fragments are too sparse to assess whether it addresses post-treatment selection with latent confounders in the specific interventional causal discovery framework proposed by the original paper.

6. Causal-TSF: A Causal Intervention Approach to Mitigate Confounding Bias in Time Series Forecasting

URL: [View paper](#)

Brief Assessment

Causal Time Series[4] focuses on mitigating confounding bias in time series forecasting through causal intervention, not on causal discovery with post-treatment selection bias and latent confounders from interventional data.

7. Partial Structure Discovery is Sufficient for No-regret Learning in Causal Bandits

URL: [View paper](#)

Brief Assessment

Partial Structure Discovery[73] addresses causal bandits with unknown causal graphs and latent confounders for regret minimization, not interventional causal discovery with post-treatment selection bias. The candidate focuses on identifying optimal intervention arms in bandit settings, while the original paper develops a framework for distinguishing post-treatment selection from causal relations using distributional changes.

8. Mediation and moderation of treatment effects in randomised controlled trials of complex interventions

URL: [View paper](#)

Brief Assessment

Mediation Moderation Treatment[74] focuses on mediation analysis in randomized controlled trials with post-randomisation intermediate variables, not on causal discovery with latent confounders and post-treatment selection bias. The candidate addresses treatment effect decomposition in clinical trials, while the original develops interventional causal discovery methods.

9. Constraint-based causal discovery for non-linear structural causal models with cycles and latent confounders

URL: [View paper](#)

Brief Assessment

Cycles Latent Confounders[72] addresses causal discovery in non-linear structural causal models with cycles and latent confounders, but does not explicitly model post-treatment selection bias. The paper focuses on σ -separation for handling cycles and confounders, not on distinguishing post-treatment selection from causal relations.

Contribution 2: FI-Markov equivalence and F-PAG graphical representation

Description: The authors define a Fine-grained Interventional Markov equivalence class (FI-Markov equivalence) that refines traditional equivalence classes by exploiting interventional data. They introduce F-PAG, an extension of the Partial Ancestral Graph with novel edge types, to provide a more expressive graphical representation of this equivalence class.

This contribution was assessed against **9 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Sample Efficient Bayesian Learning of Causal Graphs from Interventions

URL: [View paper](#)

Brief Assessment

Bayesian Interventions Learning[57] focuses on Bayesian learning of causal graphs with limited interventional samples and uniform DAG sampling, not on defining fine-grained interventional Markov equivalence classes or novel graphical representations like F-PAG for post-treatment selection scenarios.

2. Efficient Causal Structure Learning from Multiple Interventional Datasets with Unknown Targets

URL: [View paper](#)

Brief Assessment

Multiple Interventional Datasets[55] focuses on interventional Markov equivalence classes (I-MEC) for multiple datasets with unknown intervention targets, while the original paper addresses post-treatment selection and latent confounders with known interventions, defining FI-Markov equivalence with F-PAG representation—fundamentally different problem settings and graphical frameworks.

3. Causal discovery from observational and interventional data across multiple environments

URL: [View paper](#)

Brief Assessment

Multiple Environments Discovery[52] focuses on learning causal structures across multiple domains using selection diagrams and s -nodes to represent domain changes, whereas the original paper addresses post-treatment selection within interventional causal discovery using F-PAG to distinguish selection from causal relations. These are fundamentally different problem settings with distinct graphical representations.

4. Permutation-based causal structure learning with unknown intervention targets

URL: [View paper](#)

Brief Assessment

Permutation Structure Learning[53] focuses on interventional Markov equivalence classes (I-MECs) for DAGs with unknown intervention targets in the absence of latent confounders and selection bias. The original paper addresses a fundamentally different problem: fine-grained interventional Markov equivalence (FI-Markov equivalence) that explicitly models post-treatment selection alongside latent confounders, introducing novel F-PAG representations with specialized edge types (\blacktriangleleft , \blacktriangle , \square) not present in standard PAG frameworks.

5. Interventional Causal Structure Discovery over Graphical Models with Convergence and Optimality Guarantees

URL: [View paper](#)

Brief Assessment

Interventional Structure Discovery[51] focuses on causal structure learning from observational and interventional data using polynomial optimization methods, not on defining Markov equivalence classes or graphical representations like F-PAG for post-treatment selection scenarios.

6. Discovering causal structures in Bayesian Gaussian directed acyclic graph models

URL: [View paper](#)

Brief Assessment

Gaussian DAG Discovery[58] focuses on Bayesian active learning for optimal intervention design in Gaussian DAGs, addressing Markov equivalence through sequential intervention selection. It does not propose new equivalence class definitions or graphical representations like F-PAG that explicitly model post-treatment selection.

7. Jointly interventional and observational data: estimation of interventional Markov equivalence classes of directed acyclic graphs

URL: [View paper](#)

Brief Assessment

Interventional Observational Data[56] focuses on jointly interventional and observational data for estimating interventional Markov equivalence classes in Gaussian causal models, but does not address post-treatment selection or latent confounders in the same framework as the original paper's FI-Markov equivalence.

8. Causal discovery from soft interventions with unknown targets: Characterization and learning

URL: [View paper](#)

Brief Assessment

Soft Interventions Discovery[2] focuses on soft interventions with unknown targets in non-Markovian systems, defining Σ -Markov equivalence and Σ -PAG. The original paper addresses post-treatment selection bias with FI-Markov equivalence and F-PAG, which are fundamentally different problems requiring distinct graphical representations.

9. Causal identification under Markov equivalence: calculus, algorithm, and completeness

URL: [View paper](#)

Brief Assessment

Markov Equivalence Calculus[54] focuses on causal identification from Markov equivalence classes (PAGs) in the context of interventional data, not on handling post-treatment selection or latent confounders with the specific FI-Markov equivalence framework proposed in the original paper.

Contribution 3: F-FCI algorithm for causal discovery with soundness and completeness guarantees

Description: The authors develop the F-FCI algorithm, which recovers causal structures, latent confounders, and post-treatment selection up to FI-Markov equivalence from observational and interventional data. The algorithm is proven to be both sound and complete under the proposed formulation.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Causal discovery with unobserved confounding and non-gaussian data

URL: [View paper](#)

Brief Assessment

Non-gaussian Causal Discovery[68] focuses on recovering causal structure from observational data with latent confounders using non-Gaussian assumptions, but does not address post-treatment selection or interventional data, which are central to the F-FCI algorithm's novelty.

2. On the completeness of orientation rules for causal discovery in the presence of latent confounders and selection bias

URL: [View paper](#)

Brief Assessment

Orientation Rules Completeness[67] focuses on proving completeness of orientation rules for standard causal discovery settings, whereas the original paper develops F-FCI specifically for post-treatment selection scenarios with novel graphical representations (F-PAG) and fine-grained interventional equivalence classes.

3. Constraint-based causal discovery with tiered background knowledge and latent variables in single or overlapping datasets

URL: [View paper](#)

Brief Assessment

Tiered Background Knowledge[59] focuses on constraint-based causal discovery with tiered background knowledge in settings with latent variables and overlapping datasets, introducing the TFCI and TIOD algorithms. The original paper's F-FCI addresses post-treatment selection alongside latent confounders using interventional data, which is a fundamentally different problem setting and methodological approach.

4. Identifying macro conditional independencies and macro total effects in summary causal graphs with latent confounding

URL: [View paper](#)

Brief Assessment

Macro Conditional Independencies[60] focuses on summary causal graphs for time series data with macro/micro queries, not interventional causal discovery with latent confounders and post-treatment selection as in the original paper.

5. Modular Learning of Deep Causal Generative Models for High-dimensional Causal Inference

URL: [View paper](#)

Brief Assessment

Modular Deep Causal[63] focuses on learning deep causal generative models for high-dimensional data (e.g., images) using adversarial training and pre-trained models, not on causal structure discovery from observational/interventional data with latent confounders and selection bias.

6. Conditional Instrumental Variable Regression with Representation Learning for Causal Inference

URL: [View paper](#)

Brief Assessment

Conditional Instrumental Variable[66] focuses on causal effect estimation using instrumental variables in the presence of unobserved confounders, not on causal structure discovery algorithms. The paper does not address causal discovery, Markov equivalence classes, or graphical model learning.

7. Sound and complete causal identification with latent variables given local background knowledge

URL: [View paper](#)

Brief Assessment

Sound Complete Identification[62] addresses causal identification with local background knowledge in the presence of latent confounders, not post-treatment selection. The candidate focuses on orientation rules given local BK, while the original paper handles post-treatment selection bias—a fundamentally different problem setting.

8. On the completeness of causal discovery in the presence of latent confounding with tiered background knowledge

URL: [View paper](#)

Brief Assessment

Completeness Latent Confounding[64] addresses causal discovery with tiered background knowledge using the standard FCI algorithm, whereas the original paper proposes F-FCI specifically for handling post-treatment selection alongside latent confounders. The candidate focuses on a different problem setting (tiered knowledge constraints) rather than post-treatment selection mechanisms.

9. High-recall causal discovery for autocorrelated time series with latent confounders

URL: [View paper](#)

Brief Assessment

Autocorrelated Time Series[61] focuses on causal discovery from time series data with autocorrelation, while the original paper addresses post-treatment selection in interventional settings. These are fundamentally different problem domains with distinct technical challenges.

10. Causal discovery with hidden confounders using the algorithmic Markov condition

URL: [View paper](#)

Brief Assessment

Algorithmic Markov Condition[65] focuses on discovering latent confounders using the algorithmic Markov condition and MDL principle, not on handling post-treatment selection or interventional data. The technical approaches and problem settings differ fundamentally.

Appendix: Text Similarity Detection

No high-similarity text segments were detected across any compared papers.

References

- [0] Characterization and Learning of Causal Graphs with Latent Confounders and Post-treatment Selection from Interventional Data [View paper](#)
- [1] Learning unknown intervention targets in structural causal models from heterogeneous data [View paper](#)
- [2] Causal discovery from soft interventions with unknown targets: Characterization and learning [View paper](#)
- [3] Causal inference and counterfactual prediction in machine learning for actionable healthcare [View paper](#)
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