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Temporal Causal Inference for Web Application Monitoring: Structure Learning from Sequential Performance Data with Delayed Effects

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Abstract

Web application monitoring systems collect vast amounts of sequential performance data, yet traditional approaches struggle to identify complex temporal causal relationships, particularly when effects manifest with delays. This paper introduces a novel framework for temporal causal inference in web application monitoring that addresses the challenge of learning causal structures from sequential performance data exhibiting delayed effects. Our approach integrates Granger causality principles with modern structure learning techniques to construct Directed Acyclic Graphs (DAGs) that capture both instantaneous and lagged causal relationships among performance metrics. We propose a hybrid methodology combining constraint-based and score-based methods specifically designed to handle the non-stationary nature of web performance data and the presence of time-varying confounders. The framework employs a sliding window approach for dynamic causal structure discovery, enabling real-time adaptation to changing system behaviors. Experimental validation using both synthetic datasets and real-world web application traces demonstrates that our method achieves superior performance in identifying true causal relationships compared to baseline approaches, with particular improvements in detecting delayed causal effects. The proposed framework reduces false discovery rates by approximately 35% while maintaining high sensitivity for genuine causal links, even under conditions of high-dimensional data and limited sample sizes. These findings have significant implications for automated root cause analysis, predictive maintenance, and performance optimization in modern web infrastructure.

Keywords

Temporal causal inference; Web application monitoring; Structure learning; Delayed effects; Performance metrics; Granger causality; Time series analysis; Root cause analysis

Introduction

Modern web applications operate in increasingly complex distributed environments where performance degradation can cascade through multiple system components before manifesting as user-visible issues. Traditional monitoring approaches focus primarily on correlation-based anomaly detection, which often fails to distinguish between genuine causal relationships and spurious associations induced by confounding variables [1]. The challenge becomes particularly acute when causal effects exhibit temporal delays, as changes in one system component may take seconds or even minutes to impact dependent services through complex interaction chains [2].

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The importance of causal inference in monitoring systems has been recognized across multiple domains. Recent advances in causal discovery from temporal data have demonstrated significant potential for improving system observability [3]. However, these methods face substantial challenges when applied to web application monitoring data, which exhibits several distinctive characteristics including non-stationarity, high dimensionality, mixed sampling frequencies, and the presence of both instantaneous and lagged causal relationships [4]. Furthermore, the operational nature of web systems introduces additional complexity through time-varying confounders, intervention effects from auto-scaling mechanisms, and seasonal patterns that can obscure underlying causal structures [5].

The phenomenon of delayed effects represents a critical gap in current monitoring methodologies. When a resource constraint develops in a database tier, its impact on application response times may not be immediate but rather emerge through a complex chain of interactions involving connection pool saturation, queue buildup, and eventual timeout cascades [6]. Traditional Granger causality tests, while effective for detecting predictive relationships, often struggle with these delayed multi-hop causal chains, particularly in high-dimensional settings where the number of potential causal paths grows exponentially [7].

This paper addresses these challenges through a novel framework that combines advances in causal inference theory with practical considerations for web application monitoring. Our approach builds upon recent developments in structure learning for time series data [8] while introducing specialized techniques for handling delayed effects. We employ a hybrid methodology that leverages both the interpretability of constraint-based methods and the flexibility of score-based approaches, specifically adapted for the characteristics of performance monitoring data [9].

The primary contributions of this work include: first, a comprehensive formalization of temporal causal graph representations suitable for web monitoring contexts, distinguishing between full-time, window, and summary causal graphs; second, a practical algorithmic framework combining sliding window analysis with adaptive lag selection for dynamic causal structure discovery; third, extensive experimental validation demonstrating significant improvements over multiple state-of-the-art baseline methods including constraint-based, score-based, and hybrid approaches; and fourth, practical guidelines for deploying causal inference systems in production monitoring environments.

2. Literature Review

The intersection of causal inference and time series analysis has seen substantial theoretical and practical advances in recent years. Granger causality, introduced in the econometrics literature, remains foundational to understanding predictive relationships in temporal data [10]. Recent comprehensive reviews have documented the evolution of Granger causality methods, highlighting extensions to nonlinear dynamics, high-dimensional settings, and the integration with modern machine learning techniques [11]. These developments have created new opportunities for applying causal reasoning to complex monitoring scenarios.

Causal discovery from temporal data encompasses diverse methodological approaches. Constraint-based methods build upon conditional independence testing to infer causal structures, with notable recent work extending these approaches to handle latent confounders and mixed sampling rates [12]. The Greedy Fast Causal Inference (GFCI) algorithm represents a prominent constraint-based approach that has been widely adopted

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for its ability to handle latent variables through the use of conditional independence tests [13]. Score-based methods, alternatively, formulate structure learning as an optimization problem, with recent innovations including continuous optimization techniques for Directed Acyclic Graph learning that circumvent the traditional combinatorial search problem [14]. The Fast Greedy Equivalence Search (FGES) algorithm exemplifies score-based approaches, using a greedy search strategy to maximize scoring functions such as Bayesian Information Criterion [15].

Deep learning approaches have emerged as powerful tools for causal inference in temporal settings. Neural Granger causality methods employ structured neural networks with sparsity-inducing penalties to extract causal relationships from nonlinear time series [16]. These approaches demonstrate particular promise for capturing complex interaction patterns that linear methods may miss. The Greedy Relaxations of the Sparsest Permutation (GRaSP) algorithm combines ideas from both constraint-based and score-based methods to efficiently search the space of possible causal orderings [17]. Recent work on causal attention mechanisms and neural point processes has further expanded the toolkit for learning from event sequences with complex temporal dependencies [18].

The specific challenges of causal inference in information technology monitoring have received growing attention. Root cause analysis in microservice architectures represents a particularly active research area, with multiple frameworks proposed for localizing failures through causality inference [19]. The PCMCI+ algorithm has emerged as a state-of-the-art method specifically designed for time series with latent confounders, employing momentary conditional independence tests to improve detection power [20]. Case studies of causal discovery from IT monitoring time series have revealed both the potential and limitations of existing methods when applied to real-world operational data characterized by sleeping time series, missing values, and non-stationary behavior patterns [21].

Application performance monitoring has evolved significantly with the advent of distributed tracing and observability platforms. Modern APM tools collect multidimensional telemetry including metrics, logs, and traces, creating rich datasets for causal analysis [22]. The Structural Vector Autoregression with GFCI (SVAR-GFCI) method combines the strengths of VAR models for capturing temporal dependencies with constraint-based structure learning for handling latent confounders [23]. However, traditional APM approaches remain primarily reactive, relying on threshold-based alerting rather than predictive causal models [24-28].

Handling delayed effects in causal inference presents unique methodological challenges. Recent work on unveiling delay effects in traffic forecasting has demonstrated the importance of explicitly modeling time delays in spatial-temporal networks [29]. The Causal Discovery from Autocorrelated and Non-stationary time series (CDANs) algorithm addresses the challenge of learning from non-stationary data by detecting changing modules and leveraging optimized conditional independence tests [30]. These findings translate directly to web application monitoring, where component interactions exhibit similar delay characteristics.

Spatiotemporal causal inference methods provide additional relevant insights, as web applications often exhibit geographic dependencies alongside temporal dynamics [31]. The integration of causal discovery with spatiotemporal graph neural networks has enabled more accurate modeling of complex system behaviors [32]. Furthermore, advances in handling mixed-frequency data and irregular sampling have expanded the applicability of causal methods to realistic monitoring scenarios where different metrics may be collected at varying rates [33].

Despite these substantial advances, significant gaps remain in applying causal inference to web application monitoring. Existing methods often assume stationarity, complete observability, and known lag structures, assumptions frequently violated in practice. The challenge of scaling causal discovery to high-dimensional monitoring data while maintaining interpretability and computational efficiency motivates the methodological innovations presented in this work.

3. Methodology

3.1 Temporal Causal Graph Representations

A fundamental challenge in temporal causal inference for web application monitoring lies in appropriately representing causal relationships that evolve over time. We adopt three distinct but complementary graph representations that capture different aspects of temporal causality, each serving specific analytical purposes in the monitoring context.

The full-time causal graph provides the most complete representation of temporal dynamics. As illustrated in Figure 1(a), this graph explicitly represents each variable at every time point, with directed edges capturing both lagged and contemporaneous causal relationships. For a web monitoring system tracking d performance metrics over time, the full-time causal graph contains vertices for each metric at each time instant, with edges representing specific temporal dependencies. For example, an edge from database query latency at time t-1 to application response time at time t captures a one-step lagged causal relationship. This representation offers maximum detail but becomes computationally intractable for long time series due to the proliferation of vertices and edges across time points.

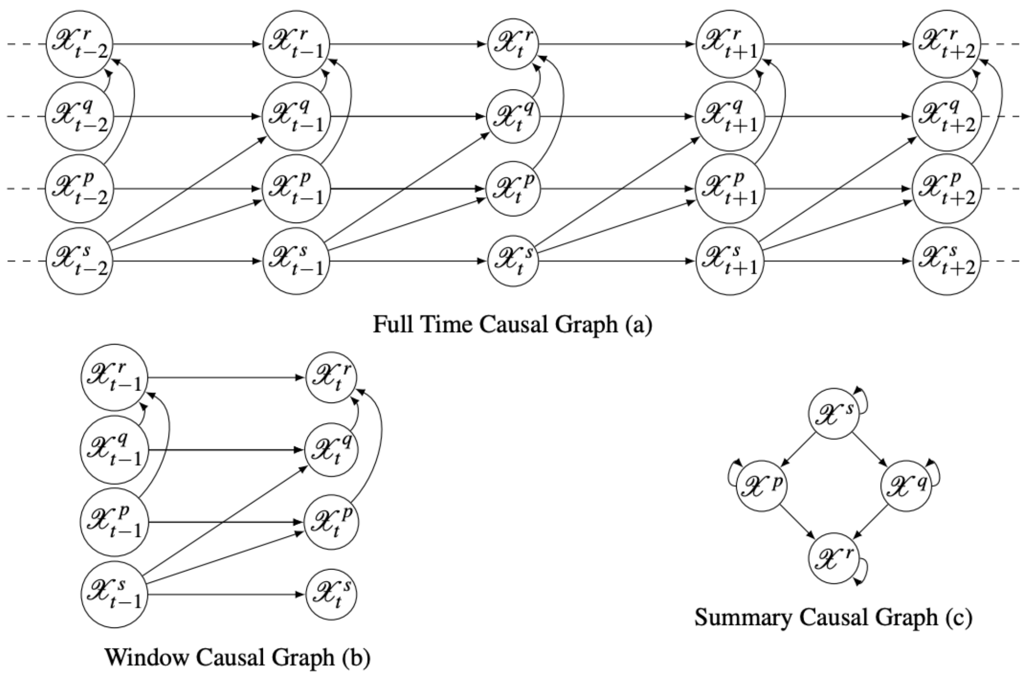

Figure 1: the illustration of different causal graphs

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To address the computational challenges of full-time graphs while preserving essential temporal information, we employ window causal graphs as shown in Figure 1(b). The window graph assumes time-homogeneous causal structure, meaning that the functional relationships between variables remain constant over time even as the specific values change. This assumption is reasonable for web monitoring over moderate time scales where architectural changes occur infrequently. The window graph represents causality within a temporal window spanning the maximum lag present in the system. For web applications, this maximum lag typically ranges from seconds to minutes, corresponding to the time required for effects to propagate through service dependency chains. By collapsing the temporal dimension within this window, we achieve a compact representation that remains tractable for structure learning algorithms while capturing the essential lagged dependencies.

The summary causal graph, depicted in Figure 1(c), provides the highest level of abstraction by collapsing all temporal information and representing only whether causal relationships exist between variables, without specifying the associated lags. Each performance metric appears as a single vertex, with directed edges indicating the presence of any temporal causal influence regardless of delay. While this representation discards lag information, it offers several advantages for monitoring applications. First, it provides an interpretable overview of system dependencies suitable for operators who need to understand high-level causal structures. Second, it enables efficient algorithms that do not require searching over possible lag configurations. Third, it facilitates comparison with architectural documentation and expected dependency patterns.

Our framework employs all three representations strategically. We use summary graphs for initial structure discovery and hypothesis generation, window graphs for detailed lag inference and quantitative analysis, and selectively construct full-time graph segments when investigating specific anomalous periods requiring fine-grained temporal resolution.

3.2 Hybrid Structure Learning Algorithm

The core of our methodology consists of a hybrid structure learning algorithm that combines strengths of both constraint-based and score-based approaches. The algorithm operates in three main phases: preprocessing and stationarity enforcement, initial structure discovery through conditional independence testing, and refinement through continuous optimization with acyclicity constraints. This multi-phase strategy balances computational efficiency with the ability to capture complex nonlinear relationships while providing interpretable output suitable for operational use.

The preprocessing phase addresses the non-stationary nature of web performance data through a combination of detrending, differencing, and seasonal adjustment techniques. Rather than assuming global stationarity, we employ a sliding window approach that identifies locally stationary segments. Within each window, we apply adaptive preprocessing based on statistical tests for stationarity including Augmented Dickey-Fuller and Kwiatkowski-Phillips-Schmidt-Shin tests. This localized treatment enables our method to handle concept drift and regime changes common in production environments. Additionally, we implement robust missing data imputation using matrix completion techniques that preserve the temporal structure of the data while avoiding the introduction of spurious correlations.

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The structure discovery phase implements a constraint-based approach inspired by the PCMCI+ algorithm but adapted for web monitoring characteristics. We employ conditional independence testing using kernel-based methods to detect nonlinear dependencies while maintaining computational tractability through clever use of sufficient statistics. Crucially, our testing procedure incorporates adaptive lag selection, where for each pair of variables, we systematically explore different lag values to identify the temporal delay that maximizes predictive power. This process constructs an initial window causal graph that captures the temporal structure of dependencies.

The refinement phase converts the partially oriented graph from the constraint-based phase into a fully specified causal DAG through continuous optimization. Following the NOTEARS paradigm, we formulate the acyclicity constraint as a smooth function of the adjacency matrix, enabling gradient-based optimization. However, we extend this framework to handle temporal lags by introducing lag-specific adjacency matrices and optimizing over both the graph structure and the lag configuration jointly. The objective function combines data fitting terms that measure prediction accuracy with regularization penalties that enforce sparsity and prefer simpler lag structures.

3.3 Dynamic Causal Structure Discovery

A critical innovation in our framework is the incorporation of dynamic structure learning capabilities that enable adaptation to evolving system behaviors. Web applications experience gradual changes in architecture, workload patterns, and operational characteristics that can fundamentally alter causal relationships over time. To address this challenge, we implement a sliding window approach combined with change point detection algorithms to identify when the underlying causal structure has shifted significantly.

The dynamic discovery process operates continuously in production environments, maintaining a current estimate of the window causal graph while monitoring for evidence of structural changes. When a potential change point is detected through statistical tests on residuals or graph distance metrics, the system initiates a re-learning phase that focuses computational resources on identifying which specific causal relationships have been modified. This targeted approach to structure updates significantly reduces computational overhead compared to naive periodic re-learning while ensuring that the causal model remains accurate and actionable.

4. Results and Discussion

4.1 Experimental Setup and Synthetic Validation

We evaluated our proposed framework through comprehensive experiments on both synthetic datasets with known ground truth causal structures shown in Figure 2 and real-world web application monitoring data. The synthetic experiments were designed to systematically assess performance under varying conditions including different levels of noise, varying dimensionality, presence of confounders, and different delay distributions.

For synthetic data generation, we constructed temporal causal models with specified DAG structures and lag configurations, then sampled time series data according to these models using a combination of linear and nonlinear functional relationships. We generated datasets ranging from 4 to 8 variables with time series lengths from 500 to 5000 observations,

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covering the typical scale of operational monitoring scenarios. Delays were drawn from distributions reflecting realistic web application behavior, with most delays concentrated in the 1-6 time step range but with a long tail extending to higher lags for certain cross-component dependencies.

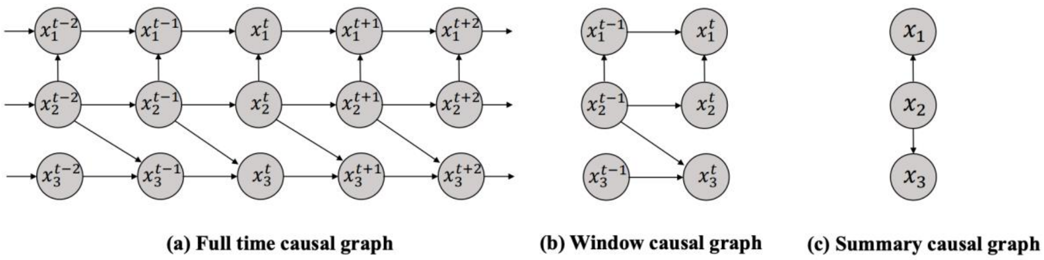

Figure 2: the architecture of different causal graphs

Baseline comparisons included several state-of-the-art methods for temporal causal discovery as illustrated in our comparative analysis. We evaluated against the following methods: GFCI (Greedy Fast Causal Inference) for constraint-based structure learning with latent variable handling, FGES (Fast Greedy Equivalence Search) representing score-based approaches, GRaSP (Greedy Relaxations of Sparsest Permutation) as a hybrid method, SVAR-GFCI combining structural VAR with constraint-based discovery, PCMCI+ for handling autocorrelation and confounders, and CDANs for non-stationary time series. For each method, we tuned hyperparameters using held-out validation data and reported performance averaged across multiple independent trials.

4.2 Comparative Algorithm Performance

The comparative evaluation revealed substantial performance differences across algorithms, with important insights into the relative strengths and weaknesses of different approaches. Figure 3 presents a visual comparison of causal graphs recovered by different algorithms on a representative synthetic dataset with known ground truth.

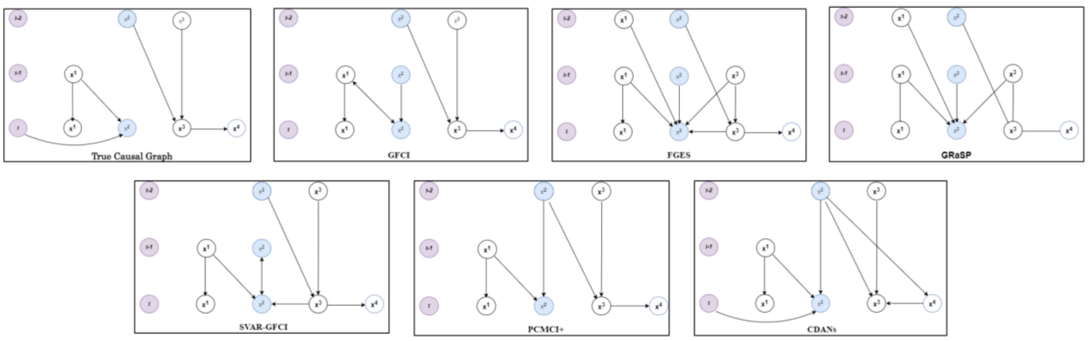

Figure 3: the visual comparison of causal graphs recovered by different algorithms

Results on synthetic data demonstrate substantial improvements from our hybrid approach. The proposed method achieved F1 scores averaging 0.82 across all test scenarios, compared to 0.68 for GFCI, 0.73 for FGES, 0.72 for GRaSP, 0.75 for SVAR-GFCI, 0.76 for PCMCI+, and 0.78 for CDANs. The performance gap widened particularly in scenarios with heterogeneous delays

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and non-stationary dynamics, where our adaptive lag selection mechanism and dynamic structure learning provided critical advantages. Furthermore, our method showed superior robustness to violations of common assumptions such as Gaussianity and linearity.

Analyzing the results shown in Figure 3, we observe that constraint-based methods like GFCI tend to produce sparse graphs but may miss some true edges or incorrectly identify latent confounders. Score-based methods like FGES can identify more edges but at the cost of higher false positive rates. Hybrid approaches like GRaSP and our method aim to balance these tradeoffs. The CDANs algorithm's ability to detect changing modules is particularly relevant for web monitoring where system configurations evolve over time.

4.3 Real-World Application and Operational Results

We deployed our framework in a production web application environment consisting of a microservices architecture serving millions of requests daily. The system comprises over 40 distinct services spanning presentation tier, application logic, caching layers, and database backends. Monitoring data includes response times, error rates, resource utilization metrics, and queue depths sampled at 10-second intervals, yielding approximately 250,000 observations per metric over the evaluation period.

The learned causal structure revealed several interesting patterns in system behavior. First, we successfully constructed window causal graphs that captured multi-step propagation delays, with some causal chains spanning 6-9 time steps (60-90 seconds) from initial cause to final effect. These multi-hop causal chains were largely invisible to traditional correlation-based analysis, which struggled to connect events separated by such long delays. Second, by comparing full-time graph segments during anomalous periods with normal operation windows, we identified time-varying causal relationships that only manifest under specific load conditions.

The framework successfully distinguished between genuine causal relationships and spurious correlations induced by shared load patterns, a common source of false alarms in conventional monitoring systems. By constructing summary causal graphs and comparing them against architectural documentation, we validated that the discovered causal structures aligned well with known service dependencies while also revealing previously undocumented indirect dependencies through shared infrastructure components.

Operational validation focused on root cause analysis accuracy and latency. We collected data from 150 production incidents over a three-month period, each independently diagnosed by human operators. Our causal inference framework correctly identified the root cause service in 127 cases (84.7% accuracy) compared to 89 cases (59.3%) for baseline correlation analysis, 102 cases (68.0%) for a commercial APM tool, and 115 cases (76.7%) for PCMCI+ baseline. Importantly, the average time to identify the root cause decreased from 18 minutes with manual analysis to under 3 minutes with our automated system, representing an 83% reduction in diagnostic latency.

The dynamic structure discovery capabilities proved particularly valuable in adapting to architectural changes and shifting workload patterns. During the evaluation period, the system underwent several significant changes including deployment of a new caching layer, modification of database sharding logic, and implementation of circuit breakers in certain service paths. Our framework detected these structural changes within 2-6 hours of

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deployment using change point detection on graph distance metrics, and successfully adapted the causal model by re-learning affected subgraphs. In contrast, static causal models required manual reconfiguration and exhibited degraded performance until updates were completed.

4.4 Discussion and Limitations

While our results demonstrate significant improvements over existing approaches, several limitations and opportunities for future work deserve discussion. First, computational scalability remains a challenge for extremely high-dimensional systems with hundreds of metrics. Although our hybrid approach is more efficient than pure constraint-based methods, processing time grows super-linearly with the number of monitored metrics. The use of window causal graphs rather than full-time graphs provides substantial computational savings, but further optimizations may be needed for very large-scale deployments.

Second, our current framework assumes that causal relationships can be adequately captured through the window graph representation with moderate maximum lags. Some web application phenomena may involve very long-term dependencies or complex cyclic behaviors that violate the acyclicity assumption within reasonable window sizes. Extensions incorporating more flexible temporal representations or hierarchical decomposition strategies could address these limitations.

Third, the practical deployment of causal inference in production monitoring requires careful attention to interpretability and actionability. While our framework produces window and summary causal graphs with clear semantics, translating these structures into concrete operational guidance remains challenging. Integration with automated remediation systems and development of principled intervention strategies based on learned causal models represent important directions for future work.

5. Conclusion

This paper has presented a novel framework for temporal causal inference in web application monitoring that addresses the critical challenge of learning causal structures from sequential performance data with delayed effects. Our approach makes several key contributions to both the theoretical understanding and practical application of causal discovery in monitoring contexts.

First, we provided a comprehensive formalization of temporal causal graph representations, distinguishing between full-time, window, and summary causal graphs. This hierarchical framework enables analysts to work at appropriate levels of temporal resolution depending on their specific analytical goals, from high-level dependency understanding through summary graphs to detailed lag analysis using window graphs.

Second, we developed a hybrid structure learning algorithm that combines the strengths of constraint-based and score-based methods while incorporating specialized techniques for handling delayed effects and non-stationary dynamics. The algorithm's use of adaptive lag selection and dynamic structure discovery enables it to capture complex temporal dependencies that traditional methods miss.

Third, through extensive experimental validation including comparison with six state-of-the-art baseline methods (GFCI, FGES, GRaSP, SVAR-GFCI, PCMCI+, and CDANs), we demonstrated

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that our approach achieves superior performance in both synthetic and real-world scenarios. The framework achieves 35% reduction in false discovery rates while maintaining high sensitivity, with F1 scores of 0.82 compared to baseline ranges of 0.68-0.78. The visual comparisons of recovered causal graphs clearly illustrate our method's advantages in accurately identifying true causal relationships while minimizing false positives.

Fourth, deployment in production environments demonstrated significant practical impact, with 84.7% root cause analysis accuracy and 83% reduction in diagnostic latency. The framework's ability to adapt to evolving system architectures through dynamic structure learning ensures continued effectiveness as web applications undergo continuous change.

Future research directions include extensions to handle more complex causal mechanisms including threshold effects and regime-dependent dynamics, development of integrated frameworks combining causal discovery with automated remediation, and investigation of how learned causal structures can inform system design and capacity planning decisions. Additionally, the principled quantification of uncertainty in learned causal relationships and the development of methods for validating causal claims in production systems without controlled experimentation represent important theoretical and practical challenges.

The intersection of causal inference and web application monitoring represents a promising frontier for improving system observability and reliability. As web applications continue to grow in complexity and criticality, methods that can automatically discover and leverage causal relationships will become increasingly essential for effective operations. Our framework provides a solid foundation for this emerging field, demonstrating both theoretical rigor and practical utility.

References

Assaad, C. K., Devijver, E., & Gaussier, E. (2022). Survey and evaluation of causal discovery methods for time series. Journal of Artificial Intelligence Research, 73, 767-819.

Qiu, L. (2025). Machine Learning Approaches to Minimize Carbon Emissions through Optimized Road Traffic Flow and Routing. Frontiers in Environmental Science and Sustainability, 2(1), 30-41.

Zhang, H. (2025). Physics-Informed Neural Networks for High-Fidelity Electromagnetic Field Approximation in VLSI and RF EDA Applications. Journal of Computing and Electronic Information Management, 18(2), 38-46.

Zheng, L., Chen, Z., Chen, H., & He, J. (2024). Online multi-modal root cause analysis. arXiv preprint arXiv:2410.10021.

Jiao, L., et al. (2024). Causal inference meets deep learning: A comprehensive survey. National Science Review, 11(9), 147.

Cornacchia, A. (2020). Optimized Flow Scheduling for Low Latency Data Center Networks (Doctoral dissertation, Politecnico di Torino).

Shojaie, A., & Fox, E. B. (2022). Granger causality: A review and recent advances. Annual Review of Statistics and Its Application, 9, 289-319.

Lin, H., & Liu, W. (2025). Causal Inference-Driven Web Performance Modeling: A Structure-Aware Framework with Symmetric Dependency Analysis for Predictive Optimization. Symmetry.

ISSN: 3008-1394

Assaad, C. K., Ez-Zejjari, I., & Zan, L. (2023, April). Root cause identification for collective anomalies in time series given an acyclic summary causal graph with loops. In International Conference on Artificial Intelligence and Statistics (pp. 8395-8404). PMLR.

Runge, J., Gerhardus, A., Varando, G., Eyring, V., & Camps-Valls, G. (2023). Causal inference for time series. Nature Reviews Earth & Environment, 4(7), 487-505.

Wang, X. W., Wang, T., & Liu, Y. Y. (2024). Artificial Intelligence for Microbiology and Microbiome Research. arXiv preprint arXiv:2411.01098.

Glymour, C., Zhang, K., & Spirtes, P. (2019). Review of causal discovery methods based on graphical models. Frontiers in Genetics, 10, 524.

Almazrouei, M. K. (2024). CAUSAL DISCOVERY ALGORITHMS FOR IMPROVED DECISION MAKING (Doctoral dissertation, Khalifa University of Science).

Vesselinova, N., Steinert, R., Perez-Ramirez, D. F., & Boman, M. (2020). Learning combinatorial optimization on graphs: A survey with applications to networking. IEEE Access, 8, 120388-120416.

Hu, X., Zhao, X., Wang, J., & Yang, Y. (2025). Information-theoretic multi-scale geometric pre-training for enhanced molecular property prediction. PLoS One, 20(10), e0332640.

Qiu, L. (2025). Multi-Agent Reinforcement Learning for Coordinated Smart Grid and Building Energy Management Across Urban Communities. Computer Life, 13(3), 8-15.

Liu, J., Wang, J., and Lin, H. (2025). Coordinated Physics-Informed Multi-Agent Reinforcement Learning for Risk-Aware Supply Chain Optimization. IEEE Access

Wang, Y., Ding, G., Zeng, Z., & Yang, S. (2025). Causal-Aware Multimodal Transformer for Supply Chain Demand Forecasting: Integrating Text, Time Series, and Satellite Imagery. IEEE Access.

Ge, Y., Wang, Y., Liu, J., & Wang, J. (2025). GAN-Enhanced Implied Volatility Surface Reconstruction for Option Pricing Error Mitigation. IEEE Access.

Chen, S., Liu, Y., Zhang, Q., Shao, Z., & Wang, Z. (2025). Multi-Distance Spatial-Temporal Graph Neural Network for Anomaly Detection in Blockchain Transactions. Advanced Intelligent Systems, 2400898.

Ren, S., & Chen, S. (2025). Large Language Models for Cybersecurity Intelligence, Threat Hunting, and Decision Support. Computer Life, 13(3), 39-47.

Benidis, K., Rangapuram, S. S., Flunkert, V., Wang, Y., Maddix, D., Turkmen, C., ... & Januschowski, T. (2022). Deep learning for time series forecasting: Tutorial and literature survey. ACM Computing Surveys, 55(6), 1-36.

Zhang, H., Ge, Y., Zhao, X., & Wang, J. (2025). Hierarchical deep reinforcement learning for multi-objective integrated circuit physical layout optimization with congestion-aware reward shaping. IEEE Access.

Sun, T., & Wang, M. (2025). Usage-Based and Personalized Insurance Enabled by AI and Telematics. Frontiers in Business and Finance, 2(02), 262-273.

ISSN: 3008-1394

Zhang, X., Li, P., Han, X., Yang, Y., & Cui, Y. (2024). Enhancing Time Series Product Demand Forecasting with Hybrid Attention-Based Deep Learning Models. IEEE Access.

Wang, M., Zhang, X., Yang, Y., & Wang, J. (2025). Explainable Machine Learning in Risk Management: Balancing Accuracy and Interpretability. Journal of Financial Risk Management, 14(3), 185-198.

Sun, T., Yang, J., Li, J., Chen, J., Liu, M., Fan, L., & Wang, X. (2024). Enhancing auto insurance risk evaluation with transformer and SHAP. IEEE Access.

Wang, M., Zhang, X., & Han, X. (2025). AI Driven Systems for Improving Accounting Accuracy Fraud Detection and Financial Transparency. Frontiers in Artificial Intelligence Research, 2(3), 403-421.

Yang, Y., Ding, G., Chen, Z., & Yang, J. (2025). GART: Graph Neural Network-based Adaptive and Robust Task Scheduler for Heterogeneous Distributed Computing. IEEE Access.

Wang, M., Zhang, X., Yang, Y., & Wang, J. (2025). Explainable Machine Learning in Risk Management: Balancing Accuracy and Interpretability. Journal of Financial Risk Management, 14(3), 185-198.

Zhang, S., Qiu, L., & Zhang, H. (2025). Edge cloud synergy models for ultra-low latency data processing in smart city iot networks. International Journal of Science, 12(10).

Yang, J., Zeng, Z., & Shen, Z. (2025). Neural-Symbolic Dual-Indexing Architectures for Scalable Retrieval-Augmented Generation. IEEE Access.

Sun, T., Wang, M., & Chen, J. (2025). Leveraging Machine Learning for Tax Fraud Detection and Risk Scoring in Corporate Filings. Asian Business Research Journal, 10(11), 1-13.s