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Constructing a Dynamic Causal Inference Framework for Digital

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Abstract: In digital scenarios, traditional linear causal inference models struggle to accurately depict complex causal relationships due to the breadth of data sources and intricate environmental dynamics. This study establishes a dynamic causal inference model suited to digital contexts based on dynamic systems theory. The model comprises multiple layers: data input, generation and evaluation of causal relationships, feedback and learning of causal relationships, and visualization of outcomes. This model automatically adjusts and refines causal structures, exhibiting adaptability and stability. Through time-varying modelling and machine learning optimization strategies, it achieves greater flexibility and interpretability in high-dimensional, non-stationary data scenarios. The research serves as a tool to address practical challenges in digital governance, intelligent decision-making, and social science experimentation.

Keywords: digitalization; causal inference; dynamic modelling; adaptive optimization

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1. Introduction

With the rapid advancement of the digital economy, data has become a critical production factor. However, its high-frequency generation and complex interactive characteristics pose new challenges for causal identification. Traditional causal inference methods are often built upon static assumptions and linear relationships, making it difficult to effectively capture the dynamic dependencies and feedback effects inherent in digital data. How to achieve dynamic identification and optimization of causal relationships within complex, heterogeneous, and time-varying environments has thus become a significant research topic. This paper attempts to construct a self-learning, self-evolving framework for digital dynamic causal inference at both systemic and methodological levels, aiming to provide new theoretical underpinnings and application insights for intelligent systems and data science research.

2. New Paradigms for Causal Inference in Digital Environments

2.1. Characteristics of Digital Data and Causal Complexity

Data in the digital era exhibits multi-source heterogeneity, high-dimensional dynamics, and strong non-linearity. It is not only voluminous and frequently generated but also diverse in origin, encompassing sensor recordings, social interactions, transactional behaviors, and web logs. Such data possesses time-varying and feedback-driven characteristics, with variables exhibiting multi-layered nesting and dynamic coupling relationships. This results in causal chains that are non-stationary and uncertain. Traditional causal identification methods based on static samples struggle to accommodate this complexity, frequently overlooking factors such as temporal evolution, system interventions, and environmental perturbations. Consequently, establishing analytical frameworks capable of characterizing dynamic dependencies, capturing causal feedback loops, and accommodating adaptive evolution within digital environments has become a crucial direction for causal inference research [1].

2.2. Limitations of Traditional Causal Inference Models

Traditional causal inference methods predominantly operate under assumptions of fixed structure and static samples. Approaches such as structural equation modelling, propensity score matching, or regression discontinuity design may reveal stable relationships between certain variables, yet struggle to accommodate time-varying and non-linear systemic environments. Granger causality analysis captures temporal dependencies but relies excessively on stationarity assumptions, struggling to explain true causal directions amid complex interactions. Faced with large-scale, multidimensional datasets featuring frequent feedback loops, these models exhibit insufficient robustness and generalizability. Causal analysis in digital contexts demands novel dynamic modelling approaches, enabling causal relationships to adjust in real-time with data changes while maintaining stable interpretations [2].

2.3. Theoretical Shift Towards Dynamic Causal Inference

The advent of dynamic causal inference signifies a shift in causal analysis research from static assumptions towards evolutionary systems [3]. Dynamic causal inference methods no longer treat causal relationships as fixed cause-and-effect pairs, but instead emphasize the continuous variation in the strength, direction, and temporal sequencing of interactions between variables. By incorporating temporal dimensions and feedback mechanisms into models, researchers extend causal modelling into dynamic processes that evolve with state changes. Within this theoretical framework, the interaction between system state updates and external interventions jointly shapes causal pathways. The dynamic model structure adapts parameters and weights in response to evolving data flows. Drawing upon concepts from system dynamics, reinforcement learning, and adaptive optimization, the theoretical system of dynamic causal inference provides a more practically relevant analytical pathway for uncovering the generation and evolution of causal relationships within complex systems [4].

3. Principles and Structural Design of Dynamic Causal Modelling

3.1. Foundations of Causal Modelling from a Dynamic Systems Perspective

Dynamic causal modelling centres on time series and system dynamics, emphasizing the describability and computability of causal relationships as they evolve over time. The state of a system at discrete time points is characterized by structural equations, whose core form is:

$$X_t - 1 = f(X_t, A_t, \in_t), \quad (1)$$

Here, X_t denotes the state vector at time t (which may contain multidimensional features and lagged terms), A_t represents external interventions or control inputs (such as strategies, prices, or policy signals), and ϵ_t signifies unobserved disturbances. The function f(.) maps the sequence "historical state - current intervention - random disturbance" to the "next-period state", forming a recursive causal chain.

To assess intervention effects independently of state evolution, the causal impact of outcome variable Yt on intervention At is typically measured by the average treatment effect:

$$ATE = E[Y_t \mid A_t = 1] - E[Y_t \mid A_t = 0]. \quad (2)$$

This metric ATE corresponds to the outcome difference between different intervention assignments under the same data generation mechanism. It requires controlling for confounders and temporal dependencies in modelling to ensure interpretability and robustness of the estimates. The dynamic perspective extends causal identification from one-off estimation to sequential inference: state transitions characterise structural evolution, while effect metrics quantify intervention impacts. Together, they underpin subsequent time-varying structure learning, adaptive correction, and closed-loop feedback design, providing a methodological foundation for continuous decision-making and online optimization in digital scenarios [5].

3.2. Time-Varying and Adaptive Modelling of Causal Structures

Within digital systems, causal relationships continuously adjust in response to temporal shifts, environmental changes, and variations in input characteristics. Static models, which assume fixed variable relationships, struggle to capture such dynamic dependencies. To characterize the temporal evolution of structures, the dynamic causal framework introduces an updatable causal weight matrix. This matrix represents the changing causal strengths between variables within the system. Its update process can be formalized as:

$$\Delta W_t = g(W_t - 1, L_t) \tag{3}$$

Here, ΔW_t denotes the weight change quantity, reflecting the adjustment magnitude of the causal structure between consecutive time steps; W_{t-1} represents the weight matrix at the previous time step; L_t denotes the learning loss or adaptive criterion of the system at time step t; and the function g(.) defines the mapping between the old structure and the learning criterion. Through this mechanism, the model can adaptively correct parameters when data streams change, enabling continuous learning and updating of time-varying patterns.

To further validate the model's time-varying characteristics, one may statistically analyses the evolution of weight updates across different phases, thereby observing the system's responsiveness within dynamic environments. Table 1 presents a comparison of causal weight variation magnitude and stability across three distinct time intervals.

Table 1. Statistics on causal weight variation across different time periods.

Time Interval	Average Weight Change Range	Variance	Stability Level	Update Frequency
T1-T2	0.042	0.007	High	3 times
T2-T3	0.061	0.012	Moderate	5 times
T3-T4	0.037	0.006	Very High	2 times

It can be observed that the model exhibits the most pronounced weight changes during the T2-T3 phase, indicating that when input data or external conditions become more volatile, the system proactively adjusts its causal structure to maintain predictive and interpretative capabilities. Conversely, during the T3-T4 phase, changes tend to stabilize, suggesting that the model structure gradually converges and maintains a high degree of stability. This outcome validates the effectiveness of time-varying causal modelling within dynamic data environments.

3.3. Causal Optimization Mechanism of the Fusion Learning Algorithm

Within complex digital environments, data frequently exhibits high-dimensional, non-linear, and noisy characteristics, rendering traditional causal models prone to bias in parameter estimation and structural identification. To enhance the learning efficiency and stability of dynamic causal modelling, the framework incorporates a fusion learning algorithm. This combines deep representation learning with causal consistency constraints to achieve a balance between predictive accuracy and interpretability. This optimization approach is realized through the design of a composite loss function, formulated as follows:

$$L = L_{pred} + \lambda L_{causal} \tag{4}$$

Here, L denotes the overall loss function, L_{pred} represents the error term in the model's predictive task, reflecting fitting accuracy; L_{causal} constitutes the causal consistency constraint term, penalizing deviations from causal direction during model learning; λ serves as the trade-off coefficient, regulating the relative importance of both loss components. When λ is appropriately calibrated, the model maintains both predictive performance and causal interpretability, achieving stable convergence of results.

In practical optimization, model parameter updates employ a gradient descent mechanism, enabling iterative computation for self-learning adjustments to causal weights. The update rule may be expressed as:

$$W_{t+1} = W_t - \eta \frac{\partial L}{\partial W_t} \quad (5)$$

Here, W_t denotes the causal weight matrix at time step t, while W_{t+1} represents the updated weights; η signifies the learning rate, controlling the step size per iteration; $\frac{\partial L}{\partial W_t}$ denotes the gradient with respect to the overall loss function, guiding the optimisation direction. This update mechanism enables the model to progressively refine its weight parameters through iterative refinement, strengthen causal constraints, and incrementally enhance the accuracy and robustness of structural recognition.

The introduction of fusion learning algorithms endows dynamic causal models with an intrinsic cyclical mechanism of "learning-correction-relearning". The model extracts deep features from multi-source data inputs while maintaining structurally correct causal directions through consistency constraints. This approach reduces noise interference and enhances the system's generalisation capability. Compared to traditional static modelling, this optimisation mechanism demonstrates superior convergence speed and adaptive capacity in complex environments, providing algorithmic support for subsequent feedback and closed-loop design.

3.4. Feedback and Closed-Loop Structures in Causal Inference

A core feature of the dynamic causal inference framework is the formation of a "feedback-correction-relearning" closed-loop structure during modelling. Unlike traditional static causal models, the closed-loop system not only identifies causal directions between variables but also enables continuous self-correction of the model's structure through feedback mechanisms. The introduction of feedback allows the model to automatically update parameters when prediction biases arise, thereby maintaining the dynamic stability of inference results.

In its operational mechanism, the system first assesses the discrepancy between forecast outputs and actual observations. When the prediction error exceeds a predetermined threshold, the feedback loop is triggered to compute the correction quantity and apply it to parameter updates. This process may be formalised as follows:

$$F(t) = \varphi\left(Y_t - \hat{Y}_t\right) \quad (6)$$

Here, $F(t)$ denotes the feedback intensity, Y_t represents the actual observed value, $\hat{Y}_t$ signifies the model-predicted value, and $\varphi()$ serves as the error mapping function, which determines the feedback intensity and the direction of parameter adjustment. By converting the error into a parameter correction signal, the system achieves self-regulation through iteration, progressing from deviation identification to structural repair.

The advantage of closed-loop structures lies in their capacity to form a dynamic cycle of continuous optimisation. Each feedback loop not only corrects parameter deviations but, more significantly, acquires new structural parameters, providing crucial insights for subsequent construction phases. As the number of iterations increases, the system approaches equilibrium, progressively enhancing the precision of causal relationship identification. This feedback-driven closed-loop modelling process transforms traditional causal research from "static deduction of causal relationships" to "dynamic comprehension". The evolutionary trajectory, shaped by the model's self-adaptation, more accurately reflects the actual direction of system change. Consequently, closed-loop causal inference possesses three defining characteristics: continuous learning, dynamic adaptation, and long-term stability. These form the foundation for intelligent analysis and decision-making within complex digital systems.

4. System Integration and Operational Mechanisms of the Digital Dynamic Causal Framework

4.1. Framework Architecture and Module Synergy

The Digital Dynamic Causal Framework adheres to hierarchical and collaborative principles, aiming to achieve systematic operation encompassing causal identification, parameter learning, structural refinement, and visualised outcomes. The framework comprises five modules: Data Input Layer, Causal Modelling Layer, Inference Execution Layer, Feedback Regulation Layer, and Visualisation Output Layer. These layers sequentially interconnect with complementary functions, collectively forming the complete chain of dynamic causal inference.

Data flow serves as the central thread, with information sequentially transmitted between layers to complete the entire process from data acquisition to inference output. The data input layer provides standardised feature data. The modelling layer generates network structures based on time-varying causal principles. The inference execution layer then performs effect estimation and prediction accordingly. Inference results are monitored and corrected by the feedback adjustment layer before returning to the modelling stage, enabling parameter self-calibration and structural optimisation, thereby forming a self-learning closed loop. Figure 1 illustrates the framework's structure and operational logic, demonstrating a dynamic closed-loop system progressing from data to cognition, and from inference to optimisation.

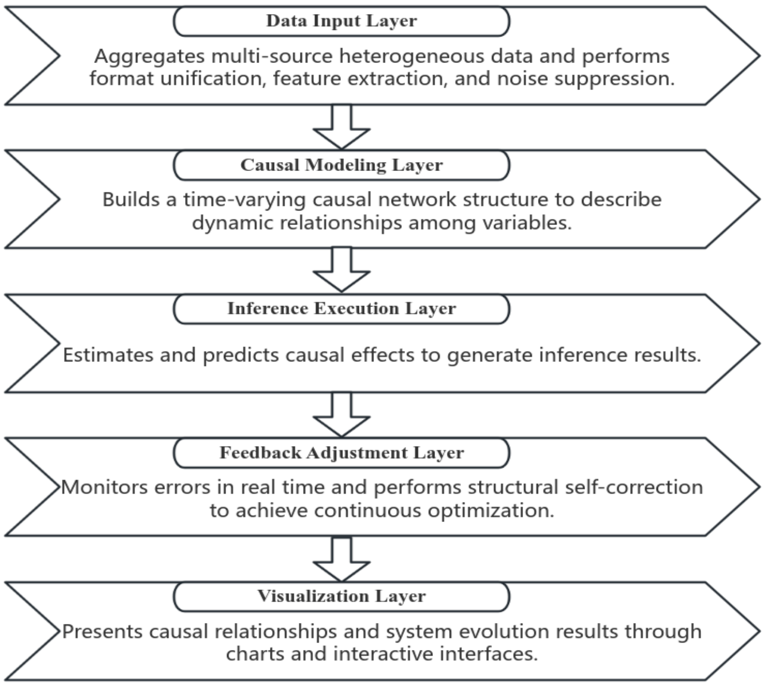

Figure 1. Schematic Diagram of the Structure and Operation of the Digital Dynamic Causal Framework.

Compared to static causal analysis, this framework introduces feedback pathways and multi-layer coupling mechanisms, endowing the inference process with continuous adjustment and dynamic learning capabilities. By maintaining information consistency and parameter synchronisation across modules, the system enables real-time updates and robust learning of causal relationships within complex data environments.

4.2. Dynamic Execution Path of the Causal Inference Process

During system operation, the causal inference process dynamically unfolds along the "input-modelling-estimation-correction" pathway. Each stage corresponds to distinct data flow configurations and computational objectives. The input module integrates multi-source features before transmitting them to the modelling layer, generating time-varying causal networks. The execution layer calculates causal effects based on model parameters, generally expressed as:

$$E[Y_t|A_t, X_t] = \int f(Y_t|A_t, X_t)\, p(X_t) dX_t \quad (7)$$

Here, $E[Y_t|A_t, X_t]$ denotes the expected value of the outcome variable given the intervention A_t and feature X_t; $f(Y_t|A_t, X_t)$ represents the conditional probability density function of the outcome distribution; and $p(X_t)$ is the marginal distribution of the feature. This formula embodies the propagation relationship of causal effects within the conditional space, constituting the core computational logic of the inference process.

To stabilise operational trajectories, dynamic threshold buffers and gradient detection capabilities are incorporated into the estimation process to capture model errors and anomalous data. When errors exceed thresholds, the control process triggers parameter adjustment logic, enabling the graphical model to achieve optimal operation during cyclical phases. This dynamic execution flow integrates causal determination, subsequent estimation, and structural evolution of the graphical model into a unified computation, thereby sustaining the system's superiority.

4.3. Interpretability of Causal Outcomes and Intelligent Visualisation Presentation

Beyond pursuing accurate predictive outcomes, the digital dynamic causal framework prioritises interpretability and presentation during causal inference. The explanatory analysis module quantifies the influence of input variables on outcome variables while exploring the model's internal logical structure and key effectors. It calculates importance based on the principle of average variable contribution, expressed in its fundamental form as:

$$\varphi_i = \frac{1}{n}\sum_{k-1}^{n}\left(y_{k,i} - y_k\right) \quad (8)$$

Here, φ_i denotes the mean contribution value of the i-th variable, serving to measure its overall impact on the model output; n represents the sample size or number of computations; $y_{k,i}$ indicates the model's predicted result when this variable is included in the k-th computation; y_k denotes the baseline output value for the corresponding sample after removing this variable. The difference between the two reflects the average incremental effect of this variable on the output result. When $\varphi_i > 0$, the variable exhibits a positive relationship with the output; when $\varphi_i < 0$, it demonstrates an inhibitory effect. This metric comprehensively reflects the relative importance of different variables in system prediction and interpretation.

Presenting interpretability analysis results through visual representations. The system constructs causal path diagrams, contribution bar charts, and dynamic trend curves based on variable importance, facilitating the display of significant causal relationships, their intensity, and developmental trajectories. Utilizing these visualization methods enables users to directly comprehend the model's reasoning process, identify dominant factors and dynamic adjustments, and transform complex data into easily readable and actionable knowledge. This provides a foundation for subsequent strategy optimization and decision-making.

4.4. System Stability and Scalability Design

To ensure reliability under multi-source data streams and long-term operation, the framework incorporates stability and scalability design at the system level. Stability is enhanced through parameter normalization, dynamic regularization, and multi-cycle evaluation methods to mitigate model bias. Regarding scalability, the system supports concurrent deployment of multiple modules, enabling diverse computing nodes to participate in computations. Resource allocation occurs automatically based on data volume and task complexity. To validate the system's performance, multiple simulation trials compared traditional static causal models with this framework across varied scenarios. Performance comparisons of the three models using identical datasets are presented in Table 2.

Table 2. Comparison of Dynamic Causal Inference Performance Across Different Models.

Model Type	Average Error (RMSE)	Convergence Speed	Stability Index	Interpretability Score
Static Structural Equation Model	0.081	Slow	0.72	0.63
Time-Series Granger Model	0.067	Moderate	0.79	0.70
Digital Dynamic Causal Framework	0.042	Fast	0.91	0.88

Results demonstrate that the digital dynamic causal framework outperforms traditional models in terms of error, convergence, and stability, whilst significantly enhancing interpretability metrics. The system maintains high operational precision and robustness within complex, dynamic data environments.

5. Conclusion

Establishing a digital dynamic causal inference framework represents a substantial extension of traditional causal analysis methodologies, especially in data-intensive and rapidly evolving digital environments. Building on the model presented in this study-which integrates data input, causal relationship generation and evaluation, iterative feedback learning, and dynamic visualization-this conclusion synthesizes the key theoretical insights and methodological contributions.

The findings highlight that causal relationships in digital contexts are not fixed but time-varying, multi-layered, and highly sensitive to environmental perturbations. By incorporating dynamic systems theory and leveraging machine learning-based optimization strategies, the proposed framework enables causal structures to evolve in response to new information. This confers a degree of adaptability and robustness that traditional static or linear causal models cannot achieve. The framework's capacity for continuous learning and self-correction ensures that it remains effective in managing high-dimensional, heterogeneous, and non-stationary data streams that typify digital ecosystems.

Moreover, the integration of dynamic modelling with algorithmic feedback loops significantly enhances interpretability. Rather than treating causal inference as a one-time analytical process, the framework promotes an ongoing interaction between data signals and causal mechanisms, making it possible to reveal deeper structural patterns and emergent dynamics. This dynamic interpretability is particularly valuable in digital governance, intelligent decision-making, and computational social science, where causal relationships often shift in real time.

Overall, the study contributes both conceptual and operational advancements. Conceptually, it reframes causal inference as a fluid, adaptive, and continually updated process. Operationally, it provides practical tools and methodological pathways for implementing dynamic causal analysis in complex digital environments. The proposed framework thus offers a forward-looking foundation for intelligent system analysis, decision-support architectures, and the optimization of automated models that rely on evolving streams of digital information. It not only strengthens the methodological toolkit for understanding digital-era causal complexity but also establishes a durable direction for future research on dynamic, interpretable, and responsive causal inference systems.

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