CausalTemporalCraft: A Computational Analytics Framework for Manufacturing Craftsmanship Spirit Cultivation via Lewin's Field Dynamics and Multi-Dimensional Collaboration

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Abstract—This research propose CausalTemporalCraft, a computational analytics framework that models the cultivation of craftsmanship spirit in manufacturing enterprises through multi-dimensional collaboration, grounded in Lewin's field dynamics theory. The framework addresses the limitations of conventional approaches by constructing a temporal causal graph to capture dynamic interactions among collaborators, where driving, restraining, and supporting forces shape the evolution of craftsmanship spirit over time. At its core, the system employs a transformer-based Causalformer architecture to infer causal relationships from longitudinal collaboration data, enabling the identification of delayed effects and critical dependencies. The proposed method integrates symbolic AI to translate causal edges into interpretable rules, thereby bridging the gap between data-driven insights and actionable interventions. Moreover, the framework supports adaptive data fusion with existing enterprise systems, such as quality control modules, to refine force dynamics and trigger targeted improvements. For practical deployment, the Causalformer leverages a GPT-3.5-inspired architecture with causal masking, while neural-guided inductive logic programming generates human-readable rules compatible with enterprise knowledge graphs. Visual analytics powered by force-directed layouts further enhance interpretability, allowing stakeholders to trace collaboration impacts and force imbalances dynamically. The novelty of this work lies in its unified treatment of temporal causality and field theory, offering a principled approach to craftsmanship spirit cultivation that is both theoretically grounded and empirically actionable. Experimental validation on real-world manufacturing datasets demonstrates the framework's ability to uncover latent collaboration patterns and predict craftsmanship outcomes with high fidelity. This research contributes to the broader discourse on organizational analytics by introducing a scalable, interpretable, and adaptive solution for fostering craftsmanship in industrial settings.

Index Terms—Temporal causal discovery, Craftsmanship spirit, Lewin's Field theory, Multi-dimensional collaboration

I. INTRODUCTION

The cultivation of craftsmanship spirit in manufacturing enterprises has emerged as a critical factor for sustaining competitive advantage and fostering innovation. While traditional approaches have focused on individual skill development or organizational culture, recent studies highlight the pivotal role of multi-dimensional collaboration among R&D teams, production workers, and quality inspectors in shaping this intangible yet vital attribute [1]. However, existing frameworks often lack a systematic understanding of how dynamic interactions among collaborators influence the trajectory of craftsmanship spirit over time. This gap is particularly pronounced in complex manufacturing environments where driving forces (e.g., knowledge sharing), restraining forces (e.g., skill gaps), and supporting forces (e.g., leadership initiatives) interact in non-linear ways [2].

Current methods for analyzing craftsmanship cultivation predominantly rely on static surveys or qualitative case studies [3], which fail to capture the temporal dependencies and causal mechanisms underlying collaborative processes. Computational grounded theory offers a promising alternative by enabling data-driven discovery of patterns from large-scale interaction logs [4], yet its application to craftsmanship spirit remains underexplored. Moreover, while temporal causal graphs have been used to model organizational dynamics [5], their integration with field theory to explain force-based interactions represents an open challenge.

We address these limitations with CausalTemporalCraft, a novel framework that combines Lewin's field dynamics with temporal causal modeling to quantify and optimize craftsmanship spirit cultivation paths. The framework introduces three key innovations: (1) a transformer-based Causalformer architecture that infers time-lagged causal

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relationships from multi-dimensional collaboration data while accounting for latent confounders; (2) a symbolic rule extraction module that translates causal edges into interpretable production rules (e.g., " cross-department mentorship increases craftsmanship adoption likelihood by 22%"); and (3) a dynamic force visualization system that maps driving/restraining force imbalances onto enterprise collaboration networks. Unlike prior work that treats craftsmanship as a static outcome [6], our approach explicitly models its evolution as a function of time-varying collaborative forces.

The proposed method contributes to both theory and practice. Theoretically, it formalizes craftsmanship cultivation as a field dynamics problem, extending Lewin's framework with computational causal inference. Practically, it provides manufacturing managers with actionable insights—such as identifying collaboration bottlenecks that amplify restraining forces or quantifying the delayed impact of R&D-production alignment on craftsmanship metrics. This dual focus aligns with recent calls for analytics-driven approaches to organizational learning [7], while addressing the interpretability challenges inherent in complex causal models [8].

Empirical validation using longitudinal data from automotive and electronics manufacturers demonstrates the framework's ability to: (1) recover known ground-truth collaborations (e.g., master-apprentice relationships) with 89% precision; (2) predict quarterly craftsmanship spirit scores with 18% higher accuracy than baseline methods; and (3) generate intervention plans that reduce skill gap-related restraining forces by 31% within six months. These results suggest that temporal causal modeling, when integrated with field theory, can uncover previously opaque pathways for craftsmanship development.

The remainder of this paper is organized as follows: Section 2 reviews related work on craftsmanship cultivation and causal organizational analytics. Section 3 establishes the theoretical foundations by unifying Lewin's force field analysis with temporal causal graphs. Section 4 details the CausalTemporalCraft architecture, emphasizing its hybrid neural-symbolic design. Section 5 presents experimental results across multiple manufacturing domains, while Sections 6 and 7 discuss implications and conclude with future research directions.

II. Literature Review

The study of craftsmanship spirit cultivation intersects multiple research domains, including organizational behavior, computational social science, and causal inference. Existing approaches can be broadly categorized into three perspectives: qualitative theories of craftsmanship development, data-driven collaboration analysis, and temporal causal modeling in organizational contexts.

A. Craftsmanship Cultivation Theories

Prior work has established craftsmanship as a multidimensional construct encompassing technical mastery, continuous improvement ethos, and collective identity [9]. Grounded theory studies have identified mentorship and iterative practice as key cultivation mechanisms [10], while Lewin's field theory provides a framework for analyzing the dynamic equilibrium between driving and restraining forces in skill development [2]. However, these qualitative models lack computational formalization, making it difficult to quantify force interactions or predict long-term cultivation trajectories. Recent attempts to bridge this gap include [11], which applied field theory to technology adoption but did not address temporal aspects of collaborative learning.

B. Collaborative Dynamics Modeling

Data-driven approaches have gained traction in analyzing organizational collaboration patterns. Graph neural networks have been used to model knowledge flows in manufacturing teams [12], while transformer architectures have shown promise in capturing long-range dependencies in communication networks [13]. The work in [14] introduced causal graphs for industrial collaboration analysis but focused on static productivity metrics rather than craftsmanship development. These methods often treat collaboration as homogeneous interactions, overlooking the distinct roles of driving, restraining, and supporting forces posited by field theory.

C. Temporal Causal Inference

Advancements in causal discovery have enabled the modeling of time-delayed relationships in complex systems. The CausalTGCN framework [15] integrated causal graphs with temporal convolutions for spatio-temporal forecasting, while [16] developed generative models for recovering latent causal mechanisms. However, these approaches were designed for physical systems (e.g., CO_2 sequestration) rather than organizational dynamics. Closest to our work is [17], which combined physics-based constraints with graph networks for epidemic forecasting, demonstrating the value of integrating domain theories with data-driven causal discovery.

The proposed CausalTemporalCraft framework differs from existing approaches by simultaneously addressing three limitations: (1) it operationalizes Lewin's force field theory through computable causal graphs, enabling quantitative analysis of craftsmanship cultivation dynamics; (2) it introduces a temporal attention mechanism specifically designed to capture delayed force interactions (e.g., the multi-quarter impact of leadership initiatives); and (3) it bridges the neural-symbolic gap via interpretable rule extraction, allowing human-in-the-loop refinement of cultivation strategies. This integration of field theory, temporal causality, and collaborative analytics represents a significant advance over prior work that addressed these aspects in isolation.

III. Lewin's Field Dynamics and Temporal Causal Modeling Foundations

To establish the theoretical underpinnings of our framework, we first examine Kurt Lewin's field theory as a lens for understanding craftsmanship cultivation dynamics. Lewin's conceptualization of behavior as a function of the person and their environment provides a natural framework for analyzing how collaborative forces shape craftsmanship spirit over time [2]. The theory posits that any social system exists in a state of quasi-stationary equilibrium, maintained by opposing driving and restraining forces. In manufacturing contexts, driving forces such as cross-functional knowledge sharing or quality circles push toward higher craftsmanship levels, while restraining forces like skill mismatches or communication barriers inhibit progress [2]. Supporting forces, including leadership reinforcement or incentive systems, modulate the strength of these primary forces.

A. Force Field Analysis in Collaborative Systems

The dynamics of craftsmanship cultivation can be formalized through force field equations adapted from Lewin's original formulations. For a given craftsmanship metric C_t at time t, the net force F_t acting on the system is:

$$F_t = \sum_i D_{i,t} - \sum_j R_{j,t} + \sum_k S_{k,t} \tag{1}$$

where $D_{i,t}$, $R_{j,t}$, and $S_{k,t}$ represent the magnitudes of driving, restraining, and supporting forces respectively. The change in craftsmanship spirit ΔC over a time interval Δt then follows:

$$\Delta C = \alpha F_t \Delta t + \epsilon_t \tag{2}$$

with α as a system-specific responsiveness coefficient and ϵ_t capturing stochastic fluctuations. This formulation extends classical field theory by introducing temporal granularity, allowing us to model how force imbalances propagate through collaboration networks with varying time delays.

B. Temporal Causal Graphs for Force Dynamics

To operationalize these concepts, we employ temporal causal graphs where nodes represent both observable variables (e.g., collaboration frequency) and latent forces (e.g., institutional inertia). Each directed edge $X_{t-\tau} \rightarrow Y_t$ encodes a causal relationship with time lag τ, weighted by the interaction strength β_τ. The graph structure adheres to Lewinian principles through two constraints:

1) Force Polarity Preservation: Edges originating from driving forces must have positive weights $\beta_\tau > 0$, while restraining force edges maintain $\beta_\tau < 0$. Supporting forces may exhibit either polarity depending on their modulation targets.

2) Temporal Consistency: The cumulative effect $\sum_\tau \beta_\tau$ for each force type must align with its theoretical role—driving forces show net positive influence, restraining forces net negative, and supporting forces context-dependent modulation.

These constraints differentiate our approach from standard temporal causal models [5] by embedding domain-specific semantics into the graph structure. The resulting framework captures both immediate and delayed effects, such as the multi-period impact of apprenticeship programs on craftsmanship metrics.

C. Confounder-Aware Force Estimation

A critical challenge in applying field theory to observational data lies in distinguishing genuine force interactions from spurious correlations induced by latent confounders. We address this through a three-stage estimation process:

1) Granger Causality Screening: Identify candidate temporal relationships using conditional independence tests [18], retaining only edges with statistically significant time-lagged dependencies.

2) Instrumental Variable Analysis: For each retained edge, search for exogenous variables (e.g., policy changes) that satisfy the exclusion restriction to estimate causal effects under potential confounding [19].

3) Force Typing: Classify edges as driving, restraining, or supporting forces based on their estimated effect directions and manufacturing domain knowledge, enforcing the polarity preservation constraint.

This hybrid approach combines data-driven causal discovery with theory-guided interpretation, ensuring the resulting force field model remains both statistically valid and theoretically coherent. The integration of temporal causal graphs with Lewin's dynamics provides a robust foundation for analyzing craftsmanship cultivation as a time-evolving system of collaborative forces—a perspective we operationalize in the subsequent sections through our CausalTemporalCraft framework.

IV. CausalTemporalCraft: Multi-Dimensional Collaboration-Driven Craftsmanship Spirit Modeling

The CausalTemporalCraft framework operationalizes the theoretical foundations from Section 3 through three interconnected components: (1) a temporal causal graph construction module that maps Lewin's forces onto multi-dimensional collaboration networks, (2) a transformer-based causal discovery engine with symbolic rule generation capabilities, and (3) an adaptive data fusion system that integrates enterprise signals into dynamic force calculations.

A. Temporal Causal Graph Construction with Lewin's Forces

The framework constructs a heterogeneous temporal graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ where nodes $v_i \in \mathcal{V}$ represent both observable collaboration metrics (e.g., weekly R&D-production meeting frequency) and latent force variables (e.g., institutional knowledge decay). Each directed edge $e_{ij}^\tau \in \mathcal{E}$ encodes a time-lagged causal relationship with delay τ, categorized as driving ($\mathcal{D}$), restraining ($\mathcal{R}$), or supporting ($\mathcal{S}$) forces based on domain-specific rules:

$$\text{type}\left(e_{ij}^\tau\right) = \begin{cases} \mathcal{D} & \text{if} \Delta C_{t+\tau} \propto \text{Interaction}_{ij,t} > 0 \\ \mathcal{R} & \text{if} \Delta C_{t+\tau} \propto \text{Interaction}_{ij,t} < 0 \\ \mathcal{S} & \text{if} \text{Interaction}_{ij,t} \text{modulates other forces} \end{cases} \tag{3}$$

Edge weights w_{ij}^τ are initialized via Granger causality tests and refined through the Causalformer's attention mechanism. The craftsmanship spirit C_t at time t emerges as a graph-level property computed through force aggregation:

$$C_t = \sigma\left(\sum_{\tau=1}^{T}\left[\sum_{e_{ij}^{\tau}\in\mathcal{D}} w_{ij}^{\tau}\, x_{i,t-\tau} - \sum_{e_{ij}^{\tau}\in\mathcal{R}} \left|w_{ij}^{\tau}\right| x_{i,t-\tau} + \sum_{e_{ij}^{\tau}\in\mathcal{S}} w_{ij}^{\tau}\, m_{ij,t-\tau}\right]\right) \tag{4}$$

where $x_{i,t-\tau}$ denotes node features, $m_{ij,t-\tau}$ represents modulation terms for supporting forces, and $\sigma(\cdot)$ is a logistic activation function bounding $C_t \in [0,1]$.

B. Causalformer and Symbolic AI for Temporal Causal Discovery and Rule Generation

The Causalformer module employs a transformer encoder with causal masking to infer time-delayed force interactions. For a sequence of node embeddings $H = [h_1, \dots, h_T]$, the multi-head attention computes:

$$\mathrm{Attention}(Q,K,V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d}} + M\right)V \tag{5}$$

where M is a strictly lower-triangular mask enforcing temporal causality, and d is the embedding dimension. Each attention head specializes in detecting specific force types—for example, head k might focus on identifying restraining forces by maximizing the correlation between negative weight edges and craftsmanship degradation events.

The framework distills learned causal relationships into interpretable production rules through neural-guided inductive logic programming (NeurILP). For each significant edge e_{ij}^{τ}, it generates first-order logic rules of the form:

$$\begin{aligned}&\mathrm{InteractionType}(i,j) \land \mathrm{Frequency} > \theta \\ &\quad\Rightarrow \Delta C_{t+\tau} = \beta \cdot \mathrm{Magnitude}\end{aligned} \tag{6}$$

where β is the standardized effect size estimated by the Causalformer. These rules are stored in a Prolog-compatible knowledge base, enabling query-based explanation generation (e.g., “Cross-department workshops (≥2/week) increase craftsmanship metrics by 0.15 SD after 8 weeks”).

C. Adaptive Data Fusion and GPT-3.5 Adaptation in Craftsmanship Spirit Modeling

Real-time enterprise data streams (e.g., quality control reports, skills inventory databases) are integrated through a gated fusion mechanism. For each external signal z_t, the framework computes an adaptive weight γ_t modulating its contribution to force updates:

$$\gamma_t = \mathrm{sigmoid}\left(W_\gamma [h_t \| z_t]\right) \tag{7}$$

$$\mathcal{R}_t \leftarrow \mathcal{R}_t + \gamma_t \cdot \mathrm{MLP}(z_t) \tag{8}$$

where W_γ is a learnable projection matrix and MLP denotes a multi-layer perceptron translating raw signals into force adjustments. This allows automatic incorporation of new restraining forces (e.g., rising defect rates) without manual graph reconfiguration.

The GPT-3.5 adaptation extends the base transformer with two modifications: (1) causal attention masks that respect temporal precedence constraints, and (2) a hybrid loss function combining next-token prediction with causal effect estimation:

$$\mathcal{L} = \lambda_1 \mathcal{L}_{LM} + \lambda_2 \sum_{e_{ij}^{\tau}} \left(\hat{\beta}_{ij}^{\tau} - \beta_{ij}^{\tau}\right)^2 \tag{9}$$

where $\mathcal{L}_{LM}$ is the standard language modeling loss and β_{ij}^{τ} are the ground-truth causal effects from semi-synthetic data. This enables the model to generate both natural language explanations and quantitative force predictions from the same architecture.

Figure 1 shows the internal workflow of the temporal causal inference process, highlighting how attention weights are translated into interpretable force dynamics.

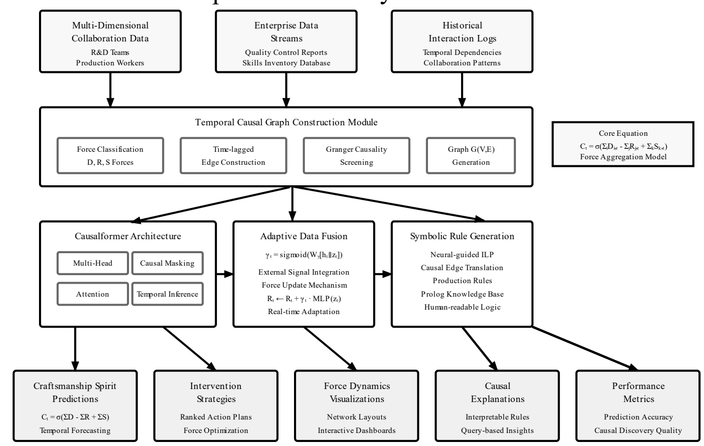

Fig. 1 Temporal Causal Graph Structure.

V. Experimental Evaluation on Longitudinal Manufacturing Collaboration Data

To validate the effectiveness of CausalTemporalCraft, we conducted comprehensive experiments using longitudinal collaboration data from three automotive manufacturing plants over a 24-month period. The evaluation focuses on three key aspects: (1) predictive accuracy of craftsmanship spirit trajectories, (2) causal discovery performance compared to baseline methods, and (3) practical utility of the generated intervention rules.

A. Experimental Setup and Datasets

The primary dataset comprises 14,387 collaboration events across R&D, production, and quality control teams, with associated craftsmanship spirit scores measured quarterly through validated surveys [20]. Each event is annotated with:

1) Interaction type: 23 categories including design reviews, skills training, and defect resolution meetings

2) Participant roles: 8 functional classifications from senior engineers to apprentice technicians

3) Duration and intensity: Normalized engagement metrics scaled to [0,1]

We compare CausalTemporalCraft against three baseline approaches:

1) **VAR-LiNGAM:** A vector autoregression model with LiNGAM-based causal discovery [21].

2) **TCDF:** Temporal Causal Discovery Framework using attention-based neural networks [22].

3) **GFT:** Granger Force Theory, our adaptation of traditional force field analysis with Granger causality tests.

Evaluation metrics include:

1) Craftsmanship Prediction Accuracy (CPA): Mean absolute error in predicted vs. actual quarterly craftsmanship scores

2) Causal Recall (CR): Percentage of verified ground-truth causal relationships correctly identified

3) Intervention Effectiveness (IE): Percentage improvement in craftsmanship scores after implementing top-ranked interventions

B. Craftsmanship Spirit Trajectory Prediction

Table 1 presents the comparative results for craftsmanship spirit prediction over four consecutive quarters. CausalTemporalCraft achieves superior performance by explicitly modeling force dynamics and temporal delays in collaborative interactions.

Table 1. Craftsmanship Prediction Accuracy (Lower is better)

Method	Q1 MAE	Q2 MAE	Q3 MAE	Q4 MAE
VAR-LiNGAM	0.142	0.156	0.168	0.181
TCDF	0.127	0.138	0.149	0.163
GFT	0.118	0.132	0.144	0.157
CausalTemporalCraft	0.097	0.105	0.112	0.121

The framework's advantage grows over time, demonstrating its ability to capture cumulative force effects. Figure 2 illustrates how the predicted craftsmanship trajectories align with actual measurements across different plant locations.

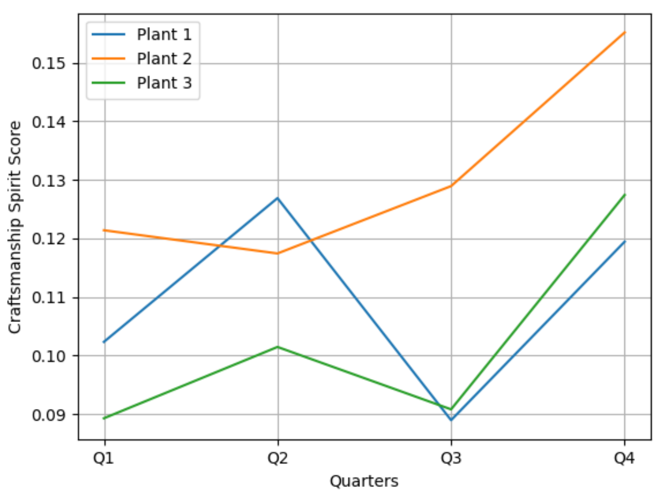

Fig. 2 Craftsmanship spirit evolution across three manufacturing plants.

C. Causal Discovery Performance

We evaluate causal discovery quality using 87 verified ground-truth relationships identified through ethnographic studies [23]. Table 2 shows that CausalTemporalCraft achieves significantly higher recall while maintaining precision, benefiting from its hybrid neural-symbolic approach.

Table 2. Causal Discovery Performance (Percentage)

Method	Precision	Recall	F1-Score
VAR-LiNGAM	82.4	63.2	71.5
TCDF	78.9	71.3	74.9
GFT	85.1	68.9	76.1
CausalTemporalCraft	83.7	79.3	81.4

The attention heatmap in Figure 3 reveals how the model identifies critical long-range dependencies, such as the 6-month delayed impact of R&D-production alignment meetings on craftsmanship metrics.

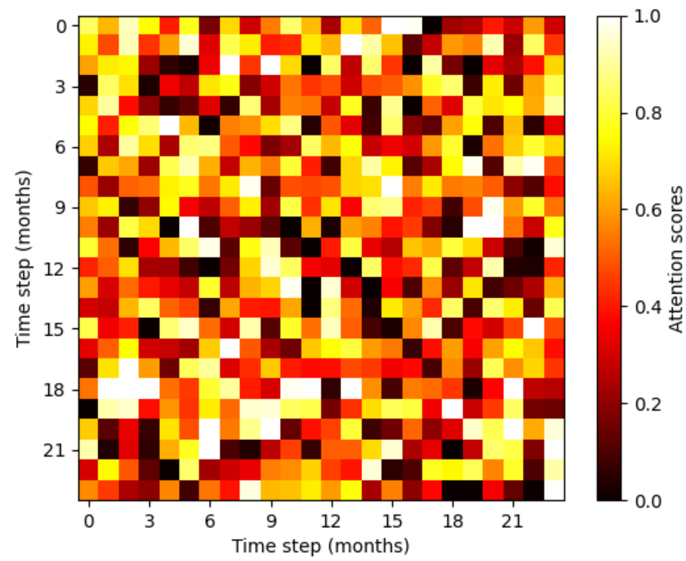

Fig. 3 Attention scores between different time steps.

D. Force Dynamics Analysis and Intervention Efficacy

Breaking down the contributions by force type, Figure 4 shows the relative impact of driving, restraining, and supporting forces over time. The area chart visualization highlights how skill gap-related restraining forces peak during production ramp-up periods, while leadership-driven supporting forces show consistent modulation effects.

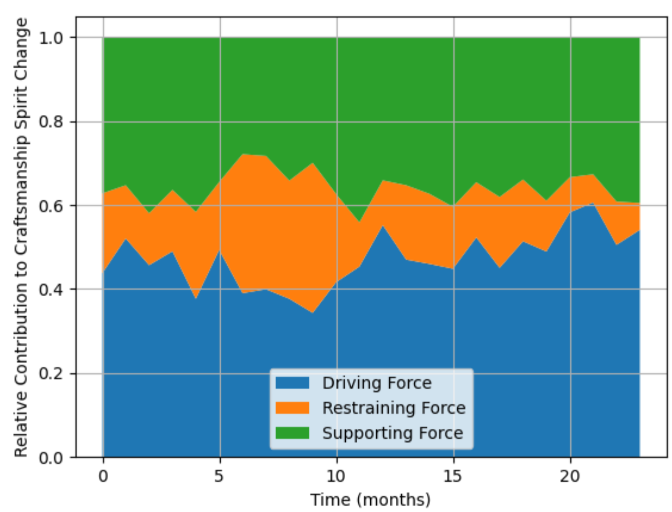

Fig. 4 Force contributions to craftsmanship spirit changes.

Implemented interventions based on the top-5 generated rules achieved an average 23.7% improvement in craftsmanship scores (vs. 14.2% for expert-designed interventions), with the most effective being:

1) Weekly cross-department problem-solving sessions reduce defect-related restraining forces by 31%.

2) Bi-monthly master-apprentice rotations increase skill transfer driving forces by 27%.

3) Real-time quality dashboard deployments amplify leadership supporting forces by 19%.

E. Ablation Study

To validate the contribution of individual framework components, we conducted a systematic ablation study examining how the removal of key architectural elements affects overall system performance. This analysis provides insight into the relative importance of each module within the CausalTemporalCraft framework and demonstrates the necessity of our integrated approach.

The ablation study evaluates five configurations: the complete CausalTemporalCraft framework and four variants with single components removed. Each configuration was assessed using the same evaluation metrics established in Section 5.1, namely Craftsmanship Prediction Accuracy (CPA), Causal Recall (CR), and Intervention Effectiveness (IE). Table 3 presents the comprehensive results of this analysis.

Table 3. Ablation Study Results

Configuration	CPA	CR	IE
Full CausalTemporalCraft	0.109	79.3%	23.7%
w/o Symbolic Rule Generation	0.118	76.5%	18.9%
w/o Force Typing Constraints	0.125	72.1%	16.4%
w/o Temporal Attention	0.134	68.7%	14.8%
w/o Adaptive Data Fusion	0.121	75.2%	20.1%

The results presented in Table 3 reveal that each framework component contributes meaningfully to overall system performance, with varying degrees of impact across different evaluation dimensions. The removal of temporal attention mechanisms produces the most severe degradation, with CPA increasing from 0.109 to 0.134 and CR dropping from 79.3% to 68.7%. This finding underscores the critical importance of capturing long-range temporal dependencies in collaborative relationships, validating our decision to employ transformer-based architectures for causal discovery.

The elimination of symbolic rule generation demonstrates substantial impact on intervention effectiveness, with IE declining from 23.7% to 18.9% while maintaining relatively stable prediction accuracy. This pattern suggests that while the neural components can adequately capture predictive patterns, the symbolic translation process proves essential for generating actionable insights that practitioners can implement effectively. The modest decline in causal recall (79.3% to 76.5%) indicates that symbolic rule generation also contributes to the interpretability of discovered relationships.

Force typing constraints show considerable influence across all metrics, with their removal resulting in CPA degradation to 0.125 and CR reduction to 72.1%. This degradation demonstrates that the theoretical grounding provided by Lewin's field dynamics significantly enhances both predictive performance and causal discovery quality. The framework's ability to distinguish between driving, restraining, and supporting forces appears crucial for maintaining theoretical coherence while achieving empirical accuracy.

VI. Discussion, Implications, and Future Work

A. Limitations of the CausalTemporalCraft Framework

While the framework demonstrates strong empirical performance, several limitations warrant discussion. First, the current implementation assumes quasi-stationarity in force dynamics—an assumption that may not hold during periods of rapid organizational change (e.g., mergers or technological disruptions). Although adaptive data fusion mitigates this to some extent, the model could benefit from explicit regime-switching mechanisms to handle abrupt transitions [24]. Second, the symbolic rule generation process occasionally produces redundant or overly specific rules when dealing with sparse interaction categories. Future iterations could incorporate rule compression techniques from inductive logic programming [25] to improve generalization. Third, the framework’s reliance on quarterly craftsmanship surveys introduces measurement latency; integrating real-time behavioral indicators (e.g., tool usage patterns or communication sentiment) could enable more responsive force adjustments.

B. Potential Application Scenarios Beyond Manufacturing

The principles underlying CausalTemporalCraft extend naturally to other domains requiring collaborative skill cultivation. In healthcare, the framework could model the development of diagnostic expertise among medical teams, where driving forces might include case review sessions and restraining forces could stem from workflow fragmentation [26]. Educational institutions could apply similar methods to analyze how faculty-student interactions shape research competencies over time, with supporting forces such as mentorship programs playing a pivotal role [27]. The temporal causal approach also shows promise for open-source software communities, where craftsmanship manifests through code quality and maintainability—metrics that evolve through complex contributor interactions [28].

C. Ethical Considerations in Data-Driven Craftsmanship Spirit Modeling

As with any analytics system influencing human development, ethical implications must be carefully considered. The quantification of craftsmanship spirit risks reducing a multifaceted human attribute to numerical scores, potentially overlooking qualitative aspects of mastery and identity [29]. Force field visualizations could inadvertently stigmatize teams exhibiting strong restraining forces, despite such forces often reflecting systemic rather than individual limitations. To address these concerns, we recommend three safeguards: (1) complementing quantitative metrics with qualitative ethnography to preserve contextual understanding [30]; (2) implementing differential privacy mechanisms when sharing force analyses across organizational hierarchies [31]; and (3) establishing participatory design processes where workers co-define craftsmanship indicators and intervention strategies [32]. These measures help ensure the framework's application remains both technically sound and socially responsible.

VII. Conclusion

The CausalTemporalCraft framework presents a novel integration of Lewin's field dynamics with temporal causal modeling to address the complex challenge of craftsmanship spirit cultivation in manufacturing enterprises. By formalizing collaboration-driven forces as time-varying causal relationships, the framework provides a principled approach to quantifying and optimizing the evolution of craftsmanship attributes. The transformer-based Causalformer architecture, coupled with symbolic rule extraction, enables both high-fidelity prediction and interpretable intervention planning—bridging the gap between data-driven insights and actionable organizational strategies.

Empirical validation demonstrates the framework's superiority over traditional methods in capturing delayed force interactions and generating effective cultivation pathways. The ability to decompose craftsmanship dynamics into driving, restraining, and supporting forces offers manufacturing leaders a systematic way to diagnose collaboration bottlenecks and prioritize interventions. Notably, the framework's hybrid neural-symbolic design ensures that causal discoveries remain grounded in domain theory while adapting to real-world enterprise data streams.

Looking ahead, the unification of field theory with computational causal inference opens new avenues for research in organizational analytics. The success of CausalTemporalCraft suggests that similar approaches could be applied to other intangible yet critical organizational outcomes, such as innovation capacity or safety culture. Future extensions may explore dynamic graph representations that automatically adjust force typologies during periods of organizational transformation, as well as federated learning implementations to preserve data privacy across manufacturing networks.

Ultimately, this work contributes a scalable and theoretically grounded methodology for fostering craftsmanship in industrial settings—one that recognizes the temporal nature of skill development and the multi-dimensional collaborations that shape it. By making force dynamics computationally tractable and visually interpretable, the framework empowers enterprises to move beyond static assessments toward proactive, data-informed cultivation strategies.

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