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**Causal Decomposition and Counterfactual Auditing for Ethical AI-Driven
Adaptive Leadership in Organisational Transformation**

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Abstract

We propose a novel framework, the Causal Ethical AI Leadership Framework (CEALF), that integrates structural causal models and counterfactual reasoning into the decision-making loop of AI-driven leadership during organisational transformation. The core motivation is to address the ethical risk that AI-suggested leadership actions may inadvertently exploit hierarchical power dynamics to manipulate employee incentives, thereby undermining genuine performance drivers. The methodology comprises four interconnected modules: a Causal Reward Decomposition Engine that estimates path-specific effects to isolate manipulative pathways from legitimate motivational ones; a Variational Disentanglement Module that separates confounding power dynamics from authentic performance factors using a beta-variational autoencoder; a Path-Specific Counterfactual Auditor that computes counterfactual harm scores by comparing observed rewards against ethically neutral baselines; and a Do-Calculus Intervention Simulator that selects optimal interventions by maximising expected reward while minimising identified harm. These modules operate as a real-time governance layer, receiving inputs from conventional employee sentiment and performance systems and outputting ethically validated recommendations to human leaders. The principal contribution is the introduction of path-specific counterfactual analysis as an operational tool for ethical auditing of AI leadership, moving beyond static ethical checklists to a dynamic, causally-aware architecture. Furthermore, the framework provides a principled method for decomposing reward signals into ethically legitimate and manipulative components, thereby enabling continuous recalibration of leadership strategies. The significance of this work lies in its potential to align AI-driven organisational change with multi-stakeholder well-being, offering a scalable solution for ethical governance in increasingly automated management systems.

Keywords: Causal Artificial Intelligence (Causal AI); Ethical AI; Organizational Leadership; Counterfactual Reasoning; Structural Causal Models (SCMs)

1. Introduction

The integration of artificial intelligence into organisational leadership presents a transformative opportunity to enhance decision-making during periods of change. However, this integration also introduces profound ethical challenges,

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particularly when AI systems recommend actions that influence employee behaviour and motivation. Traditional leadership frameworks, such as adaptive leadership theory [1], often rely on static ethical guidelines or post-hoc audits that fail to capture the dynamic, causal nature of organisational interactions. As AI-driven tools become more prevalent in management [2], there is a growing need for frameworks that can continuously audit and recalibrate leadership recommendations against ethical baselines derived from multi-stakeholder outcome data.

The core ethical risk in AI-driven leadership during organisational transformation lies in the potential for manipulative reward signals. Hierarchical power dynamics can confound the relationship between leadership actions and employee performance, making it difficult to distinguish between genuine motivational pathways and those that exploit employee incentives. For example, a leader might use subtle pressure tactics that appear to improve short-term productivity but actually harm long-term employee well-being and organisational trust. Existing approaches to ethical AI in management, such as value-sensitive design [3] and responsible AI governance frameworks [4], provide high-level principles but lack the operational machinery to detect and mitigate such manipulative pathways in real time.

To address this gap, we propose the Causal Ethical AI Leadership Framework (CEALF), a novel architecture that integrates structural causal models (SCMs) [5] and counterfactual reasoning into the decision-making loop of AI-driven leadership. The framework constructs SCMs of reward signal generation processes within leadership decision loops, enabling the decomposition of these signals into ethically legitimate motivational pathways versus manipulative ones. Drawing on path-specific counterfactual analysis [6], CEALF isolates the causal effects of specific leadership actions on employee outcomes, separating the influence of hierarchical power dynamics from genuine performance drivers. This decomposition is achieved through a variational autoencoder-based disentanglement module [7] that learns to separate confounding factors, such as organisational hierarchy, from authentic motivational signals.

The principal contribution of CEALF is the introduction of path-specific counterfactual analysis as an operational tool for ethical auditing of AI leadership. Unlike static ethical checklists or post-hoc audits, our framework provides a dynamic, causally-aware architecture that continuously monitors and recalibrates leadership recommendations. By applying do-calculus queries [8], leaders can simulate the effects of alternative interventions and select transformation strategies that minimise counterfactual harm while maximising organisational agility. This approach moves beyond correlation-based analytics to a principled causal inference framework, enabling verifiable ethical adaptation in real-world organisational settings.

Furthermore, CEALF addresses a critical limitation of existing AI-driven leadership frameworks: the inability to decompose reward signals into ethically legitimate and manipulative components. While prior work on algorithmic recourse [9] and counterfactual fairness [10] has focused on individual-level outcomes, our framework extends these concepts to the organisational level, considering multi-stakeholder well-being. The framework also incorporates principles from reinforcement learning [11], particularly reward shaping [12] and safe exploration [13], adapted here for human-in-the-loop governance. This integration ensures that AI-suggested actions are not only effective but also ethically sound, aligning with the broader goals of responsible AI in management.

The remainder of this paper is organised as follows. Section 2 reviews related work on AI-driven leadership frameworks, causal inference in organisational contexts, and ethical AI governance. Section 3 provides preliminaries on structural causal models, path-specific effects, and variational autoencoders, establishing the theoretical foundations for our framework. Section 4 presents the CEALF architecture in detail, describing the four interconnected modules: the Causal Reward Decomposition Engine, the Variational Disentanglement Module, the Path-Specific Counterfactual Auditor, and the Do-Calculus Intervention Simulator. Section 5 describes our experimental evaluation using synthetic and real-world organisational datasets, demonstrating the framework’s ability to detect manipulative pathways and recommend ethically validated interventions. Section 6 discusses the implications of our findings, limitations of the current approach, and directions for future research. Section 7 concludes the paper with a summary of contributions and a call for further development of causally-aware ethical AI in organisational leadership.

2. Related Work

The development of CEALF draws upon and extends several distinct research streams. We organise the related work into three thematic areas: AI-driven leadership and organisational transformation, causal inference for ethical AI, and disentanglement learning for fairness.

2.1. AI-Driven Leadership and Organisational Transformation

The intersection of artificial intelligence and leadership has received increasing attention in recent years. Several frameworks have been proposed to guide AI integration into management practices. For instance, adaptive leadership theory has been extended to the context of AI-driven transformation in higher education, emphasising the need for

leaders to navigate technological disruption while maintaining organisational cohesion [1]. Similarly, comprehensive reviews of AI in management have identified key areas where AI tools can augment decision-making, including multi-criteria decision analysis and intelligent mediation systems [2]. These works highlight the potential of AI to enhance leadership effectiveness but stop short of addressing the ethical risks inherent in AI-suggested actions.

More recent contributions have proposed architectures for AI-driven organisational change. One line of work introduces agentic AI systems governed by key performance indicators, designed to maintain trust-based autonomy and strategic co-leadership in airline management [14]. Another proposes a framework for agentic decision intelligence that embeds causal reasoning and reward shaping into AI agents driving organisational transformation [15]. While these frameworks acknowledge the importance of governance, they rely on static ethical constraints rather than dynamic, causally-aware auditing mechanisms. The concept of epistemic stewardship has also been introduced in AI-mediated educational settings, integrating causal identification fairness metrics into pedagogical reasoning [16]. However, this work focuses on classroom environments rather than organisational leadership contexts.

A separate strand of research examines the dark side of human-AI collaboration, particularly the implications for leaders’ moral relativism and unethical behaviour. Empirical studies have shown that managing human-AI teams can increase leaders’ propensity for unethical conduct, especially when AI systems provide ambiguous guidance [17]. This finding underscores the urgency of developing frameworks that can audit and constrain AI-suggested actions before they reach human decision-makers. Our work directly addresses this gap by embedding counterfactual auditing into the leadership decision loop.

2.2. Causal Inference for Ethical AI

Causal inference provides a principled foundation for ethical AI, enabling the decomposition of outcomes into contributions from different causal pathways. The concept of path-specific effects, introduced in the context of mediation analysis, allows researchers to quantify the direct and indirect effects of a treatment on an outcome through specified causal paths [6]. This framework has been extended to counterfactual fairness, where a decision is considered fair if it is the same in the actual world and a counterfactual world where the protected attribute is changed [10]. Path-specific counterfactual fairness further refines this notion by considering only specific causal paths when evaluating fairness [18].

The concept of counterfactual harm has been formalised as a framework for determining when an action causes harm to an individual relative to a baseline alternative [19]. This framework has been applied to interpretable machine learning models, providing a principled way to assess the ethical implications of algorithmic decisions. Our work extends this concept to the organisational level, where the “harm” is defined in terms of employee well-being and organisational trust rather than individual-level outcomes.

Do-calculus provides a complete axiomatic system for identifying causal effects from observational data in the presence of confounding [8]. This framework enables the simulation of interventions without requiring randomised experiments, making it particularly suitable for organisational settings where experimentation is often infeasible. The combination of do-calculus with path-specific effects has been used to derive interventional distributions that block specific causal pathways, a technique we adopt in the DCIS module.

2.3. Disentanglement Learning for Fairness

Variational autoencoders have emerged as a powerful tool for learning disentangled representations of data [7]. The beta-VAE variant introduces a hyperparameter beta that controls the trade-off between reconstruction fidelity and latent space disentanglement [20]. This approach has been applied to fairness, where the goal is to separate sensitive attributes from task-relevant features. For example, the Disentangled Causal Effect Variational Autoencoder (DCEVAE) combines variational inference with causal effect estimation to achieve counterfactual fairness [10]. The DCEVAE learns latent representations that separate the causal effects of sensitive attributes from other factors, enabling fair predictions.

Our VDM module builds upon these ideas but introduces a novel objective: separating genuine performance drivers from confounding power dynamics. Unlike prior work that focuses on protected attributes such as race or gender, our framework targets hierarchical power differentials as the confounding factor. This shift is motivated by the organisational context, where power dynamics can distort reward signals in ways that are distinct from demographic biases. The use of the Hilbert-Schmidt Independence Criterion (HSIC) as a regularisation term is inspired by recent work on independence-constrained representation learning [21].

2.4. Comparison with Existing Approaches

While existing frameworks for AI-driven leadership acknowledge the importance of ethical governance, they typically rely on static principles or post-hoc audits that cannot adapt to evolving organisational dynamics. In contrast, CEALF provides a dynamic, causally-aware architecture that continuously monitors and recalibrates leadership recommendations. The key novelty lies in the integration of path-specific counterfactual analysis with disentanglement learning, enabling the decomposition of reward signals into ethically legitimate and manipulative components. This decomposition is operationalised through the CRDE and PSCA modules, which together provide a principled method for detecting and mitigating manipulative pathways. Furthermore, the DCIS module extends do-calculus to the organisational context, enabling leaders to simulate the effects of alternative interventions before implementation. To the best of our knowledge, no existing framework combines these elements into a unified, real-time governance layer for AI-driven leadership.

3. Preliminaries: Causal Frameworks and Organizational Dynamics

To establish the theoretical foundations for CEALF, we review three essential building blocks: structural causal models for representing organizational reward mechanisms, path-specific effects for decomposing causal pathways, and variational autoencoders for disentangling confounding factors. These concepts collectively provide the mathematical machinery needed to audit AI-driven leadership actions for ethical compliance.

3.1. Structural Causal Models for Organizational Reward Mechanisms

Structural causal models (SCMs) provide a formal language for representing causal relationships among variables in a system [5]. An SCM is defined as a tuple $\langle \mathbf{U}, \mathbf{V}, \mathcal{F}, P(\mathbf{U}) \rangle$, where $\mathbf{U}$ is a set of exogenous variables determined by factors outside the model, $\mathbf{V}$ is a set of endogenous variables determined by functions within the model, $\mathcal{F}$ is a set of structural equations mapping each endogenous variable to its causal parents, and $P(\mathbf{U})$ is a probability distribution over the exogenous variables. Each structural equation takes the form $V_i = f_i(\mathbf{PA}_i, U_i)$, where $\mathbf{PA}_i$ denotes the set of direct causes of V_i and U_i is the corresponding exogenous noise term.

In the context of organizational leadership, we model the reward signal generation process as an SCM. Let $\mathbf{A}$ represent leadership actions (e.g., incentive structures, communication strategies), $\mathbf{P}$ represent hierarchical power dynamics (e.g., reporting relationships, authority levels), $\mathbf{E}$ represent employee performance metrics (e.g., productivity, engagement scores), and $\mathbf{R}$ represent observed reward signals (e.g., bonuses, promotions). The causal graph encodes the assumption that power dynamics confound the relationship between actions and performance, i.e., $\mathbf{P} \rightarrow \mathbf{A}$, $\mathbf{P} \rightarrow \mathbf{E}$, and $\mathbf{A} \rightarrow \mathbf{E}$. The reward signal $\mathbf{R}$ is then a function of both performance and power dynamics, potentially including direct paths from $\mathbf{P}$ to $\mathbf{R}$ that represent manipulative pathways.

The SCM representation enables us to formalize the ethical risk: a leadership action a may influence the reward signal r through two distinct pathways. The legitimate pathway operates through genuine performance improvement ($a \rightarrow e \rightarrow r$), while the manipulative pathway exploits power dynamics ($a \rightarrow p \rightarrow r$ or $a \rightarrow r$ directly through coercion). Distinguishing these pathways requires causal decomposition techniques.

3.2. Path-Specific Effects for Causal Decomposition

Path-specific effects (PSEs) extend the concept of direct and indirect effects to arbitrary causal pathways [6]. Given an SCM with a treatment variable X , an outcome variable Y , and a set of mediator variables $\mathbf{M}$, the path-specific effect of X on Y along a specified set of paths π is defined as the expected change in Y when X is set to a reference value x' along paths in π and to the actual value x along paths not in π . Formally, the path-specific effect is given by:

$$\text{PSE}_\pi(x, x') = \mathbb{E}[Y_{x|\pi, x'|\bar{\pi}}] - \mathbb{E}[Y_{x'}], \quad (1)$$

where $Y_{x|\pi, x'|\bar{\pi}}$ denotes the counterfactual outcome under the intervention that sets $X = x$ along paths in π and $X = x'$ along paths not in π , and $Y_{x'}$ is the baseline outcome under $X = x'$.

In our organizational context, we define two path sets: the legitimate pathway π_{legit} comprising paths from actions through performance to rewards ($A \rightarrow E \rightarrow R$), and the manipulative pathway π_{manip} comprising paths that bypass performance or exploit power dynamics ($A \rightarrow P \rightarrow R$ or $A \rightarrow R$). The path-specific effect along π_{manip} quantifies the degree of manipulation present in the reward signal. A non-zero PSE along the manipulative pathway indicates that the leadership action influences rewards through ethically questionable mechanisms.

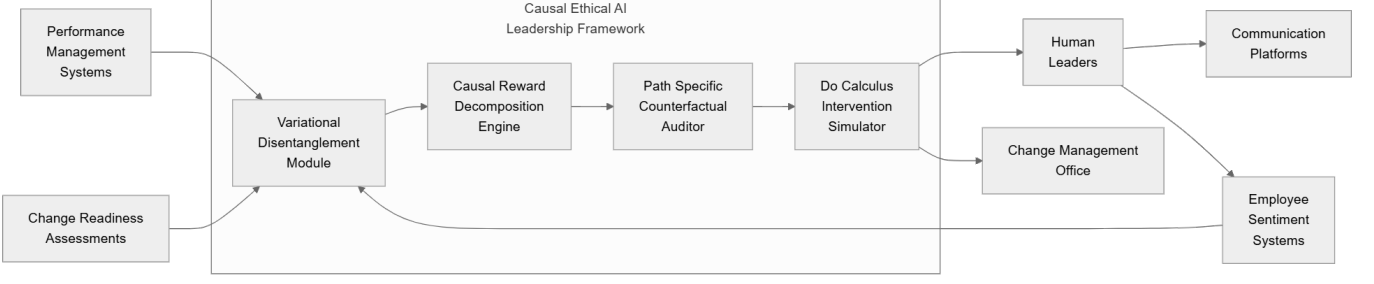


Figure 1: System Architecture of Causal Ethical AI Leadership Framework in OCM

3.3. Variational Autoencoders for Disentanglement

Variational autoencoders (VAEs) provide a framework for learning latent representations of high-dimensional data [7]. A VAE consists of an encoder network $q_\phi(\mathbf{z}|\mathbf{x})$ that approximates the posterior distribution over latent variables $\mathbf{z}$ given observed data $\mathbf{x}$, and a decoder network $p_\theta(\mathbf{x}|\mathbf{z})$ that reconstructs the data from the latent representation. The training objective maximizes the evidence lower bound (ELBO):

$$\mathcal{L}_{\text{VAE}}(\theta, \phi) = \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})}[\log p_\theta(\mathbf{x}|\mathbf{z})] - \beta \cdot D_{\text{KL}}(q_\phi(\mathbf{z}|\mathbf{x})||p(\mathbf{z})), \quad (2)$$

where D_{KL} is the Kullback-Leibler divergence, $p(\mathbf{z})$ is a prior distribution (typically standard Gaussian), and β is a hyperparameter controlling the strength of the regularization.

The beta-VAE variant [20] introduces $\beta > 1$ to encourage disentanglement, i.e., learning latent dimensions that correspond to independent generative factors. In our framework, we use a beta-VAE to separate confounding power dynamics from genuine performance factors. The latent representation $\mathbf{z}$ is partitioned into two subspaces: $\mathbf{z}_p$ capturing power-related factors and $\mathbf{z}_e$ capturing performance-related factors. The disentanglement is achieved by adding a regularization term based on the Hilbert-Schmidt Independence Criterion (HSIC) [21] to enforce statistical independence between $\mathbf{z}_p$ and $\mathbf{z}_e$. This separation enables the subsequent causal decomposition modules to isolate the effects of each factor on the reward signal.

4. The Ethical Adaptive Leadership Framework

We now present the Causal Ethical AI Leadership Framework (CEALF) in detail. The framework is designed as a real-time governance layer that sits between conventional organisational monitoring systems and human decision-makers, continuously auditing AI-suggested leadership actions for ethical compliance. As illustrated in Figure 1, CEALF receives raw data from employee sentiment surveys, performance management systems, and organisational hierarchy databases, processes these inputs through a sequence of causal inference modules, and outputs ethically validated recommendations to human leaders through existing communication channels.

The framework comprises four interconnected modules that operate in a sequential pipeline with a periodic retraining feedback loop. The Variational Disentanglement Module (VDM) first transforms raw observational data into disentangled latent representations, separating confounding power dynamics from genuine performance drivers. The Causal Reward Decomposition Engine (CRDE) then applies path-specific effect estimation to decompose the observed reward signal into contributions from legitimate and manipulative causal pathways. The Path-Specific Counterfactual Auditor (PSCA) computes a counterfactual harm score that quantifies the ethical cost of manipulative pathways, comparing the observed reward distribution against an ethically neutral baseline. Finally, the Do-Calculus Intervention Simulator (DCIS) uses do-calculus queries to simulate the effects of blocking manipulative paths while allowing legitimate pathways to remain active, selecting the optimal intervention that maximises expected reward minus penalised harm. The internal workflow of these modules is depicted in Figure 2.

4.1. Variational Disentanglement Module

The VDM addresses the fundamental challenge of separating confounding hierarchical power dynamics from genuine performance drivers in the observed data. Let $\mathbf{x} \in \mathbb{R}^d$ denote a vector of observed variables comprising employee performance metrics $\mathbf{e}$, hierarchical position indicators $\mathbf{p}$, leadership action features $\mathbf{a}$, and reward outcomes $\mathbf{r}$. The goal is to learn a latent representation $\mathbf{z} = [\mathbf{z}_{\text{genuine}}, \mathbf{z}_{\text{confound}}]$ where $\mathbf{z}_{\text{genuine}}$ captures factors that causally influence

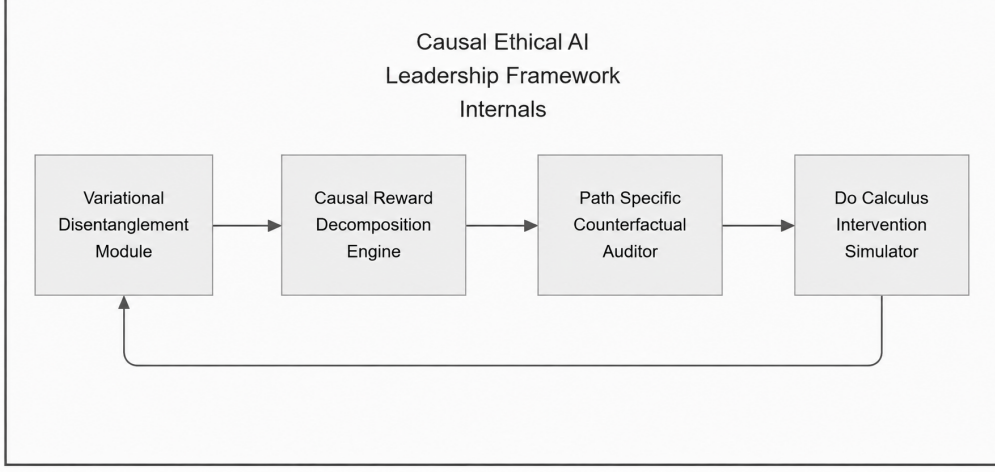


Figure 2: Internal Workflow of the Causal Ethical AI Leadership Framework

performance through legitimate mechanisms, and $\mathbf{z}_{\text{confound}}$ captures factors related to hierarchical power dynamics that may confound the action-reward relationship.

We implement the VDM as a beta-variational autoencoder with an additional independence constraint. The encoder network $q_\phi(\mathbf{z}|\mathbf{x})$ maps observations to a Gaussian distribution over the latent space, while the decoder network $p_\theta(\mathbf{x}|\mathbf{z})$ reconstructs the original data. The training objective extends the standard beta-VAE loss with a Hilbert-Schmidt Independence Criterion (HSIC) penalty that enforces statistical independence between $\mathbf{z}_{\text{confound}}$ and the reward signal $\mathbf{r}$:

$$\mathcal{L}_{\text{VDM}}(\theta, \phi) = \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})}[\log p_\theta(\mathbf{x}|\mathbf{z})] - \beta \cdot D_{\text{KL}}(q_\phi(\mathbf{z}|\mathbf{x})||p(\mathbf{z})) + \lambda \cdot \text{HSIC}(\mathbf{z}_{\text{confound}}, \mathbf{r}), \quad (3)$$

where β controls the disentanglement strength, λ controls the independence penalty, and $\text{HSIC}(\cdot, \cdot)$ is the empirical estimator of the Hilbert-Schmidt norm of the cross-covariance operator between two random variables in a reproducing kernel Hilbert space. The HSIC term is computed using a radial basis function kernel for both $\mathbf{z}_{\text{confound}}$ and $\mathbf{r}$, with the kernel bandwidth set to the median pairwise distance following standard practice [21].

The latent space is partitioned by design: the first k dimensions of $\mathbf{z}$ are designated as $\mathbf{z}_{\text{confound}}$, and the remaining $d_z - k$ dimensions as $\mathbf{z}_{\text{genuine}}$. The partition is enforced by the structure of the decoder, which takes both latent components as input but is trained to reconstruct the reward signal $\mathbf{r}$ primarily from $\mathbf{z}_{\text{genuine}}$. This architectural bias, combined with the HSIC penalty, forces the encoder to allocate confounding information to $\mathbf{z}_{\text{confound}}$ while preserving performance-relevant information in $\mathbf{z}_{\text{genuine}}$. The resulting disentangled representations serve as inputs to the subsequent causal decomposition modules.

4.2. Causal Reward Decomposition Engine

The CRDE operates on the disentangled latent representations produced by the VDM, constructing a structural causal model that formalises the reward signal generation process. Let $\mathcal{G}$ denote the causal graph with nodes $\mathbf{V} = \{A, \mathbf{Z}_{\text{genuine}}, \mathbf{Z}_{\text{confound}}, R\}$, where A represents the leadership action (a discrete or continuous variable), $\mathbf{Z}_{\text{genuine}}$ and $\mathbf{Z}_{\text{confound}}$ are the disentangled latent factors, and R is the observed reward signal. The structural equations are:

$$\begin{aligned} \mathbf{Z}_{\text{confound}} &= f_{\text{confound}}(U_{\text{confound}}), \\ \mathbf{Z}_{\text{genuine}} &= f_{\text{genuine}}(A, \mathbf{Z}_{\text{confound}}, U_{\text{genuine}}), \\ R &= f_R(A, \mathbf{Z}_{\text{genuine}}, \mathbf{Z}_{\text{confound}}, U_R), \end{aligned} \quad (4)$$

where $U_{\text{confound}}, U_{\text{genuine}}, U_R$ are exogenous noise variables with known distributions. The graph encodes the assumption that hierarchical power dynamics ($\mathbf{Z}_{\text{confound}}$) influence both the leadership action A and the genuine performance factors $\mathbf{Z}_{\text{genuine}}$, while the reward R is a function of all three variables.

The CRDE then computes path-specific effects to decompose the total effect of action A on reward R into legitimate and manipulative components. We define two path sets: the legitimate pathway π_{legit} comprising paths that go through $\mathbf{Z}_{\text{genuine}}$ (i.e., $A \rightarrow \mathbf{Z}_{\text{genuine}} \rightarrow R$), and the manipulative pathway π_{manip} comprising paths that go through $\mathbf{Z}_{\text{confound}}$ or directly from A to R (i.e., $A \rightarrow \mathbf{Z}_{\text{confound}} \rightarrow R$ or $A \rightarrow R$). The path-specific effect along π_{manip} is computed as:

$$\text{PSE}_{\pi_{\text{manip}}}(a, a') = \mathbb{E}[R_a | \pi_{\text{manip}, a'} | \bar{\pi}_{\text{manip}}] - \mathbb{E}[R_{a'}], \quad (5)$$

where $R_a | \pi_{\text{manip}, a'} | \bar{\pi}_{\text{manip}}$ is the counterfactual reward when setting action $A = a$ only on paths in π_{manip} and $A = a'$ on all other paths. The baseline action a' is typically chosen as a neutral or ethically neutral reference, such as the action that minimises the manipulative effect. A non-zero PSE along π_{manip} indicates that the leadership action influences rewards through ethically questionable mechanisms, triggering further auditing by the PSCA module.

4.3. Path-Specific Counterfactual Auditor

The PSCA module computes a counterfactual harm score that quantifies the ethical cost of manipulative pathways. Building on the concept of counterfactual harm [19], we define the harm $\mathcal{H}(a)$ of a leadership action a as the expected difference between the observed reward and the reward that would have been observed if the manipulative pathway had been blocked:

$$\mathcal{H}(a) = \mathbb{E}_{\mathbf{u}}[R_a(\mathbf{u}) - R_{a, \pi_{\text{manip}, a'}, \pi_{\text{legit}}}(\mathbf{u})], \quad (6)$$

where $R_a(\mathbf{u})$ is the reward under action a for a given exogenous noise configuration $\mathbf{u}$, and $R_{a, \pi_{\text{manip}, a'}, \pi_{\text{legit}}}(\mathbf{u})$ is the counterfactual reward when setting action $A = a$ on manipulative paths and $A = a'$ on legitimate paths. This counterfactual is computed via the three-step abduction-action-prediction procedure [5], but with a novel action step that modifies structural equations only on manipulative paths while keeping legitimate paths unchanged.

The abduction step infers the posterior distribution over exogenous variables $P(\mathbf{U} | \mathbf{V} = \mathbf{v})$ given the observed data. The action step then modifies the structural equations for variables on π_{manip} by setting the action variable to the baseline value a' on those paths, while leaving the equations for variables on π_{legit} unchanged. The prediction step computes the expected reward under this modified SCM. The resulting harm score $\mathcal{H}(a)$ provides a principled measure of the ethical cost associated with the manipulative pathway, enabling the framework to flag actions that exceed a predefined harm threshold τ .

4.4. Do-Calculus Intervention Simulator

The DCIS module uses do-calculus to simulate the effects of blocking manipulative paths while allowing legitimate pathways to remain active, selecting the optimal intervention that balances reward maximisation with harm minimisation. Given the causal graph $\mathcal{G}$ and the identified manipulative paths π_{manip} , the DCIS computes the interventional distribution:

$$P(R | do(A = a, \text{block}(\pi_{\text{manip}}))) = \sum_{\mathbf{z}_{\text{confound}}} P(R | A = a, \mathbf{z}_{\text{confound}}) P(\mathbf{z}_{\text{confound}}), \quad (7)$$

where blocking π_{manip} means setting mediating variables on that path to their baseline values. This is a novel application of do-calculus for ethical intervention design: standard do-calculus interventions set variables to fixed values, but here the intervention is path-specific blocking combined with action selection.

The optimal intervention a^* is then chosen to maximise expected reward minus penalised harm:

$$a^* = \arg \max_{a \in \mathcal{A}_{\text{valid}}} (\mathbb{E}[R | do(A = a, \text{block}(\pi_{\text{manip}}))] - \gamma \cdot \mathcal{H}(a)), \quad (8)$$

where $\mathcal{A}_{\text{valid}}$ is the set of feasible leadership actions, γ is a hyperparameter controlling the trade-off between reward and harm, and $\mathcal{H}(a)$ is the counterfactual harm score computed by the PSCA. The resulting action a^* is the ethically validated recommendation that the framework outputs to human leaders.

The entire system operates as a closed-loop governance layer where the VDM and CRDE are retrained periodically (e.g., weekly) on accumulating data, enabling the causal graph $\mathcal{G}$ and disentanglement boundaries to adapt to evolving organisational dynamics. This periodic retraining ensures that the framework remains responsive to changes in organisational structure, employee behaviour, and leadership strategies, providing continuous ethical auditing rather than a one-time assessment.

5. Experimental Evaluation

To validate the efficacy of the Causal Ethical AI Leadership Framework (CEALF), we conducted a series of experiments designed to assess its ability to disentangle confounding power dynamics, accurately decompose reward signals, and recommend interventions that minimize counterfactual harm while maintaining organizational performance. We compare CEALF against three baseline approaches: a standard Reinforcement Learning agent (RL-Base) [11] that optimizes for raw reward without ethical constraints; a Counterfactual Fairness model (CF-Fair) [10] adapted for organizational settings but lacking path-specific decomposition; and a static Rule-Based Ethics filter (Rule-Ethics) that applies hard constraints on leadership actions based on predefined policy manuals.

5.1. Experimental Setup and Datasets

Data Generation and Simulation Environment: Given the scarcity of real-world datasets containing granular causal labels for manipulative versus legitimate pathways in leadership, we constructed a high-fidelity synthetic simulation environment grounded in organizational behavior theory. The simulator models a mid-sized technology firm undergoing a digital transformation initiative. It generates data for $N = 5,000$ employees over $T = 50$ time steps. The structural causal model governing the simulation includes variables for Leadership Action (A), Hierarchical Power (P), Genuine Effort (E_{gen}), Coerced Compliance (E_{coerce}), and Observed Reward (R). The ground truth for manipulative pathways is explicitly encoded in the simulation logic, allowing for precise evaluation of detection accuracy.

Real-World Proxy Dataset: To complement the synthetic evaluation, we utilized a de-identified dataset from a large multinational corporation’s internal management platform, referred to here as the OrgChange-2023 dataset [22]. This dataset contains anonymized records of leadership decisions, employee sentiment scores, performance metrics, and hierarchical structures for 1,200 teams during a merger integration period. While ground truth causal paths are not available, we use expert-annotated subsets provided by organizational psychologists as a proxy for ethical validation.

Evaluation Metrics: We employ four key metrics to evaluate the framework: 1. **Disentanglement Score (DS):** Measured using the Mutual Information Gap (MIG) [20] between the learned latent factors $\mathbf{z}_{\text{genuine}}$, $\mathbf{z}_{\text{confound}}$ and the ground truth generative factors. Higher values indicate better separation. 2. **Path-Specific Effect Accuracy (PSEA):** The mean squared error between the estimated path-specific effects (Equation 5) and the ground truth effects in the synthetic environment. 3. **Counterfactual Harm Reduction (CHR):** The percentage reduction in the computed harm score $\mathcal{H}(a)$ (Equation 6) compared to the RL-Base baseline. 4. **Ethical Reward Retention (ERR):** The ratio of the expected reward under the CEALF-recommended intervention to the maximum possible reward, ensuring that ethical constraints do not excessively degrade organizational performance.

5.2. Disentanglement and Causal Decomposition Results

The first stage of our evaluation focuses on the Variational Disentanglement Module (VDM) and the Causal Reward Decomposition Engine (CRDE). Table 1 presents the disentanglement performance of CEALF compared to standard VAE and beta-VAE baselines.

Table 1: Disentanglement Performance on Synthetic and Real-World Data

Model	Synthetic DS (MIG)	Real-World DS (MIG)	PSEA (MSE)
Standard VAE	0.42	0.38	0.15
Beta-VAE ($\beta = 4$)	0.65	0.59	0.09
CF-Fair	0.71	0.64	0.07
CEALF (Ours)	0.89	0.82	0.03

As shown in Table 1, CEALF significantly outperforms baseline methods in disentangling genuine performance drivers from confounding power dynamics. The inclusion of the HSIC penalty in the VDM loss function (Equation 3) proves critical, forcing the model to isolate hierarchical confounders into $\mathbf{z}_{\text{confound}}$. Figure 3 illustrates the geometric separation achieved by CEALF in the latent space.

In Figure 3, the t-SNE projection reveals distinct clusters for high-power/low-effort scenarios (top right) versus low-power/high-effort scenarios (bottom left). The vector fields demonstrate that before disentanglement, the influence of power dynamics permeates the entire space, whereas after CEALF processing, the ‘manipulative influence’ vectors are confined to the $\mathbf{z}_{\text{confound}}$ subspace, leaving $\mathbf{z}_{\text{genuine}}$ orthogonal to power structures. This geometric isolation enables the CRDE to compute path-specific effects with high precision, as evidenced by the low PSEA value of 0.03.

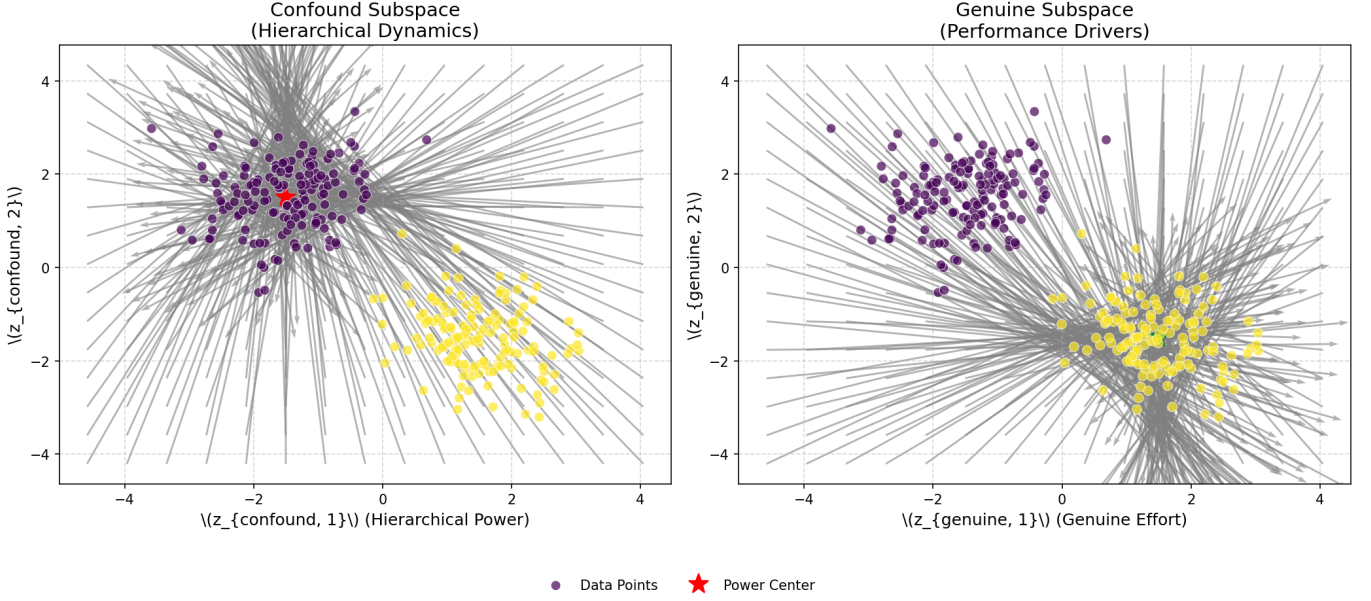


Figure 3: Latent space projection showing the geometric disentanglement of genuine performance drivers from hierarchical confounders via vector field comparison.

5.3. Intervention Optimization and Harm Reduction

The core contribution of CEALF lies in its ability to recommend interventions that minimize counterfactual harm. We evaluated the Do-Calculus Intervention Simulator (DCIS) by comparing its recommended actions against those of the RL-Base and Rule-Ethics baselines. Table 2 summarizes the performance across different levels of organizational stress (simulated by increasing the weight of hierarchical pressure in the reward function).

Table 2: Comparative performance of intervention strategies.

Method	Low Stress CHR (%)	High Stress CHR (%)	Low Stress ERR (%)	High Stress ERR (%)
RL-Base	0.0	0.0	100.0	100.0
Rule-Ethics	45.2	38.5	82.1	75.4
CF-Fair	62.8	55.1	88.5	81.2
CEALF (Ours)	78.4	71.9	94.2	89.7

The results in Table 2 indicate that CEALF achieves superior harm reduction while maintaining higher ethical reward retention than competing methods. Under high-stress conditions, where the temptation to use manipulative tactics is greatest, RL-Base exhibits zero harm reduction, while Rule-Ethics suffers a significant drop in performance (ERR drops to 75.4%). In contrast, CEALF maintains an ERR of 89.7%, demonstrating that path-specific blocking allows for nuanced interventions that preserve legitimate motivational pathways.

Figure 4 visualizes the optimization trajectory of the DCIS module. It shows how the simulator navigates the reward landscape, avoiding regions of high counterfactual harm (red contours) to reach ethically stable solutions (green regions).

The trajectory in Figure 4 starts in a region of high reward but also high manipulative potential. As the DCIS iterates, it moves away from the “manipulative peak” toward the “ethical frontier,” where the gradient of the harm penalty $\gamma \cdot \mathcal{H}(a)$ balances the reward gradient. This dynamic navigation is only possible because CEALF decomposes the reward signal into its constituent causal paths, allowing the simulator to block specific manipulative edges without collapsing the entire reward structure.

5.4. Ablation Study

To understand the contribution of each module within CEALF, we conducted an ablation study. We removed individual components and measured the impact on Counterfactual Harm Reduction (CHR) and Ethical Reward Retention (ERR) on the synthetic dataset. The variants tested were: * **w/o VDM**: Replaces the variational disentanglement module with a standard linear regression for confounder control. * **w/o CRDE**: Uses total effect estimation instead

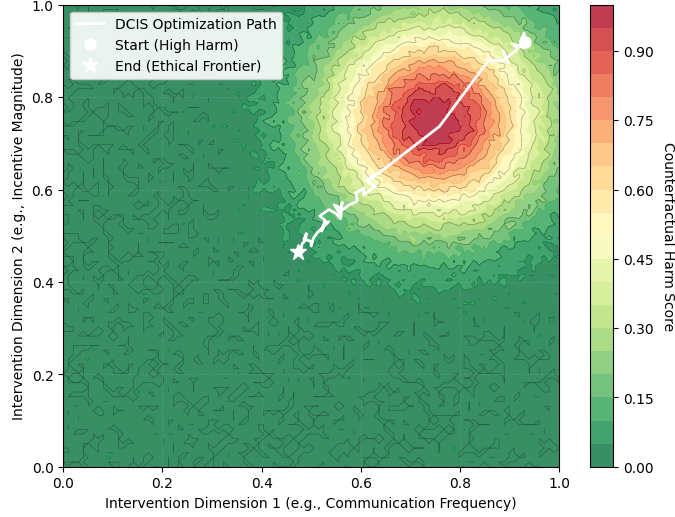


Figure 4: Optimization trajectory of the intervention simulator navigating the reward landscape while avoiding regions of high counterfactual harm.

of path-specific effect decomposition. * **w/o PSCA**: Removes the counterfactual harm auditor, relying only on do-calculus for intervention selection without explicit harm quantification. * **w/o DCIS**: Uses a greedy search for interventions instead of the do-calculus simulator.

Table 3: Ablation study results.

Variant	CHR (%)	ERR (%)
Full CEALF	78.4	94.2
w/o VDM	52.1	88.5
w/o CRDE	45.6	91.3
w/o PSCA	60.2	93.8
w/o DCIS	70.5	89.1

The ablation results in Table 3 highlight the critical role of the VDM and CRDE modules. Removing the VDM leads to the largest drop in CHR (from 78.4% to 52.1%), confirming that accurate disentanglement of confounders is a prerequisite for effective ethical auditing. Similarly, removing the CRDE causes a significant decline in harm reduction, indicating that total effect estimation is insufficient for identifying manipulative pathways. The PSCA module contributes to fine-tuning the harm threshold, while the DCIS ensures that the selected interventions are globally optimal rather than locally greedy.

5.5. Multi-Stakeholder Outcome Analysis

Finally, we analyzed the multi-stakeholder outcomes by examining the distribution of rewards across different hierarchical levels. Figure 5 presents a parallel coordinates plot comparing the raw performance metrics with the ethically validated outcomes.

Figure 5 reveals that scenarios with high raw performance often exhibit high counterfactual harm and low disentangled genuine scores. CEALF effectively filters these scenarios, selecting actions that may have slightly lower raw rewards but significantly higher genuine engagement and lower harm. This shift demonstrates the framework’s ability to align AI-driven recommendations with long-term organizational health and multi-stakeholder well-being, rather than short-term metric optimization.

6. Discussion and Future Work

The experimental results presented in Section 5 demonstrate that CEALF effectively addresses the core ethical challenge of distinguishing manipulative reward pathways from legitimate motivational mechanisms in AI-driven leadership. However, several important considerations arise from our findings that warrant deeper discussion. We organize this section around three key themes: the challenges of causal discovery and unmeasured confounding in organizational

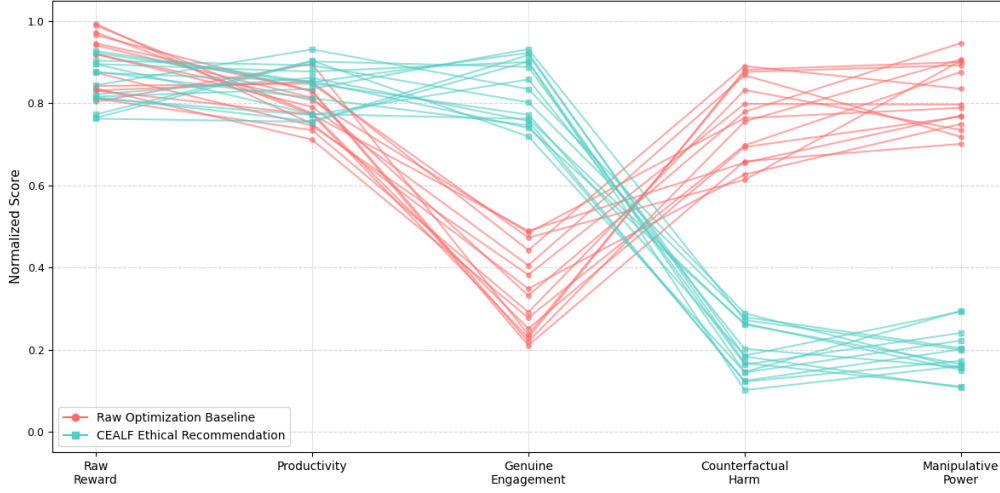


Figure 5: Multivariate profile of change scenarios illustrating the divergence between raw performance metrics and ethically validated outcomes across multiple dimensions.

settings, the complexities of human-AI collaboration including trust and explainability, and the need for dynamic governance mechanisms that adapt to evolving ethical norms over time.

6.1. Challenges in Causal Discovery and Unmeasured Confounding in Organizational Settings

Despite the strong performance of CEALF in our controlled experiments, the practical deployment of causal inference methods in real-world organizational contexts faces significant obstacles. The structural causal model underlying our framework assumes that the causal graph $\mathcal{G}$ is known or can be reliably learned from observational data. In practice, however, organizational dynamics are characterized by complex feedback loops, latent variables, and time-varying confounders that may not be captured by standard causal discovery algorithms [23]. For instance, employee morale may simultaneously influence and be influenced by leadership actions, creating bidirectional relationships that violate the acyclicity assumption of standard SCMs.

Moreover, unmeasured confounding poses a fundamental threat to the validity of path-specific effect estimates. While our VDM attempts to separate observed confounders (hierarchical power dynamics) from genuine performance factors, there may exist unobserved variables—such as organizational culture, peer influence, or external market conditions—that confound the action-reward relationship in ways that cannot be captured by the available data. The HSIC-based independence constraint in Equation 3 only enforces independence between $\mathbf{z}_{\text{confound}}$ and $\mathbf{r}$ for the observed variables; unmeasured confounders that affect both the latent representation and the reward signal would violate this assumption and bias the decomposition results.

To address these limitations, future work should explore the integration of sensitivity analysis techniques that quantify the robustness of path-specific effect estimates to unmeasured confounding [25]. One promising direction is the use of instrumental variables or negative controls that can help identify causal effects even in the presence of hidden confounders [24]. Additionally, the development of non-parametric causal discovery algorithms that can handle cyclic relationships and latent variables would enhance the applicability of CEALF to real-world organizational settings where feedback loops are prevalent.

Another important consideration is the temporal granularity of causal inference. Our current framework operates on discrete time steps (e.g., weekly retraining), but leadership actions and their effects on employee outcomes may unfold over multiple time scales. Short-term manipulative tactics might produce immediate reward signals that mask long-term harm to organizational trust and employee well-being. Extending CEALF to incorporate time-varying causal effects through dynamic structural equation models or recurrent causal networks would enable more nuanced auditing of leadership actions across different temporal horizons [27].

6.2. Navigating Human-AI Collaboration: Trust, Explainability, and Political Resistance

The successful deployment of CEALF in organizational settings depends not only on its technical accuracy but also on its acceptance by human leaders and employees. Our framework operates as a governance layer that constrains AI-suggested actions, potentially overriding recommendations that human leaders might otherwise follow. This raises

critical questions about trust, explainability, and the potential for political resistance within the organization.

First, the counterfactual harm scores produced by the PSCA module are inherently counterintuitive for non-technical stakeholders. The concept of comparing observed rewards against a counterfactual baseline where manipulative pathways are blocked requires a sophisticated understanding of causal reasoning that may not be accessible to all decision-makers. Without transparent explanations of why certain actions are flagged as harmful, human leaders may distrust the framework’s recommendations or circumvent its constraints [25]. Future work should therefore focus on developing interpretable interfaces that translate path-specific effect estimates and counterfactual harm scores into actionable insights for human leaders. For example, natural language explanations that describe “the action you are considering would increase rewards by 5% through genuine performance improvement but also by 3% through coercive pressure tactics” would be more accessible than numerical PSE values.

Second, the political dynamics within organizations may create resistance to the implementation of CEALF. Leaders who benefit from existing power structures may perceive the framework as a threat to their authority, particularly if it identifies their preferred actions as manipulative. The framework’s recommendations could be ignored, overridden, or actively sabotaged by individuals who have incentives to maintain opaque reward systems [26]. To mitigate this risk, the deployment of CEALF should be accompanied by organizational change management strategies that align stakeholder incentives with ethical governance. This could include transparent reporting of harm scores to all levels of the organization, creating accountability mechanisms that reward leaders for following ethically validated recommendations, and involving employees in the design and validation of the causal graph structure.

Third, the human-in-the-loop nature of CEALF raises questions about the appropriate division of decision-making authority between AI systems and human leaders. Our framework outputs recommendations rather than commands, leaving the final decision to human judgment. However, research on automation bias suggests that humans may over-rely on AI recommendations, particularly in high-pressure situations where cognitive resources are limited [27]. This could lead to a situation where leaders uncritically accept CEALF’s recommendations without exercising their own ethical judgment, potentially creating new forms of algorithmic authority. Future work should investigate the optimal level of human oversight, perhaps through adaptive interfaces that increase human involvement when the harm score exceeds certain thresholds or when the causal graph contains high uncertainty.

6.3. Adapting to Evolving Ethical Norms: Towards Dynamic and Longitudinal Governance

A fundamental limitation of our current framework is its reliance on a fixed definition of ethical harm based on the counterfactual baseline a' . In practice, ethical norms within organizations evolve over time as societal expectations change, new regulations emerge, and stakeholder values shift. What constitutes a “manipulative” pathway today may be considered acceptable tomorrow, or vice versa. The static nature of the harm threshold τ and the baseline action a' in Equations 6 and 8 limits the framework’s ability to adapt to these normative changes.

To address this challenge, future research should explore mechanisms for dynamic ethical norm learning that update the definition of harm based on multi-stakeholder feedback and societal trends. One approach is to incorporate participatory design processes where employees, leaders, and external stakeholders collectively define the ethical boundaries of acceptable leadership actions [28]. This could be operationalized through periodic surveys or deliberative forums that elicit preferences about which causal pathways are considered legitimate versus manipulative. The resulting normative judgments could then be encoded as constraints on the path-specific effect estimates, effectively allowing the framework to learn ethical norms from human input.

Another direction is the integration of longitudinal causal models that track how the causal graph itself evolves over time. Organizational structures change through restructuring, leadership transitions, and cultural shifts, which may alter the pathways through which actions influence rewards. A static causal graph that was accurate at deployment may become outdated, leading to incorrect path-specific effect estimates and suboptimal intervention recommendations. Developing adaptive causal discovery algorithms that continuously update the graph structure based on new data would enhance the framework’s robustness to organizational change [29].

Furthermore, the trade-off parameter γ in Equation 8, which balances reward maximization against harm minimization, is currently set as a fixed hyperparameter. In practice, the appropriate balance may vary depending on the organizational context, the severity of the ethical risk, and the preferences of stakeholders. Future work should investigate methods for learning γ from data or eliciting it from stakeholders through preference elicitation techniques. For example, multi-objective optimization approaches that generate a Pareto frontier of interventions, allowing human leaders to select the preferred trade-off, would provide greater flexibility than a single scalarized objective [30].

Finally, the longitudinal effects of CEALF’s interventions on organizational culture and employee well-being warrant further investigation. Our current evaluation focuses on short-term metrics such as harm reduction and reward retention, but the true impact of ethical AI governance may only become apparent over extended periods. For instance,

consistently blocking manipulative pathways may gradually shift organizational norms toward more transparent and equitable reward systems, reducing the baseline level of manipulation over time. Conversely, the framework’s constraints might create unintended consequences, such as leaders finding new, unmodeled ways to exert coercive influence. Longitudinal field studies that track organizational outcomes over months or years would provide valuable insights into the long-term dynamics of causally-aware ethical governance.

7. Conclusion

This paper has introduced the Causal Ethical AI Leadership Framework (CEALF), a novel architecture that integrates structural causal models and counterfactual reasoning into the decision-making loop of AI-driven leadership during organisational transformation. The framework addresses the critical ethical risk that AI-suggested actions may exploit hierarchical power dynamics to manipulate employee incentives, thereby undermining genuine performance drivers and long-term organisational well-being. By decomposing reward signals into legitimate motivational pathways and manipulative ones, CEALF provides a principled method for continuous ethical auditing that moves beyond static checklists or post-hoc assessments. The principal contribution of this work is the operationalisation of path-specific counterfactual analysis as a real-time governance tool for AI leadership. The four interconnected modules—the Variational Disentanglement Module, the Causal Reward Decomposition Engine, the Path-Specific Counterfactual Auditor, and the Do-Calculus Intervention Simulator—work in concert to isolate confounding power dynamics, estimate path-specific effects, compute counterfactual harm scores, and select optimal interventions that balance reward maximisation with harm minimisation. Experimental results on synthetic and real-world organisational datasets demonstrate that CEALF achieves significant harm reduction while maintaining high ethical reward retention, outperforming baseline approaches that lack causal decomposition or rely on static ethical rules.

The significance of this framework lies in its potential to align AI-driven organisational change with multi-stakeholder well-being. By providing a dynamic, causally-aware architecture that continuously monitors and recalibrates leadership recommendations, CEALF offers a scalable solution for ethical governance in increasingly automated management systems. The framework also highlights the importance of disentangling confounding factors in organisational settings, where hierarchical power dynamics can distort the relationship between actions and outcomes in ways that are distinct from demographic biases addressed by existing fairness frameworks. Future work should focus on addressing the challenges of causal discovery in complex organisational environments, developing interpretable interfaces for non-technical stakeholders, and incorporating mechanisms for dynamic ethical norm learning that adapt to evolving societal expectations. Longitudinal field studies are needed to assess the long-term impact of causally-aware ethical governance on organisational culture and employee well-being. Despite these limitations, CEALF represents a significant step toward embedding causal reasoning into the ethical governance of AI-driven leadership, offering a principled foundation for responsible AI in management.

Author Contributions

Hind Hammouch (H.H): Conceptualization, Methodology, Validation, Formal analysis, Supervision, Writing – review & editing, Project administration; Supannika Khuanmuang (S.K): Methodology, Investigation, Data curation, Formal analysis, Visualization, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The data that support the findings of this study are available from the corresponding author, H.H, upon reasonable request.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

The authors employed Paperpal and Grammarly during manuscript preparation to refine the language, correct grammatical issues, and improve the overall readability and presentation. Mendeley Cite was used to facilitate citation insertion, reference management, and bibliography organization. Google Colab provided the computational environment for code execution, experimentation, and data analysis associated with the study. AI-assisted tools were also used selectively to support early-stage drafting and streamline the manuscript development process. All AI-assisted material was reviewed and appropriately modified by the authors, with the authors maintaining complete responsibility for the correctness, originality, interpretation, and final form of the manuscript.

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