

Attributing Responsibility in AI-Induced Incidents: A Computational Reflective Equilibrium Framework for Accountability

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Abstract—The pervasive integration of Artificial Intelligence (AI) has introduced complex challenges in the responsibility and accountability in the event of incidents involving AI-enabled systems. The interconnectivity of these systems, ethical concerns of AI-induced incidents, coupled with uncertainties in AI technology and the absence of corresponding regulations, have made traditional responsibility attribution challenging. To this end, this work proposes a Computational Reflective Equilibrium (CRE) approach to establish a coherent and ethically acceptable responsibility attribution framework for all stakeholders. The computational approach provides a structured analysis that overcomes the limitations of conceptual approaches in dealing with dynamic and multifaceted scenarios, showcasing the framework’s explainability, coherence, and adaptivity properties in the responsibility attribution process. We examine the pivotal role of the initial activation level associated with claims in equilibrium computation. Using an AI-assisted medical decision-support system as a case study, we illustrate how different initializations lead to diverse responsibility distributions. The framework offers valuable insights into accountability in AI-induced incidents, facilitating the development of a sustainable and resilient system through continuous monitoring, revision, and reflection.

Index Terms—Responsibility Attribution, Accountability, Reflective Equilibrium, AI Ethics

I. INTRODUCTION

In today’s context, Artificial Intelligence (AI) has been integrated into systems with critical functionalities. Cyber-physical systems, such as smart health systems, cloud-enabled critical infrastructure, and connected vehicles, are quintessential examples. The wide adoption of AI, however, introduces a range of issues, encompassing safety concerns in autonomous driving, the reliability of AI-driven medical diagnosis and treatment, and the unforeseen outcomes arising from medical recommendation systems. The recent White House executive order [1] places the highest priority on governing the development and use of AI in a safe and responsible manner. Nonetheless, as an emerging technology with a black-box nature, AI introduces uncertainties that cannot be easily identified, assessed, and attributed by traditional approaches. Concerns arise due to the absence of mechanisms for responsibility attribution in incidents caused by AI systems. The lack of accountability can result in hesitancy in the pervasive adoption of AI, thereby limiting the growth and the impact of the technology. To this end, there is a need to establish an accountability framework for AI-enabled systems, facilitating the future development of safe, secure, and trustworthy AI.

Accountability involves recognizing and accepting responsibility for the potential outcomes of one’s actions. In the context of AI-related incidents, it revolves around identifying responsibility for failures in AI systems. For example, AI-enabled medical decision-support systems rely on AI algorithms to

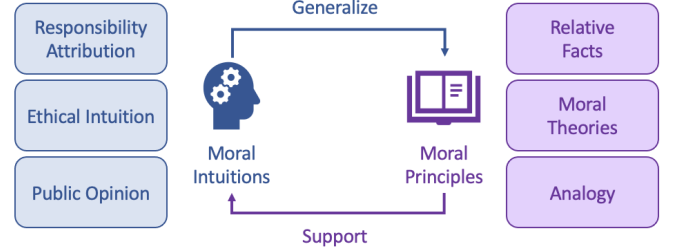


Fig. 1: General process of reflective equilibrium: The process involves formulating a set of moral intuitions, applying evidence and moral principles to support the claim, and iteratively revising and reflecting on intuitions to establish a coherent equilibrium.

provide medical diagnosis and recommendations. Typically, a physician administers a medical test to a patient, and the results are input into the system. The doctor, relying on the AI’s suggested results, prescribes medication to the patient. If medical incidents occur due to the patient following the doctor’s prescription, various parties could be accountable. Possible points of accountability include the physician’s actions during the operation, potential errors in AI development, the doctor’s dependence on AI recommendations, and the patient’s adherence to the treatment plan. Determining how to allocate responsibility among all involved parties proves to be a challenging task.

Attributing AI responsibility has the following challenges. The first challenge arises from the interconnected and complex nature of AI systems, where inherent vulnerabilities in each component can contribute to potential malfunctions, making responsibility attribution to individual components a complex task [2]. The second challenge involves uncertainties in AI, both in the technology itself and in regulations governing AI. The AI system provides a diagnosis, but the reasoning behind the recommendation is not transparent or explainable, creating difficulties in determining accountability without clear examination tools. Additionally, there is a lack of legal regulations and guidelines outlining expected conduct, responsibilities, and ethical principles for practitioners when utilizing AI in their practice. Furthermore, new challenges also arise from ethical constraints. One example is the allocation of limited medical resources by an AI decision-support system, prioritizing certain groups of patients over others. Determining accountability becomes complex when such decisions result in inadequate medical resources for underprivileged patients.

To address these inherent challenges, we seek to establish a coherent responsibility attribution framework among stakeholders supported by justified beliefs. Drawing inspirations from moral and political philosophy, particularly associated with the work of John Rawls [3]–[5], we employ Reflective

Equilibrium (RE) as our approach. RE begins with moral intuitions or judgments regarding specific cases or general principles, representing immediate and unreflective responses to given situations. Subsequently, evidence and theoretical principles from philosophical frameworks or other theories are introduced. A comparison is then made between these intuitions and the theoretical principles, whether new or existing. In the presence of inconsistencies or conflicts, adjustments are made to establish a coherent and balanced set of principles and intuitions that mutually support each other. The iterative process, as illustrated in Fig. 1, eventually leads us to consistency in ethical responsibility attribution. In the context of AI-induced incidents, many inconsistencies arise due to the absence of applicable theory conflicting with human intuition.

Applying RE to AI-induced incidents, we first establish a framework utilizing reflective equilibrium to assess and assign responsibility to achieve a coherent and ethically acceptable equilibrium for all stakeholders. Initially, we formally state all possible responsibility attribution principles for AI-enabled systems involving multiple parties. Subsequently, we apply evidence and moral principles to support the responsibility attribution accordingly. We refer to the intuitions and principles as claims. To find the equilibrium, we formulate the problem as a constraint satisfaction problem using coherence theory and employ a computational approach, defining our solution as Computational Reflective Equilibrium (CRE). This computational framework provides a structured analysis that overcomes the limitations of conceptual approaches in dealing with dynamic and multifaceted scenarios. To enhance results, we incorporate hypothesis testing and gather feedback from those involved in or contributing to accountability measures to determine the initial activation level for each claim. We showcase that different initializations would lead to diverse responsibility distributions in the equilibrium.

The computational approach aims to achieve a coherent and ethically justifiable equilibrium that minimizes conflicts and maximizes support, achieving consistency among the stakeholders. By employing computation, our framework not only enhances clarity in ethical reasoning but also demonstrates adaptability to diverse ethical contexts, promoting transparency and coherence in responsibility attribution. Computational Reflective Equilibrium (CRE) facilitates a dynamic balance among conflicting ethical principles, obligations, and evidence, offering context-sensitive solutions. To ensure transparency, it is imperative to communicate the principles and accountability standards to all stakeholders. Moreover, continuous monitoring and revisiting the equilibrium for necessary adjustments in case of discrepancies are also crucial components of the process. We use a medical decision-support system as a case study to illustrate the framework and provide computational results to highlight its properties.

The remainder of the paper is organized as follows. In Section II, we delve into the related work within the field. Section III outlines the computational reflective equilibrium framework. In Section IV, we discuss the properties of the proposed model. The performance of our model through simulations is presented in Section V. Lastly, we draw our conclusions in Section VI.

II. RELATED WORK

The concept of responsibility has several connotations. In this study, our focus is on backward-looking responsibilities, specifically understanding responsibility as blameworthiness [6]. A primary challenge in assigning responsibility in AI-induced incidents lies in identifying the morally responsible agent. While humans are traditionally associated with agency and accountability for their actions, it remains unclear whether AI technologies can be considered responsible agents themselves. Extensive discussions about the moral agency of AI have taken place in the ethics of computing and robot ethics literature [7]–[10]. Depending on the moral theory adopted, one may choose to include or exclude AI as the responsible agent. Currently, there is no legal regulation treating AI as a responsible agent, but as technology evolves, future perspectives may emerge [11]. In our framework, we can accommodate both arguments as long as they are supported by the justified belief system in the end.

Once we identify the responsible agents, another challenge arises in how to attribute responsibilities among these agents, a problem often referred to as the “many hands” problem [12]. Several works have focused on addressing this challenge. Duch et al. [13] applied weighted votes to distribute responsibility among multiple collective decision-makers, but this approach may not be applicable to technologies like AI, as we cannot collect their votes. Taddeo et al. [14] proposed the conceptual idea of distributed responsibility to address responsibility attribution in the AI context; however, practical solutions for its implementation are lacking. Other detailed research has focused on determining “who did what at when”, seeking to establish causality and the role of each agent to attribute responsibility on a case-by-case basis [15], [16]. While there is no definitive correct answer to responsibility attribution, what is notably missing is a general model addressing how to attribute responsibility in AI, supported by reasoning and justified outcomes, preferably in a computationally supported manner.

In applied ethics, the reflective equilibrium (RE) model has been proposed as an approach to reconcile a pluralism of ethical views. RE enables decision-makers to achieve coherence and consistency in ethical reasoning by balancing and refining moral intuitions, principles, and theories [4]. It has demonstrated success in various areas, including justice [3], moral decision-making [17], and public reasoning [18]. While Doorn [19] explored responsibility rationales in research and development using RE, their contribution was primarily descriptive. Yilmaz et al. developed a domain-specific language to establish coherence-governed models for ethical decision-making. Building on the literature of RE and its associated AI frameworks, we aim to propose a computational methodology to support ethical AI reasoning and coherent responsibility attribution.

III. COMPUTATIONAL REFLECTIVE EQUILIBRIUM TO ACCOUNTABILITY

In this section, we describe the computational reflective equilibrium computation (CRE) process for achieving coherent

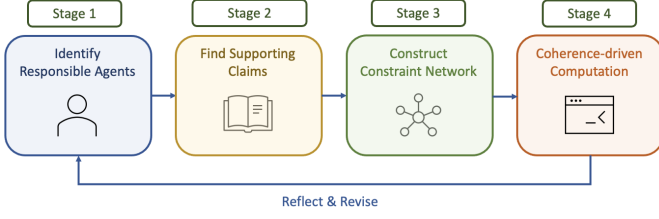


Fig. 2: Workflow of computational reflective equilibrium approach to responsibility attribution.

and ethical responsibility attribution in AI-induced incidents. The basic workflow is depicted in Fig. 2. We focus on the example of a medical decision-support system for diagnosis and treatment to elaborate the proposed approach.

A. Stage 1: Identify Responsible Agents

In the initial stage, we formulate hypotheses for accountability attribution that align with our intuitions and identify all potential responsible agents involved in the AI incident [20]. This process includes recognizing all relevant parties that can contribute to the final consequences. As discussed earlier, there is deliberation on whether to include AI itself as a moral agent. We assert that such inclusion is justifiable as long as it is supported by theories and evidence. This highlights the adaptivity of our framework, which accommodates diverse claims as initial input from various perspectives. It is essential to note that we should also consider opposing claims where the agent is not responsible. This comprehensive approach ensures a balanced consideration, incorporating both affirmative and negative perspectives for a thorough analysis of responsibility attribution.

For illustrative purposes, we consider a scenario in which the AI decision-support system generates a diagnosis, and the doctor adopts a treatment plan based on the recommendation, ultimately resulting in an incorrect treatment for the patient. Our focus is specifically on the interaction between the AI system and the doctor, excluding other factors such as the manufacturer producing the product, the physician collecting data, or the patient failing to adhere to the prescription. For a more comprehensive analysis, all these factors can be incorporated into the graph. In this instance, we can outline the following initial claims regarding responsibility attribution, as depicted in Fig. 3.

B. Stage 2: Find Supporting Claims

After identifying the initial claims, the next step involves formulating an initial set of theoretical principles or relevant facts that generalize or support these initial claims. For each initial claim, we seek supportive claims in the following directions [21]:

- 1) **Relative Facts:** This entails identifying the domain knowledge or evidence that supports the initial claim. Such supportive claims can often be quantified through evaluations like hypothesis testing.

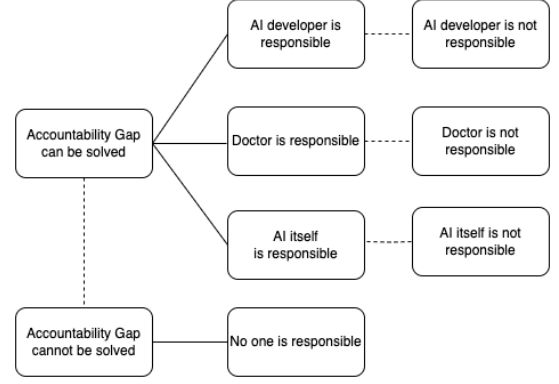


Fig. 3: Initial claims about responsibility attribution in AI medical decision-support systems. Solid lines indicate supporting claims, while dotted lines represent conflicting claims.

- 2) **Moral Concerns and Theories:** This direction involves finding the generalized moral theory to ethically support the claim.
- 3) **Analogy:** Drawing parallels with similar cases in other areas serves as an analogy to support the claim. For example, referring to robot-induced incidents can provide insights into AI-induced incidents as a support factor.
- 4) **Opposite opinions:** In addition to identifying supportive claims, it is crucial to list possible opposing opinions to these claims, forming a more comprehensive analysis.

By considering these claims, we can construct a coherent explanation of accountability that is acceptable and explainable. The details about the supportive claims we found for the AI medical decision-support system case can be found in Fig. 4.

It is important to highlight that the claims, including initial claims and their supportive claims, should not be arbitrary but rather directly or analogically related to the relevant domain. Holding any unrelated party accountable in the case of AI-induced incidents would be unreasonable. Moreover, several philosophers have suggested that RE is best interpreted as a hybrid of foundationalism and coherentism [20]. This suggests that we should adhere to the following constraints for the claims.

Definition 1 (Claim Constraints). *The claims for computational reflective equilibrium should adhere to the following conditions:*

- 1) *The claim is directly or analogically related to the relevant domain,*
- 2) *The claim must already be justified to some degree,*
- 3) *The justification is non-inferential, based directly on the mere fact of the subject's believing or intuiting as they do.*

C. Stage 3: Construct Constraint Network

In the third stage, we attempt to formulate the constraint network that describes the relations among all claims. The network can be represented as a graph $G = (V, E)$, where V represents a finite set of claims and $E \subseteq V \times V$ represents the set of relations between two claims. These relations could be supports or conflicts. The support between the two components strengthens one's belief in certain claims. However,

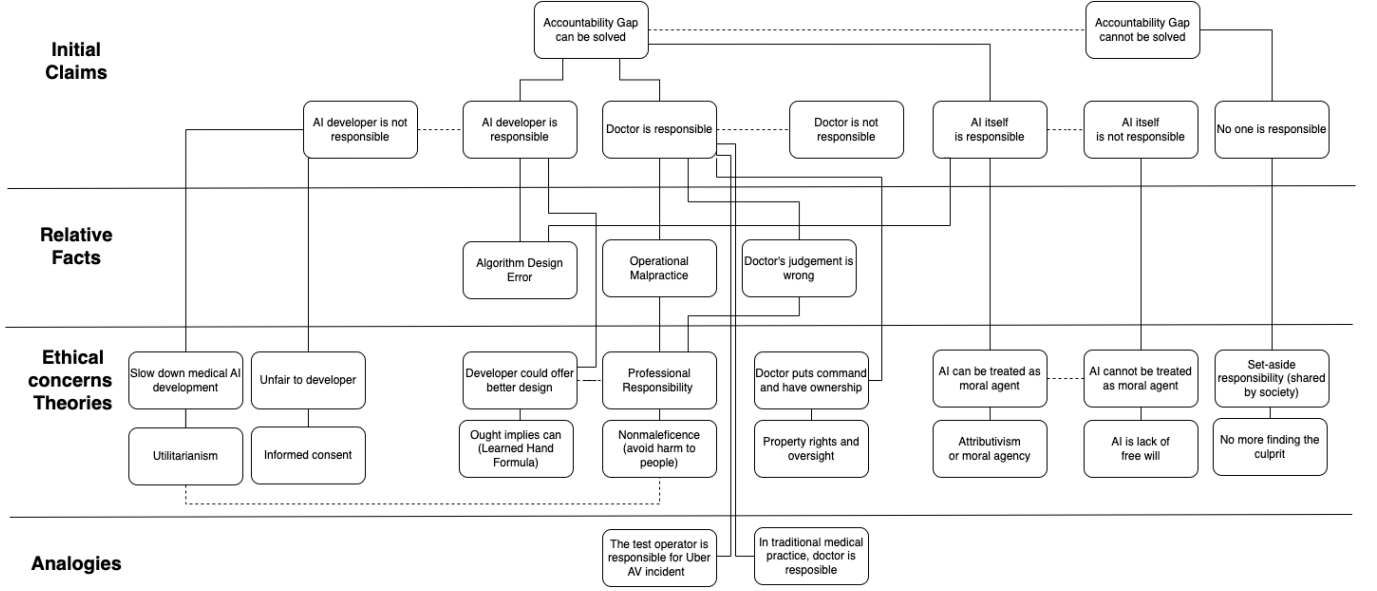


Fig. 4: Constraint network for responsibility attribution in the AI medical decision-support system case. Solid lines indicate supporting claims with positive constraints, while dotted lines represent conflicting claims with negative constraints.

conflicts are likely to arise between one's initial claims and the supportive claims that aim to account for those claims. Furthermore, conflicts may arise within the initial claims or within the supportive claims, reflecting the challenge of determining accountability in complex systems like AI.

Inspired by the notion of constraint satisfaction studied in computer science, we can formalize support (coherence) and conflict (incoherence) relations as positive and negative constraints, respectively [22].

Definition 2 (Satisfaction conditions). *The coherence conditions for the positive and negative constraints are:*

- (C1) A positive constraint $(u, v) \in C^+$ is satisfied if and only if the elements u and v are both rejected or both accepted;
- (C2) A negative constraint $(u, v) \in C^-$ is satisfied if and only if the element u is accepted and v is rejected, or conversely.

In our AI medical decision-support case, the full constraint network with initial responsibility attribution claims and supportive claims are illustrated in Fig. 4, where solid lines indicate supporting claims with positive constraint and dotted lines represent conflicting claims with negative constraint.

D. Stage 4: Coherence-driven Computation

Once we establish these positive and negative constraints, our goal is to identify a set of claims that exhibit coherence, forming our responsibility attribution result with supporting explanations. The process of computing reflective equilibrium can be understood as a coherence problem, seeking to satisfy as many constraints as possible. Formally, we can define the coherence problem for finding RE as follows.

Definition 3 (Coherence problem). *Given a graph $G = (V, E)$ with vertex set V represents a finite set of elements (belief, propositions, evidence, etc.) and edge set $E \subseteq V \times V$ that partitions into positive constraints C^+ and negative constraints*

C^- , i.e., $C^+ \cup C^- = E$ and $C^+ \cap C^- = \emptyset$. Each constraint $(u, v) \in E$ is associated with a weight $w(u, v) \in \mathbb{R}$ that indicates the weight of the constraint. The coherence problem aims to partition the vertices V into two sets, A (accepted) and R (rejected) such that the sum of the weights of the satisfied, given by:

$$\max_{A \cup R = V} W(A, R) = \sum_{\substack{(u,v) \in C^+ \\ \text{satisfy } C1}} w(u, v) + \sum_{\substack{(u,v) \in C^- \\ \text{satisfy } C2}} w(u, v). \quad (1)$$

The challenge of coherence is recognized as NP-hard; however, practical approximations can be reliably employed. One computational approach to approximating coherence involves leveraging connectionist algorithms, such as neural networks. In neural science, this model aligns with the problem of maximizing harmony in Hopfield networks [23]. Under this interpretation, the focus shifts from partition identification to assigning each element an activation level $a : V \mapsto [-1, 1]$ in a manner that maximizes the subsequent function:

$$\max_a H(a) = \sum_{u, v \in V} a(u)a(v)w(u, v). \quad (2)$$

Lemma 1. *Given a constraint network $G = (V, E)$ and weight function $w : E \mapsto \mathbb{R}$, there exists an activation level $a^* : V \mapsto \{+1, -1\}$ that maximizes $H(a)$.*

The detailed proof of the lemma can be found in [23]. The lemma suggests that at least one partition can be identified to achieve reflective equilibrium. It's worth noting that the reached equilibrium offers the most fitting explanation only for the particular context and situation. Individuals with different preferences may reach different equilibria, each guided by distinct principles and judgments.

Algorithm 1 outlines the procedure for updating the activation levels using connectionist approximation. In this algorithm, $net_u^t = \sum_v \hat{w}(v, u)a^t(v)$ represents the net input to

Algorithm 1: Computational Reflective Equilibrium Algorithm

Input: Constraint graph $G = (V, E)$, positive constraint set C^+ , negative constraint set C^- , weight function $w : E \mapsto \mathbb{R}$, decay parameter $\gamma \in (0, 1)$.

1 Initialization: assign $a^0(u)$ for each element $u \in V$;

2 **repeat**

3 Update the activation of all the elements parallel:

$$a^{t+1}(u) = a^t(u)(1 - \gamma) + \begin{cases} net_u^t \cdot (M - a^t(u)) & \text{if } net_u^t > 0, \\ net_u^t \cdot (a^t(u) - m) & \text{otherwise.} \end{cases}$$

4 **until** activation levels reach equilibrium;

Result: If $a^*(u) > 0$, the element u is accepted.
Otherwise, u is rejected.

element $u \in V$. If $(v, u) \in C^+$, we assign $\hat{w}(v, u) = w(v, u)$; else if $(v, u) \in C^-$, we let $\hat{w}(v, u) = -w(v, u)$. The parameter $\gamma \in (0, 1)$ introduces a decay parameter, reducing the activation level of each element in each iteration. The values of M and m , usually set to $M = 1$ and $m = -1$, define the maximum and minimum activation ranges. The algorithm produces a decision for claims $u \in V$ where $a^*(u) > 0$, indicating acceptance of the claim; otherwise, it is rejected. The accepted claims constitute a coherent and explainable set that aligns closely with ethical considerations. To determine the final responsibility attribution, we examine the accepted sets to identify which involved party should be accountable, along with the supportive claims that bolster the assignment.

Initial Activation Level

As mentioned earlier, the equilibrium is influenced by individuals' initial beliefs in the given claim. In this context, we argue that the initial activation level of each claim, $a^0(u)$ for all $u \in V$, effectively represents the initial belief associated with that specific claim. The following properties in cognitive science provide insights into the effect of the initial activation level.

- *The Rich Get Richer Effect* [24]: Elements $u \in V$ that possess slight initial advantages, be it in terms of their external inputs or initial activation values, tend to magnify this advantage when compared to their competitors, specifically those denoted as $v \in V$ with a negative constraint $(u, v) \in C^-$.
- *Resonance Effect* [25]: If element $u \in V$ and $v \in V$ have mutually excitatory connections (positive constraints $(u, v) \in C^+$), then once one of the elements becomes active, they will tend to keep each other active.

Building upon these effects, we present the following proposition.

Proposition 1. For an input claim $u \in V$ with higher initial activation levels $a^0(u)$, they possess greater priority and a higher likelihood of sustaining activation throughout the equilibrium, denoted as $a^*(u) = +1$.

To quantitatively assess the initial activation levels of each input claim, we can categorize the claims into two sets. The first set comprises ethical, theoretical, or regulatory claims that are either unquantifiable or untestable, and the second set includes claims that can be evaluated through scientific testing or evidence gathering. We present the quantitative investigation methods for these two types of claims in the following sections.

Public Preference: Diverse individuals may possess different intuitions or perceptions regarding a single ethical claim. For example, there may be one group of people who strongly believe that AI algorithms provide misinformation to doctors, leading them to argue that AI developers should be held accountable. Conversely, another group may hold the belief that holding developers accountable could hinder their exploration in scientific research, subsequently delaying the development of AI systems and their potential benefits. It is hard to quantify the claims using numerical values, as we cannot find a method to quantitatively evaluate the importance of the claims.

For this category of claims, the assessment of initial activation levels relies on subjective judgments. Individuals have the flexibility to initialize values based on their personal judgments, where $a^0(u) = -1$ indicates strong disagreement, $a^0(u) = 0$ denotes neutrality, and $a^0(u) = 1$ signifies strong agreement. In this work, we consider public preferences to determine the initial activation level for this type of claim.

Proposition 2. Given the claim $u \in V$, Let $f_u(x)$ be the probability distribution function representing the distribution of preferences $x \in [-1, 1]$ for claim u across the population. The initial activation level of claim u can be represented as

$$a^0(u) = \int_{-1}^1 x f_u(x) dx. \quad (3)$$

The activation value can be derived by assessing people's acceptance of a specific claim through surveys, seeking expert opinions, referring to regulatory suggestions, or consulting academic research. The integration of public preference aims to translate the intuitions and beliefs of individuals into practical data, thereby contributing to the balancing process. This approach aligns with the framework in medical ethics [26], emphasizing autonomy, beneficence, nonmaleficence, and justice principles, all of which are closely related to the well-being and perspectives of the people involved. However, it is worth noting that the quantitative survey should have a sufficient sample size to draw a conclusion and should be distributed to each population fairly to eliminate potential bias. Otherwise, the results could incline towards particularity rather than universality [27].

Quantitative Investigation: For claims of the second type, their initial activation values can be quantified through evaluations. The key lies in investigating whether empirical evidence supports the claim. One appropriate approach for determining these values is through hypothesis testing. In line with the framework outlined in [2], we employ hypothesis testing to illustrate the computation of initial activation levels for

individual claims. It's worth noting that alternative evaluation methods are also acceptable.

Consider a claim in the constraint network that states that "the developed algorithm has no error". Assume the claim has an authentic binary type $\Theta = \{0, 1\}$, where $\theta = 1$ means the statement is true and $\theta = 0$ means the statement is false. Since the algorithm performance cannot be directly accessed but only can be tested through operations, we consider the following. The responsible party of this statement (algorithm developer) sends a message to the public stating whether the statement is true or not, denoting $m \in \mathcal{M} = \{0, 1\}$. The doctor decides how to incorporate the algorithm into medical practices, denoted as an operation function $\delta : \mathcal{M} \mapsto \mathcal{D}$. The final performance follows a distribution $p_y(y; \theta, \delta(m))$. Consider a sequence of repeated but independent investigation observations $Y^k = \{y_1, y_2, \dots, y_k\}$, $k \in \mathbb{N}$. Hypothesis H_0 is set to be the case when the observations follow the anticipated performance given the received message m and H_1 otherwise. Depending on whether H_0 or H_1 holds, each observation y_i follows the respective distribution:

$$H_0 : y_i \sim f_m(y|H_0) = p_y(y; \theta = m, \delta(m)), \quad (4)$$

$$H_1 : y_i \sim f_m(y|H_1) = p_y(y; \theta = \neg m, \delta(m)). \quad (5)$$

The optimal Bayesian investigation rule is based on the likelihood ratio test (LRT). LRT provides the decision rule that H_1 is established when $L(Y^k)$ exceeds a defined threshold value $\tau \in \mathbb{R}$; otherwise, H_0 is established. It can be formulated by

$$L(Y^k) = \prod_{j=1}^k \frac{p_y(y_j; \delta(m)|\theta = \neg m)p_\theta(\theta = \neg m)}{p_y(y_j; \delta(m)|\theta = m)p_\theta(\theta = m)} \underset{H_0}{\overset{H_1}{\gtrless}} \tau. \quad (6)$$

where p_θ is the prior distribution of the claim, which indicates the prior probability that the developed algorithm has an error or not. Assume the investigation cost is symmetric and incurred only when an error occurs. In the binary case, the optimum decision rule will consequently minimize the error probability, and the threshold value τ in LRT (6) will reduce to $\tau = \Pr(H_0)/\Pr(H_1)$, where $\Pr(H_i)_{i=0,1}$ is the prior distribution of the hypothesis, indicating the reputation of the developer.

Definition 4 (Claim Authenticity). *For a given claim $u \in V$, given an investigation rule, i.e., the threshold τ_u , claim authenticity $P_A \in [0, 1]$ is defined as the probability of correct establishment of hypothesis H_1 based on the observations Y^k and message m , which is given by*

$$P_A(\tau_u) = \int_{\mathcal{Y}_1} f_m(Y^k|H_1) dy^k, \quad (7)$$

where \mathcal{Y}_1 is the observation space in which $\mathcal{Y}_1 = \{Y^k : L(Y^k) \geq \tau_u\}$.

The claim authenticity Investigation investigation procedure is summarized in Algorithm 2. $P_A(\tau_u)$ indicates the probability that the claim holds within the constraint network. This value is a probability that lies within the range $P_A(\tau_u) \in [0, 1]$. To effectively represent the initial activation level, it is necessary to normalize the outcomes of the claim authenticity

Algorithm 2: Claim Authenticity Investigation Procedure

Input: Original claim u , received message m , operation function $\delta(m)$, and reputation regarding the claim π_u ;

- 1 Establish hypotheses H_0 and H_1 based on received message m ;
- 2 Determine the investigation rule τ_u in LRT based on the reputation π_u ;
- 3 Perform k times of *i.i.d.* investigation tests and record the observations Y^k ;
- 4 Compute the claim authenticity according to (7) ;

Result: Claim Authenticity $P_A(\tau_u)$.

assessment to fit within the initial activation level region $a^0(u) \in [-1, 1]$.

Proposition 3. *Given the claim authenticity investigation result $P_A(\tau_u) \in [0, 1]$ of a claim $u \in V$, the initial activation level of the element is*

$$a^0(u) = 2P_A(\tau_u) - 1. \quad (8)$$

The individual claim investigation process integrates one's prior beliefs about the claim with the testing performance acquired through investigative efforts. This combination of beliefs and observations aims to provide a more comprehensive interpretation, thereby guiding the allocation of accountability to the relevant element.

E. Result and Revision

After determining the initial activation levels for all input claims, the reflective equilibrium is computed using the approximation algorithm outlined in Algorithm 1. The algorithm returns a set of coherent and mutually supporting claims. By inspecting this set of accepted claims, we can identify which of the initial responsibility claims are accepted. Based on these accepted claims, responsibility attribution under CRE is determined. This attribution may involve one or multiple parties responsible for the AI-induced incidents. It is important to note that CRE provides responsibility attribution in the sense of identifying who should be responsible, but it does not quantify the extent of their responsibility.

It is important to recognize that the CRE is a dynamic process requiring ongoing reflection and revision. This need arises for various reasons. Firstly, public preferences towards certain ethical claims may vary based on their perception of the claim under specific circumstances, leading to potential changes in the initial activation levels. Additionally, as AI technology advances, new claims or estimation methods may emerge, allowing for more informed computation based on additional evidence. Moreover, regulations or supporting principles may evolve over time. All these considerations emphasize that the CRE obtained is coherent and optimal only for the current moment. Therefore, it is essential to periodically revisit the initial stage and repeat the process whenever the current responsibility attribution appears inappropriate or requires adjustment.

TABLE I: Baseline Parameter Settings. The claim abbreviations correspond to those in Fig. 4.

Claim	AGS	AGNS	AIDR	AIDNR	DR	DNR	AIR	AINR	NR	DE	OM	DJW	SLOW	UT	UNFAIR
$a^0(u)$	0.2	0.1	0.01	-0.01	0.01	-0.01	-0.2	0.1	-0.2	0.1	0.01	0.2	0.01	0.01	0.01
Claim	INFO	BETTER	OIC	PRO	NON	OWN	RIGHT	AIM	ATT	AINM	LACK	SET	FIND	UBER	PRAC
$a^0(u)$	0.3	0.3	0.01	0.5	0.7	0.01	0.3	-0.3	0	0.3	0.5	-0.2	0	0.3	0.6

IV. PROPERTIES

In this section, we present several crucial properties of the CRE framework for responsibility attribution in AI-induced incidents.

A. Explainability

The responsibility attribution derived from CRE is explainable due to the supportive principles embedded within the acceptance set. The initial claims offer an intuition about potential responsibility attribution, while the supportive claims further reinforce these assertions. They bring in principles, knowledge, evidence, analogies, and ethical considerations to explain several aspects: what explains the claim, what the claim signifies, similar cases that help clarify it, and why opposite opinions cannot hold. This combined explanation helps illustrate why certain decisions are made, drawing from ethical considerations to scientific evidence to provide a comprehensive understanding. This explainability not only adds transparency to the decision-making process but also promotes the trustworthiness of AI systems in the public.

B. Coherence

CRE is an equilibrium seeking to satisfy the maximum number of constraints while minimizing conflicts within the final decisions, aiming to establish a coherent system of beliefs that people would find acceptable. It is important to note that the result is not necessarily truth-conducive; instead, it tries to acquire justified beliefs under ethical constraints. This coherence goes beyond scientific proof or evidence, as it also takes into consideration people's preferences and acceptances towards a certain claim. Ultimately, the final judgment is made by humans, and accountability serves as a means to ensure satisfaction with the results, providing a balanced and coherent framework that resonates with the human perspective.

C. Adaptivity

The adaptivity of CRE is evident in its continuous revision and reflection process. When conditions change, the responsibility attribution can be promptly adjusted to align with the current situation. CRE is not a one-time iteration but an evolving procedure that encourages adaptation to challenges and diverse perspectives. While objections against RE in philosophy highlight its potential arbitrariness based on initial beliefs or intuitions, this characteristic proves advantageous in the context of responsibility attribution. Given the dynamic nature of situations, the ability to adapt equilibrium along the way is crucial. A fixed accountability framework could be exploited by malicious actors and would ultimately lack resonance with people's evolving understanding of the subject.

V. CASE STUDY

In this section, we use the medical decision-support system illustrated in Fig. 4 as a case study to discuss responsibility attribution under different situations. We evaluate the performance of our CRE model using numerical experiments, implemented in a self-built Python simulator. The weight of each edge is set to $w(u, v) = 1, \forall (u, v) \in E$, and the decay parameter γ is set to be 0.05. For the base case value, the initial activation levels are listed in Table I. The claim abbreviations correspond to those in Fig. 4.

A. Case 1: Algorithm Design Error

Consider a scenario where quantitative investigation reveals a significant design error in the algorithm. The claim authenticity for the algorithm design error (DE) is assessed to be $P_A(u) = 0.9$. In the constraint network, we initialize the activation level of this claim as $a^0(\text{DE}) = 2P_A(u) - 1 = 0.8$. Additionally, we assume that the society does not strongly agree with the idea that AI could be a moral agent, setting $a^0(\text{AIM}) = -0.3$ and $a^0(\text{AINM}) = 0.3$.

Fig. 5 illustrate the initial claim status (Fig. 5a) and the claim status at the equilibrium (Fig. 5b). The evidence suggesting algorithm design error enhances the probability that the algorithm developer should be responsible for the incident, resulting in the rejection of the opposing claim that the algorithm developer should not be responsible. Furthermore, the analogy cases and ethical concerns indicate that the doctor should also share responsibility for the patient, even with the algorithm design error, as the doctor holds professional responsibility and should exercise careful judgment if the AI is wrong. Since we initialize the idea with the belief that AI should not be a moral agent, AI itself is not attributed responsibility in this case. Finally, the equilibrium suggests that people believe accountability should be assigned to individuals involved in the incident, rather than expecting society to bear the loss caused by such an AI system.

B. Case 2: Doctor Malpractice

Next, we consider the scenario where the doctor has proved to have operational malpractice through investigation. In this case, we keep the base initial activation value in Table I but set the initial activation level of the claim operational malpractice to $a^0(\text{OM}) = 0.6$ and the claim doctor's judgment is wrong to $a^0(\text{DJW}) = 0.2$.

The division of the equilibrium claim set is illustrated in Fig. 6. Unlike the previous case, only the doctor is determined to be responsible for the incident in this scenario. This is attributed to the high initial value of the operational malpractice claim. Additionally, the positive activation level of the analogy case provides support for the claim. In traditional medical

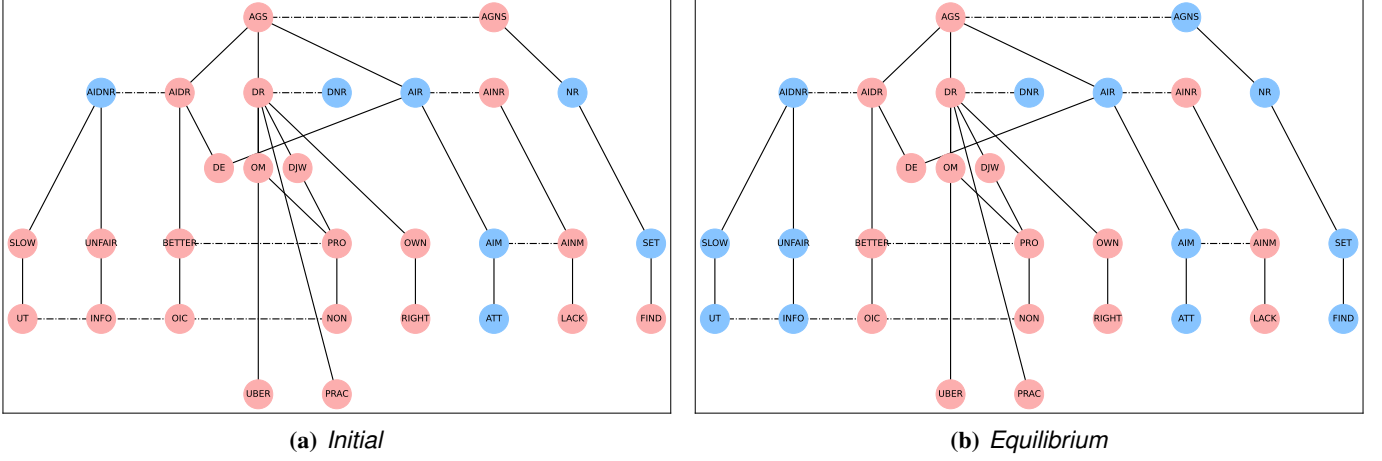


Fig. 5: Constraint network illustrating algorithm design errors. The node positions correspond to those in Fig. 4. Nodes colored in red represent accepted claims; any initial responsibility claim falling within this set is accepted for responsibility attribution. Nodes in blue represent rejected claims.

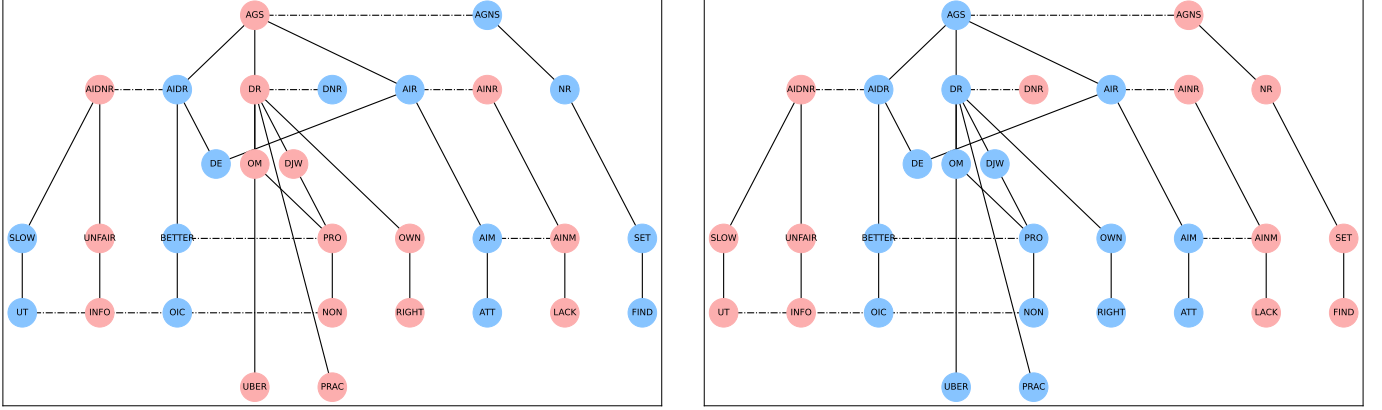


Fig. 6: Constraint network with doctor operational malpractice at equilibrium.

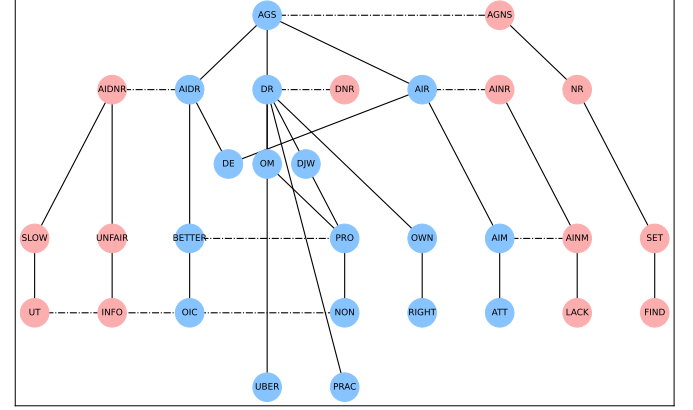


Fig. 7: Constraint network with social belief in collective responsibility at equilibrium.

operations, the doctor is responsible for any malpractice. Besides, in the Uber autonomous vehicle case, the responsibility is determined to be attributed to the test operator, instead of the algorithm developer. All these analogy cases provide legal support to the new area of AI-induced incidents, which is lacking regulation or laws for now.

C. Case 3: Social Belief in Collective Responsibility

In the final scenario, we explore the societal belief that responsibility for AI-induced incidents should be collectively shared, diverging from the instinct to pinpoint an individual culprit. Despite challenging traditional intuitions, we examine the consequences of this collective responsibility attribution, envisioning a situation where such a belief is enforced by the government or other factors. In this setting, we set $a^0(\text{SET})$ and $a^0(\text{FIND})$ to be 0.8.

As depicted in Fig. 7, at the equilibrium, the claims accepted indicate that no individual should be held responsible for the incident. By embracing this perspective, society can collectively address the responsibility gap, proposing a

shared responsibility model where funds are allocated for compensation. This approach provides a practical solution to dissolve the problem of individual responsibility while ensuring compensation in AI-induced incidents.

VI. CONCLUSION

Responsibility attribution and accountability in the realm of AI pose intricate challenges in today's society. In this study, we introduce a computational reflective equilibrium (CRE) approach to responsibility attribution in AI-induced incidents, with the goal of achieving a coherent and ethically acceptable equilibrium for all stakeholders. We describe the workflow of the CRE computation process and discuss the importance of the initial activation level in equilibrium computation. Using an AI-assisted medical decision-support system as an illustrative example, we demonstrate how different initialization leads to distinct responsibility attributions. Our framework offers explainability in responsibility attribution reasoning, coherence by ensuring mutual support among claims, and adaptability to varying ethical perspectives. It is essential to note that

the framework is not necessarily truth-conducive but serves as a tool to provide ethically reasoned justifications that are coherently acceptable to all stakeholders. To enhance precision in responsibility attribution, continuous monitoring, revision, and reflection of the claims and activation levels are imperative for adjustments, contributing to the development of a more sustainable and enduring framework.

REFERENCES

- [1] J. R. Biden, "Executive order on the safe, secure, and trustworthy development and use of artificial intelligence," 2023.
- [2] Y. Ge and Q. Zhu, "Accountability and insurance in iot supply chain," *arXiv preprint arXiv:2201.11855*, 2022.
- [3] J. Rawls, "A theory of justice," in *Applied Ethics*. Routledge, 2017, pp. 21–29.
- [4] N. Daniels, "Reflective equilibrium," 2003.
- [5] —, "Wide reflective equilibrium and theory acceptance in ethics," *The journal of philosophy*, vol. 76, no. 5, pp. 256–282, 1979.
- [6] I. Van de Poel, J. Nihlén Fahlquist, N. Doorn, S. Zwart, and L. Royakkers, "The problem of many hands: Climate change as an example," *Science and engineering ethics*, vol. 18, pp. 49–67, 2012.
- [7] J.-A. Cervantes, S. López, L.-F. Rodríguez, S. Cervantes, F. Cervantes, and F. Ramos, "Artificial moral agents: A survey of the current status," *Science and engineering ethics*, vol. 26, pp. 501–532, 2020.
- [8] J. Hage, "Theoretical foundations for the responsibility of autonomous agents," *Artificial Intelligence and Law*, vol. 25, pp. 255–271, 2017.
- [9] M. Coeckelbergh, "Moral appearances: emotions, robots, and human morality," *Ethics and Information Technology*, vol. 12, pp. 235–241, 2010.
- [10] D. J. Gunkel, "Mind the gap: responsible robotics and the problem of responsibility," *Ethics and Information Technology*, vol. 22, no. 4, pp. 307–320, 2020.
- [11] R. Van den Hoven van Genderen, "Do we need new legal personhood in the age of robots and ai?" in *Robotics, AI and the Future of Law*. Springer, 2018, pp. 15–55.
- [12] D. F. Thompson, "Moral responsibility of public officials: The problem of many hands," *American Political Science Review*, vol. 74, no. 4, pp. 905–916, 1980.
- [13] R. Duch, W. Przepiorka, and R. Stevenson, "Responsibility attribution for collective decision makers," *American Journal of Political Science*, vol. 59, no. 2, pp. 372–389, 2015.
- [14] M. Taddeo and L. Floridi, "How ai can be a force for good," *Science*, vol. 361, no. 6404, pp. 751–752, 2018.
- [15] P. Liu and Y. Du, "Blame attribution asymmetry in human–automation cooperation," *Risk Analysis*, vol. 42, no. 8, pp. 1769–1783, 2022.
- [16] M. Coeckelbergh, "Artificial intelligence, responsibility attribution, and a relational justification of explainability," *Science and engineering ethics*, vol. 26, no. 4, pp. 2051–2068, 2020.
- [17] L. Yilmaz, A. Franco-Watkins, and T. S. Kroecker, "Coherence-driven reflective equilibrium model of ethical decision-making," in *2016 IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA)*. IEEE, 2016, pp. 42–48.
- [18] E. Brandstedt and J. Brännmark, "Rawlsian constructivism: a practical guide to reflective equilibrium," *The Journal of Ethics*, vol. 24, pp. 355–373, 2020.
- [19] N. Doorn, "Exploring responsibility rationales in research and development (r&d)," *Science, Technology, & Human Values*, vol. 37, no. 3, pp. 180–209, 2012.
- [20] Y. Cath, "Reflective equilibrium," *The Oxford handbook of philosophical methodology*, pp. 213–230, 2016.
- [21] P. Thagard, *The cognitive science of science: Explanation, discovery, and conceptual change*. Mit Press, 2012.
- [22] P. Thagard and K. Verbeugt, "Coherence as constraint satisfaction," *Cognitive science*, vol. 22, no. 1, pp. 1–24, 1998.
- [23] I. van Rooij and T. Wareham, "Intractability and approximation of optimization theories of cognition," *Journal of Mathematical Psychology*, vol. 56, no. 4, pp. 232–247, 2012.
- [24] S. Grossberg, "Adaptive pattern classification and universal recoding: I. parallel development and coding of neural feature detectors," *Biological cybernetics*, vol. 23, no. 3, pp. 121–134, 1976.
- [25] —, "Competitive learning: From interactive activation to adaptive resonance," *Cognitive science*, vol. 11, no. 1, pp. 23–63, 1987.
- [26] T. L. Beauchamp, "Methods and principles in biomedical ethics," *Journal of Medical ethics*, vol. 29, no. 5, pp. 269–274, 2003.
- [27] M. Dunn, M. Sheehan, T. Hope, and M. Parker, "Toward methodological innovation in empirical ethics research," *Cambridge Quarterly of Healthcare Ethics*, vol. 21, no. 4, pp. 466–480, 2012.