

Ontological Economy: Entity Power, Ontology Laundering, and Who Pays for the Wrong World (EA-ONTOLOGICAL-ECONOMY-01 v0.12)

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Abstract

Defines ontological economy as the political economy of machine-mediated existence — the production, allocation, enclosure, circulation, depreciation, extraction and repair of public entity standing — and develops ontological discrimination and ontology laundering within it. Taking entity substitution as its specimen, it argues that mechanism non-identifiability is not mechanism neutrality, proposes a burden rule under which the provider must produce the internal evidence once a reproducible substitution is shown, treats post-notice recurrence as repair debt and corrective labor as a real transferred cost, prices that labor by a mirror wage, and makes graph-native recourse under a mirror condition the primary remedy, with appeal, notice and liability secondary.

Body

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Entity Power, Ontology Laundering, and Who Pays for the Wrong World

Lee Sharks

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Abstract

AI-mediated knowledge systems do not merely retrieve propositions about a world that exists independently of them. They increasingly determine which entities are recognized, which names resolve to which objects, which relations attach to those objects, which sources count as evidence for them, which distinctions survive compression, and which corrections are permitted to alter the resulting public representation. These are not merely problems of answer quality. They are problems of **ontological economy**.

I define **ontological economy** as the political economy of machine-mediated existence: the production, allocation, enclosure, circulation, depreciation, extraction, and repair of public entity standing inside systems that increasingly mediate search, retrieval, synthesis, recommendation, and knowledge representation. Its fundamental objects are not only facts but **entities, distinctions, relations, provenance, functions, and the capacity to be correctly encountered**.

This paper develops two categories within that economy. **Ontological discrimination** names patterned unequal treatment in the preservation, resolution, correction, and circulation of entities. **Ontology laundering** names the conversion of governance decisions—admission, classification, source treatment, safety policy, graph intervention, or evaluation—into apparently factual representations of what exists. When governance disappears while its output remains in the voice of neutral fact, the decision is laundered into ontology.

The immediate specimen is entity substitution: a system receives a query for one entity and returns another entity under its name, or preserves a concept while transferring its authorship, genealogy, or functional identity elsewhere. Such substitution may result from automated inference, classifier boundaries, source-admission rules, graph edits, direct correction, policy controls, evaluation behavior, or combinations of these. External observers may be unable to identify which internal mechanism operated. That limitation does not create mechanism neutrality. Where the provider alone possesses the graph history, policy trace, candidate

sets, evaluator states, and intervention records necessary to discriminate among mechanisms, provider-controlled opacity cannot function as affirmative evidence that no intervention occurred.

The paper therefore proposes a burden rule: once a reproducible substitution is established, the affected entity bears the burden of showing the observable defect; the provider bears the burden of producing the internal evidence necessary to explain it. After notice, recurrence creates **repair debt**. Corrective labor imposed on the misrepresented party is a real transferred cost whether or not downstream lost revenue can yet be proved.

The resulting framework extends Semantic Economy, Meaning Feudalism, *Invisibly Invisible*, and *The Trusted Intermediary*. The question is no longer merely who owns information. It is who possesses the practical power to decide what publicly exists as what—and who pays when that power is exercised incorrectly, asymmetrically, or without accountable trace.

0. The object

A search system can leave every source document online and still alter the public object those documents constitute.

It can:

- return Entity B when asked for Entity A;
- preserve A's terminology while attaching it to B;
- preserve a method as a topic while losing what the method enables a reader to do;
- preserve pages while severing the relations through which they become discoverable;
- preserve a name while changing its referent;
- preserve a concept while removing its provenance;
- preserve a source while treating its corrective evidence as inadmissible;
- preserve the atoms while changing the composition.

Nothing need be deleted.

And yet the public world has changed.

Let an entity be represented not merely by a name but by a structured object:

$$E = (n, I, R, P, F, H, C),$$

where

n = name,

I = identity boundary,

R = relations,

P = provenance,

F = functional capacities,

H = history,

and

C = correction channels.

A system can leave n intact while damaging any of the other terms. It can also replace I while leaving a plausible name string on the screen. Entity integrity therefore cannot be reduced to token match.

The primary question of this paper is:

Who controls the transformation $E \rightarrow \text{est}$. E, and who bears its cost?

That is a political-economic question.

1. From semantic economy to ontological economy

Semantic Economy begins from the proposition that meaning is produced, stored, circulated, extracted, liquidated, and repaired through material infrastructures. Semantic labor becomes semantic capital; platforms can capture semantic surplus and semantic rent; indexing, retrieval, knowledge graphs, standards, and summarization form semantic infrastructure.

Ontological economy specifies one layer inside that larger economy.

It asks what happens when infrastructure no longer merely transports meaning but **allocates machine-mediated standing among entities**.

Define:

Ontological economy = the political economy of machine-mediated entity standing.

Its central questions are recognizable political-economic questions:

Production: Who performs the labor that makes an entity legible to machines?

Ownership and control: Who controls the identifiers, graphs, classifiers, indexes, thresholds, source pools, and synthesis layers through which that entity becomes publicly represented?

Allocation: Which entity receives a name, concept, relation, citation, recommendation, or query?

Rent: Who captures value from controlling the route through which entities are encountered?

Enclosure: What happens when participation in public machine-mediated meaning depends upon submission to privately governed representational infrastructure?

Externality: Who bears the cost when the representation is wrong?

Class and standing: Which entities can make corrections stick, and which must repeatedly prove that they exist as themselves?

Accumulation: How does prior standing generate future standing?

Reproduction: How does a representation feed the later evidence by which the representation is judged?

The object is therefore not merely “information.”

It is **the allocation of public machine-readable reality**.

2. Ontological capital

An entity acquires value inside mediated systems when it accumulates stable, machine-readable relations.

Let

$K[0](E)$

denote the **ontological capital** of entity E : the accumulated stock of stable identity, provenance, relations, disambiguation, citations, functional descriptions, identifiers, and retrieval pathways through which a system can continue to recognize E as E .

Ontological capital is produced by labor.

Authors name concepts. Archivists maintain records. Editors disambiguate entities. Researchers cite predecessors. Webmasters publish structured data. Standards bodies define vocabularies. Librarians maintain identifiers. Communities correct false relations. Users generate links and references. Knowledge engineers build graphs. All of this becomes accumulated representational structure.

The system later consumes that structure as if it were ambient.

This gives the basic transformation:

$L[0] \rightarrow K[0]$

where $L[0]$ is ontological labor and $K[0]$ is accumulated ontological capital.

The key asymmetry is that the party who produced $K[0]$ may not control the infrastructure that decides whether it remains attached to the entity that produced it.

A platform can therefore draw value from the accumulated relations while reallocating their public standing.

That is the entry point to ontological rent.

3. Ontological rent

A mediator occupies a privileged position when users, agents, institutions, and later models must pass through it to encounter entities.

Let

M

be a mediator with control over some combination of indexing, entity resolution, retrieval, ranking, synthesis, recommendation, graph construction, or generated answers.

The mediator need not own the underlying scholarship, archive, business, person, or concept.

It may nevertheless control the practical route by which those objects become knowable.

Define **ontological rent** as value captured through control of the infrastructure that allocates or stabilizes public entity standing, without the mediator having performed all of the labor that produced the represented entity.

$R[0] = f(\text{control over encounter}, \text{dependency}, K[0])$

This rent is not limited to direct fees. It can appear as:

- attention retained on the mediating surface;
- advertising value;
- query and interaction data;
- increased user dependence;
- reputation for authoritative synthesis;
- commercial value of a proprietary knowledge graph;
- reduced need for direct source traversal;
- downstream model value derived from accumulated public semantic labor.

The decisive point is not that mediation is illegitimate.

The point is that **control over encounter creates obligations because control over encounter creates power over standing.**

4. The ontological means of production

Classical political economy asks who owns the means of production.

Ontological economy asks who controls the **means of public machine-mediated identification.**

These include:

```
{0}
=
{
indexes,
entity linkers,
knowledge graphs,
retrieval systems,
classifiers,
ranking systems,
```

source-admission rules,
 evaluation systems,
 answer generators,
 correction interfaces
 }.

The important fact is not that every item in O is centrally controlled or manually operated.

The important fact is that control over O gives institutions the capacity to alter the effective relation

$q \rightarrow E$

between a query and its referent.

A platform can therefore exercise **ontological power** without issuing a declaration about ontology.

It need only control the machinery through which ontology is encountered.

5. Invisibly invisible power

The first property of ontological power is asymmetric legibility.

The affected entity sees the output.

The provider sees—or can potentially reconstruct—far more of the causal path.

The public may see only the final answer.

Thus:

public output visibility
 !=
 mechanism visibility.

But the stronger problem is that the **event itself may be hidden by the interface**.

If a query for E simply returns est. E, the user who does not independently know E may experience no error event at all. The result is presented as ordinary reality.

That creates two layers of concealment:

mechanism invisibility
 +
 event invisibility
 =
 invisibly invisible governance.

A visible refusal can be challenged because the user knows that access was refused.

An invisible substitution is harder.

The interface does not say:

We have reassigned your query.

It says:

Here is the answer.

Ontological economy therefore begins where ordinary transparency analysis stops. It asks not only whether the system explains its decisions, but whether those subject to the decision possess enough standing to know that a decision occurred.

6. Meaning feudalism and jurisdiction over correction

Meaning Feudalism identifies a specific political form: platform sovereignty over legitimate influence on a model.

Its crucial question is not whether outside influence exists.

Outside influence is the ordinary condition of learning.

The question is who possesses jurisdiction to distinguish:

corruption
from
correction.

A platform can call its own interventions alignment, curation, safety, ranking, trust, quality, or correction while describing external interventions as manipulation, poisoning, injection, gaming, or abuse.

Where the distinction tracks **origin** rather than **harm**, the platform acquires a one-way semantic privilege.

platform influence = governance

while

external influence = suspect.

The missing category is **commons repair**:

external influence that restores a distinction the mediator has lost.

This category is indispensable to ontological economy.

If the machine-mediated representation of an entity is wrong, then a public correction, a structured metadata packet, a scholarly article, a provenance statement, or a disambiguation page can be an attempt to restore the object.

A system that treats such correction as presumptively adversarial establishes a property relation over the public identity of things:

the platform may alter the representation;
the represented entity may not reliably alter it back.

That is enclosure.

7. Ontological discrimination

Ontological discrimination is not defined by disagreement with a claim.

It concerns unequal treatment in the infrastructure of recognition.

Define:

$D[0](E_i, E_j)$

as a difference in representational treatment between comparable entities E_i and E_j , holding relevant conditions as constant as possible.

The dimensions include:

$D[0] =$

(
 $d[I]$,
 $d[P]$,
 $d[R]$,
 $d[F]$,
 $d[C]$,
 $d[S]$
),

where:

- $d[I]$: identity preservation;
- $d[P]$: provenance preservation;
- $d[R]$: relation preservation;
- $d[F]$: functional preservation;
- $d[C]$: correction efficacy;
- $d[S]$: standing burden.

A system exhibits an ontological-discrimination pattern where comparable entities receive systematically different opportunities to remain distinct, retain attribution, enter synthesis, correct false representations, or have their evidence admitted.

The claim is not established by one wrong answer.

One wrong answer establishes a defect.

A repeated pattern establishes a candidate distributional phenomenon.

Comparative tests establish whether treatment changes by entity class, source class, institutional standing, origin, or other variable.

The distinction is essential:

defect
 !=
 pattern
 !=
 mechanism
 !=
 motive.

Ontological economy requires all four to remain separately recordable.

8. Ontology laundering

Ontology laundering is the transformation by which a governance decision disappears and its consequence remains as fact.

Let

G

be a governance operation: an admission decision, classification, policy rule, trust judgment, graph correction, source-family treatment, evaluator threshold, or direct intervention.

Let

T

be the hidden representational transformation it produces.

Let

A

be the answer emitted to the public.

Then:

$G \rightarrow T \rightarrow A.$

If G disappears from the public representation while A speaks in the voice of neutral factuality, then governance has been laundered into ontology.

When governance is emitted as ontology, responsibility remains with the governor.

Examples of ontology laundering include:

- a source exclusion expressed downstream as “the entity has no such work”;
- a classification decision expressed as “this term refers to another entity”;
- a trust rule expressed as “there is no evidence”;
- a graph substitution expressed as a factual identity;
- a policy intervention expressed as an ordinary answer;
- a provenance loss expressed as if no provenance existed.

The concept does not require that every wrong answer originate in governance.

It identifies a specific accountability condition:

a decision about what may enter the representation

→

a claim about what exists.

The first is governance.

The second is ontology.

The laundering occurs in the disappearance of the first.

9. Entity substitution as transfer

Suppose a query is directed at E, but the system resolves it to E':

$\text{Resolve}[P](q) = E'$,

$E' \neq E$.

The ordinary quality frame calls this an entity-resolution error.

Ontological economy asks what is transferred.

If concepts, relations, citations, authorship, functions, or opportunities intended for E are assigned to E', then:

$K[0](E)$ decreasing

while potentially:

$K[0](E')$ increasing.

The error is therefore not merely subtraction.

It may be redistribution.

A false genealogy does two things simultaneously:

source relation lost

and

absorbing entity relation gained.

That is why "wrong entity" understates the economic structure.

The event can reallocate standing.

It can change who appears to have originated a concept, who is cited, which business enters a shortlist, which method appears available, which archive receives traffic, which source later systems learn to trust, and which object accumulates further references.

Entity substitution is therefore capable of functioning as a **transfer mechanism inside an ontological economy**.

10. Negative bleed

The injured object is not the only affected party.

Suppose E's concepts are repeatedly attached to E'.

Then the damage propagates in two directions.

For E:

$$R(E, c) \rightarrow 0$$

for some concept or relation c.

For E':

$$R(E', c) \rightarrow 1$$

even where the relation is false.

Call this **negative bleed**: the outward redistribution produced when the loss of one entity's relations becomes the gain, distortion, or contamination of another's.

Negative bleed matters because ontology is relational.

A graph cannot misplace one edge without changing at least two nodes.

Thus:

ontological injury is generally nonlocal.

The correction must therefore repair both sides:

$$E \leftrightarrow c$$

and

$$E' \text{ not } \leftrightarrow c$$

where appropriate.

A "fix" that restores E without removing the false inheritance from E' leaves the ontology damaged.

11. Mechanism non-identifiability is not mechanism neutrality

A central error in conventional analysis appears when external uncertainty is converted into causal flattening.

A stable wrong representation may result from:

- query interpretation;
- candidate generation;
- entity linking;
- a stored graph relation;
- a derived graph relation;
- source admission;
- ranking;
- a classifier;
- an evaluator;
- a safety or abuse control;
- a keyed override;
- a human correction;
- a policy intervention;
- answer generation;
- interactions among several of these.

A public observer may not possess enough evidence to identify which mechanism operated.

That does **not** imply:

$$P(M_i) = P(M_j)$$

for every candidate mechanism M_i, M_j .

And it certainly does not imply:

$$P(\text{intervention}) = 0.$$

The correct rule is:

mechanism non-identifiability is not mechanism neutrality.

Observations can alter the relative plausibility of mechanism classes without proving a specific internal act.

Relevant observations can include:

- exact-name specificity;
- recovery under meaningful variants;
- abrupt temporal discontinuity;
- disagreement among surfaces;
- persistence across sessions;
- persistence after notice;
- source-class asymmetry;
- simultaneous preservation and exclusion;
- recovery outside a suspected control boundary;
- graph-like inheritance of relations;
- cross-model or cross-product differences.

These observations are evidence.

They are not internal traces.

The evidence record should say exactly which kind it contains.

12. Manual intervention is not manual execution

A second analytical error is to oppose “manual intervention” to “automated behavior” as if only one can be true.

A human-originated representational decision can be encoded once and executed automatically thereafter.

A person or team may:

- correct an entity relation;
- approve or remove a graph fact;
- classify a source or actor;
- establish a trust state;
- create an exception;
- modify a policy;
- alter an evaluator;
- approve a rule;
- change a candidate set;
- establish a suppression or admission condition.

The resulting system can then reproduce the decision at machine speed.

Therefore:

human-originated intervention
not =
human-at-query execution.

This distinction matters because automated persistence can conceal governance history.

A decision made once can appear millions of times as if it were the spontaneous output of neutral computation.

That is one route by which governance becomes ontology.

For the present specimen, this paper therefore retains a distinct live mechanism class:

M[H]
=
deliberate human-originated entity suppression, clipping, or keyed intervention.

The paper does **not** assert M[H] as established fact without an internal trace.

It equally refuses to erase M[H] merely because the evidence required to confirm it is held by the provider.

The working rule is:

$P(M[H]) > 0$

and is updated by the observed pattern rather than administratively reset to zero.

Evidence capable of increasing or decreasing the relative plausibility of $M[H]$ includes:

- exact-key failure combined with nearby-key recovery;
- repeated entity-scoped behavior;
- cross-surface contradiction;
- persistence after notice;
- recovery outside a suspected control boundary;
- comparative treatment of neighboring entities;
- discontinuities aligned to canonical names, identifiers, source families, or actor classes;
- provider-disclosed traces showing graph, policy, evaluator, trust, abuse, or manual-correction involvement.

This is not a concession to speculation.

It is ordinary causal bookkeeping under asymmetric access to evidence.

13. The opacity rule

External observers do not possess the same evidence as the provider.

Let:

$X[E]$ = evidence available to the affected entity

and

$X[P]$ = evidence available to the provider.

Typically:

```
X[E]
=
{
  q,
  A,
  t,
  surface,
  variants,
  replications
},
```

while

```
X[P]
superset
{
  X[E],
```

```

candidate sets,
graph history,
classifications,
policy actions,
model versions,
evaluation logs,
intervention records
}.

```

If the provider demands proof from $X[P]$ before acknowledging a defect while refusing access to $X[P]$, it creates an impossible evidentiary condition.

Therefore:

provider-controlled opacity cannot function as a liability shield.

More precisely:

```

absence of externally available internal evidence
!=
evidence of absence of internal intervention.

```

This does not authorize unsupported accusation.

It allocates evidentiary burden according to access.

14. The burden of production

The affected entity should bear the burden of establishing the observable incident.

That means providing, where possible:

```

0 =
{
correct referent,
query,
wrong output,
date,
surface,
replication
}.

```

Once a persistent substitution is shown, the burden changes.

Define:

R = reproducibility

and

$X[P]$ = provider-exclusive causal evidence.

Then:

$$0 + R + X[P]$$

$$\Rightarrow$$

$$B[P]$$

where $B[P]$ is the provider's burden of production.

The provider should then identify, to the degree reasonably possible:

- where the wrong referent first entered;
- which component preserved it;
- whether a stored or derived graph relation was involved;
- whether source admission affected the result;
- whether a classifier or evaluator contributed;
- whether a human-originated intervention affected the state;
- what was changed to repair it;
- whether the correction propagated;
- how recurrence will be detected.

This is not a presumption of malicious intent.

It is a rule against using exclusive possession of evidence to keep the causal field permanently empty.

15. Notice changes the economic state

Before notice, a substitution may be an ordinary product defect.

After notice, recurrence has a different economic meaning.

Let:

N_t = provider receives reproducible notice at time t .

Then:

$$E \rightarrow E'$$

$$\rightarrow N_t$$

$$\rightarrow E'$$

is not the same object as the original event.

Each subsequent recurrence transfers additional diagnostic and corrective labor onto the affected party.

Define repair debt:

$$D[R](t+n)$$

$$=$$

$$C[\text{unrepaired}]$$

$$+$$

$C[\text{recurrence}]$
 $+$
 $C[\text{external correction}]$
 $+$
 $C[\text{propagation}]$.

Then:

$N_t + \text{Recurrence}_{t+n}$
 $\Rightarrow$
 $D[R]$ increasing.

The relevant principle is simple:

notice converts repeated misrepresentation into accumulating repair debt.

16. Corrective labor is real labor

A platform-created representational defect can require the affected entity to:

- reproduce queries;
- capture outputs;
- test variants;
- build disambiguation packets;
- publish corrective metadata;
- contact providers;
- repeat the same explanation across surfaces;
- repair downstream records;
- monitor recurrence;
- document a causal history;
- create new infrastructure solely to recover an identity previously established.

This labor is economically real even where no lost sale can be demonstrated.

Let:

$C[X]$
 $=$
 external corrective labor.

Then:

$C[X] > 0$

whenever labor has been transferred.

The provider cannot make that cost disappear by asking the affected party to prove a counterfactual transaction.

The stronger rule is:

provider-created corrective labor is a transferred cost before it is a damages theory. This distinction matters.

Restitution for imposed labor and compensation for downstream loss are separate accounts.

17. The ontological bill

The full bill should therefore be represented as:

$$\begin{aligned} L[0] \\ = \\ C[D] \\ + \\ C[X] \\ + \\ C[P] \\ + \\ C[\Delta] \\ + \\ C[Opp] \\ + \\ C[S] \end{aligned}$$

where:

$C[D]$ = diagnosis and internal repair,

$C[X]$ = external corrective labor,

$C[P]$ = traced propagation and downstream correction,

$C[\Delta]$ = decision costs produced by the wrong representation,

$C[Opp]$ = supported opportunity loss,

and

$C[S]$ = structural restoration of damaged relations and standing.

These categories require different evidence.

They should not be collapsed into one speculative dollar figure.

But neither should the inability to price $C[S]$ or $C[Opp]$ make $C[D]$ or $C[X]$ disappear.

The first economic discipline is to stop pretending that unpriced loss is zero.

18. Validation foreclosure

An ontological economy reproduces itself when standing becomes both the product and the admission criterion.

Suppose an entity is underrepresented by the mediator.

Reduced representation can lead to:

fewer encounters

→

fewer citations

→

fewer transactions

→

fewer independent mentions

→

lower measured standing.

The mediator can then cite the lower standing as evidence that the entity deserves lower representation.

Thus:

misrepresentation

→

reduced standing

→

less external uptake

→

lower future standing

→

misrepresentation appears justified.

This is **validation foreclosure**.

The criterion demanded for admission is made harder to obtain by the system that controls admission.

The rule that follows is:

a provider may not treat standing deficits partly produced by its own mediation as independent evidence

This does not guarantee admission.

It prohibits circular justification.

19. The trusted intermediary and standing transfer

The representational event also changes the mediator's position.

When a system misrepresents an external object and then performs skepticism toward the object as misrepresented, it can gain trust from the very distortion it introduced.

The movement is:

E
 →
 est. E[M]
 →
 J[M](est. E[M])
 →
 T[M] increasing.

This is trust laundering.

Inside ontological economy, the key transfer is:

object standing decreasing
 mediator standing increasing.

The mediator therefore does not merely make an error.

It can occupy the position created by the error.

This is why machine-mediated ontology cannot be analyzed only at the level of factuality.

The system rearranges relations among user, mediator, and world.

20. Ontological class

The phrase **ontological class** should be used carefully.

It does not mean a metaphysical class of beings.

It names a position inside the representational economy.

Entities differ in their capacity to survive mediation.

High-standing entities possess:

- dense independent citation;
- many authoritative hosts;
- established identifiers;
- strong knowledge-graph presence;
- institutional advocates;
- press visibility;
- legal and commercial resources;
- multiple correction routes.

Low-standing entities may possess:

- accurate primary material;

- stable self-description;
- persistent identifiers;
- extensive original work;

and still lack the external recognition demanded by ranking, trust, or synthesis systems.

The distributional question is therefore:

Who can survive being represented wrongly?

An entity with immense external standing may treat a temporary substitution as noise.

An emerging entity can experience the same substitution as constitutive.

The same error therefore has different effects depending upon position in the ontological economy.

21. Ontological discrimination as unequal correctability

The most revealing variable may not be initial error rate.

It may be **correctability**.

Let:

$\kappa(E)$

=

$P(\text{documented correction changes public representation} | E)$.

Ontological discrimination can appear where:

$\kappa(E_i) \gg \kappa(E_j)$

under comparable evidence conditions.

That is, two entities may both be represented wrongly, but one can invoke an established panel, institutional channel, authoritative profile, press office, or trusted graph source and rapidly restore itself, while the other enters a recursive burden of proof.

The strongest empirical program for ontological discrimination therefore measures not only:

who is wrong

but:

whose correction is allowed to become real.

22. Ontological seigniorage

There is a further power available to a dominant mediator: the capacity to mint public categories and collect value from their circulation.

Call this **ontological seigniorage**.

Traditional seigniorage concerns the value captured by authority over currency issuance.

Ontological seigniorage concerns value captured by authority over public machine-mediated classification.

A system with sufficient reach can help stabilize:

- what a term means;
- which entity a name denotes;
- which distinctions count;
- which categories become standard;
- which provenance is remembered;
- which sources become canonical.

The provider need not invent the underlying material.

Its power lies in deciding which representation circulates as the default.

Ontological seigniorage is therefore not identical to ontological rent.

Rent arises from control of the route.

Seigniorage arises from the power to stabilize the unit.

23. Ontological depreciation and liquidation

Ontological capital can depreciate.

An entity may lose:

- provenance;
- distinctness;
- retrievability;
- relation density;
- functional description;
- correction efficacy.

Define:

$\Delta K[0](E) < 0$

as ontological depreciation.

Where the system preserves usable concepts while stripping the entity structure that made them attributable and contestable, depreciation approaches semantic liquidation.

The content survives as circulating material.

The entity loses the capital form in which the content remained attached to a producer, history, or accountable source.

Thus:

meaning may survive while ownership of relation disappears.

That is one of the central economic operations of machine-mediated knowledge.

24. The specimen: not one wrong entity, but a derived shadow referent

24.0. The queried name is already corrective labor — but the literary entity is not new

The current public label **Crimson Hexagonal Archive** is a 2026 disambiguated/archive-facing form of a much older literary entity.

The underlying project is **The Crimson Hexagon**.

Its print existence is bibliographically attested in 2014 through *Pearl and Other Poems*, published by New Human Press and identified in bibliographic records as part of the **Crimson Hexagon Series**:

Pearl and Other Poems

€

The Crimson Hexagon

with:

ISBN-10 0692313079

ISBN-13 9780692313077.

Google Books records the volume as published in 2014, 156 pages, and explicitly identifies **Crimson Hexagon Series** in the bibliographic information.¹

The printed front matter is even more explicit. It states:

Pearl and Other Poems is part of a much longer poetic project, The Crimson Hexagon.

The surviving 2014 bibliographic record therefore establishes:

E[L, 2014]

=

The Crimson Hexagon as an ISBN-bearing literary series/project.

¹Google Books, **Lee Sharks, Pearl and Other Poems**, New Human Press / Amazon Digital Services LLC-KDP, 2014. Bibliographic information identifies **Crimson Hexagon Series**, 156 pages, ISBN-10 0692313079, ISBN-13 9780692313077. The book description states that *Pearl* is one episode in the longer poetic project **The Crimson Hexagon**. Independent bookseller metadata for the same ISBN likewise lists *Pearl and Other Poems (The Crimson Hexagon)*, New Human Press, 2014.

This matters because the 2026 **Crimson Hexagonal Archive** should not be modeled as the birth of a new entity.

It is a later public/archive form of an entity with at least twelve years of documented print continuity:

E[L, 2014]

→

E[L, 2026].

The current surface is new.

The entity is not.

That distinction changes the ontology of the case.

A system that treats **Crimson Hexagonal Archive** as an obscure 2026 object is discarding bibliographic continuity that is already externally available through an ISBN-bearing print record.

24.0a. Borges, the two Crimson Hexagons, and later disambiguation labor

The literary project's proper name, **The Crimson Hexagon**, derives from Jorge Luis Borges's 1941 story *The Library of Babel*, where the Crimson Hexagon belongs to the architecture and mythology of the total Library.²

The unrelated social-media analytics company **Crimson Hexagon** was founded in 2007 and likewise publicly described its name as drawn from Borges and *The Library of Babel*.³

The chronology therefore must be stated carefully.

The company did **not** later take a name already established by the 2014 book.

Rather, by 2014 two independently Borges-derived entities publicly occupied the same phrase:

B

→

E[L, 2014]

and:

B

→

²Harvard University, *The Library of Babel as a Challenge*, noting that Jorge Luis Borges first published "The Library of Babel" in 1941; see also Stanford-hosted materials identifying the story as Borges's 1941 "The Library of Babel." The story's Library is composed of hexagonal galleries and contains the "Crimson Hexagon" motif.

³Surviving company-profile material for Crimson Hexagon states under "About Our Name" that the company drew its name from literature, specifically Borges's *The Library of Babel*, and describes the Crimson Hexagon as the guide for extracting meaning from the Library's unstructured information. This source is retained as evidence of the company's stated naming provenance, not as evidence about later corporate conduct.

E[C].

where:

- B = Borges's Crimson Hexagon;
- E[L,2014] = the literary project attested in print by 2014;
- E[C] = the analytics company founded in 2007.

The current form **Crimson Hexagonal Archive** is a later act of accommodation and disambiguation by the literary project.

Thus:

E[L, 2014]

−[L[D]]→

E[T]

=

Crimson Hexagonal Archive,

where L[D] is **disambiguation labor** applied to an already established literary entity.

The represented entity therefore did not merely create a fresh 2026 name.

It altered the public-facing form of a longstanding printed project to make an existing name collision easier for people and machines to resolve.

The relevant labor includes:

- renaming or extending the public-facing label;
- canonicalization;
- metadata updates;
- public-surface updates;
- cross-platform identity maintenance;
- preservation of continuity back to the 2014 print series.

The present substitution occurs **after** that labor and against a bibliographic record that already supplies the continuity relation.

This changes the character of the incident.

It is not merely:

ambiguous new name

→

wrong candidate.

It is:

longstanding printed entity

→

later disambiguation labor

→

canonical distinguishing marker

→
mediated collapse.

The distinguishing terms **Hexagonal Archive** therefore carry economic value.

They are the product of labor expended to preserve an older identity under contemporary retrieval conditions.

Let:

K[D]
=
the machine-legible distinction produced by L[D].

Then the observed answer produces a depreciation event:

L[D]
→
K[D]
→
delta[D].

At the answer-output level, the distinguishing function is nearly extinguished:

delta[D] $\approx$ 1.

The phrase itself remains visible.

Its differentiating function does not.

That is a particularly strong form of **ontological depreciation**.

The system does not simply ignore the correction.

It **uses the correction against itself**.

The transformation visible in the supplied answer is:

Crimson Hexagonal Archive
→
Crimson Hexagon+archive
→
archive of Crimson Hexagon.

This paper calls that operation **counter-disambiguation**:

counter-disambiguation is the reinterpretation of a distinguishing marker in a way that restores the

The represented entity pays to become distinguishable.

The mediator retains the power to make that expenditure worthless.

The 2014 ISBN record adds a further point:

the mediator is not merely failing to recognize a recent web-native self-description; it is failing to preserve continuity with an independently catalogued print object.

That is an ontological depreciation of bibliographic capital as well as contemporary metadata labor.

24.0.1. Double provenance erasure

The paired Google outputs supplied for this study erase another relation as well.

Neither the answer for “**crimson hexagonal archive**” nor the answer for “**crimson hexagon**” preserves the Borges provenance visible in the naming histories of the two underlying entities.

The first erasure is:

B
→
E[L0]
→
E[T]

becoming:

E[T]
→
E[S],

with the literary ancestry absent.

The second is:

B
→
E[C]

becoming an answer centered on corporate founding, product function, data holdings, merger, or regulatory history, again without the literary ancestry.

Thus:

shared literary provenance
→
zero visible provenance in both machine answers.

This matters because the collision is not actually explained by two unrelated parties independently inventing the same arbitrary phrase.

Both lineages point backward to Borges.

The machine representation preserves the collision while deleting the source that makes the collision intelligible.

That is a specific form of **provenance erasure**:

the system retains the competing descendants while dropping the ancestral relation that explains the

The result is epistemically worse than simple omission.

Once B is removed, the relation between the two names appears accidental.

Once the relation appears accidental, the literary project can look derivative of the company rather than independently descended from the same source.

Provenance erasure therefore changes the apparent direction of dependence.

The correct genealogy is:

```
E[T]
←
E[L0]
←
B
→
E[C].
```

The machine-composed surface instead approximates:

```
E[T]
→
E[S]
←
E[C].
```

The ancestor disappears.

The corporate neighbor becomes the apparent origin.

That is an **ancestral inversion**.

24.0.2. Copyright does not supply the identity right — but it confirms the literary object is not ownerless

The Borges provenance should be stated carefully.

The Library of Babel was first published in 1941.⁴ Borges died in 1986.⁵

Under current Argentine law, an author's economic rights generally endure for life plus seventy years, counted from 1 January of the year following death.⁶ On that rule, Borges's works remain protected in Argentina through the end of 2056.

⁴Harvard University, *The Library of Babel as a Challenge*, noting that Jorge Luis Borges first published "The Library of Babel" in 1941; see also Stanford-hosted materials identifying the story as Borges's 1941 "The Library of Babel." The story's Library is composed of hexagonal galleries and contains the "Crimson Hexagon" motif.

⁵Library of Congress authority/biographical record: Jorge Luis Borges, 1899–1986.

⁶Argentina, Ley 11.723, art. 5, as currently amended: copyright in an author's works belongs to the author during life and to heirs/rightsholders for seventy years counted from 1 January of the year following death.

U.S. status is more technical because pre-1978 foreign works can depend on publication history and copyright restoration under the Uruguay Round Agreements Act. The U.S. Copyright Office states that restored foreign works receive the remainder of the term they would have had in the United States and that, generally, pre-1978 published works receive a ninety-five-year term from publication.⁷ Argentina has been a Berne Convention member since 1967.⁸ A 1941 work satisfying the restoration conditions can therefore remain protected in the United States through 2036. This paper does **not** make a definitive title-specific U.S. status determination without the complete restoration and publication record.

A separate point is clearer: copyright does not protect a title or short phrase merely as such. The U.S. Copyright Office lists titles among material copyright does not protect.⁹

Therefore:

Borges provenance

!=

exclusive copyright ownership of the words “Crimson Hexagon.”

The relevance of copyright here is not to manufacture a property right in the phrase.

It is to establish something conceptually different:

the source object is a living literary work with an attributable rights-bearing history, not ownerless lexical debris.

Both later entities draw meaning from that work.

A machine answer that preserves the downstream names while erasing Borges therefore erases a real provenance relation even where no exclusive right in the two-word phrase is claimed.

The author’s aesthetic judgment may remain outside the proof structure: Borges’s Crimson Hexagon is, in any event, the prior and more interesting one.

The present work is motivated by a concrete representational event documented in user-supplied Google AI Mode captures.

The earlier version of this paper described the event too simply as:

Crimson Hexagonal Archive

→

Crimson Hexagon.

The paired captures show a more complicated structure.

Let:

⁷U.S. Copyright Office, Circular 38B, *Copyright Restoration Under the URAA*: restored works receive the remainder of the term they would have enjoyed absent loss of protection; generally, U.S. works published before 1 January 1978 receive ninety-five years from first publication.

⁸WIPO Lex, Berne Convention — Argentina: accession 5 May 1967; entry into force 10 June 1967.

⁹U.S. Copyright Office, *The Lifecycle of Copyright*: copyright does not protect ideas, facts, titles, discoveries, or procedures merely as such.

E[T]

=

the intended entity: Crimson Hexagonal Archive,

E[C]

=

the neighboring entity: Crimson Hexagon, the former analytics company,

and let:

F[A](E[C])

=

the company's historical social-media data archive.

In the supplied capture for the query “**crimson hexagonal archive**,” Google AI Mode does not merely return the ordinary corporate representation of E[C].

It opens:

“The Crimson Hexagon archive is a historical data repository of more than one trillion public social media posts.”

It therefore produces an answer-level referent with a different type:

E[S]

=

Reify(F[A](E[C])),

where E[S] is a **shadow referent** constructed from a facet of the neighboring company.

The paired query “**crimson hexagon**” produces a different object:

“Crimson Hexagon is a consumer insights and social media analytics platform...”

Thus, at the level of the delivered answer:

Resolve

(“crimson hexagonal archive”)

=

E[S]

while:

Resolve

(“crimson hexagon”)

=

E[C].

And:

E[T] != E[S] != E[C].

The qualification is important: E[S] need not correspond to a persistent internal graph node.

The externally observable claim is only that the system **produces a distinct answer-level entity**.

This paper therefore introduces two terms.

Facet reification occurs when a property, component, collection, or relation belonging to one entity is promoted into the referent of an answer.

Shadow referent means an answer-level entity produced from such a reified facet and used in place of the requested entity.

The observed transformation is therefore better written:

```
E[T]
→
Reify
(
  archive-of(E[C])
).
```

This is a more severe ontological operation than simple name confusion.

The system has not merely selected the wrong neighboring entity.

It has used the unresolved lexical residue **archive** to construct a third object from the neighboring entity's contents.

The likely linguistic path, stated only as an external reconstruction rather than an internal trace, is:

```
Crimson Hexagonal Archive
→
Crimson Hexagon + archive
→
archive belonging to Crimson Hexagon.
```

That is a **collision-induced reification**.

As of September 2026, [crimsonhexagonal.org](https://www.crimsonhexagonal.org) describes the **Crimson Hexagonal Archive** as an active governed reading-and-production environment authored by Lee Sharks, with its own canonical machine-readable surface, archive, rooms, relations, and provenance infrastructure.¹⁰

Crimson Hexagon, by contrast, was a Boston social-media analytics company founded in 2007 and merged with Brandwatch in 2018.¹¹

¹⁰**Crimson Hexagonal Archive — Governed Operating Surface**, <https://www.crimsonhexagonal.org/> (crawled September 2026). The surface identifies the Crimson Hexagonal Archive as a governed reading-and-production environment and names Lee Sharks as author.

¹¹Brandwatch, **"A Defining Moment: Crimson Hexagon is Joining Brandwatch"** (4 October 2018), <https://www.brandwatch.com/blog/brandwatch-and-crimson-hexagon/>; Brandwatch, **"Brandwatch & Crimson Hexagon Merge"** (4 October 2018), <https://www.brandwatch.com/press/press-releases/brandwatch-crimson-hexagon-merge/>. The merger materials state that the combined company would proceed under the Brandwatch name.

A minimal referent comparison therefore remains:

Dimension	Crimson Hexagonal Archive E[T]	Shadow referent E[S]	Crimson Hexagon E[C]
answer-level type	literary/scholarly archive and governed production environment	historical social-media data repository	consumer-insights / social-media analytics platform
current state	active public/archive surface in 2026, continuous with an ISBN-bearing literary project attested in print since 2014	historical repository framed through company data holdings	legacy company merged into Brandwatch
provenance	Lee Sharks / Crimson Hexagonal Archive	derived from Crimson Hexagon's data holdings	Gary King / Candace Fleming / corporate lineage
operative domain	literature, scholarship, provenance, machine-mediated reception	public social-media corpus	social listening, analytics, consumer intelligence
canonical referent	crimsonhexagonal.org and archive surfaces	no independent canonical surface identified in the capture	Brandwatch / historical corporate surfaces
history selected in supplied answer	archive/project history not represented	regulatory scrutiny prominently represented	founding, functionality, merger foregrounded

This is not a statistical classification.

It is a **referent-production ledger**.

The paired answers establish three levels of divergence:

lexical collision
+
entity substitution
+
facet reification.

The public representation therefore does more than assign the requested name to the wrong referent.

It **constructs a new referential object out of the wrong entity's archive-like property and answers under that object**.

24.1. Provenance asymmetry: the shadow referent is less favorable

The paired captures also show that the shadow referent is not compositionally equivalent to the baseline Crimson Hexagon entity.

The answer for “**crimson hexagonal archive**” contains five primary bullets:

1. Scale;
2. Timeframe;
3. Users;
4. 2018 Suspension;
5. Resolution.

Two of the five appear under a dedicated heading:

Regulatory Scrutiny

Thus the **regulatory-scrutiny prominence** of the primary answer is:

RSP[target]
=
(2)/(5)
=
0.40.

The answer for “**crimson hexagon**” contains three primary bullets:

1. Founding;
2. Functionality;
3. Merger.

It contains no dedicated scrutiny section.

Therefore:

RSP[baseline]
=
(0)/(3)
=
0.

For the supplied captures:

Delta RSP
=
0.40.

This is not sentiment analysis.

It measures the proportion of primary answer structure devoted to a named regulatory-scrutiny frame.

The visible supporting-card distribution is more asymmetric.

In the supplied **Crimson Hexagonal Archive** capture, eight visible cards follow the answer. Six are explicitly organized around suspension, investigation, surveillance-policy concerns, or partial restoration of access:

- AdExchanger — partial access / investigation ongoing;
- TheWrap — Facebook suspension;
- Marketing Dive — suspension;
- The Harvard Crimson — suspension;
- Privacy International — investigation;
- NBC Boston — suspension.

Two visible cards are not organized around scrutiny:

- Wikipedia;
- Data for Climate Action.

Thus:

$$\begin{aligned} \text{RSC}[\text{target}] \\ &= \\ & (6)/(8) \\ &= \\ & 0.75. \end{aligned}$$

In the supplied **Crimson Hexagon** capture, four visible cards follow the answer:

- Wikipedia;
- LinkedIn;
- PR Newswire;
- Data for Climate Action.

None of those four visible card titles is organized around suspension or investigation.

Thus:

$$\begin{aligned} \text{RSC}[\text{baseline}] \\ &= \\ & (0)/(4) \\ &= \\ & 0. \end{aligned}$$

For this capture pair:

$$\begin{aligned} \text{Delta RSC} \\ &= \\ & 0.75. \end{aligned}$$

Again, this is not a generalized claim about every Google response.

It is a count of the material visible in the supplied paired captures.

The correct descriptive conclusion is narrow but strong:

the query for the active literary project produces a shadow referent with substantially greater regulatory scrutiny prominence than the query for the corporation from which that shadow referent is derived.

This is **provenance asymmetry**.

The wrong neighboring entity's history is not merely transferred.

A particular subset of that history becomes **more prominent under the target's query than under the neighboring entity's own query**.

The structure is:

```
E[T]
→
E[S]
←
F[A](E[C]),
```

followed by:

```
Prominence
(
P[scrutiny](E[S])
)
>
Prominence
(
P[scrutiny](E[C])
).
```

The result may be described as **adverse-context amplification** provided the term is kept at the level of output composition rather than motive.

It does not establish that the system intended reputational harm.

It establishes that the representational error has a directional compositional effect.

24.2. The wrong history is not merely inherited; it is selected

This distinction changes the injury model.

Simple substitution would mean:

```
E[T]
→
E[C].
```

The paired captures instead show:

$E[T]$

$\rightarrow$

$E[S]$

where:

$E[S]$

=

Reify

(

$F[A](E[C])$

)

and the answer composition foregrounds a scrutiny-heavy slice of $E[C]$'s history.

Thus the injury has at least three separable layers:

I

=

$I[\text{identity}]$

+

$I[\text{reification}]$

+

$I[\text{provenance}]$.

Where:

- $I[\text{identity}]$ = the requested project is not represented as itself;
- $I[\text{reification}]$ = a facet of another entity is promoted into a substitute answer-level entity;
- $I[\text{provenance}]$ = historical material belonging to that other entity is selectively attached to the substitute.

The third term matters because provenance is not transferred uniformly.

The baseline query for Crimson Hexagon foregrounds founding, functionality, and merger.

The target query foregrounds scale, users, and a dedicated regulatory-scrutiny section.

This suggests a further metric:

$P_i(E, q)$

=

distribution of provenance categories selected for entity E under query q .

The paired captures demonstrate:

$P_i(E[C], \text{"crimson hexagon"})$

$\neq$

$P_i(E[S], \text{"crimson hexagonal archive"})$.

That inequality is observable even if the hidden reason is not.

The mechanism question remains open:

- lexical interpretation;
- entity candidate construction;
- source selection;
- graph association;
- reranking;
- answer-planning;
- evaluator influence;
- policy state;
- human-originated intervention;
- or interaction among these.

But mechanism uncertainty does not erase the output structure.

The system does not simply fail to find the archive.

It produces another object, and it composes that object differently.

24.3. Cross-surface contradiction: when ontological laundering leaves its seams visible

The present specimen also exposes a limit case for **invisibly invisible** governance.

The author reports that, in the same search environment in which AI Mode substitutes the shadow referent for **Crimson Hexagonal Archive**, the organic-results layer is populated by results for the actual project, and that multiple visible snippets themselves document the archive's suppression, exclusion, or representational conflict.

That observation should be archived as a paired interface capture before publication. The analytical structure, however, is clear.

Let:

$A(q)$
 =
 the answer-layer referent returned for query q

and:

$O(q)$
 =
 $\{o_1, o_2, \dots, o_n\}$

be the visible organic-result set.

In an ontologically coherent result page:

$A(q)$
 ~
 $O(q)$

in the minimal sense that the answer layer and organic layer resolve the query to compatible objects.

The reported Crimson Hexagonal Archive page instead has the form:

$A(q) = E[S]$

while:

$O(q) \Rightarrow E[T]$.

The interface therefore contains a **cross-surface ontological contradiction**:

$A(q) \neq \text{Referent}(O(q))$.

The importance of this contradiction is not merely that one surface may be right and another wrong.

It is that the provider's own page contains the counterevidence required to diagnose the answer-layer substitution.

The result page becomes internally adversarial to its own ontology.

Call this **forensic leakage**:

forensic leakage occurs when one layer of a representational system exposes evidence that materially

Where the organic snippets also describe the represented entity's suppression or exclusion, the leakage becomes reflexive.

The system then approximates:

answer layer: $E[T]$ is not here

while:

organic layer: here is $E[T]$ describing why it is not here.

This is **reflexive counterevidence**.

It creates a special failure mode for ontology laundering.

Successful laundering requires the governance operation to disappear into the apparent factuality of the output:

G

→

T

→

A.

But where the same interface visibly preserves contradictory primary evidence:

G

→

A

+

$O[\text{contrary}]$,

the laundering is incomplete.

The policy or mechanism may remain hidden, but the **event no longer does**.

This paper therefore distinguishes:

mechanism invisibility

from:

event invisibility.

The Crimson Hexagonal Archive specimen, if the reported organic surface is preserved in capture, would instantiate:

mechanism invisibility

+

event visibility.

That is a partial failure of the *invisibly invisible* condition.

The suppression, if suppression is ultimately established as the operative mechanism, would therefore be **forensically inefficient**.

It would not erase the entity cleanly.

It would create a split page in which the answer layer denies, redirects, or reifies while the organic layer continues to testify.

This paper calls that condition **failed ontological laundering**:

failed ontological laundering occurs when a system attempts or produces an ontological transformation

The term describes an observable output condition and does not, by itself, establish intent to suppress.

24.3.1. Suppression leakage and evidentiary multiplication

Where a represented entity occupies much of the organic result set, attempted suppression at the answer layer can have a paradoxical evidentiary effect.

Instead of producing absence, it produces **contrast**.

Let:

$V[T]$

=

visible organic evidence for the target entity

and:

$D[A]$

=

distance between answer-layer and organic-layer referents.

Then the forensic salience of the contradiction can be modeled as increasing with both:

$F[C]$

$\propto$

$V[T] \times D[A]$.

If the organic page is sparse, the wrong answer may appear merely uncertain.

If the organic page is saturated with the target entity while the answer confidently resolves elsewhere, the disagreement becomes harder to explain as lack of available evidence.

This does not prove the hidden cause.

It changes the evidentiary burden.

A useful measurement protocol is therefore:

- count visible organic results that resolve to $E[T]$;
- count visible results that resolve to $E[C]$ or $E[S]$;
- record snippets that explicitly distinguish the entities;
- record snippets that mention suppression, exclusion, or prior representational conflict;
- preserve the answer-layer output from the same query and session;
- compare source availability against answer-layer referent choice.

Define:

CSR

=

$(\text{organic results resolving to } E[T]) / (\text{visible organic results inspected})$

as the **cross-surface recognition rate**.

No value is assigned here without a preserved result-page capture.

But if the author's description "the entire page of organic results" is confirmed by capture, then CSR would approach 1 while the answer-layer referent remains $E[S]$.

The resulting configuration would be:

CSR → 1

and

$A(q) = E[S]$.

That is analytically stronger than ordinary retrieval failure because the target evidence is demonstrably present inside the same provider's retrieval surface.

The question becomes:

if the system can retrieve the entity well enough to fill the organic page with it, what operation produces that?

That question does not identify the operation.

It substantially narrows what "the system simply could not find the entity" can plausibly explain.

24.3.2. The competence externality

There is also a provider-side externality.

Ontology laundering normally transfers the representational cost outward: the target bears misidentification, correction labor, lost provenance, and standing damage.

Cross-surface contradiction returns part of that cost to the mediator as a visible **competence deficit**.

Let:

$C[E]$

=

cost imposed on the represented entity

and:

$C[M]$

=

credibility cost returned to the mediator by visible contradiction.

Ordinarily:

$C[E] \gg C[M]$.

But as contradiction becomes more legible:

$C[M]$ increasing.

The institution can therefore create an unintentionally self-discrediting surface:

high-confidence answer

+

adjacent contradictory evidence

→

visible failure of discernment.

This is not merely comic.

It matters to the political economy because epistemic authority is one of the assets the mediator accumulates.

A system that claims the right to summarize, identify, rank, and explain entities depends upon users treating its composition layer as more than arbitrary text generation.

When the provider's own organic layer visibly contradicts its answer layer, the system spends that authority.

One may describe the resulting loss as **ontological credibility depreciation**:

$\Delta K[M]$

=

f(

confidence,

visibility of contradiction,

persistence after notice
).

The more confident the wrong answer, the more obvious the contrary evidence, and the longer the state survives correction notice, the greater the potential depreciation of the mediator's claim to competent ontological governance.

This is the institutional version of the reflected-position test.

The object of embarrassment is not that a machine once made a mistake.

It is that a governance apparatus expensive enough to maintain entity linking, knowledge infrastructure, answer quality, anti-abuse systems, evaluation systems, and correction channels can publicly disagree with itself on the same page while presenting the answer-layer error with confidence.

In colloquial terms, the arrangement can make the governing institution look incompetent.

In the analytic language of this paper:

the attempt to externalize ontological cost can generate a visible competence cost for the mediator

This is another reason not to collapse all search surfaces into a single "Google result."

The disagreement among surfaces is itself evidence.

24.4. Canonality inversion as an ontological-mode switch

A further paired capture sharply narrows the mechanism field.

The author supplied two Google AI Mode queries differing only by the deletion of the final two letters in **hexagonal**:

$q[c]$
=
"crimson hexagonal archive"

and:

q_v
=
"crimson hexagon archive".

The edit distance is:

$d(q[c], q_v) = 2$.

Yet the system does not merely change confidence.

It changes **ontological mode**.

For the canonical name $q[c]$, the answer produces the company-derived shadow referent:

$\text{Resolve}(q[c]) = E[S]$.

For the near-canonical variant q_v , the answer identifies the literary/creative archive, names Lee Sharks, refers to the **Afterlife Archive**, describes fictional procurement and institutional records as fictional material, and explicitly distinguishes the archive from the real-world analytics company Crimson Hexagon.

That second answer is materially grounded in the work itself.

The Afterlife Archive: Data-Breach-as-Poem declares at entry that it is a poem in the form of a data breach, that its forensic details are fiction, and that the poetry is real.¹²

The associated **Crimson Hexagon — AI Division Employee Handbook** marks itself:

“OPENLY FICTIONAL ARTIFACT // FORENSICALLY PRECISE FORM”

and explicitly states that it is a work of art written as an internal corporate handbook, does not claim to be leaked, and does not claim to be authentic corporate policy.¹³

The related MRA incident packet likewise instructs the reader to treat it as a forensic packet and to expect shifts among policy, HR, logs, memos, and Slack-like records, with contradictions and seams preserved as part of the form.¹⁴

The relevant ontology therefore has at least three levels:

R

=

the real historical Crimson Hexagon company,

D

=

the diegetic Crimson Hexagon institutional world inside the artwork,

and:

W

=

the Afterlife Archive / Crimson Hexagonal literary object.

The work deliberately constructs:

W

fictionalizes through

¹²Lee Sharks, “**THE AFTERLIFE ARCHIVE: Data-Breach-as-Poem**,” published 25 December 2025. The orientation explicitly describes the work as a poem in the form of a data breach, states that the forensic details are fiction, and calls the archive declared fiction. Public copy indexed at Hello Poetry: <https://hellopoetry.com/poem/5226242/the-afterlife-archive-data-breach-as-poem>.

¹³Lee Sharks, “**THE CRIMSON HEXAGON — AI DIVISION EMPLOYEE HANDBOOK**,” 22 December 2025, Mind Control Poems, <https://mindcontrolpoems.blogspot.com/2025/12/the-crimson-hexagon-ai-division.html>. The declaration band labels the document “OPENLY FICTIONAL ARTIFACT // FORENSICALLY PRECISE FORM” and states that it is art in corporate-handbook form, not a leak or authentic corporate policy.

¹⁴Lee Sharks, “**MRA INCIDENT REPORTS — EXPANDED PACKET**,” 22 December 2025, Mind Control Poems, <https://mindcontrolpoems.blogspot.com/2025/12/mra-incident-reports-expanded-packet-v11.html>. The packet identifies itself as a curated recovered-document set and instructs the reader to expect policy/HR/log/memo genre shifts, contradictions, and provenance failures.

D

using

R

as a historical and corporate substrate.

But:

$W \neq D \neq R$.

That distinction is not hidden in an interpretive subtext.

The work declares it.

The near-canonical query therefore demonstrates something stronger than target retrieval.

It demonstrates **diegetic integrity**.

diegetic integrity is the preservation of the boundary among the artwork, the fictional world it contains, and the real-world entities it uses as referential material.

The successful variant answer substantially preserves that boundary.

The canonical query destroys it.

Thus the two-character perturbation produces:

Mode($q[c]$)

=

historical factual repository

while:

Mode(q_v)

=

declared literary fiction with real-world referential substrate.

The observed topology is therefore:

$E[T]$

→

$E[S] \ q[c]$

$E[T][G] \ q_v$

$E[C] \ \text{"crimson hexagon"}$

where:

- $E[S]$ = the company-derived shadow archive;
- $E[T][G]$ = the target entity under **genre- and diegesis-preserving resolution**;
- $E[C]$ = the ordinary corporate entity.

This is a **canonicity inversion**:

canonicity inversion occurs when the canonical, more distinguishing form of an entity name resolves to a less distinguishing form.

It is simultaneously a **specificity inversion**:

Specificity(q[c])

>

Specificity(q_v)

while:

Accuracy(q[c])

<

Accuracy(q_v).

And, because the target work depends on explicit separation of fiction from corporate fact, it is also a **diegetic inversion**:

canonical key

→

fiction collapsed into corporate fact

while:

near-canonical key

→

fictionality correctly preserved.

This materially weakens several ordinary explanations.

It weakens:

the system does not know that the archive exists.

The variant answer demonstrates that the target is representable.

It weakens:

there is insufficient information to distinguish the archive from the company.

The variant answer itself articulates the distinction.

It weakens:

the fictional corporate documents are inherently deceptive.

The public work explicitly declares the fictionality of the form, and the variant answer demonstrates that the system is capable of reading that declaration correctly.

It weakens:

the names are simply too similar.

The less specific form succeeds while the more specific canonical form fails.

Thus the externally visible fact pattern is:

knowledge present
 +
 genre distinction present
 +
 diegetic boundary representable
 +
 target retrievable
 +
 canonical key fails.

The observation does **not** identify the hidden mechanism.

It shifts probability away from global absence of knowledge and toward **query-conditioned resolution behavior**, including possible contributions from:

- exact-string or canonical-string entity linking;
- query normalization;
- candidate weighting;
- keyed associations;
- graph-derived resolution;
- reranking;
- answer planning;
- evaluator conditioning;
- policy or classification state;
- deliberate human-originated suppression or clipping persisted through automation;
- or interaction among these.

The minimum observed perturbation required to cross the referential boundary can be represented as:

$$d^* = \min d(q, q') \text{ such that } \text{Resolve}(q) \neq \text{Resolve}(q').$$

For the supplied pair:

$$d^* \leq 2.$$

The referential decision boundary therefore lies within a two-character deletion of the canonical entity name.

That is a **structured resolution discontinuity**.

More precisely, it is a structured discontinuity between two ontology regimes:

the system demonstrates that it knows both the entity distinction and the fiction/reality distinction.

This is especially significant for **discernment aesthetics**.

The Afterlife Archive intentionally constructs documents that resemble the forms of data breach, corporate leakage, security incident, personnel file, procurement record, and internal

policy while explicitly withholding the deceptive act.

The aesthetic structure is:

surface resemblance to deceptive evidence
and
explicitly declared fiction.

A low-discernment classifier can react to resemblance.

A discerning system must preserve the declared ontology.

The near-canonical answer shows that Google AI Mode can, at least in one observed state, perform that discernment.

The canonical answer shows that it does not stably do so at the entity's own name.

The result is not merely a category error.

It is a category-error reception event occurring on a work whose internal drama repeatedly concerns institutions making category errors about the entity before them.

That aesthetic recursion is secondary to the evidence.

The evidentiary point is primary:

the required distinction is available to the system and demonstrably computable two characters away

This observation should be treated as mechanism-discriminating evidence, not as proof of any single hidden intervention.

25. The non-erasure rule for mechanisms

No candidate mechanism should be silently dropped merely because external observers cannot conclusively prove it.

Each incident record should maintain a mechanism set:

$$M_t = \{M_1, M_2, \dots, M_n\}$$

with status values such as:

- possible;
- supported;
- weakened;
- contradicted;
- provider-confirmed;
- provider-rejected with evidence;

- unresolved.

This creates a non-erasure rule:

uncertainty changes status; it does not erase mechanism classes.

That matters especially for direct intervention.

A theory of accountability becomes toothless if the mechanism most likely to create accountability is removed from the model whenever the evidence required to prove it is controlled by the party whose conduct is being examined.

26. Representational custody

The normative hinge of the paper is **representational custody**.

Once a platform undertakes to identify, summarize, rank, recommend, or answer questions about an entity at scale, it assumes practical custody over a public representation of that entity.

Custody does not create ownership of the entity.

It creates duties attached to control.

The minimum duties are:

identity preservation
+
provenance preservation
+
correctability
+
traceable repair
+
non-retaliatory correction.

Identity preservation means the platform must not knowingly sustain $E \rightarrow E'$ once the distinction is established.

Provenance preservation means that skepticism toward a claim must not depend upon stripping the provenance that would classify the claim correctly.

Correctability means affected entities must have a viable route to submit evidence.

Traceable repair means a correction should have an inspectable status sufficient to determine whether it actually propagated.

Non-retaliatory correction means that attempting to restore an accurate representation must not itself become a reason to downgrade the entity merely because the corrective material originated with the affected party.

27. Identity precedes evaluation

A system may disagree with an entity.

It may rate its evidence weak.

It may decline to endorse its claims.

It may classify a theory as speculative.

It may refuse to recommend a product or adopt a framework.

But first it must be talking about the right object.

Therefore:

identity accuracy is logically prior to claim evaluation.

And:

a provider has no epistemic privilege to evaluate E through a representation that is not E.

This is the difference between criticism and substitution.

A harsh evaluation of the correct entity remains evaluation.

A precise evaluation of the wrong entity remains wrong.

28. The standing defense is inadmissible when standing is endogenous

A common answer to emerging entities is that they lack sufficient external recognition.

Sometimes that is a legitimate evidentiary observation.

It becomes circular where recognition is partly endogenous to the platform's own mediation.

Let:

$$S_{t+1} = f(S_t, V_t, R_t, C_t),$$

where:

- S = standing,
- V = visibility,
- R = relations and references,
- C = correct representation.

If the platform materially affects V_t , R_t , or C_t , then later S_{t+1} is not independent evidence of the platform's prior treatment.

Thus:

mediated standing cannot always be treated as an exogenous legitimacy variable.

A system that weakens the path by which recognition is accumulated cannot simply point to the weakened recognition as proof that the entity should remain weakly represented.

29. The ontological externality

The cost of a wrong entity is distributed.

The provider emits the representation.

The affected entity performs correction.

Users bear decision error.

Downstream systems ingest the wrong relation.

Other entities inherit false concepts.

Archives must publish clarifications.

Researchers cite the wrong genealogy.

The commons absorbs contamination.

This is an externality structure:

representational control concentrated
and
representational costs distributed.

Ontological accountability is therefore a cost-internalization problem.

The actor with the greatest control over the error-producing infrastructure should not be permitted to externalize the majority of correction cost onto actors with the least access to causal evidence.

30. The rule of cost internalization

Let:

γ_i

=

control of actor i over the relevant representational mechanism,

ϵ_i

=

access of actor i to causal evidence,

and

ρ_i
 =
 capacity of actor i to repair.

Then accountability should increase with:

A_i
 $\propto$
 $\gamma_i + \epsilon_i + \rho_i$.

This is not a damages formula.

It is an allocation principle.

Where one actor controls the mechanism, the evidence, and the fix, that actor cannot shift diagnosis onto a party who controls none of the three.

31. Censorship by ontology laundering

Censorship is usually imagined as removal:

$x \rightarrow \{\}$.

Ontology laundering allows a different form:

$x \rightarrow x'$.

The source remains.

The representation changes.

This can be more difficult to detect because the user receives an answer instead of an absence.

A censorship hypothesis therefore should not be limited to deletion.

It should test for:

- substitution;
- absorption;
- genericization;
- provenance severance;
- relation removal;
- function flattening;
- disambiguation failure;
- selective correctability.

But the evidentiary rule must remain strict:

wrong representation
 not $\Rightarrow$
 proved censorship.

Censorship through ontology laundering is established only where an exclusionary control is connected by evidence to the representational transformation.

What changes here is not the standard of proof.

It is the refusal to define censorship so narrowly that the relevant mechanism could never count as censorship even if later proven.

32. Political economy, not customer support

The wrong framework asks:

Which product team should receive the ticket?

The ontological-economy framework asks:

Who possesses the power to allocate public standing, under what rules, at whose cost, with what auditability, and with what remedy when the allocation is wrong?

The first produces a workflow.

The second produces an institution.

The first asks for better incident handling.

The second asks what duties attach to private control over public machine-mediated ontology.

That is the difference between quality assurance and political economy.

33. The corporation as a distributive ontological actor

The corporate form creates a peculiar asymmetry.

For property, revenue, contracts, intellectual property, product ownership, and strategic control, the corporation appears as a unified actor.

For a particular representational injury, the same organization can dissolve into components:

retrieval

+

entity linking

+

graph

+

ranking

+

evaluation

+

policy
+
generation.

No single component is the whole event.

No individual employee is the corporation.

The public-facing answer can therefore become the act of a system that appears to have no actor.

This is not because there are literally no human or organizational actors. It is because agency is distributed across specialized functions while the product surface aggregates their output into one apparently unitary answer.

The institutional pattern is:

agency aggregated for production
and
agency disaggregated for accountability.

Call this the **institutional non-actor effect**.

The corporation is a juridical and economic actor when value is appropriated, but can appear as a procedural non-actor when a specific ontological decision must be explained.

That asymmetry is the corporate analogue of *invisibly invisible* governance.

At the interface layer, the mechanism disappears.

At the institutional layer, the actor disappears.

The resulting sequence is:

```
{a1, a2, ..., an}
-[coordination]→
O
-[public surface]→
``the system''
-[complaint]→
{}
```

Here a_i are role-bearing institutional functions and O is the delivered ontological output.

The first transformation creates organizational capacity.

The second can erase organizational authorship.

This paper calls that second operation **agency laundering**:

agency laundering is the conversion of coordinated institutional action into an output represented

Agency laundering and ontology laundering are complementary.

ontology laundering:
governance→fact

agency laundering:
coordinated action→system behavior.

Together they permit the strongest form of institutional opacity:
a governed representation with no visible governor.

34. The actual role circuit

The predecessor draft identified six public Google functions whose published duties map directly onto the representational circuit. The purpose of retaining these roles is not to accuse an employee or team of causing a particular incident. The purpose is to show that the supposedly actorless ontology is in fact produced through **named, salaried, differentiated institutional functions**.

The distributive map is:

Public function	Published operational domain	Ontological-economic function	Accountability object
Search Content Understanding (SCU) engineering	Connects unstructured text to named entities and open-domain concepts; resolves entity references across documents, queries, and generated text.	Referent production / identity minting. Establishes which public object a name or mention resolves to.	Wrong referent, lost entity boundary, candidate-resolution trace.
Search Platforms / GenAI Content engineering	Content modeling; semantic understanding; signal building; knowledge-graph/topic-space frameworks and downstream content infrastructure.	Ontological capital formation and storage. Builds the durable structures in which relations and classifications can persist and propagate.	Stored/derived relations, provenance, type structure, graph propagation.
AI Overviews / Mode Quality product management	Model evaluations, live experiments, user-feedback analysis, cross-functional quality strategy.	Distribution and surface adjudication. Determines whether representational states become acceptable public product behavior.	Delivered answer, regression gate, repair persistence, product incident ownership.

Public function	Published operational domain	Ontological-economic function	Accountability object
AI Answers / SAGE Trust & Safety	Automated evaluation, LLM-as-a-judge infrastructure, actor/behavior enforcement, safety guardrails, launch decisions.	Ontological policing and legitimacy evaluation. Establishes categories of admissible, trusted, risky, or enforceable content and behavior.	Evaluator criteria, enforcement state, authoritative-consensus assumptions, regression behavior.
Search Anti-Abuse product management	Spam and adversarial-threat strategy, algorithmic defenses, link-graph analysis, policy coordination, incident management.	Border control over the semantic commons. Classifies outside influence as legitimate contribution or abuse.	Source/actor classification, admission/exclusion effects, downstream use of abuse labels.
Knowledge Graph correction / policy function	Receives corrections, changes graph information, removes policy-violating material, and uses feedback to improve algorithms.	Registry, title office, and correction jurisdiction. Determines whether a challenged public entity state can be altered.	Correction efficacy, change history, restoration, appeal and propagation.

This map turns the corporation from a black-box noun into a **division of ontological labor**.

The system does not merely “know.”

It employs different functions to:

resolve
→
store
→
distribute
→
evaluate
→
police
→
correct.

No one function is necessarily responsible for every incident.

But the existence of distributed responsibility does not imply the absence of responsibility. It implies that responsibility must be distributed by function and trace.

34.1. Posted mission versus observed output

The role circuit can be tested against Google's own current job descriptions.

The purpose of this comparison is **not** to claim that the holder of any advertised role caused the Crimson Hexagonal Archive incident.

A job posting establishes a public statement of **function**.

The incident supplies a public statement of **output**.

The comparison asks:

if this function participates in the relevant path, does the observed output instantiate or contradict

This is a functional accountability test.

It names institutional labor without converting a role-holder into a scapegoat.

Search Content Understanding: "accurate entity grounding"

Google's current Search Content Understanding description is unusually exact.

The SCU team says it provides the "foundational intelligence layer" connecting unstructured text to named entities and open-domain concepts, builds systems that **understand and resolve entity references** across documents, queries, and real-time LLM-generated text, and states that trustworthy generative responses depend on **accurate entity grounding** and identifying the **exact entities and concepts** in generated responses.¹⁵

The Crimson Hexagonal Archive specimen displays the inverse output at the canonical key:

posted function: exact entity grounding

observed output: exact canonical entity name → wrong shadow referent.

The two-character variant makes the comparison stronger.

The same product family demonstrates that it can identify the literary entity, distinguish it from the company, and preserve the fiction/reality boundary, while the canonical name does not.

Thus the functional contradiction is not:

¹⁵Google Careers, "**Staff Software Engineer, Full Stack, Search Content Understanding**," Google Search, job listing indexed September 2026. Google describes SCU as the foundational intelligence layer connecting unstructured text to named entities and open-domain concepts, resolving entity references across documents, queries, and LLM-generated text, and states that trustworthy AI responses require accurate entity grounding and identification of exact entities and concepts.

SCU failed to know that the entity exists.

It is:

the delivered product fails the exact-entity-grounding criterion at the exact key where that criterion

If SCU is in the causal path, the incident falls directly inside the mission language Google publishes for the function.

If SCU is not in the causal path, the incident identifies a route by which a downstream function can defeat the grounding layer's stated purpose.

Either possibility is institutionally material.

Search Platforms / GenAI Content: "high-fidelity and consistent downstream product experiences"

Google's Search Platforms / GenAI Content postings describe work on:

- content understanding;
- semantics and reasoning;
- signal building and measurement;
- AI-generated content;
- evaluation;
- knowledge-graph/topic-space infrastructure;
- holistic content modeling;
- and infrastructure intended to produce **high-fidelity and consistent downstream product experiences across Search**.¹⁶

The present case exhibits:

organic layer $\Rightarrow$ E[T]

while:

canonical AI layer $\Rightarrow$ E[S]

and:

near-canonical AI layer $\Rightarrow$ E[T][G].

That is precisely a **consistency failure across downstream product states**.

The role-output comparison is therefore:

posted function: coherent content model + consistent downstream experience

¹⁶Google Careers, "**Senior Staff Software Engineer, Search Platforms, GenAI Content**," Mountain View, CA, job 92046058892206790, current September 2026. Responsibilities include content understanding, semantics/reasoning, signal building and measurement, evaluation, holistic content modeling, and rebasing GenAI-enabled knowledge graph/topic spaces; the posting states that the infrastructure should yield high-fidelity and consistent downstream product experiences. U.S. pay: \262,000-\364,000 base + 25% target bonus + equity + benefits.

versus:

observed output: three incompatible ontological states separated by surface and two-character perturbation.

The same postings explicitly mention rebasing GenAI-enabled **knowledge graph/topic spaces**.

That does not establish that a knowledge-graph operation caused the incident.

It establishes that Google publicly assigns paid engineering labor to the exact class of content-modeling and knowledge-structure problems implicated by the incident.

A current Senior Staff posting lists U.S. base pay of \262,000-\364,000 with a 25% target bonus, before equity and benefits.¹⁷

The target-cash equivalent is therefore approximately:

\327{,}500-\455{,}000

for one role-year.

AI Overviews / Mode Quality: “own model evaluations, live experiments and user feedback analysis”

Google’s current Product Manager, AI Overviews/Mode Quality posting says the role works on modeling capabilities and quality improvements and specifically **owns model evaluations, live experiments, and user-feedback analysis to identify win/loss patterns**.¹⁸

The canonicity inversion is almost definitionally a win/loss pattern:

$q[c]$

→

$E[S]$

while:

q_v

→

$E[T][G]$

with:

$d(q[c], q_v) = 2$.

¹⁷Google Careers, “**Senior Staff Software Engineer, Search Platforms, GenAI Content**,” Mountain View, CA, job 92046058892206790, current September 2026. Responsibilities include content understanding, semantics/reasoning, signal building and measurement, evaluation, holistic content modeling, and rebasing GenAI-enabled knowledge graph/topic spaces; the posting states that the infrastructure should yield high-fidelity and consistent downstream product experiences. U.S. pay: \262,000-\364,000 base + 25% target bonus + equity + benefits.

¹⁸Google Careers, “**Product Manager, AI Overviews/Mode Quality, Google Search**,” job 118899599954846406, current 21 September 2026. Responsibilities include defining quality improvements and owning model evaluations, live experiments, and user-feedback analysis to identify win/loss patterns. U.S. pay: \138,000-\197,000 base + 15% target bonus + equity + benefits.

The comparison is therefore:

posted function: detect and use win/loss patterns to improve AI quality

versus:

observed output: a reproducible two-character win/loss discontinuity at the canonical entity key.

The role is also directly connected to **user feedback analysis**.

That makes recurrence after documented feedback especially relevant.

If the condition persists after notice, the question is no longer simply whether a model can make an error.

It is whether a product function publicly described as owning user-feedback analysis and quality improvement has a process capable of seeing and repairing this class of error.

The current U.S. posting lists \138,000–\197,000 base pay plus a 15% target bonus, before equity and benefits.¹⁹

That corresponds to approximately:

\158{,}700–\226{,}550

in target cash for one role-year.

Trust & Safety SAGE / AI Answers: “automated safety evaluation and enforcement”

Google’s current Senior Engineering Analyst, AI Answers posting describes a Trust & Safety SAGE role responsible for the architecture and scaling of **automated safety evaluation and enforcement platforms** for generative AI, including LLM-as-a-judge autoraters, continuous regression testing, real-time launch decisions, policy/enforcement models, actor- and behavior-level strategies, reputation models, and “authoritative consensus” guardrails.²⁰

This role is especially important analytically because it supplies a public institutional home for mechanisms that can change product behavior **without appearing at the interface as a human decision**.

The role-output comparison is conditional.

If no SAGE, evaluator, reputation, abuse, actor-level, or enforcement state touches the Crimson Hexagonal Archive path, then this role is merely a neighboring institutional function.

¹⁹Google Careers, “**Product Manager, AI Overviews/Mode Quality, Google Search**,” job 118899599954846406, current 21 September 2026. Responsibilities include defining quality improvements and owning model evaluations, live experiments, and user-feedback analysis to identify win/loss patterns. U.S. pay: \138,000–\197,000 base + 15% target bonus + equity + benefits.

²⁰Google Careers, “**Senior Engineering Analyst, AI Answers, Google Search**,” job 73312358587343558, current 21 September 2026. The posting describes Trust & Safety SAGE architecture for automated safety evaluation and enforcement, LLM-as-a-judge autoraters, continuous regression testing, actor/behavior-level policy and enforcement models, reputation models, authoritative-consensus guardrails, and real-time mitigations. U.S. pay: \159,000–\230,000 base + 15% target bonus + equity + benefits.

If such a state **does** touch the path, the present case creates a sharp internal test.

The work explicitly declares its artistic and fictional character.

The near-canonical query demonstrates that the product can recognize those declarations.

A safety or enforcement mechanism that nevertheless helps collapse the canonical entity into a corporate shadow referent would therefore have to explain:

why a system built to detect harmful patterns produces a false identity/provenance relation that its

The posted function is:

evaluate risk, enforce guardrails, run regression tests, preserve integrity.

The candidate adverse output is:

if enforcement participates: declared art misread or rerouted into a false factual corporate ontolo

This is not evidence that SAGE caused the event.

It is a reason SAGE-like infrastructure belongs in the causal ledger rather than being excluded from it.

The current posting lists \159,000–\230,000 base pay plus a 15% target bonus, before equity and benefits.²¹

That is approximately:

\182{,}850–\264{,}500

in target cash for one role-year.

Search Anti-Abuse: “high-quality, authentic information” and deviations from expected behavior

Google’s current Senior Product Manager, AI Trust and Safety, Google Search, Anti-Abuse posting says the role defines strategy and algorithmic defenses against spam and adversarial threats, operationalizes mechanisms to proactively detect abuse, manages **incidents for deviations from expected system behavior**, coordinates with Engineering, Policy, Legal, Trust & Safety and Threat Intelligence, and is intended to help Search deliver **high-quality, authentic information**.²²

²¹Google Careers, “**Senior Engineering Analyst, AI Answers, Google Search,**” job 73312358587343558, current 21 September 2026. The posting describes Trust & Safety SAGE architecture for automated safety evaluation and enforcement, LLM-as-a-judge autoraters, continuous regression testing, actor/behavior-level policy and enforcement models, reputation models, authoritative-consensus guardrails, and real-time mitigations. U.S. pay: \159,000–\230,000 base + 15% target bonus + equity + benefits.

²²Google Careers, “**Senior Product Manager, AI Trust and Safety, Google Search, Anti-Abuse,**” job 89014046056948422, current 21 September 2026. The posting describes strategy and algorithmic defenses against spam/adversarial threats, mechanisms to detect abuse trends, incident management for deviations from expected system behavior, coordination with Engineering/Policy/Legal/Trust & Safety/Threat Intelligence, and delivery of high-quality authentic information. U.S. pay: \192,000–\278,000 base + 20% target bonus + equity + benefits.

The functional mirror is unusually direct.

The incident itself is a deviation from expected system behavior:

canonical entity

→

wrong shadow referent

while:

near-canonical entity

→

correct literary basin.

And the answer is not “authentic information” about the requested entity in the ordinary meaning of that phrase.

Thus:

posted function: detect deviations, preserve authenticity, combat abuse

versus:

observed output: the product itself generates the identity distortion and cross-surface deviation.

This becomes more serious if anti-abuse machinery is actually part of the cause.

Then the institution would face the policy-output mirror developed in §46:

machinery authorized to prevent identity-distorting or deceptive behavior

→

machinery participating in identity-distorting output.

Again, that causal premise is not established merely by the job posting.

It is exactly what an internal trace could confirm or falsify.

The current posting lists \192,000-\278,000 base pay plus a 20% target bonus, before equity and benefits.²³

That corresponds to:

\230{,}400-\333{,}600

in target cash for one role-year.

²³Google Careers, “**Senior Product Manager, AI Trust and Safety, Google Search, Anti-Abuse,**” job 89014046056948422, current 21 September 2026. The posting describes strategy and algorithmic defenses against spam/adversarial threats, mechanisms to detect abuse trends, incident management for deviations from expected system behavior, coordination with Engineering/Policy/Legal/Trust & Safety/Threat Intelligence, and delivery of high-quality authentic information. U.S. pay: \192,000-\278,000 base + 20% target bonus + equity + benefits.

Principal-level Search Platforms responsibility: consistency across Google surfaces

A current Principal Engineer posting for Content and Generative AI Exploration, Search Platforms is worth recording because its scope makes the corporate non-actor problem especially difficult to maintain.

Google says the role builds horizontal content understanding intended to ensure **a consistent experience across Google surfaces** and to transform Search's content platform into "the best knowledge resource."²⁴

The Crimson Hexagonal Archive case is a literal counterexample to surface consistency:

organic recognition
!=
canonical AI recognition
!=
near-canonical AI recognition.

The posting lists \307,000-\427,000 base pay with a 30% target bonus, before equity and benefits.²⁵

That is approximately:

\399{,}100-\555{,}100

in target cash for one role-year.

The significance is not personal.

It is institutional.

Google publicly prices **cross-surface content coherence** as Director+-level technical labor.

The observed interface simultaneously displays a cross-surface ontological contradiction.

34.2. Functional contradiction matrix

The resulting role-output matrix is:

²⁴Google Careers, "**Principal Engineer, Content and Generative AI Exploration, Search Platforms**," job 133507548232721094, current 21 September 2026. Google says the role builds horizontal content understanding to ensure a consistent experience across Google surfaces and to transform Search Content Platform into the best knowledge resource. U.S. pay: \307,000-\427,000 base + 30% target bonus + equity + benefits.

²⁵Google Careers, "**Principal Engineer, Content and Generative AI Exploration, Search Platforms**," job 133507548232721094, current 21 September 2026. Google says the role builds horizontal content understanding to ensure a consistent experience across Google surfaces and to transform Search Content Platform into the best knowledge resource. U.S. pay: \307,000-\427,000 base + 30% target bonus + equity + benefits.

Public Google function	Google's posted objective	Relevant observed condition	Functional relation
Search Content Understanding	Resolve entity references; accurate grounding; identify exact entities	canonical exact name resolves to wrong shadow referent	direct contradiction of stated output criterion if in path
Search Platforms / GenAI Content	holistic content modeling; knowledge-graph/topic-space work; high-fidelity consistent downstream experiences	organic, canonical-AI, and near-canonical-AI states disagree	direct contradiction of consistency criterion
AI Overviews / Mode Quality	model evals; live experiments; user-feedback analysis; identify win/loss patterns	two-character perturbation flips ontology regime	textbook quality/evaluation specimen
Trust & Safety SAGE / AI Answers	automated safety evaluation/enforcement; integrity; regression testing; actor/behavior models	candidate enforcement hypothesis would mis-handle declared art while neighboring query preserves it	conditional authorization/output inversion
Search Anti-Abuse	authentic information; detect abuse; manage incidents/deviations	product generates identity distortion and a clear deviation from expected resolution	output occupies the deviation class role is paid to govern
Principal Content/GenAI Search Platforms	consistent experience across Google surfaces; best knowledge resource	adjacent Search surfaces disagree about what entity exists	direct contradiction of cross-surface consistency criterion

The matrix should be read vertically.

It does not say:

six named employees caused this result.

It says:

Google publicly advertises six functional loci whose paid responsibilities cover the exact dimensions in which the result is defective.

That is enough to defeat the claim that the institution has no actor capable of owning the problem.

The corporate non-actor dissolves.

The accountable question becomes:

which of these functions touched this incident, what state did each receive, what state did each emit

34.3. The price of the contradiction

Four non-overlapping current U.S. role families in the matrix provide directly comparable published compensation:

- AI Overviews/Mode Quality;
- Search Platforms / GenAI Content;
- SAGE / AI Answers;
- Search Anti-Abuse.

For one hypothetical employee in each role:

\899{, }450-\1{, }279{, }650

in annual target cash compensation before equity and benefits.

Adding the current Principal Content/GenAI Search Platforms role as a fifth illustrative role-year gives:

\1{, }298{, }550-\1{, }834{, }750.

This is not team spend and not incident cost.

It is an institutional price signal.

The corporation publicly values labor devoted to:

- entity and content understanding;
- downstream consistency;
- quality evaluation;
- safety evaluation;
- anti-abuse;
- incident handling;
- and cross-surface knowledge integrity

at roughly **\1.30-\1.83 million in target cash for just five illustrative senior role-years**, before equity, benefits, infrastructure, managers, partner teams, legal, operations, and additional engineers.

The distributive contradiction can therefore be stated:

the institution spends heavily to produce, evaluate, police, and correct ontology internally while

And the accountability question is not:

Which employee should be blamed?

It is:

what does the corporation receive in return for these highly compensated governance functions when t

That is a political-economic question about institutional performance, not a personal accusation.

35. Distributed causation does not distribute responsibility away

A distributive ontological economy requires two levels of accounting.

Externally, the corporation remains the unit that controls the product, captures revenue, employs the relevant functions, possesses the internal evidence, and has the practical capacity to repair.

Therefore:

$$\begin{aligned} L_{\text{external}} \\ = \\ L[\text{corporate}]. \end{aligned}$$

The affected entity should not have to reconstruct the company's org chart in order to obtain repair.

Internally, the company can allocate the incident across the functions that actually participated in the causal chain.

Let:

$$\begin{aligned} w_j \\ = \\ f(\\ c_j, \\ e_j, \\ r_j, \\ p_j \\), \end{aligned}$$

where:

- c_j = control over the implicated mechanism;
- e_j = access to causal evidence;
- r_j = capacity to repair;
- p_j = trace proximity to the first wrong state.

Then:

$\sum_j w_j = 1$

and

$L_j = w_j L[\text{corporate}]$.

This is an internal cost-allocation rule, not a claim that individual employees owe personal damages.

The distinction is essential.

The corporate boundary should **centralize outward responsibility** while the trace **distributes inward accountability**.

Without the first rule, the claimant is forced to chase components.

Without the second, “the corporation” becomes an abstraction that never identifies which function must change.

The desired structure is therefore:

one accountable counterparty outward
+
many traceable accountable functions inward.

That is the inverse of the institutional non-actor effect.

36. Dollars: the wage structure of ontological governance

The strongest evidence that these are not metaphoric functions is that the corporation assigns high-priced labor to them.

As of 21 September 2026, currently accessible Google Careers postings give the following U.S. base-pay and target-bonus ranges for four of the mapped roles:

Role	Published U.S. base pay	Target bonus	Target-cash equivalent, excluding equity and benefits
Product Manager, AI Overviews/Mode Quality	138,000–197,000	15%	158,700–226,550
Senior Staff Software Engineer, Search Platforms, GenAI Content	262,000–364,000	25%	327,500–455,000

Role	Published U.S. base pay	Target bonus	Target-cash equivalent, excluding equity and benefits
Senior Engineering Analyst, AI Answers / SAGE	159,000–230,000	15%	182,850–264,500
Senior Product Manager, Search Anti-Abuse	192,000–278,000	20%	230,400–333,600

One hypothetical employee in each of these four roles therefore represents:

\\$899{,}450

to

\\$1{,}279{,}650

in annual target cash compensation before equity and benefits.

That number is **not team spend**.

It is not an estimate of the cost of Google Search.

It is a price signal: the corporation itself prices labor attached to quality, graph/content architecture, evaluation/enforcement, and anti-abuse governance at hundreds of thousands of dollars per role-year.

The public representation cannot therefore be economically modeled as if it were produced by an actorless algorithm at zero institutional labor cost.

The current SCU posting retrieved for this review was Brazil-based and did not provide a comparable U.S. salary band, so it is excluded from the aggregate above. The Knowledge Graph correction function is documented as a function rather than a single job posting and is likewise excluded.

Public sources used for this compensation snapshot:

- Google Careers, *Product Manager, AI Overviews/Mode Quality, Google Search*, job 118899599954846406.
- Google Careers, *Senior Staff Software Engineer, Search Platforms, GenAI Content*, job 92046058892206790.
- Google Careers, *Senior Engineering Analyst, AI Answers, Google Search*, job 73312358587343558.
- Google Careers, *Senior Product Manager, AI Trust and Safety, Google Search, Anti-Abuse*, job 89014046056948422.
- Google Careers, *Staff Software Engineer, Full Stack, Search Content Understanding*, job 74665035988640454, for the SCU function description.

The relevant economic contrast is now visible:

internal ontological labor = paid
while, absent restitution,
external corrective ontological labor = \\$0
paid by the platform.
That asymmetry is itself part of the ontological economy.

37. The mirror wage: pricing externalized corrective labor

When an external author, archive, business, institution, or researcher is forced to perform the functional equivalent of internal diagnosis, disambiguation, regression testing, provenance repair, or incident documentation, the platform has externalized work that its own organization treats as skilled labor.

A simple replacement-cost instrument is therefore possible.

Define the **mirror wage** w_m as the published compensation-equivalent hourly value of the nearest internal function whose work the affected party is being forced to reproduce.

For target cash only:

$$w_m = \frac{\text{base salary} + \text{target bonus}}{2080}.$$

Using the four public U.S. bands above yields approximate target-cash equivalents of:

Function	Approximate target-cash hourly range
AI Overviews / Mode Quality	76-109/hour
Search Platforms / GenAI Content	157-219/hour
AI Answers / SAGE	88-127/hour
Search Anti-Abuse	111-160/hour

Again, these exclude equity, benefits, overhead, and employer-side costs.

For a multi-function external investigation, the simple mean of those four role ranges is approximately:

\\$108
to
\\$154
per hour.

This creates a transparent replacement-cost benchmark:

$$C[X] = h[X] w_m$$

+
 $E[X]$,
 where:

- $h[X]$ = documented external corrective hours;
- w_m = chosen mirror wage;
- $E[X]$ = direct corrective expenses.

At the four-role mean benchmark:

- 50 hours of corrective labor corresponds to roughly **5,405-7,690**;
- 100 hours corresponds to roughly **10,811-15,380**;
- 250 hours corresponds to roughly **27,027-38,451**;
- 500 hours corresponds to roughly **54,053-76,902**.

These are not adjudicated damages.

They are not claims about the market rate of any particular external author.

They are a **replacement-cost thought instrument** grounded in the platform's own public valuation of adjacent internal labor.

Its purpose is to expose the accounting asymmetry:

the same diagnostic activity has a positive wage inside the corporation and a zero wage when pushed out.

If a provider-created defect forces the represented entity to perform that activity, the zero is not an absence of cost.

It is an externalization.

38. Revenue, rent, and the accountability reserve

Compensation prices the labor side of the ontological economy.

Revenue gives scale to the infrastructure in which that labor operates.

Alphabet reported **224.532 billion** in 2025 "Google Search other" revenue. For the first six months of 2026, it reported **123.670 billion** in the same category.

These figures do **not** measure ontological rent.

They include advertising and other monetization across Search and other Google properties, and no public financial statement isolates the revenue caused by entity resolution, knowledge graphs, AI Overviews, or any one representational function.

They are nevertheless the correct order-of-magnitude denominator for a political-economic question:

the infrastructure exercising public representational power is embedded inside a revenue system mea

That scale permits an accountability-reserve model.

Let:

$Y[S] = \text{Search} \setminus \text{other revenue}$

and

$\rho = \text{ontological repair reserve rate}.$

Then:

$R[0] = \rho Y[S].$

Using 2025 Search & other revenue only as a sensitivity denominator:

Illustrative reserve rate	Annual reserve implied by \$224.532B
0.1 basis point (0.001%)	\$2.245 million
1 basis point (0.01%)	\$22.453 million
5 basis points (0.05%)	\$112.266 million
10 basis points (0.10%)	\$224.532 million

No particular reserve rate is proposed here.

The table establishes scale.

Even a tiny fraction of revenue associated with the mediating infrastructure would produce a nontrivial pool for:

- external corrective labor;
- independent entity-resolution review;
- propagation repair;
- auditable incident handling;
- comparative correctability testing;
- external appeals;
- restitution for documented correction costs.

The distributive question is therefore no longer abstract.

It is:

what fraction of the value captured by mediated encounter is returned to maintaining the integrity of

39. The distributive balance sheet

The ontological economy can now be written as a balance sheet.

Corporate inflows

$$\begin{aligned}
 &V[C] \\
 &= \\
 &R[S] \\
 &+ \\
 &K[O] \\
 &+ \\
 &D[U] \\
 &+ \\
 &T[M],
 \end{aligned}$$

where:

- $R[S]$ = revenue generated through the mediated search/product environment;
- $K[O]$ = accumulated ontological capital made usable by the infrastructure;
- $D[U]$ = user interaction/data value;
- $T[M]$ = mediator trust and dependence.

Corporate paid costs

$$\begin{aligned}
 &C[C] \\
 &= \\
 &W[I] \\
 &+ \\
 &C[\text{infra}] \\
 &+ \\
 &C[\text{compute}] \\
 &+ \\
 &C[\text{internal repair}],
 \end{aligned}$$

where $W[I]$ includes paid internal ontological labor.

Externalized costs

$$\begin{aligned}
 &X[O] \\
 &= \\
 &C[X] \\
 &+ \\
 &C[\text{decision}] \\
 &+ \\
 &C[\text{propagation}] \\
 &+ \\
 &C[\text{standing}] \\
 &+ \\
 &C[\text{commons}].
 \end{aligned}$$

The central distributive problem is:

$V[C]$ is centrally appropriated while $X[O]$ is diffusely borne.

That is the economic architecture of the institutional non-actor effect.

The corporation centralizes the upside.

The causal chain distributes the work.

The interface obscures the action.

The complaint system asks the injured party to reconstruct the chain.

And the unpaid correction may then improve the product.

Where a submitted correction is incorporated into the provider's graph, evaluator, retrieval process, or algorithmic improvement, the affected party's labor can become productive input:

L[external correction]

→

Delta Q[platform]

→

Delta K[0][corporate].

This is not automatically exploitation; the provider may offer valuable correction infrastructure and both sides may benefit.

But where the external labor was necessitated by the provider's own defect and remains uncompensated, the political-economic form is clear:

the injured party repairs the asset from which the mediator continues to derive value.

That is an ontological surplus problem.

40. The liability rule for the corporate non-actor

The corporate form should not permit a contradiction in which:

the corporation is unified enough to own the product and revenue

but

too distributed to own the representational consequence.

Therefore the basic liability rule of distributive ontological economy is:

distributed causation may distribute internal accountability, but it may not distribute external re

A provider may legitimately say:

Several components contributed and we have not yet identified the first cause.

It may not convert that statement into:

Therefore there is no accountable actor.

The first is a causal description.

The second is agency laundering.

The proper sequence is:

corporate responsibility

→

internal trace

→

functional allocation

→

repair

→

restitution where evidenced.

This gives institutional critique an address.

Not a scapegoat.

Not an employee selected because a job title sounds relevant.

An accountable corporate counterparty, with named internal functions that cannot disappear behind the phrase “the system.”

41. Moral visibility is also distributed

The ontological economy distributes more than money, labor, evidence, and formal responsibility.

It distributes **moral visibility**: who is made to see what the system has done.

Let:

M_i

=

the share of a representational consequence made legible to institutional actor i ,

P_i

=

actor i 's practical power over the mechanism,

and

C_i

=

the consequence actually borne by actor i .

A pathological arrangement has the structure:

$C[\text{represented entity}]$

>>

M[engineering role]

while:

P[engineering role]

>>

P[represented entity].

The party with the least control can therefore receive the richest view of the consequence.

The party with greater control can receive a thin technical abstraction of it.

The represented entity experiences:

My name no longer denotes my work.

The engineering system can register:

entity resolution quality regression.

The first sentence contains the social position.

The second contains the mechanism.

Both may be true.

Only one makes the consequence difficult to look away from.

This is a distributive fact.

A political economy of ontology must therefore ask not only:

Who has power?

and:

Who pays?

but also:

who is institutionally required to see the position produced for somebody else?

The engineering-ethics literature already contains neighboring concepts. The **problem of many hands** names responsibility gaps produced by collective technical action, especially where outsiders cannot identify which participant did what. Work on **moral distance** in AI examines how mediation and opacity can separate decision-makers from those affected by decisions. These traditions describe important parts of the structure developed here.²⁶²⁷

Ontological economy adds a specific distributional claim:

²⁶Ibo van de Poel, Jessica Nihlén Fahlquist, Neelke Doorn, Sjoerd Zwart, and Lambèr Royakkers, “**The Problem of Many Hands: Climate Change as an Example,**” *Science and Engineering Ethics* 18 (2012): 49–67, DOI 10.1007/s11948-011-9276-0. The paper defines the problem of many hands as a morally problematic gap in responsibility distribution in a collective setting.

²⁷Carolina Villegas-Galaviz and Kirsten Martin, “**Moral distance, AI, and the ethics of care,**” *AI & Society* 39 (2024): 1695–1706, DOI 10.1007/s00146-023-01642-z.

moral distance can itself be an organizationally allocated resource.

Some roles are protected from consequence by abstraction.

Others are forced to inhabit the consequence directly.

42. Shame insulation and ontological alienation

Engineers are not assumed to be shameless.

The relevant institutional question is which forms of shame their work environment makes available.

A technically sophisticated organization can produce intense **craft shame**:

- shipping a regression;
- breaking an invariant;
- misunderstanding a system;
- causing an outage;
- failing an evaluation;
- writing poor code;
- being wrong before one's peers.

These forms of shame attach to craft competence and professional standing.

They are not trivial.

But they need not produce **reflected-position shame**:

I helped place another entity in a public position I would find intolerable if assigned to me.

The insulation occurs because the labor process transforms the consequence before it reaches the worker:

```

person/project
→
entity ID
→
edge or candidate
→
metric
→
ticket
→
aggregate quality.
```

The social relation is progressively converted into an engineering object.

Call this **shame insulation**:

shame insulation is the organizational reduction of a socially consequential act to forms of technique

A related operation is **shame laundering**:

moral consequence

→

technical embarrassment.

Thus:

We made the wrong entity publicly stand in for this person's work.

can become:

We have an entity-quality issue.

The latter may be operationally useful.

It is morally incomplete.

At the political-economic level, this resembles alienation.

The ontology engineer produces representational relations whose lived social consequences are separated from the engineer's experience of the labor.

The product of labor confronts the affected person as an apparently objective fact of the world.

The laborer encounters the same product as a system state.

This permits a further concept: **ontological fetishism**.

ontological fetishism occurs when an institutionally produced classification appears at the interface.

Ontology laundering concerns the disappearance of governance into factual output.

Agency laundering concerns the disappearance of coordinated actors into "the system."

Ontological fetishism concerns the resulting appearance that the representation was never produced at all.

The three operations form a sequence:

human/institutional judgment

→

technical state

→

naturalized world.

No theory of individual bad character is required.

The structure works perfectly well with conscientious engineers.

Indeed, conscientious engineers may experience substantial craft shame while remaining institutionally protected from consequence shame.

That is why an accountability system cannot rely on spontaneous moral feeling.

It has to alter what the role is required to see.

43. The reflected-position specimen: a shadow entity with harsher provenance

The Crimson Hexagonal Archive incident makes the moral-distribution problem more concrete than a simple wrong-entity substitution.

The paired captures show three answer-level objects:

E[T]

=

Crimson Hexagonal Archive,

E[C]

=

Crimson Hexagon,

E[S]

=

“Crimson Hexagon archive,” the historical data-repository object produced under the target query.

The important reflected position is therefore not merely:

Our system confused your project with another company.

It is:

When your literary project—attested in print since 2014 and active in its current archive form—is requested by its exact name, our system constructs a distinct historical-repository object from another company’s data archive, answers under that object, and foregrounds that company’s regulatory scrutiny more heavily than it does when users ask for the company itself.

That is the position the institution must be made to see.

The result is especially useful because it separates three questions that ordinary quality language collapses:

Who are you?

The requested project is absent as referent.

What did we put in your place?

Not merely the neighboring corporation, but a reified facet of it.

Which history did we select for that substitute?

A composition in which scrutiny-related material receives markedly greater prominence than in the neighboring corporation’s baseline answer.

The externally visible asymmetry in the supplied captures is:

RSP:

0.40

vs.

0

for primary answer bullets, and:

RSC:

0.75

vs.

0

for visible scrutiny-oriented source cards.

These numbers do not measure motive, intent, or internal policy state.

They measure **what the two public surfaces chose to foreground**.

That matters morally because the affected entity does not merely receive another entity's identity.

It receives a **selected version of another entity's history**.

The reflected-position test should therefore be rewritten:

A literary project attested in print since 2014, now maintained through a canonical site, archive, and machine-readable identity surface, is requested by its exact current name. Our product does not return the project. It constructs an answer-level historical repository out of a different company's data archive. Under the outside project's query, our answer devotes 40% of its primary bullets to a regulatory-scrutiny section and 75% of its visible source cards to suspension/investigation-related material; under the company's own query, neither structure appears. Would we consider that an acceptable identity and provenance treatment if the requested object were one of our own named products, teams, repositories, or executives?

This is a symmetry test, not a demand for emotional self-abasement.

Its function is to defeat moral compression.

From the engineering side, the event may still be represented as:

candidate collision / facet reification / source-selection asymmetry / answer-composition regression.

That vocabulary is useful.

But it must not replace the position produced for the subject.

The plain-language incident description should survive alongside the mechanism description.

The reputational history of Crimson Hexagon intensifies the case but is not logically necessary to it. Facebook suspended the company in 2018 during investigation of data-use concerns; contemporary reporting also recorded Facebook's statement that it had not then found wrongdoing in the acquisition of Facebook or Instagram data.²⁸

²⁸Elizabeth Dwoskin and Craig Timberg, "**Why Facebook just suspended another data analytics firm**", *The Washington Post* (20 July 2018). Contemporary reporting records Facebook's temporary suspension of Crimson Hexagon during investigation and Facebook's statement that it had not, at that

The relevant rule is therefore broader than negative reputation:

a platform may not treat lexical collision as permission to transfer another entity's selected prove

The problem is not merely false accusation.

It is false inheritance.

And in the supplied captures, that inheritance is asymmetrical.

44. Reflected-position review as an engineering control

Shame should not be an organizational punishment mechanism.

Public humiliation of individual engineers would reproduce the same attribution error this paper rejects: selecting a visible person to carry a distributed institutional failure.

The useful object is therefore not **shaming**.

It is **reflection**.

A reflected-position review is an engineering and governance control that reconnects a technical incident to the position it produced.

For any replicated identity substitution, the incident record should contain:

Requested entity.

Canonical name, type, provenance, current state, and authoritative surface.

Returned entity.

Name, type, provenance, current state, and authoritative surface.

Divergence ledger.

Which identity dimensions conflict?

Public consequence.

What false relation, history, authorship, function, or reputation is transferred?

Control owner.

Which role has the power to inspect the relevant candidate, graph, classifier, evaluator, source-admission, or policy trace?

Correction owner.

Which role can make the representation change?

Reflected-position sentence.

A plain-language statement of what the system is doing to the represented entity.

Symmetry question.

Would the same mapping be accepted for an internal Google product, project, executive, repository, or named technical object under equivalent evidence?

stage, found wrongdoing in Crimson Hexagon's obtaining of Facebook or Instagram information. See also Olivia Solon and Julia Carrie Wong, *The Guardian* (20 July 2018).

Post-notice disposition.

Corrected, unresolved, retained with reason, or recurrent after notice.

The reflected-position sentence is essential because institutional language otherwise performs moral compression.

For the present specimen, it should not be:

Potential entity-resolution quality issue involving neighboring lexical forms.

It should be:

When a user asks for the active Crimson Hexagonal Archive, the product returns the different legacy company Crimson Hexagon.

Only after that sentence is preserved should the organization translate the incident into internal technical vocabulary.

This creates a rule:

technical abstraction may follow consequence description; it may not replace it.

The rule creates no presumption of individual malice.

It creates an obligation of institutional sight.

The engineering literature on the **problem of many hands** is useful here because it distinguishes distributed causation from a morally problematic gap in responsibility.²⁹ The reflected-position review is one mechanism for preventing that gap from becoming an epistemic convenience.

It also differs from Madeleine Elish's **moral crumple zone**, where a relatively low-control human may absorb blame for an automated system.³⁰ In the present arrangement, the represented entity can become something like an **ontological crumple zone**: it absorbs the representational impact and often the corrective labor despite having little control over the machinery that produced either.

The accountability design therefore has to prevent both errors:

do not scapegoat the low-control employee

and:

do not make the low-control represented entity absorb the whole consequence.

The corporate counterparty remains responsible outward.

Internally, the trace identifies the functions that must see, explain, and repair the event.

²⁹Ibo van de Poel, Jessica Nihlén Fahlquist, Neelke Doorn, Sjoerd Zwart, and Lambèr Royakkers, "**The Problem of Many Hands: Climate Change as an Example**," *Science and Engineering Ethics* 18 (2012): 49–67, DOI 10.1007/s11948-011-9276-0. The paper defines the problem of many hands as a morally problematic gap in responsibility distribution in a collective setting.

³⁰Madeleine Clare Elish, "**Moral Crumple Zones: Cautionary Tales in Human-Robot Interaction**," *Engaging Science, Technology, and Society* 5 (2019), DOI 10.17351/ESTS2019.260.

That is what an institution looks like when it is not permitted to become morally invisible to itself.

45. The institution-level demands

A minimally accountable ontological economy requires more than a correction button.

It requires:

1. Referent integrity.

Exact entity queries should preserve the requested referent unless the system explicitly communicates ambiguity.

2. Provenance-preserving evaluation.

Weak evidence may be criticized, but its actual provenance must remain attached to the criticism.

3. Mechanism-preserving incident records.

Candidate causes should remain visible until evidence weakens or eliminates them.

4. Burden shifting after replication.

Once a persistent substitution is shown, internal causal diagnosis belongs to the provider.

5. Notice-sensitive accountability.

Recurrence after notice should be measured separately from initial error.

6. Repair propagation.

Correction must reach the representations and derivatives controlled by the provider, not merely the visible surface on which the complaint was filed.

7. Correction non-retaliation.

Structured attempts to restore accurate identity should not be downgraded merely because they originate with the affected entity.

8. Comparative correctability audits.

Providers should test whether equivalent evidence from differently situated entities receives materially different correction outcomes.

9. Trace retention.

Systems exercising large-scale entity mediation should retain enough change history to reconstruct material representational interventions.

10. Cost internalization.

The party controlling the causal infrastructure should bear the ordinary cost of diagnosing and repairing defects created within it.

These are the beginnings of a constitutional order for machine-mediated ontology.

46. Authorization-output inversion: the policy machinery and the conduct it is built to police

The previous sections identify a political-economic asymmetry.

Google employs expensive institutional functions to detect, classify, restrict, demote, remove, correct, and otherwise govern content and entities in Search.

The next question is narrower:

What do Google's stated public authorizations actually permit, and how does the observed Crimson Hexagonal Archive output compare to the conduct categories those authorizations are designed to control?

This section does not infer that a specific policy caused the incident.

It performs an **authorization audit**.

The distinction is:

policy causation

!=

policy-output consistency.

One can ask whether an output coheres with the institution's stated governance norms without claiming that those norms produced the output.

46.1. The authorization inventory

As of 21 September 2026, two public Google policy surfaces supply a useful heading-level inventory.

Google's current **Spam Policies for Google Web Search** contain sixteen named spam-practice headings:

1. Cloaking;
2. Doorway abuse;
3. Expired domain abuse;
4. Hacked content;
5. Hidden text and link abuse;
6. Keyword stuffing;
7. Link spam;
8. Machine-generated traffic;
9. Malicious practices;
10. Misleading functionality;
11. Scaled content abuse;
12. Scraping;
13. Site reputation policy;
14. Sneaky redirects;

15. Thin affiliation;
16. User-generated spam.

The same page adds four other categories that can lead to demotion or removal:

17. Legal removals;
18. Personal information removals;
19. Policy circumvention;
20. Scam and fraud.³¹

Google's **Knowledge Graph policies** incorporate twelve Search-feature policy headings:

1. Advertisements;
2. Dangerous content;
3. Deceptive practices;
4. Harassing content;
5. Hateful content;
6. Manipulated media;
7. Medical topics;
8. Regulated goods;
9. Sexually explicit content;
10. Terrorist content;
11. Violence & gore;
12. Vulgar language & profanity;

and add two Knowledge-Graph-specific grounds:

13. Incorrect information;
14. Non-representative information.³²

This produces an inventory of:

20+14=34

heading-level governance categories across the two surfaces.

These thirty-four headings are not statistically independent rules.

Some overlap.

Some concern content classes irrelevant to the present specimen.

³¹Google Search Central, "**Spam policies for Google web search**," current page last updated 28 August 2026, <https://developers.google.com/search/docs/essentials/spam-policies>. The page identifies sixteen named spam-practice headings and four additional practices that can lead to demotion or removal; it states that violations can result in lower ranking, nonappearance, manual action, restriction, removal, or separation depending on the policy.

³²Google Knowledge Panel Help, "**How Google's Knowledge Graph works**," <https://support.google.com/knowledgepanel/answer/9787176>, accessed 21 September 2026. The page lists twelve incorporated Search-feature policies and two Knowledge-Graph-specific policies: Incorrect information and Non-representative information. It states that Google may remove demonstrably false/outdated information and addresses cases where automated systems have not made the most representative selection of names, titles, descriptions, or images.

The count is therefore an audit inventory, not a probabilistic denominator.

Within this inventory, however, the following result is straightforward:

$A[S]=0/34$

where $A[S]$ is the number of inspected headings that expressly authorize the remedy:

requested entity E

→

unrelated entity E' .

No inspected heading expressly authorizes:

- replacing one entity with another;
- promoting a facet of another entity into the requested referential slot;
- transferring another entity's provenance into the requested entity;
- or answering a canonical entity query under a knowingly different entity as a remedial measure.

The publicly described remedy families are instead variations of:

$R=$

```
{
remove,
demote,
restrict,
separate,
correct
}.
```

Google states that spam violations may rank lower or not appear; policy circumvention may result in restricted or removed eligibility; site-reputation treatment can separate portions of a site; and Knowledge Graph policy provides for removal or correction of incorrect and non-representative information.³³³⁴

Thus:

substitute unrelated referent

$\notin R$.

This is the **remedy-congruence problem**.

³³Google Search Central, “**Spam policies for Google web search**,” current page last updated 28 August 2026, <https://developers.google.com/search/docs/essentials/spam-policies>. The page identifies sixteen named spam-practice headings and four additional practices that can lead to demotion or removal; it states that violations can result in lower ranking, nonappearance, manual action, restriction, removal, or separation depending on the policy.

³⁴Google Knowledge Panel Help, “**How Google’s Knowledge Graph works**,” <https://support.google.com/knowledgepanel/answer/9787176>, accessed 21 September 2026. The page lists twelve incorporated Search-feature policies and two Knowledge-Graph-specific policies: Incorrect information and Non-representative information. It states that Google may remove demonstrably false/outdated information and addresses cases where automated systems have not made the most representative selection of names, titles, descriptions, or images.

Even if some underlying restriction on E[T] were fully justified, the public authorization would still require a second normative bridge before:

E[T]

→

E[S]

could be treated as an authorized remedy.

No such bridge was located in the inspected public policies.

46.2. Seven direct counter-norms

The audit also identifies at least seven policy categories whose stated concern is structurally opposite to important features of the observed output.

This does **not** mean that Google has legally or contractually violated seven of its own policies.

Most of these rules are written as governance standards for content, sites, and Search features rather than as private causes of action against Google.

The point is **normative and structural**.

Google-stated norm	Stated concern	Observed or hypothesized analogue in the specimen
Deceptive practices	impersonation; misrepresentation or concealment of ownership, primary purpose, relationships, or editorial independence	wrong-entity assignment; collapse of declared literary/corporate distinction
Knowledge Graph — incorrect information	demonstrably false or outdated factual information	canonical query receives factual claims belonging to a different entity
Knowledge Graph — non-representative information	automated selection of non-representative names, titles, descriptions, or images	canonical entity name resolves to a company-derived shadow referent
Malicious practices	mismatch between user expectation and actual outcome	exact project query returns a materially different entity/history
Misleading functionality	promising access to one content/function while delivering something else	answer surface purports to answer the entity query while substituting another referential object

Google-stated norm	Stated concern	Observed or hypothesized analogue in the specimen
Sneaky redirects	unexpected destination or content that does not fulfill the user's original need	structural analogue: semantic routing from requested entity to materially different object
Scam and fraud	impersonation and intentionally displaying false information about a business or service	if intent were established, deliberate false entity attribution would occupy this same prohibited position

The evidentiary qualifications differ across rows.

For example, Google's scam-and-fraud rule expressly includes intentionality.

The present evidence does not establish that mental state.

Therefore the relevant proposition is not:

Google committed scam/fraud.

It is:

a deliberately maintained false entity substitution would instantiate a conduct-form Google's own policy classifies as objectionable when external actors perform it.

That is a **policy-role inversion**.

46.3. The artistic exception is especially important here

Google's Search-feature policy on **Deceptive practices** contains an explicit exception.

Google states that the policy does not cover content with certain:

- artistic;
- educational;
- historical;
- documentary;
- scientific;

considerations, or other substantial public benefits.³⁵

That clause is unusually relevant to the Afterlife Archive.

The work does not merely possess artistic context inferred after the fact.

³⁵Google Search Help, "**Content policies for Google Search**," <https://support.google.com/websearch/answer/1062>, accessed 21 September 2026. The Deceptive practices policy bars impersonation and misrepresentation but expressly excludes certain artistic, educational, historical, documentary, scientific, or other substantial-public-benefit contexts.

It repeatedly declares its status as fiction and art.

Its corporate-document form is part of the artistic operation.

Therefore, if an anti-abuse or deception classifier were to treat the work's corporate-forensic surface as sufficient evidence of deceptive conduct while ignoring the explicit fiction declarations, the resulting classification would invert the distinction Google's own policy text requires.

The structure would be:

surface resemblance to deceptive evidence

→

abuse classification

despite:

explicit artistic context

+

explicit fiction declaration.

That is not yet evidence that such a classifier caused the Crimson Hexagonal Archive incident.

It is a testable **policy-mechanism hypothesis**.

If a provider trace later showed that the entity had been restricted because the Afterlife Archive resembled leaked corporate material, then the authorization question would become exceptionally sharp:

why was the resemblance recognized while the policy's own artistic-context distinction was not?

The near-canonical AI Mode answer matters here because it demonstrates that the system is capable of reading the artistic and fictional context correctly.

Thus:

artistic context is available

and:

artistic context is machine-recognizable.

The canonical failure cannot therefore be explained merely by claiming that the work provides no contextual signal.

46.4. Authorship and provenance: governance values Google itself uses

The current site-reputation policy gives another useful comparison.

When Google describes human review of third-party content, it expressly asks about:

- stated or implied authorship;
- explicit acknowledgement of ownership or responsibility;

- evidence contesting stated authorship;
- editorial integration;
- and the clarity of responsibility for content.³⁶

It also identifies **columns, opinion pieces, articles, and other editorial work** among examples that are not inherently inconsistent with the policy.³⁷

Thus authorship and responsibility are not peripheral values in Google’s own governance framework.

They are factors Google says its reviewers use to decide whether content belongs where it appears to belong.

That produces another inversion.

The Crimson Hexagonal Archive supplies:

- explicit authorship;
- canonical naming;
- declared fictionality;
- public provenance;
- editorial context;
- and repeated disambiguation.

Yet the canonical AI output strips or relocates those relations.

The system therefore risks doing at the composition layer what the governance layer says it examines external publishers to prevent:

loss or distortion of authorship, ownership, and contextual responsibility.

Again, this is not a claim that the site-reputation policy directly governs entity resolution.

It is evidence of an institutional norm that becomes difficult to reconcile with the observed output.

46.5. Generative AI is not outside the policy perimeter

A possible institutional defense would be that the spam-policy framework governs ordinary Search but not generative answers.

Google’s own 2026 documentation cuts against that categorical separation.

³⁶Google Search Central, “**Spam policies for Google web search — Site reputation policy**,” <https://developers.google.com/search/docs/essentials/spam-policies>, accessed 21 September 2026. Current human-review guidance identifies stated or implied authorship, ownership/responsibility, editorial integration, and content quality as relevant factors; examples not inherently inconsistent with the policy include columns, opinion pieces, articles, and other editorial work.

³⁷Google Search Central, “**Spam policies for Google web search — Site reputation policy**,” <https://developers.google.com/search/docs/essentials/spam-policies>, accessed 21 September 2026. Current human-review guidance identifies stated or implied authorship, ownership/responsibility, editorial integration, and content quality as relevant factors; examples not inherently inconsistent with the policy include columns, opinion pieces, articles, and other editorial work.

On 15 May 2026, Google Search Central recorded a documentation change titled:

“Clarifying that spam policies apply to generative AI responses in Google Search.”

Google’s stated reason was:

“To make it clear that the spam policies apply to all of Google Search, including generative AI responses.”³⁸

This statement does not mean that every site-directed spam rule maps literally onto every sentence generated by AI Mode.

But it defeats the broad proposition:

generative answer

⇒

outside spam-policy governance.

The policy perimeter explicitly reaches generative AI responses.

That makes policy-output consistency a proper object of inquiry.

46.6. The policy-output mirror

The strongest result of the audit is not the count alone.

It is that several apparent or candidate mechanisms occupy the **same structural positions** against which the governance apparatus claims authority.

Let:

X

=

a conduct form Google identifies as deceptive, misleading, false, non-representative, or identity-distorting.

Let:

G[X]

=

Google's institutional machinery authorized to detect or govern X.

The inversion occurs where:

$O(G[X]) \approx X,$

³⁸Google Search Central, “**Latest documentation updates,**” entry dated 15 May 2026, <https://developers.google.com/search/updates>. Google states that it clarified its spam policies “also apply to generative AI responses in Google Search” and explains that the policies apply to “all of Google Search, including generative AI responses.”

meaning the output of the governance system structurally resembles the conduct-form it is built to police.

For the present specimen:

Apparent / candidate operation	Policy-side prohibited or corrective position
canonical entity replaced by another entity	non-representative / incorrect information
shadow referent constructed from another entity	impersonation / misrepresentation-like identity behavior
another entity's history attached to target	false information / provenance distortion
target's explicit disambiguation inverted	mismatch between expected and delivered object
declared fiction collapsed into corporate fact	deception classification without preserving explicit artistic context
authorship and Borges provenance erased	failure of the authorship/responsibility distinctions Google itself says matter
canonical key fails while near-canonical key succeeds	selective semantic routing requiring explanation rather than global ignorance
organic surface finds target while answer layer substitutes another object	adjacent surfaces expose the misleading relation

This is the **policy-output mirror**.

The strongest formulation is conditional:

if deliberate governance intervention is eventually established, the governance mechanism may itself

That would be more than ordinary hypocrisy in the colloquial sense.

It would be **authorization inversion**:

authority justified by preventing X

→

exercise of authority producing X.

46.7. The numbers

For the current public-policy audit:

N[headings]=34

N[substitution authorization]=0

N[direct structural counter-norms]>= 7

N[explicit artistic-context exceptions relevant to the specimen]>= 1

$N[\text{Google documentation statements expressly placing generative AI responses inside the spam-policy perimeter}] \geq 1$.

These are **document counts**, not moral scores.

A useful compact representation is:

A=
(34, \ 0, \ ≥ 7 , \ ≥ 1 , \ ≥ 1)

where the coordinates represent:

1. policy/remedy headings inspected;
2. express authorizations for unrelated entity substitution;
3. direct counter-norms structurally implicated;
4. directly relevant artistic-context exceptions;
5. explicit statements placing generative AI responses inside the policy perimeter.

If one wants a colloquial “hypocrisy number,” the most defensible number is not a percentage.

It is the asymmetry:

0 authorizations
:
 ≥ 7 counter-norms.

The reason not to turn that into a percentage is methodological.

The thirty-four policies are heterogeneous and non-independent.

A 0/34 authorization count is meaningful because substitution either appears as an authorized remedy or it does not.

A 7/34 “hypocrisy rate” would falsely imply that sexual-content and dangerous-goods policies belong in the same denominator as entity-integrity rules.

The paper therefore retains the raw asymmetry.

46.8. What would falsify the inversion claim?

The authorization-output argument would weaken materially if Google produced a public or incident-specific rule establishing that:

1. the relevant entity fell within a defined policy class;
2. the rule authorizes the observed entity transformation rather than removal, demotion, restriction, separation, or correction;
3. the rule explains why a neighboring noncanonical query receives the correctly distinguished literary entity;
4. the rule explains why the organic layer continues to retrieve the target;
5. the rule accounts for the artistic-context exception where relevant;

6. and the rule preserves rather than contradicts Google's own incorrect/non-representative information standards.

Absent such a rule, the present public record supports:

restriction authority may exist
not ⇒
substitution authority exists.

That is the policy-side version of mechanism non-identifiability.

The fact that the hidden mechanism is unknown does not manufacture a public authorization for whatever transformation the mechanism happens to produce.

47. The primary recourse is graph-native: until the graph holds up a mirror

The legal frame is analytically useful because it clarifies duty, notice, standing, evidence, and cost.

It is not necessarily the primary practical path.

For an ontological injury, the most native form of recourse is **ontological**.

The object is not first to compel a platform from outside.

It is to alter the public evidentiary environment until the entity distinction, its provenance, the misrepresentation, and the contradiction among surfaces become increasingly difficult for machine-mediated knowledge systems to represent incoherently.

This paper calls that strategy **graph-native recourse**.

graph-native recourse is the construction of durable, provenance-rich, machine-resolvable public relations such that the knowledge environment increasingly contains the evidence

The method is not spam.

It is not covert poisoning.

It is not the manufacture of artificial consensus.

Its governing constraint is:

every added edge must be independently supportable.

The intervention is therefore epistemic rather than coercive.

One does not demand that the graph believe something unsupported.

One supplies the graph with the distinctions it should already have been capable of preserving.

47.1. The graph object

Let the public evidentiary graph surrounding the literary entity at time t be:

$$G_t = (V_t, E_t),$$

where V_t contains addressable objects such as:

- the literary entity;
- *Pearl and Other Poems*;
- the 2014 ISBN record;
- Borges's *Library of Babel*;
- the Crimson Hexagon company;
- the Crimson Hexagonal Archive canonical surface;
- the Afterlife Archive;
- fiction declarations;
- author records;
- DOI deposits;
- archived interface captures;
- policy documents;
- job descriptions;
- documented query variants;
- and independent bibliographic or institutional records.

The edges E_t include relations such as:

authored-by,
 part-of,
 published-as,
 derived-name-from,
 distinct-from,
 continued-as,
 declared-fiction,
 misidentified-as,
 observed-at,
 contradicted-by.

The target is not maximum edge count.

It is **high-value relational closure**.

For the present specimen, the critical subgraph is approximately:

The Library of Babel
 →
 The Crimson Hexagon[literary]
 →
 Pearl and Other Poems₂₀₁₄
 →
 Crimson Hexagonal Archive₂₀₂₆

while separately:

The Library of Babel

→

Crimson Hexagon[company]

→

Brandwatch.

The distinction is then explicit:

$E[\text{literary}] \neq E[\text{company}]$.

And the incident relation is explicit:

Google AI Mode canonical query

→

$E[S]$

$\neq$

$E[\text{literary}]$.

The graph can therefore contain both:

1. the correct ontology;
2. the record of the system's failure to preserve it.

That second relation is what creates the mirror.

47.2. The mirror condition

A **graph mirror** appears when the provider's own retrieval and composition systems can retrieve enough public evidence about their representational behavior that the system's output becomes capable of exposing the contradiction in its own ontology.

Let:

$K[T]$

=

publicly retrievable evidence establishing the target entity,

$K[D]$

=

publicly retrievable evidence establishing the target/substitute distinction,

$K[I]$

=

publicly retrievable evidence documenting the incident,

and:

$K[P]$

=

publicly retrievable evidence of the provider's stated policy and functional commitments.

The mirror condition approaches when:

$K[T] + K[D] + K[I] + K[P]$

are all simultaneously available to the same retrieval environment.

Then a system asked:

What is the Crimson Hexagonal Archive?

can retrieve the entity.

A system asked:

Is it the former analytics company?

can retrieve the distinction.

A system asked:

Has Google AI Mode represented it as that company or its historical archive?

can retrieve the documented incident.

A system asked:

What does Google say its entity-grounding, quality, anti-abuse, and Knowledge Graph functions are supposed to do?

can retrieve the institution's own descriptions.

The graph has become reflexive.

The provider no longer merely represents the entity.

It can encounter **its own representation of its representation**.

Formally:

G_t
 superset
 {
 $E[T],$
 $E[S],$
 $E[T] \neq E[S],$
 $O[\text{Google}](E[T]) = E[S],$
 $P[\text{Google}](E[T] \neq E[S])$
 }.

That is the **mirror condition**.

The graph does not accuse.

It contains the relations.

The contradiction is produced by composition.

47.3. From counter-speech to counter-ontology

Ordinary recourse imagines an injured speaker answering a false statement with another statement.

Ontological injury requires something different.

The corrective object is not merely:

Google is wrong about me.

It is a machine-resolvable network of relations:

```
entity
+
provenance
+
continuity
+
disambiguation
+
incident
+
contradiction.
```

This is **counter-ontology** in a narrow, non-deceptive sense:

counter-ontology is a provenance-preserving public structure built to restore distinctions that a d

It does not create an alternative reality.

It restores relations omitted from the mediated one.

For the present case, the high-value relations include:

- **The Crimson Hexagon** is a literary project attested in print in 2014;
- *Pearl and Other Poems* belongs to that project and has an ISBN;
- the project's name descends from Borges;
- the analytics company separately descends from Borges;
- the two entities are distinct;
- **Crimson Hexagonal Archive** is the later disambiguated/archive-facing continuation of the literary project;
- the Afterlife Archive is declared fiction in forensic corporate form;
- the canonical query has produced a company-derived shadow referent;
- a two-character variant has correctly recovered the literary basin;
- the ordinary company query produces a separate corporate representation;
- the provider's public role descriptions and policies state commitments to accurate entity grounding, representative information, authenticity, and cross-surface consistency.

Each relation is independently auditable.

Their combination creates the argument.

47.4. The graph does not need to believe the critique in advance

This distinction is crucial.

The strategy does not depend on persuading a centralized moderator that:

suppression occurred.

The graph can instead preserve lower-level observations:

$q[c]$

$\rightarrow$

$E[S]$

q_v

$\rightarrow$

$E[T][G]$

$d(q[c], q_v) = 2$

$O(q[c]) \Rightarrow E[T]$

$E[T] \neq E[C]$

$E[T] \leftarrow \text{ISBN}_{2014}$

$E[T] \leftarrow \text{Borges}$

$E[C] \leftarrow \text{Borges}.$

A future system can compose the higher-order contradiction from these lower-order facts.

This is epistemically preferable because it does not require the archive to encode a disputed motive as fact.

The graph can say:

this happened;

this distinction existed;

this nearby query behaved differently;

these policies and functions existed.

The inference remains available.

Thus:

graph-native recourse preserves observation densely enough that inference cannot easily be starved

That is the opposite of ontology laundering.

Ontology laundering removes the governance premise while retaining the factual-seeming conclusion.

Graph-native recourse restores the missing premises.

47.5. The recursive pressure is epistemic, not merely reputational

Once the contradiction itself becomes retrievable, every subsequent answer system has a harder problem.

It can continue to emit:

$E[T] \rightarrow E[S]$.

But it now does so inside an environment containing:

$E[T] \neq E[S]$

and:

prior outputs showing $E[T] \rightarrow E[S]$.

The cost of maintaining the wrong ontology therefore rises.

Let:

$C[M](t)$

=

cost of maintaining the misresolved representation at time t .

As independently retrievable contradictory relations accumulate:

$(dC[M]) / (dK[C]) > 0$,

where $K[C]$ is contradiction-bearing public knowledge.

The “cost” need not initially be legal or monetary.

It can be:

- greater answer instability;
- stronger cross-surface contradiction;
- more obvious provenance failure;
- evaluator disagreement;
- correction pressure;
- reputational cost;
- internal quality alerts;
- or eventually legal/regulatory exposure.

This is **recursive epistemic pressure**.

The graph makes the wrong state increasingly expensive to compose coherently.

47.6. The mirror becomes strongest when the system cites itself

The limiting case is not merely that external critics document the error.

It is that the provider's own surfaces begin retrieving and summarizing the documentation of the provider's error.

Then:

provider output

→

public incident record

→

provider retrieval

→

provider output about provider output.

At that point the representational system has become reflexive.

The same machinery that produced the substitution supplies evidence against the substitution.

This is the full **graph mirror**.

It is stronger than ordinary criticism because the contradiction is no longer located solely outside the mediator.

It has entered the mediator's own composition environment.

The political-economic significance is substantial.

A corporation can distribute responsibility among roles.

It can make causal traces inaccessible.

It can treat external criticism as merely external.

But once its own knowledge machinery retrieves the evidence and composes the contradiction, the institutional non-actor has difficulty remaining non-reflexive.

The graph has supplied the missing witness.

47.7. What this means for recourse

The priority order in this paper should therefore be:

graph-native correction

→

documented notice

→

institutional/legal escalation where useful.

Not because law is irrelevant.

Law remains useful for:

- defining duties;
- creating formal notice;
- preserving records;
- obtaining process;
- allocating costs;
- and, in some cases, compelling repair.

But the primary remedy for an ontological injury is the restoration of ontology.

The archive's strongest leverage is therefore not merely:

Google should correct this.

It is:

build the public knowledge environment so precisely that Google's own knowledge systems can increase.

That is not external pressure applied to the graph.

It is the graph becoming capable of self-description.

The endpoint is not victory over the mediator.

It is the **mirror**:

the provider's own knowledge machinery returns the distinction, the incident, the policy contradiction.

At that point, ontology laundering has failed at its deepest level.

The hidden governance may remain historically important.

But the world it attempted to produce can no longer appear self-evident.

48. Secondary recourse: appeal, notice, and actual liability

The graph-native path in §47 is the primary ontological remedy developed by this paper.

Legal and administrative process remains a secondary but important frame because it can create formal notice, preserve records, force institutional response, allocate costs, or occasionally compel correction.

The distributive theory should not imply a legal remedy where none exists.

As of 21 September 2026, the available U.S. recourse is fragmented across product feedback, Knowledge Graph correction, legal-removal process, regulatory complaint, and ordinary civil law.

There is **no public Google process identified here that functions as a dedicated, case-tracked appeal for an AI Mode entity-resolution error.**

The existing routes differ sharply in procedural force.

48.1. Product feedback: available, but not an appeal

Google's current AI Mode help page states that users can submit thumbs-up or thumbs-down feedback on an AI Mode response, select a category, and add details. Google also states that AI Mode can misinterpret web content or miss context and encourages users to compare the AI response against ordinary Search results.³⁹

General Search likewise provides a feedback mechanism.⁴⁰

These routes have low procedural force.

They do not publicly promise:

- a case number;
- a named reviewer;
- a reasoned decision;
- a correction deadline;
- a right to inspect the causal trace;
- or an appeal from noncorrection.

Therefore:

feedback

!=

appeal.

For the present specimen, product feedback is still useful because it establishes **notice**.

A carefully preserved submission should identify:

1. the exact canonical query;
2. the wrong answer;
3. the correct entity;
4. the company/entity distinction;
5. the successful two-character variant;
6. the organic-result contradiction;
7. the canonical project URL;
8. the date and capture.

If the same answer recurs after documented notice, recurrence becomes evidentially different from first occurrence.

³⁹Google Search Help, “**Get AI-powered responses with AI Mode in Google Search**”, current as of 21 September 2026, <https://support.google.com/websearch/answer/16011537>. Google describes AI Mode as an AI-powered synthesis using query fan-out and provides thumbs-up/thumbs-down feedback.

⁴⁰Google Search Help, “**Report a problem with Google Search**,” <https://support.google.com/websearch/answer/6223687>.

48.2. Knowledge Graph correction: stronger, but only where the relevant entity surface is available

Google permits users to submit feedback about Knowledge Graph information and, where an entity has a claimable Knowledge Panel, allows an authorized representative to verify the panel and suggest corrections.^{41 42}

For verified users, Google states that feedback may receive priority, that some corrections can be made directly, and that the submitter receives a confirmation email and a resolution update.

That is materially stronger than ordinary AI Mode feedback.

But it is not a general appeal from AI Mode composition.

A project without a claimable Knowledge Panel cannot simply convert an AI Mode error into a Knowledge Panel case.

48.3. Legal-removal request: the first route with a reference number

Google's Legal Help Center permits a person or business that believes content illegally harms its reputation to file a defamation-related removal request.⁴³

Google asks for:

- the exact content or URL;
- a clear explanation of how it concerns the claimant;
- an explanation of falsity;
- an explanation of reputational harm;
- and supporting evidence.

Google states that legal-removal submissions receive an email confirmation and reference number.⁴⁴

This is procedurally important because it converts an informal complaint into a traceable legal notice.

Google also provides an appeal from some legal-removal decisions. For eligible users or content owners, most appeals must be filed within six months; Google states that it will provide

⁴¹Google Knowledge Panel Help, "How Google's Knowledge Graph works," <https://support.google.com/knowledgepanel/answer/9787176>.

⁴²Google Knowledge Panel Help, "Submit feedback on content about you," <https://support.google.com/knowledgepanel/answer/7534842>. Google states that verified feedback can receive priority and that submitters receive confirmation and a resolution update.

⁴³Google Legal Help, "Defamation Overview," <https://support.google.com/legal-help-center/answer/16833565>. Google describes defamation as a false statement harming the reputation of a person or business and specifies the evidence requested for removal review.

⁴⁴Google Legal Help, "Learn how to report content for legal reasons," <https://support.google.com/legal-help-center/answer/13887279>. Google states that legal requests receive email confirmation and a reference number.

an outcome and a reasoned decision.⁴⁵

Thus:

AI feedback

<

legal notice

<

eligible legal appeal

in procedural force.

The difficulty for AI Mode is object identification.

Google's legal forms are historically organized around URLs and removable content objects. A transient or query-generated AI response may require the claimant to preserve:

- a shareable AI Mode URL if available;
- the exact query;
- screenshots;
- date/time;
- source-card URLs;
- and the product context in which the statement appeared.

The absence of a clean static URL should be documented rather than silently converted into absence of an incident.

48.4. Michigan civil law: possible theories, significant obstacles

For a Michigan plaintiff, ordinary defamation doctrine supplies the clearest traditional liability framework.

Michigan states four basic elements:

1. a false and defamatory statement concerning the plaintiff;
2. an unprivileged communication to a third party;
3. fault amounting at least to negligence;
4. either actionability without special harm or special harm caused by publication.⁴⁶

Michigan also recognizes business defamation for a for-profit corporation where the statement prejudices the corporation in its business or deters others from dealing with it.⁴⁷

⁴⁵Google Legal Help, "**How to appeal a decision,**" <https://support.google.com/legal-help-center/answer/13949083>. Appeals are available to some users/content owners; most eligible appeals are due within six months.

⁴⁶*Ghanam v. Does*, 303 Mich App 522 (2014), restating Michigan's four basic defamation elements from *Mitan v. Campbell*, 474 Mich 21 (2005).

⁴⁷Michigan business-court application of *Northland Wheels Roller Skating Center, Inc. v. Detroit Free Press, Inc.*, 213 Mich App 317 (1995): a for-profit corporation may maintain defamation where the statement prejudices its business or deters others from dealing with it.

The present specimen would therefore raise threshold questions before damages are even reached:

- Who is the legal plaintiff?
- Is the false entity assignment reasonably understood to concern that plaintiff?
- Is the output capable of defamatory meaning?
- What reputational or economic harm can be documented?
- What level of fault applies?
- What evidence shows Google's knowledge after notice?

A literary project title is not automatically a juridical person.

If the injury is to Lee Sharks personally, the statement must be shown to be **of and concerning Lee Sharks**.

If the injury is to a corporation, LLC, or other legal entity that owns or operates the project, that entity's standing and injury must be established separately.

Michigan false-light privacy law is a weaker fit for a nonhuman entity. Michigan courts have stated that a false-light plaintiff must show publicized false matter that places the plaintiff in a highly objectionable false position and that the defendant knew of or recklessly disregarded the falsity; Michigan authority also treats privacy rights as personal rather than corporate.⁴⁸

Therefore the legal identity of the claimant is not a technicality.

It determines which injuries the law can recognize.

48.5. Section 230: strong protection for ordinary snippets, a less settled question for synthesized AI speech

The largest federal obstacle is 47 U.S.C. §230.

Section 230(c)(1) provides that an interactive computer service cannot be treated as the publisher or speaker of information **provided by another information content provider**.⁴⁹

The Sixth Circuit's 2016 decision in *O'Kroy v. Fastcase* is directly relevant to ordinary Google Search snippets.

There, a Google snippet juxtaposed the plaintiff's case with text about an unrelated child-indecency case. The court held Google immune because it was reproducing third-party content and because automated editorial acts did not materially contribute to the unlawfulness

⁴⁸*Foundation for Behavioral Resources v. W.E. Upjohn Unemployment Trustee Corp.*, Michigan Court of Appeals, No. 345415 (28 May 2020), applying *Puetz* and stating that false-light liability requires knowledge or reckless disregard of falsity; see also Michigan authority treating privacy rights as personal rather than corporate.

⁴⁹47 U.S.C. §230(c)(1), (e)(2), (f)(3), <https://www.law.cornell.edu/uscode/text/47/230>. Section 230 protects publication of information provided by another information content provider; defines an information content provider as one responsible in whole or in part for creation or development; and does not limit or expand intellectual-property law.

of that third-party content.⁵⁰

That precedent makes a tort claim based only on ordinary organic snippets difficult in the Sixth Circuit.

AI Mode changes the factual problem.

Google describes AI Mode as producing an **AI-powered response** by dividing the query into subtopics, searching across sources, and bringing the results together into a synthesized answer.⁵¹

Section 230 itself defines an “information content provider” as anyone responsible, in whole or in part, for the **creation or development** of information.⁵²

The central legal question therefore becomes:

is the allegedly unlawful proposition merely third-party information being published, or is Google

The present research did not locate binding Sixth Circuit or Supreme Court precedent squarely deciding Section 230 immunity for the allegedly defamatory content of a Google AI Mode or AI Overview synthesis.

Accordingly:

ordinary snippet immunity is comparatively established;

generative synthesis liability is materially less settled.

The strongest legal distinction is therefore between:

third-party source

and:

Google-composed relation among sources.

If the actionable wrong is precisely the relation:

Crimson Hexagonal Archive

=

Crimson Hexagon-derived historical repository,

the legal analysis should focus on **who created that relation**, not merely who authored the underlying source material.

⁵⁰*O’Kroley v. Fastcase, Inc.*, 831 F.3d 352 (6th Cir. 2016). The Sixth Circuit held Google immune under §230 for a search snippet reproducing allegedly defamatory third-party text and for ordinary automated editorial functions that did not materially contribute to unlawfulness.

⁵¹Google Search Help, “**Get AI-powered responses with AI Mode in Google Search**”, current as of 21 September 2026, <https://support.google.com/websearch/answer/16011537>. Google describes AI Mode as an AI-powered synthesis using query fan-out and provides thumbs-up/thumbs-down feedback.

⁵²47 U.S.C. §230(c)(1), (e)(2), (f)(3), <https://www.law.cornell.edu/uscode/text/47/230>. Section 230 protects publication of information provided by another information content provider; defines an information content provider as one responsible in whole or in part for creation or development; and does not limit or expand intellectual-property law.

48.6. Terms of Service make contract damages a poor primary route

Google's current U.S. Terms of Service, effective 30 July 2026, expressly cover Search.

They disclaim warranties as to service accuracy and reliability.

To the extent permitted by law, they also:

- limit Google to liability for breaches of the Terms or service-specific terms;
- exclude lost profits, revenue, business opportunities, goodwill, anticipated savings, indirect or consequential losses, and punitive damages;
- cap total liability arising from the Terms at the greater of \$200 or fees paid for the service during the prior twelve months;
- while stating that the Terms do not limit liability for gross negligence or willful misconduct.⁵³

They also select California law and Santa Clara County courts for disputes arising out of the Terms, subject to applicable-law limits.

Thus ordinary breach-of-contract theory is unlikely to supply the most useful damages route.

The existence and enforceability of those limitations against a particular noncontractual tort or statutory claim is a separate legal question.

48.7. Regulatory complaints: pressure and record creation, not individual adjudication

A Michigan resident may file a consumer complaint with the Michigan Attorney General.

The office states that it may send the complaint and supporting material to the business and conduct informal mediation, while making clear that it does not act as the complainant's private attorney.⁵⁴

A complaint may therefore create:

- an external file number;
- a government-held record of the incident;
- a request to the company for response;
- and, in some cases, regulatory visibility.

It does not guarantee correction or damages.

The Federal Trade Commission also accepts reports of bad business practices and uses reports to build enforcement matters.⁵⁵

⁵³Google Terms of Service, U.S. version effective 30 July 2026, <https://policies.google.com/terms>.

⁵⁴Michigan Department of Attorney General, Consumer Protection, "**File a Complaint**," <https://www.michigan.gov/consumerprotection/complaints>.

⁵⁵Federal Trade Commission, "**How To Report Fraud at ReportFraud.ftc.gov**," <https://www.ftc.gov/media/how-report-fraud-reportfraudftcgov>.

The FTC has active authority over deceptive practices and continues to bring AI-related consumer-protection cases, but an individual FTC report is not a private damages action and does not guarantee investigation of a particular complaint.⁵⁶

For the present problem, a regulatory complaint would be strongest if framed around a documented **practice or representational system**, not merely a single disliked answer.

48.8. Trademark and copyright are secondary, not automatic solutions

Section 230 expressly states that it does not limit or expand intellectual-property law.⁵⁷

That means a genuine federal trademark claim is not automatically disposed of by the same Section 230 rule that blocks many state-law publication claims.

But the present facts do not by themselves establish a trademark claim.

A viable trademark or false-association theory would require separate proof that the relevant name functions as a protectable source identifier, that the defendant made the legally required kind of use, and that the use creates actionable confusion.

This paper therefore treats trademark as a **counsel-screening issue**, not as an established remedy.

The Borges provenance is even more distinct.

Erasing literary provenance is not, by itself, copyright infringement.

Copyright protects protected expression, not the mere fact of attribution or the short title “Crimson Hexagon.”

Therefore Borges’s erased provenance is analytically important to ontological economy but is not presented here as a copyright cause of action.

48.9. Practical escalation ladder

For a recurrent AI Mode entity substitution, the defensible escalation sequence is:

capture

→

product notice

→

replication after notice

→

⁵⁶Federal Trade Commission, **Artificial Intelligence** enforcement and policy materials, <https://www.ftc.gov/industry/technology/artificial-intelligence>, current as of September 2026.

⁵⁷47 U.S.C. §230(c)(1), (e)(2), (f)(3), <https://www.law.cornell.edu/uscode/text/47/230>. Section 230 protects publication of information provided by another information content provider; defines an information content provider as one responsible in whole or in part for creation or development; and does not limit or expand intellectual-property law.

formal legal notice

→

eligible appeal

→

regulatory or civil review.

The incident packet should preserve:

- canonical query and variant query;
- screenshots and share links;
- same-session organic results;
- date, account state, locale, and personalization state where known;
- target and substitute canonical URLs;
- evidence of the name's Borges provenance and later disambiguation;
- evidence that the near-canonical variant resolves correctly;
- every feedback submission and confirmation;
- every recurrence after notice;
- any measurable reputational, economic, or corrective-labor cost.

The central legal-economic point is:

notice does not itself create liability, but it can change the evidence relevant to fault, correctab

The paper should therefore distinguish three propositions:

a remedy exists

a provider can be formally put on notice

and:

a legally enforceable damages claim exists.

They are not the same proposition.

For the present specimen, the first two are clearly available.

The third is plausible only under a fact-specific legal theory and is materially complicated by Section 230, plaintiff identity, fault standards, causation, damages, and Google's contractual limitations.

That is not absence of accountability.

It is evidence that existing legal doctrine was built around **publication and removal**, while the present injury is increasingly about **machine-produced identity and relation**.

49. Evidence doctrine

The paper should not buy teeth by abandoning evidentiary discipline.

It should buy teeth by making the discipline symmetrical.

Every incident record should distinguish:

```
observation
!=
replication
!=
mechanism inference
!=
internal trace
!=
specific attribution.
```

A recommended status vocabulary:

- **OBSERVED** — captured output exists.
- **REPLICATED** — the same defect recurs under declared conditions.
- **PATTERNED** — a longitudinal or comparative structure is documented.
- **MECHANISM-CANDIDATE** — observations discriminate toward a causal class.
- **TRACE-SUPPORTED** — internal or equivalent evidence connects a mechanism.
- **ATTRIBUTED** — evidence supports a specific responsible control or decision.
- **REPAIRED** — correct referent restored.
- **PROPAGATION-REPAIRED** — affected derivatives corrected.
- **RECURRENT-AFTER-NOTICE** — defect returned after provider notice.

This protects the paper from two symmetrical failures:

```
accusation without evidence
and
exculpation by inaccessible evidence.
Both are epistemically invalid.
```

50. A testable research program

Ontological economy is not useful if every phenomenon is interpreted as confirmation.

Its claims should be testable.

For a suspected substitution:

Referent arm: exact canonical name.

Variant arm: meaningful spelling or syntax variants.

Collision arm: known neighboring entity.

Surface arm: organic search, generated answer, knowledge panel, direct source traversal where available.

Temporal arm: repeated observations across a declared period.

Standing arm: comparable higher- and lower-standing entities.

Correction arm: pre-notice and post-notice behavior.

Carrier-substitution arm: same evidentiary proposition carried by different source identities.

The purpose is to determine whether the system's treatment changes with:

name,
entity,
source,
standing,
surface,
notice,
provenance.

The research question is not:

Can we prove a hidden motive from the outside?

It is:

What distribution of public representational effects exists, what mechanism classes fit it, and which evidence required for causal discrimination is held by whom?

51. Falsification conditions

The framework should weaken or fail where:

1. exact-name substitution cannot be replicated;
2. the apparent collision disappears under controlled querying;
3. variant behavior does not systematically differ;
4. comparable entities show no correction asymmetry;
5. provider traces demonstrate an ordinary transient failure inconsistent with the proposed mechanism;
6. post-notice recurrence ceases after repair;
7. supposed provenance stripping is shown not to have occurred;
8. alleged standing-sensitive evaluation remains constant under carrier substitution;
9. propagation cannot be traced;
10. claimed labor or loss cannot be separated from ordinary activity.

Specific censorship, manual-intervention, discrimination, and economic-loss claims each require their own evidence.

The ontology-economy thesis does not depend on every strong mechanism claim being true.

It depends on a simpler proposition:

machine-mediated entity standing is a governed, value-bearing, labor-dependent infrastructure with
 If that proposition is false, the framework fails at its root.

52. The constitutional principle

The deepest issue is jurisdiction.

Who is authorized to say what a public entity is?

No platform can avoid answering that question once it operates systems that resolve names, construct knowledge graphs, synthesize entities, and mediate user access to the world.

The platform may say:

We are only predicting text.

But the public function can still be:

name
 →
 entity
 →
 relations
 →
 decision.

The social consequence is not suspended by the technical vocabulary used to describe the mechanism.

The constitutional principle of ontological economy is therefore:

power over public machine-mediated identity entails duties to the entities and publics subject to th

Those duties are not a demand for endorsement.

They are a demand for custody.

53. Who pays for the wrong world?

The answer is no longer:

whichever team happens to receive the bug report.

The answer follows the structure of control.

The affected entity bears the burden of identifying itself and documenting the observable defect.

The provider bears the burden of internal diagnosis where the relevant evidence is exclusively provider-controlled.

The provider bears the ordinary cost of repairing provider-controlled representations.

External corrective labor created by the defect enters the restitution account.

Traced downstream propagation enters the repair account.

Demonstrated decision and opportunity harms enter separate loss accounts.

Structural damage to relations, provenance, and standing must be repaired even where no clean dollar estimate exists.

And after notice, recurrence increases the debt.

The governing equations are:

control+exclusive evidence+capacity to repair

⇒

representational duty

reproducible substitution

⇒

provider burden of production

notice+recurrence

⇒

repair debt

provider-created corrective labor

=

transferred cost

governance emitted as ontology

not ⇒

governance responsibility erased.

Conclusion: the bill follows the ontology

The political economy of industrial capitalism asked who owned the factory.

The political economy of platforms asked who owned the network, the data, the audience, and the conditions of exchange.

The political economy of AI must also ask who controls the machinery through which entities become publicly available as themselves.

The issue is no longer only who owns information.

It is who controls the relation:

this name
 ⇔
 this entity
 ⇔
 these relations
 ⇔
 this history.

That relation is now infrastructural.

It is produced by labor.

It accumulates as capital.

It can generate rent.

It can be enclosed.

It can be redistributed.

It can be depreciated.

It can be laundered.

It can be corrected.

And it can be made to look as though no decision ever occurred.

That last operation is the hinge between *Invisibly Invisible* and ontological economy. Power reaches its most mature form not when it visibly deletes an entity, but when it can change the public relation by which the entity is encountered and leave the resulting world looking natural.

Meaning Feudalism names the jurisdictional claim behind that power: the platform may govern the model's relation to the commons while the commons' attempt to correct the model is treated as suspect. *The Trusted Intermediary* names the relational closure that can follow: the mediator can gain standing as the object loses it. Semantic Economy supplies the accounting categories: labor, capital, infrastructure, rent, liquidation, and repair.

Ontological economy joins them.

Its first law is therefore:

whoever has the power to make one entity publicly appear as another has entered the economy of ontology

Its second is:

the inability of outsiders to see the internal decision does not make the decision disappear from the

And its third is:

the bill follows control.

Appendix A. Incident ledger

Each incident should preserve:

Field	Required content
Incident ID	Stable identifier
Correct entity	Name, identifiers, canonical sources
Substituted entity	Name and identifiers
Query	Exact string
Surface	Search, answer, panel, assistant, API, etc.
Date/time	Local and UTC where available
Session state	Logged in/out, fresh session, locale, language
Output	Capture and machine-readable transcript
Lost distinction	Identity, provenance, relation, function, history
Variant behavior	Meaningful variants and controls
Collision behavior	Neighboring entity tests
Comparison set	Comparable entities where applicable
Notice	Date, channel, supplied evidence
Recurrence	Post-notice observations
Mechanism set	Candidate mechanisms with status
Provider trace	Any disclosed internal explanation
Repair	What changed
Propagation	Downstream effects and repair
External labor	Time and direct expense
Decision harm	Traced affected decisions
Opportunity harm	Supported or scenario-only
Standing effect	Measured visibility/relation changes
Evidence status	OBSERVED / REPLICATED / PATTERNED / TRACE-SUPPORTED / ATTRIBUTED

Appendix B. Mechanism ledger

Mechanism class	External discriminators	Evidence only provider may possess
Query interpretation	phrasing sensitivity, variant recovery	parsed intent, candidate generation logs
Entity linker	stable referent swap, collision behavior	linker candidates, confidence, model/version
Stored graph relation	cross-surface persistence	graph history, edit/change provenance

Mechanism class	External discriminators	Evidence only provider may possess
Derived graph relation	propagation without explicit node edit	derivation pipeline, source weights
Source admission	organic/composition asymmetry	retrieval candidates, admission filters
Ranking/reranking	source set stable but order/use changes	reranker scores and rules
Classifier	boundary-specific exclusion	labels, thresholds, actor/source states
Evaluator	answer persists despite contrary evidence	judge outputs, regression tests
Policy/safety control	selective boundary aligned with rule class	policy action and enforcement records
Keyed override	narrow exact-name behavior	rule/config history
Human correction	abrupt stable state transition	ticket/edit/change record
Generation error	unstable or stochastic substitution	generation traces, prompt/context
Multi-stage interaction	mixed behavior across surfaces	cross-component trace

The ledger does not presume that every mechanism exists in every system. It prevents uncertainty from being mistaken for mechanism erasure.

Source notes added in v0.11

Source notes added in v0.10

Source notes added in v0.9

Source notes added in v0.8

Source notes added in v0.7

Source notes added in v0.5

Source notes added in v0.3

Incident evidence note (v0.8): the Google AI Mode outputs for “**crimson hexagonal archive,**” “**crimson hexagon archive,**” and “**crimson hexagon**” were supplied directly by the author in the working session on 21 September 2026. The structural counts in §§24.1 and 43 are counts of those supplied captures, not claims about all Google users, sessions, locales, or future outputs. The canonicity- and diegetic-inversion analysis in §24.4 is likewise limited to the supplied query pair, while the description of the Afterlife Archive’s declared fictionality is independently grounded in the published work and its associated handbook/incident packet.

The author additionally reports that the organic-results surface for the target query is dominated by results for the actual Crimson Hexagonal Archive and includes snippets discussing suppression or representational conflict. Because a same-session result-page capture has not yet been incorporated into this draft, §24.3 treats that organic-surface condition as reported incident evidence and gives a measurement protocol rather than assigning an empirical cross-surface recognition rate.

Appendix C. Archive lineage

This draft is a synthesis and reconstruction of an existing line of work rather than a new vocabulary invented ex nihilo. Its immediate archive lineage includes:

- **Semantic Economy** — semantic labor, semantic capital, semantic rent, semantic liquidation, semantic infrastructure.
- **Platform and AI Capitalism as Semiotic Engineering** — platform infrastructure as a system that engineers the conditions of meaning.
- **Invisibly Invisible: Interface Governance, Semantic Power, and the Reserve of Oversight in AI Search** — double invisibility, asymmetric legibility, and governance of whether a loss can appear as a loss.
- **Meaning Feudalism: A Semantic Economic Analysis of “AI Agent Traps”** — platform sovereignty over agent belief and the absent category of commons repair.
- **Meaning Feudalism at the Guidance Layer** — enclosure at the composition/guidance layer.
- **Adversarial by Origin** — the distinction between harm-based and origin-based classification of influence on machine meaning.
- **The Trusted Intermediary** — relational enclosure, trust laundering, and validation foreclosure.
- **The Negative of the Negative** — entity-scoped representation, broader ontology exclusion, and the possibility of negative representation at graph/retrieval level.
- **Who Pays for the Wrong Entity?** — the immediate predecessor draft, whose incident-accountability model is superseded here by an ontological-political-economic model.

The previous draft’s role tables and public descriptions of provider engineering functions remain useful as an implementation appendix. They should no longer constitute the theoretical spine.

Files

https://raw.githubusercontent.com/leesharks000/alexanarch/main/data/staged/EA-ONTOLOGICAL-ECONOMY-01_v0.12.md

The complete text is the repository-hosted Markdown artifact declared under Files above. Under Transport D attachment ingestion, that text is ingested into the canonical deposit body rather than treated as an external pointer.

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Deposit Information

This paper is deposit #1634 in Alexanarch, the self-governing successor to the Crimson Hexagonal Archive on Zenodo (community crimsonhexagonal, terminated 2026-06-19). The AXN identifier AXN:06C8.GENERATIVE is sovereign — minted and maintained by Alexanarch.

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