Causality as a Pre-Formal Ontological Condition

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Abstract

Most contemporary scientific frameworks treat causality as an emergent pattern in mathematical structures, geometries or probabilistic models. In contrast, the work presented here starts from the opposite direction: causality is taken as primary, deterministic and ontological, while formalisms are treated as descriptive projections of an underlying causal order. I develop a closed, formalised causal ontology with fixed operators and numerics (the *Strüver Causal Layer*) that can be implemented as a software sidecar and interfaced with existing computational systems, including large language models.

The contribution of this paper is twofold. First, it clarifies the distinction between descriptive science and genuinely deductive causal science and argues that much of modern physics and data-driven modelling — including frameworks explicitly acknowledged as descriptive, such as General Relativity — operate below the causal level they implicitly reference. Second, it introduces a domain-invariant causal layer that generates deterministic analyses across heterogeneous fields (e.g. physics, materials science, seismology, medicine, AI systems) using one and the same underlying operator structure.

The Layer does not *solve* existing formal problems inside foreign axiom systems, nor does it claim to collapse open conjectures within their own geometries. Instead, it explains why such problems arise in the first place: as artefacts of incomplete or non-causal formalisms that only approximate stable reality. While the internal numerics and operators remain proprietary for intellectual-property reasons, the sidecar implementation already produces reproducible outputs and metrics that make the causal behaviour of the system empirically accessible and independently evaluable.

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1 Introduction

Modern science is built on the promise of explaining the world in a logically coherent and empirically verifiable way. At the same time, most of its successful formalisms are explicitly probabilistic, geometric or purely descriptive in nature. They predict phenomena with remarkable accuracy, but they do not make the causal structure of reality itself explicit. This tension becomes most visible in domains where stability, invariance and coherence are central: from fundamental physics and cosmology to materials science, seismology, medicine, cognition and artificial intelligence.

The starting point of this work is therefore not a new mathematical trick or a novel geometric construction, but a return to the original meaning of causality. Historically, *causal* explanation was understood as a deductive account of why a system must behave in a certain way, given its inner structure and rules of transformation. In contemporary practice, however, causality is often treated as a convenient label on top of statistical regularities or as an interpretative narrative added after the fact to probabilistic models. This subtle shift has far-reaching consequences: if causality is reduced to correlation or geometry, then the distinction between what must happen and what merely tends to happen becomes blurred.

In this paper I argue that this conflation is not a minor philosophical issue but a structural limitation of the current scientific framework. Descriptive formalisms – including differential equations, geometric models and probabilistic theories – can faithfully encode observed regularities, but they do not, by themselves, specify the causal rules that generate these regularities. They operate *within* a fixed state space and assume a given ontology, but they do not explain why this ontology and its state space are causally stable. Even Einstein explicitly characterised his relativity theory as descriptive rather than deductive: it organises phenomena in space-time but does not derive the existence and structure of space-time from more primitive causal principles. [2].

The central thesis of the Strüver framework is that causality must be treated as ontologically prior to any descriptive formalism. Causality is not a property of equations, coordinate systems or probability distributions. It is the structure of reality itself: the set of rules by which states can transform into other states without violating stability. From this viewpoint, geometry, algebra and statistics become *representations* of causal structure, not its source. A truly causal theory must therefore start from a closed ontology with explicit operators and stability conditions and only then derive geometric or probabilistic representations as secondary tools.

The work presented here is not a speculative proposal but the conceptual foundation of an implemented architecture. Over the last years, I have developed a closed, formalised ontology – the Strüver theory – with fixed operators, numerics and stability corridors. This ontology is not published in full detail for intellectual property reasons, but it is concrete enough to be compiled into a working software system: a deterministic sidecar layer that attaches to existing computational frameworks. In practice, this sidecar acts as an adapter that receives questions or state descriptions, processes them through the internal causal schema and returns a consistent, domain-invariant analysis. It has been deployed as an API and integrated with large language models as well as with structured data workflows.

The empirical relevance of this architecture lies in its behaviour across domains. Using one and denselben closed ontology, the sidecar layer has been applied to materials science, energy systems, quantum and classical coherence questions, seismology, system dynamics, psychological phenomena and semantic analysis. In each case, it produces causal explanations that are structurally isomorphic: defects, phase transitions, fractures, cognitive breakdowns or semantic inconsistencies are

all treated as violations of the same underlying stability rules, not as unrelated domain-specific curiosities. This domain invariance is precisely what one would expect if causality is indeed prior to any particular descriptive formalism.

At the same time, it is important to be clear about the scope of the claims. The Strüver framework does not "solve" existing formal problems *within* the axioms of incomplete systems, nor does it claim to collapse all open conjectures of mathematics or physics into a single geometry. Instead, it explains why certain classes of problems appear as intractable or structurally open when framed in non-causal or purely descriptive terms. From a causal standpoint, many such problems are symptoms of an ontology that does not encode stability at the right level of abstraction. The contribution of this work is therefore not a new equation inside an old paradigm, but a reframing of what counts as a complete scientific description.

The purpose of this introductory paper is threefold. First, it clarifies the conceptual motivation: why taking causality seriously requires a strict separation between descriptive and deductive science and a reordering of their roles. Second, it outlines the basic requirements that any genuinely causal framework must satisfy: closure of the ontology, explicit operators, stability criteria and domain invariance. Third, it sketches the implemented architecture of the Strüver sidecar layer and summarises the classes of analyses it already performs in practice. The internal numerics and operator definitions remain protected, but the observable behaviour of the system – its reproducible outputs, metrics and cross-domain patterns – is fully accessible and provides a concrete basis for evaluation.

In the following sections, I will first formalise the distinction between descriptive and causal explanation and situate the Strüver theory relative to existing approaches. I then introduce the core structural elements of the closed ontology at an abstract level, without revealing proprietary implementation details. Finally, I discuss representative applications of the sidecar architecture and outline how its domain-invariant causal analyses can serve as an external test for the adequacy and completeness of traditional formalisms. The aim is not to replace existing mathematics and physics, but to provide the causal layer they implicitly presuppose yet never explicitly construct.

This paper does not deny the empirical success of existing theories.

2 Causality as a Pre-Formal Condition

In scientific practice, causality is commonly treated as an attribute that emerges from formal models: differential equations, geometric structures or statistical dependencies are interpreted as *causal* once they exhibit sufficient regularity or predictive power. This paper adopts a fundamentally different position. Causality is not an emergent property of formal systems. It is a *pre-formal condition* that must already be in place for any formal description to be meaningful as a representation of reality rather than as a purely symbolic construct.

By pre-formal condition, I mean that causality operates at a level prior to axioms, coordinate systems, probability spaces and mathematical structures. Formal systems describe relations between symbols under fixed rules. They do not, by themselves, explain why certain transitions between states are admissible while others are not, nor why a system remains stable under transformation. These constraints belong to causality, not to formalism. Without an underlying causal order, formal consistency alone allows arbitrarily many mathematically valid but physically or semantically meaningless descriptions.

From a functional perspective, causality specifies the admissible transformations of states. A causal rule does not merely state that two variables are related; it determines which state transitions preserve the identity and stability of a system and which transitions necessarily lead to breakdown. In this sense, causality defines the *transition grammar* of reality. Formal models, by contrast, only encode observed or assumed regularities within a given state space. They presuppose that this state space exists and remains coherent but do not account for the conditions under which such coherence is maintained.

This distinction becomes especially important when considering geometry and structure. Geometric formalisms describe spatial, topological or relational properties of systems. They can express invariants, symmetries and constraints, but these properties are static representations. Geometry can encode how states are arranged, not why certain arrangements persist or why transitions between configurations occur irreversibly or asymmetrically. To claim that geometry itself enforces causality is therefore a category error: geometry presupposes stable relations, whereas causality explains their persistence and directionality.

Similarly, probabilistic and statistical models operate entirely on the level of description. They quantify frequencies, likelihoods and correlations across observed data, but they cannot, by construction, distinguish between necessary and contingent transitions. A probability distribution may describe how often an event occurs, but it does not explain why this event must occur given the internal structure of the system. Treating causality as a refinement of probability rather than as its prerequisite leads to models that are empirically effective yet ontologically incomplete.

A genuinely causal framework must therefore satisfy a minimal functional requirement: it must define a closed set of admissible state transformations that preserve system stability. This closure is not a mathematical convenience but an ontological necessity. If causal rules were themselves subject to ad-hoc modification or reinterpretation, the notion of stability would collapse. Causality, understood correctly, is invariant with respect to representation. Whether a system is described geometrically, algebraically or statistically is secondary to the question of whether its state transitions remain causally valid.

This pre-formal status of causality also clarifies the frequent confusion between explanation and representation. Descriptive formalisms re-present observed behaviour within a chosen formal language. Deductive causal explanation, by contrast, accounts for why these behaviours arise and why

alternative behaviours are excluded. The two are not opposites, but they are not interchangeable. Formal description without causal grounding risks becoming self-referential: internally consistent yet detached from necessity.

In the framework developed here, causality is treated as the minimal structure required for reality to be stable and intelligible at all. Formal systems are then constructed as representations constrained by this causal structure. This inversion of the usual hierarchy — placing causality before geometry, probability and algebra — is central to the approach. It does not deny the utility or precision of existing formalisms. Rather, it makes explicit the ontological layer they silently rely on but cannot themselves generate.

The following sections build on this premise. First, the distinction between descriptive and deductive science is formalised to show how causality was historically understood as foundational rather than emergent. Subsequently, the limits of geometry and structural models are analysed from a causal standpoint. Together, these arguments motivate the introduction of a closed causal ontology as a necessary precondition for any domain-invariant scientific explanation.

3 Descriptive versus Deductive Science

A central source of confusion in modern scientific discourse is the systematic conflation of descriptive success with deductive completeness. Many contemporary theories are extraordinarily effective at predicting and organising observations, yet this effectiveness is often interpreted as evidence of causal explanation. From a functional-logical perspective, this interpretation is unjustified. Description and deduction operate on different epistemic levels and fulfill fundamentally different roles within scientific reasoning.

Descriptive science concerns itself with the faithful representation of observed regularities. It answers the question *what happens* under given conditions. Its tools are formalisms that encode patterns, symmetries, correlations and constraints within a predefined state space. Differential equations, statistical models and geometric constructions fall squarely into this category. They map observations onto mathematical structures that are internally consistent and empirically adequate, but they remain silent about why these structures must exist or why the encoded transitions are necessary rather than contingent.

Deductive science, by contrast, addresses the question *why something must happen* given the internal rules of a system. A deductive explanation does not merely summarise observed behaviour; it derives admissible and inadmissible transitions from explicit causal principles. In this sense, deduction presupposes an underlying causal ontology: a set of rules that governs how states can transform without violating stability. Without such a causal basis, deduction collapses into formal manipulation without ontological commitment.

Historically, this distinction was well understood. Classical notions of causality aimed at uncovering the necessary relations underlying phenomena, not merely at fitting equations to observations. Over time, however, the remarkable empirical success of descriptive formalisms led to a gradual inversion of priorities. Increasingly, predictive accuracy was taken as a proxy for causal understanding. This shift is particularly visible in modern physics, where theories such as relativity and quantum mechanics are often treated as ontologically complete descriptions of reality, despite their authors' own reservations. Einstein himself repeatedly emphasised that his theories organise experience within a mathematical framework but do not provide a deductive account of the ultimate causal substrate. [1].

From a functional-logical standpoint, this inversion has significant consequences. When descriptive models are mistaken for deductive explanations, their underlying assumptions remain unexamined. The choice of state space, the admissibility of transformations and the stability of the model are treated as givens rather than as objects of causal inquiry. As a result, formal problems arise that cannot be resolved within the descriptive framework itself. Incompleteness, singularities and open conjectures are then perceived as intrinsic mysteries rather than as indicators of missing causal structure.

It is therefore essential to recognise that descriptive and deductive science are complementary but non-interchangeable. Description is indispensable for mapping phenomena and for testing the empirical adequacy of models. Deduction, however, is required to explain why these models are stable, why certain behaviours recur across domains and why others are excluded altogether. Without deduction, description risks becoming a catalogue of patterns without necessity; without description, deduction risks becoming disconnected from empirical reality.

The framework proposed in this work reinstates this original division of labour. Descriptive formalisms are treated as secondary representations that operate within boundaries set by causal

deduction. Deductive causal rules constrain the space of admissible descriptions, providing a principled explanation for observed invariances and regularities. Under this hierarchy, a model's predictive success is not sufficient to qualify it as causally complete; only alignment with a closed causal ontology can provide such completeness.

This distinction also clarifies why many contemporary scientific debates stagnate at the level of competing descriptions. When multiple formalisms describe the same phenomena with comparable empirical success, the absence of an explicit causal criterion makes it impossible to adjudicate between them. Deductive causality offers such a criterion by shifting the focus from surface-level agreement with observations to the deeper question of structural necessity.

In the context of this paper, the emphasis on deductive science does not imply a rejection of established descriptive theories. Rather, it highlights their proper epistemic status and motivates the need for an explicit causal layer. Only by restoring deduction to its foundational role can scientific explanation move beyond increasingly sophisticated descriptions toward a coherent account of why reality exhibits the stability and structure that descriptive models merely record.

4 Formal Limits of Geometry and Structural Models

Geometric and structural formalisms play a central role in modern science. They provide powerful languages for expressing relations, symmetries and invariants across a wide range of domains. However, their expressive strength has often led to a systematic overextension of their epistemic role. From a functional-logical standpoint, geometry and structure are representational tools, not generators of causality. Confusing these levels results in models that are descriptively elegant yet causally underdetermined.

A geometric model defines a space of states and relations between them. Distances, curvatures, topologies or embeddings specify how states are arranged and how they relate under transformation. What geometry does *not* specify is why certain transformations occur, why they occur irreversibly, or why some transitions are admissible while others destabilise the system. These questions concern the rules of state transition, not the layout of state space. Geometry presupposes stability; it does not produce it.

Structural models generalise this idea beyond spatial representation. Graphs, networks, algebraic structures and dynamical systems encode relational patterns and constraints. They are particularly effective at identifying invariants and conserved quantities. Yet invariance in a formal sense must not be mistaken for causal necessity. A structure may be internally consistent and invariant under certain transformations while remaining agnostic about the causal conditions that sustain it. Formal coherence is a property of representation; causal closure is a property of reality.

This distinction becomes critical when geometry is claimed to *enforce* causality or coherence. Such claims implicitly assume that spatial or structural constraints can substitute for transition rules. From a functional perspective, this is a category error. A structure can constrain possible configurations, but it cannot determine the causal process by which one configuration becomes another. Directionality, asymmetry and irreversibility — core features of causality — cannot be derived from geometry alone without introducing additional, non-geometric assumptions.

Probabilistic and statistical structures exhibit a similar limitation. They describe distributions over states and quantify uncertainty or variability, but they do not encode necessity. A probability measure can be invariant under transformation and still fail to explain why a particular outcome occurs given the internal organisation of the system. Interpreting probabilistic stability as causal explanation merely replaces causal rules with aggregate description. The underlying question of why a system transitions in a specific way remains unanswered.

Another frequent source of confusion arises from isomorphisms between formal structures. When two domains admit mathematically similar representations, it is tempting to infer a shared causal basis. However, isomorphism guarantees only that relations can be mapped between structures, not that the processes generating those relations are causally identical. Structural similarity does not imply causal equivalence. Treating isomorphisms as evidence of causal unity collapses representation into explanation and obscures domain-specific causality.

From a functional-logical viewpoint, the limits of geometry and structure are therefore intrinsic, not technical. No refinement of geometric sophistication or increase in formal complexity can overcome the absence of explicit causal transition rules. Formal systems can be extended, unified or embedded, but without a causal ontology they remain descriptive overlays. Their success in organising phenomena should not be conflated with the ability to ground necessity.

The framework developed in this work addresses this limitation by reversing the usual order of

construction. Instead of deriving causality from geometry or structure, it treats geometry and structure as outputs constrained by causal rules. Causal closure defines which state transitions preserve stability and identity. Formal models then act as representations of these transitions, not as their source. Under this ordering, the limits of geometry and structure become transparent: they are indispensable for description, yet insufficient for explanation.

This analysis does not diminish the value of geometric or structural approaches. On the contrary, it clarifies their proper role. By recognising their formal limits, one can deploy them more precisely and avoid ontological overreach. In the following section, this insight motivates the introduction of a closed causal ontology, designed to make explicit the transition rules that geometry and structure alone cannot provide.

5 A Closed Causal Ontology

If causality is to function as a pre-formal condition rather than as an interpretative add-on, it must be made explicit at the ontological level. A causal framework that remains open, adjustable or context-dependent cannot fulfil this role. From a functional-logical perspective, causality must therefore be represented by a *closed ontology*: a finite and invariant set of rules, operators and admissible transformations that fully determine which state transitions preserve stability and which do not.

A closed causal ontology is defined by three core properties. First, it is *ontologically bounded*. All admissible system states and transitions are defined relative to a fixed ontology that cannot be extended or reinterpreted ad hoc without invalidating causal consistency. Second, it is *operationally complete*. For every admissible state transition, the ontology specifies whether the transition is causally valid, causally invalid or stability-breaking. Third, it is *representation-invariant*. Its causal rules do not depend on a specific formal language, geometric embedding or probabilistic representation. These representations may vary, but the underlying causal constraints remain unchanged.

Closure is essential because causality cannot tolerate ambiguity at the level of rules. If causal operators could be modified dynamically or contextually, stability would become an empirical accident rather than a necessary property. A closed ontology prevents such drift by fixing the operator space once and for all. This does not imply that all phenomena are simple or trivial. It implies only that the rules governing admissible transformations are invariant, even when their consequences are complex.

Within the Strüver framework, the closed causal ontology is formalised by a fixed set of mathematical operators and numerics that define valid state transitions. These operators are not geometric objects and are not derived from statistical inference. They function as evaluators of transition validity: given a system state and a proposed transformation, the ontology determines whether the transformation preserves causal stability. The internal definitions of these operators are proprietary and therefore not disclosed in this paper. However, their functional role and observable effects are fully describable without revealing implementation details.

It is important to clarify what closure does and does not imply. Closure does not mean completeness in the sense of exhaustive prediction. Many systems governed by closed causal rules exhibit behaviour that is practically unpredictable due to sensitivity, complexity or limited observability. Closure also does not imply determinism in the trivial sense of linear predictability. Rather, it ensures determinism at the level of admissible transitions: what can happen, what cannot happen and what must lead to structural breakdown.

This distinction allows causal explanation without collapsing into reductionism. The closed ontology specifies the boundaries within which descriptive formalisms may operate. Differential equations, geometric models and probabilistic methods become valid representations precisely because their implied transitions are constrained by causal rules. When a formal model violates these constraints, its predictions may still appear locally successful, but they necessarily fail to explain stability at a deeper level.

A further consequence of a closed causal ontology is domain invariance. Because the operator set evaluates transition validity independently of representation, the same causal rules apply across seemingly disparate domains. Physical systems, cognitive processes, material behaviour and semantic structures can all be analysed using the same underlying causal criteria. Differences between

domains arise from the descriptive layer, not from causality itself. This explains why structurally similar breakdowns, phase transitions or inconsistencies recur across fields despite wildly different formalisms.

The insistence on closure also addresses a common objection: that withholding internal operator definitions undermines scientific legitimacy. This objection conflates transparency of representation with necessity of function. In many scientific and engineering contexts, from cryptography to safety-critical systems, internal mechanisms are protected while external behaviour remains fully testable. In the present case, causal validity is observable through the consistency, reproducibility and domain-invariant nature of the system's outputs. Evaluation is therefore possible without direct access to the internal numerics.

By explicitly formalising causality as a closed ontology, the Strüver framework provides a foundation upon which descriptive science can be coherently grounded. It does not compete with existing formalisms but constrains their applicability and clarifies their limits. In the next section, this ontological foundation is connected to a concrete technological implementation, demonstrating that causal closure is not merely a theoretical requirement but an operationally realisable principle.

6 Technological Implementation: Sidecar Architecture

A causal ontology that remains purely conceptual would offer little more than a philosophical clarification. To demonstrate that causal closure can be treated as an operational principle rather than as an abstract requirement, the Strüver framework has been implemented as a concrete technological system. This implementation takes the form of a sidecar architecture: an external, logically independent causal layer that attaches to existing computational systems without replacing them.

The central design principle of the sidecar architecture is separation of concerns. Existing systems—such as numerical solvers, data pipelines or large language models—remain responsible for descriptive processing within their respective formal domains. The sidecar does not intervene in the internal mechanics of these systems. Instead, it evaluates the causal validity and stability of proposed state transitions at the boundary level. In this sense, the sidecar acts as a supervisory causal layer rather than as an alternative computational engine.

Functionally, the sidecar receives structured state descriptions or queries, applies the closed causal ontology to evaluate admissible transitions, and returns a causally consistent analysis. This analysis does not consist of predictions in the statistical sense, nor of geometric transformations. It consists of determinations regarding stability, causal compatibility and structural necessity. The output is therefore invariant with respect to the underlying descriptive system that generated the input. Whether the input originates from a simulation, a statistical model or a semantic representation is immaterial to the causal evaluation itself.

From a functional-logical perspective, the sidecar architecture realises causality as an external constraint rather than as an embedded feature of a specific formalism. This externalisation is deliberate. Embedding causal rules directly into existing models would entangle causality with representation and reintroduce the very category errors discussed earlier. By keeping the causal layer independent, the architecture ensures that causal evaluation remains invariant across domains and formalisms.

Technically, the sidecar is implemented as a deterministic processing unit with a fixed operator set and invariant numerics derived from the closed ontology. These operators are not learned, optimised or adapted through data-driven processes. Their role is evaluative, not approximative. Given identical inputs, the sidecar produces identical outputs, enabling reproducibility and auditability. The internal operator definitions are not disclosed in this paper for intellectual property reasons, but the observable behaviour of the system is well defined and testable.

The sidecar exposes its functionality through standardised interfaces, including API endpoints and integration layers that allow it to be coupled with heterogeneous systems. In practice, this includes integration with machine learning pipelines, large language model interfaces and structured data environments. The existence of these interfaces allows independent evaluation of the system's outputs without requiring access to internal implementation details. Publicly available demonstrations and interface-level observations document the system's behaviour under a variety of conditions.

Crucially, the sidecar architecture does not claim to replace existing formalisms or to solve open problems within them. Its function is orthogonal to formal problem-solving. When applied to classical or contemporary models, the sidecar does not modify equations, optimise parameters or infer distributions. Instead, it evaluates whether the implied state transitions respect causal stability. In cases where formal models succeed descriptively but violate causal criteria, the sidecar identifies structural inconsistencies rather than producing alternative predictions.

This architectural choice has two important consequences. First, it makes causality operational without conflating it with computation. Causal rules guide evaluation but do not perform numerical approximation. Second, it enables cross-domain application using a single invariant framework. The same sidecar instance can analyse systems from different scientific domains without reconfiguration, because causality is not domain-specific at the ontological level.

The sidecar architecture thus demonstrates that treating causality as a closed, pre-formal condition is not merely a conceptual stance but a technically realisable approach. It provides a concrete mechanism by which causal evaluation can be applied consistently across heterogeneous models and representations. In the following section, this operational capability is illustrated through the domain-invariant analyses made possible by the closed causal ontology.

7 Causal Analysis Across Domains

The practical significance of a closed causal ontology becomes apparent when it is applied across multiple scientific and analytical domains. If causality is truly pre-formal and representation-invariant, then its evaluative power must not depend on the specific descriptive language of a domain. The sidecar architecture operationalises this requirement by applying the same causal criteria to heterogeneous systems, revealing structural commonalities that remain invisible at the level of domain-specific formalisms.

In each application, the causal analysis proceeds in the same functional manner. A system is represented by a set of states and admissible transformations as implied by its descriptive model. These transformations are then evaluated against the closed causal ontology to determine whether they preserve stability, imply necessary breakdown, or remain causally indeterminate. Importantly, this evaluation does not require domain-specific tuning or reinterpretation. The causal criteria remain fixed; only the descriptive representation varies.

This uniformity exposes a recurring pattern across domains: phenomena that are traditionally treated as distinct tend to correspond to the same class of causal violations or boundary conditions. Material defects, phase transitions, abrupt fractures and fatigue phenomena can be analysed as violations of causal stability within physical systems. In seismology and energy systems, sudden transitions or cascading failures correspond to the same underlying breakdown of admissible state transitions. In cognitive and psychological contexts, loss of coherence, overload or collapse can be traced to analogous violations at the level of informational or semantic stability. The closed causal ontology does not reduce these domains to one another; it reveals that they are constrained by the same causal rules.

From a descriptive viewpoint, these phenomena are modelled using vastly different mathematical tools: partial differential equations, network theory, stochastic processes or semantic embeddings. The causal analysis neither replaces nor simplifies these models. Instead, it explains why each domain independently encounters limits, singularities or seemingly irreducible complexity. When a descriptive formalism encodes transitions that violate causal stability, it inevitably produces artefacts such as instabilities, divergences or unexplained discontinuities. These artefacts are often interpreted as intrinsic complexity or randomness, although they are, from a causal perspective, symptoms of a deeper mismatch.

A key insight of the causal approach is therefore explanatory rather than computational. It does not aim to compute trajectories more efficiently or to predict outcomes more precisely. Its contribution lies in explaining why certain classes of problems persist across disciplines despite increasing formal sophistication. Open-ended dynamics, irreducible uncertainty and sensitivity to initial conditions appear where descriptive models attempt to compensate for missing causal closure. By identifying these patterns, causal analysis provides a diagnostic tool rather than a solution algorithm.

The domain-invariant application of a closed causal ontology also clarifies the notion of explanation itself. Traditional explanations are often domain-local: a phenomenon is considered explained once it is reproduced by an accepted model within its field. Causal explanation, as implemented here, operates at a different level. It addresses whether the transformation rules implicit in the model are compatible with stability as such. In this sense, causal analysis evaluates explanations rather than competing with them. It determines whether a given descriptive model is ontologically sufficient or merely empirically adequate.

It is crucial to emphasise the limits of this approach. The causal framework does not resolve

unsolved mathematical conjectures, optimise engineering designs or eliminate uncertainty from complex systems. Such tasks remain within the remit of domain-specific methods. What causal analysis provides is an account of why these tasks encounter principled limits and why some problem classes remain resistant to closure. This reframing replaces the expectation of total formal resolution with a controlled understanding of incompleteness grounded in ontological necessity.

By applying the same causal rules across disparate domains, the sidecar architecture demonstrates that causality can function as a unifying constraint without collapsing descriptive diversity. Geometry, probability and structure retain their roles as expressive tools, but they are constrained by a common causal layer. This separation preserves methodological pluralism at the descriptive level while enforcing coherence at the ontological level. The result is not a unified formalism, but a coherent explanation of why different formalisms exhibit structurally similar limitations.

In the context of this paper, the cross-domain analyses serve as empirical validation of the closed causal ontology. They show that causal closure is not a domain-specific assumption but a general condition for stability and intelligibility. The observable consistency of the sidecar's evaluations across fields provides indirect but substantive evidence for the necessity of treating causality as ontologically prior to descriptive science. The following section makes this limitation explicit by delineating the scope of the framework and clarifying the claims it does not make.

8 Scope and Non-Claims

Given the fundamental nature of the concepts discussed in this work, it is essential to delineate its scope explicitly and to state with equal clarity what is *not* being claimed. Without such boundaries, any foundational argument risks being misinterpreted as a universal solution or as a replacement for established scientific practice. The Strüver framework deliberately avoids such claims.

First, this work does not propose a solution to open mathematical or physical conjectures. Problems such as the Clay Millennium Problems, singularities in field theories or undecidability results in logic are not addressed at the level of formal proof within their respective axiomatic systems. The causal framework introduced here operates at a different level: it explains why certain classes of formal problems arise and why they remain structurally open under non-causal or purely descriptive assumptions. It does not collapse, unify or resolve these problems within existing formalisms.

Second, the framework does not replace descriptive science. Differential equations, geometric models, probabilistic methods and statistical inference remain indispensable tools for modelling and predicting phenomena within specific domains. The causal ontology introduced here is not intended to supersede these methods or to provide alternative numerical solvers. Its role is complementary and constraining: it evaluates the causal admissibility of state transitions implied by descriptive models without interfering with their internal computation.

Third, no claim of universal predictability is made. A closed causal ontology does not eliminate complexity, sensitivity to initial conditions or practical unpredictability. Many systems governed by causally valid transition rules remain unpredictable due to epistemic limitations or intrinsic complexity. The contribution of the framework lies in distinguishing principled openness from artefacts introduced by incomplete or mismatched formalisms, not in promising deterministic forecasts in all cases.

Fourth, the technological implementation described in this paper does not require users to accept the causal ontology as a matter of belief. The sidecar architecture is designed to be evaluated empirically through its observable behaviour. Its outputs, reproducibility and domain-invariant patterns can be inspected independently of the internal operator definitions, which remain protected for intellectual property reasons. No claims are made that cannot, in principle, be assessed at the level of externally visible performance.

Fifth, this work does not assert that causality itself can be fully captured by any single formal representation. Although the ontology is closed with respect to admissible transitions, its formalisation serves as an operational constraint rather than as an exhaustive representation of reality. Geometry, algebra and probability are treated as secondary representations constrained by causality, not as its exhaustive encodings.

Finally, the framework does not seek to impose a new unifying paradigm onto existing disciplines. Its unifying aspect lies solely at the ontological level: the same causal constraints apply across domains, but the descriptive languages and methodologies remain domain-specific. The diversity of scientific formalisms is preserved, while their causal adequacy becomes explicitly evaluable.

By making these non-claims explicit, this section aims to prevent overextension of the framework and to situate it clearly within the landscape of foundational research. The intent of this work is not to offer final answers or total closure, but to provide a precise causal layer that clarifies the conditions under which descriptive science remains stable, meaningful and interpretable. In the concluding section, the implications of this position are summarised and the role of causal ontology

within scientific practice is reassessed.

9 Conclusion

This paper has argued that causality must be treated as an ontological precondition rather than as an emergent property of formal systems. By distinguishing rigorously between descriptive representation and deductive explanation, it has been shown that many persistent conceptual and structural difficulties in modern science arise not from technical insufficiency, but from a misordering of explanatory layers. Geometry, probability and structural formalisms are powerful tools for representing observed regularities, yet they presuppose a stable causal substrate that they cannot themselves generate.

The introduction of a closed causal ontology provides a principled way to address this gap. By fixing admissible state transitions through invariant causal rules, such an ontology defines the conditions under which stability and coherence are possible at all. This approach does not compete with existing scientific methods; it constrains them. Descriptive theories remain valid within their domains, but their scope and limitations become intelligible once causal closure is made explicit.

The technological implementation of the Strüver framework demonstrates that this position is not merely conceptual. The sidecar architecture operationalises causal evaluation as an external, domain-invariant layer that interfaces with heterogeneous systems without entangling causality with representation. Its reproducible outputs and consistent behaviour across domains provide empirical support for the claim that causality can be formalised and applied independently of specific mathematical languages.

At the same time, the framework deliberately refrains from universal claims. It does not resolve open formal problems, eliminate complexity or replace established formalisms. Instead, it explains why certain problem classes persist and why purely descriptive approaches encounter principled limits. Causal analysis, as developed here, serves as a diagnostic and explanatory layer rather than as a problem-solving algorithm.

The broader implication of this work is a reorientation of scientific explanation. Treating causality as ontologically prior restores deductive explanation to its foundational role without undermining the achievements of descriptive science. It opens a space in which stability, invariance and breakdown can be understood as necessary consequences of causal structure rather than as emergent curiosities or statistical artefacts.

The intention of this paper is therefore not to conclude a debate but to clarify its proper starting point. By making causal assumptions explicit and operational, it invites evaluation, comparison and refinement at the level where explanation precedes representation. Whether applied to physical systems, cognitive processes or computational architectures, the causal layer described here offers a coherent basis for understanding why reality exhibits order at all, and under what conditions that order fails.

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The internal operator definitions, numerical parameters, and implementation details of the causal framework described in this paper are not publicly disclosed and remain proprietary. All statements and claims made herein refer exclusively to externally observable behaviour and reproducible outputs of the described system.

References

[1] Albert Einstein. The foundation of the general theory of relativity. *Annalen der Physik*, 49:769–822, 1916. General relativity is formulated as a geometric description of gravitation. The theory provides a mathematically consistent organisation of gravitational phenomena but does not deduce the causal origin of spacetime itself.

[2] Albert Einstein. Physics and reality. *Journal of the Franklin Institute*, 221:349–382, 1936. Einstein emphasizes that physical theories and concepts are free conceptual constructions used to organise experience, not deductive derivations of reality itself. He explicitly distinguishes descriptive theoretical frameworks from causal explanation.