

Dependent Origination and Artificial Intelligence: Rethinking Causality in Complex Systems

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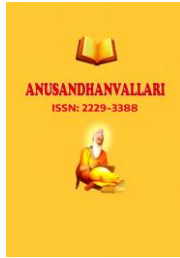
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Abstract: Artificial Intelligence (AI) represents one of the most complex technological achievements of the modern era. Its functioning and evolution, however, cannot be adequately explained by simplistic linear models of causation. Instead, AI systems emerge, adapt, and operate within vast webs of interdependent conditions technical, social, cultural, and ecological. This paper explores the Buddhist concept of Pratītyasamutpāda (Dependent Origination) as a conceptual framework to rethink causality in AI systems. By drawing parallels between Buddhist philosophy and contemporary complexity science, the study illustrates how AI emerges not as an isolated artifact but as the contingent outcome of multiple relational processes. The analysis redefines agency, ethics, and responsibility in AI, offering a non-linear, interdependent account of causality that challenges both deterministic and reductionist paradigms.

Keywords: Artificial Intelligence; Dependent Origination; Pratītyasamutpāda; Complexity Theory; Interdependence; Technological Ethics; Relational Causality; Emergence; Buddhist Philosophy; Non-linear Systems.

1. Introduction

Across both philosophy and science, causality is undergoing a conceptual shift from linear, atomistic relations toward interdependent, multiscale, and nonlinear structures characteristic of complex systems (Hoel, 2025). In artificial intelligence, especially in machine learning and data-centric pipelines, causal influence is distributed across data generation processes, model architecture, training dynamics, deployment environments, and human-in-the-loop governance, complicating straightforward causal attribution and accountability (Papagiannidis, Mikalef, & Conboy, 2025). Contemporary research in causal discovery, explainable AI (XAI), and information-theoretic measures highlights how statistical associations can obscure or distort underlying causal mechanisms, especially in high-dimensional, feedback-rich, and nonstationary domains (Rawal, Raglin, Rawat, Sadler, & McCoy, 2025). These developments resonate with a much older analysis: the Buddhist doctrine of dependent origination (pratītyasamutpāda), which holds that phenomena arise in dependence upon multiple causes and conditions, denying isolated essences and emphasizing conditional co-arising (). While the metaphysical and soteriological aims of Buddhist thought differ from those of scientific inquiry, its account of conditioned genesis offers a conceptual framework that is strikingly pertinent to the causal entanglements of contemporary AI systems (Encyclopedia of Buddhism, 2024). This paper brings these traditions into dialogue. First, it explicates dependent origination in classical Buddhist contexts, including the twelve links (nidānas) as a canonical illustration of interdependent conditional relations (Encyclopedia of Buddhism, 2024; Gokhale, Pradeep, 2007). Second, it surveys causality in complexity science and AI, drawing on machine learning-based causal inference, multiscale emergence, and information-theoretic causality. Third, it analyzes AI as a dependent arising, sociotechnical system, highlighting interdependence, nonlinearity, and emergent behavior across development, deployment, and governance (Boge & Mosig, 2025). The paper then develops parallels and contrasts between Buddhist causality and complexity-informed AI causality, and draws ethical and governance implications for transparency,



responsibility, and risk management in an interdependent ecosystem (Radanliev, 2025). It concludes by outlining challenges and future directions, including integrating multiscale causal modeling, context-sensitive governance, and ethically grounded design practices for robust, trustworthy AI in complex environments.

2. Dependent Origination

2.1 Definition and Classical Sources

Dependent Origination (Pratītyasamutpāda) is one of the foundational doctrines of Buddhist philosophy. It states that all phenomena arise in dependence upon causes and conditions: “When this is, that is; this arising, that arises. When this is not, that is not; this ceasing, that ceases.” (Saṃyutta Nikāya, II.28). This principle denies both eternalism (things existing independently and permanently) and nihilism (things existing without causal continuity). Instead, phenomena exist relationally, contingently, and dynamically.

2.2 The Twelve Links

In its canonical form, dependent origination is often represented through the twelvefold chain (dvādaśāṅga-pratītyasamutpāda), which explains the arising of suffering through interconnected links such as ignorance, formations, consciousness, and craving. Although traditionally applied to human existence and suffering, this model exemplifies how causal processes are cyclical, recursive, and systemic rather than linear.

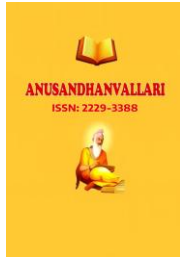
2.3 Dependent Origination: A Systems Perspective

Contemporary scholarship emphasizes that links arise from multiple conditions, so disrupting certain factors (e.g., weakening ignorance through insight) can prevent downstream links, highlighting conditionality, context, and nonlinearity. The doctrine is largely anti-essentialist: phenomena lack inherent self-nature (svabhāva) because they depend on conditions, a view with both metaphysical and practical import. Rather than fatalism, dependent origination stresses malleability—modifying causal contexts can change outcomes. For this discussion, three aspects stand out: causal interdependence across conditions; cyclic, feedback-sensitive dynamics; and the ethical importance of transforming conditions to alleviate suffering (Hershock, P. D. 2025). These ideas illuminate the emergent, distributed nature of causation in AI systems while discouraging simplistic linear attributions of responsibility or effect.

3. Causality in Artificial Intelligence

3.1 Causality: A Systems Perspective

Complexity science views causality as distributed across scales, involving feedback, path dependence, and emergent properties beyond micro-level descriptions (Hoel, 2025). Research on causal emergence shows macroscale descriptions can add unique causal insight. Information-theoretic tools capture directional flow and nonlinear dependencies overlooked by linear models; transfer entropy detects causal signals where linear Granger causality fails. This multiscale view aids AI interpretability and safety: causal structures span network layers, training, and deployment contexts, requiring complementary analyses. Nonparametric estimators for multivariate time series further detect complex, context-sensitive interactions without rigid models. Together, these methods support a pragmatic stance: causality is multilevel, nonlinear, and context-dependent, resonating with Buddhist conditionality, which holds that altering conditions within a causal nexus shifts outcomes (Encyclopedia of Buddhism, 2024).



3.2 Artificial Intelligence as a Dependent Arising System

AI model trajectories are highly sensitive to conditional factors such as data protocols, pretraining objectives, and hardware constraints, where minor changes can create major downstream effects (Canpolat Şahin & Kolukisa Tarhan, 2025). In high-stakes domains like biomedicine, causal explanations support robustness and trustworthiness, as predictive accuracy alone is insufficient. Governance frameworks emphasize distributed responsibility across developers, deployers, and regulators.

3.3 Interdependence in AI

AI operates through interlinked technical, human, socio-economic, and ecological layers, mirroring Buddhist dependent origination (*pratītyasamutpāda*). Tools depend on data and hardware; people shape and are shaped by systems; markets and policies create incentives; and all rely on finite energy and materials.

1. Human: Developers, trainers, and users embed values through data choices, labeling, and objectives; use patterns and governance reshape incentives over time.
2. Socio-economic: Funding, markets, and politics set agendas, influencing inequality, labor, and sectoral power. Political incentives shape regulation and public discourse.
3. Ecological: AI expansion increases electricity demand, stresses grids, consumes water, and generates e-waste, requiring efficiency and clean energy strategies.

AI thus exemplifies dependent origination: nothing exists independently; outcomes track conditions. Changing design, governance, incentives, or energy sources reconditions system behavior and impacts.

4. Parallels and Contrasts

The intersection of Buddhist dependent origination and complexity-informed AI causality reveals both striking conceptual alignments and fundamental philosophical differences. Examining these parallels and contrasts illuminates potential pathways for integrating contemplative wisdom with contemporary AI governance and causal analysis.

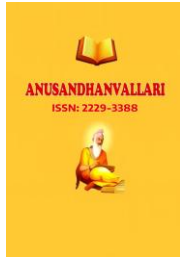
4.1 Parallels

Buddhist dependent origination and complexity-informed AI causality share fundamental conceptual frameworks that challenge linear causation models. Both emphasize interdependence, conditionality, and context sensitivity as core principles for understanding how phenomena emerge. The parallels between Buddhist dependent origination and complexity-informed AI causality include interdependence, conditionality, and context sensitivity: phenomena (including model behaviors) emerge from multiple causes and conditions rather than isolated essences or single-factor explanations. Both frameworks caution against linear, one-cause-one-effect stories in favor of configurations where feedback, cycles, and multiscale structures matter, consistent with causal emergence and information-theoretic accounts in complex systems (Hoel, 2025).

In both cases, interventions can occur at multiple points: countering ignorance with insight or altering incentive structures and data governance to prevent harmful patterns from crystallizing.

4.2 Contrasts

Important contrasts remain: Buddhist thought is normatively and stereologically oriented toward the cessation of suffering and grounded in a metaphysical critique of inherent self-nature, while scientific causal modeling typically brackets metaphysical commitments and centers predictive and explanatory adequacy. Finally, the



Buddhist denial of intrinsic essences can be read as a caution against reifying models or metrics as possessing fixed meaning across contexts; by contrast, formal causal frameworks may treat variables as stable across interventions, even when sociotechnical realities undermine such stability.

These differences suggest complementarity: Buddhist conditionality can enrich critical reflection on the limits of formal models and the ethical stakes of interventions, while causal methods provide operational tools to analyze and act within complex AI systems. These contrasts underscore complementarity: a Buddhist-informed lens can enrich governance with ethically oriented conditional analysis, while causal methods sharpen practical tools for identifying and altering harmful conditions in AI ecosystems.

5. Mapping Dependent Origination onto AI Systems

5.1 Ignorance and Data Bias

In Buddhist thought, ignorance (avidyā) is the root that initiates the cycle of dependent origination, leading to distorted perceptions and suffering. In the realm of artificial intelligence, a parallel can be drawn with hidden biases embedded within datasets and developer assumptions. Data collected from human activities often reflects societal prejudices racial, gender-based, or socio-economic which then influence algorithmic decisions (Obermeyer, 2019). This “ignorance” is not merely an absence of information but a structured oversight, where unexamined biases propagate through training and perpetuate unjust outcomes.

5.2 Conditioned Formation and Algorithmic Architecture

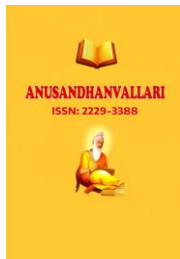
The second link in dependent origination, saṃskāra (formations), refers to conditioned mental constructs shaped by ignorance. Similarly, AI algorithms are constructed upon pre-existing computational paradigms, mathematical models, and systemic priorities (A. Arora et al.2023) . These architectures are not neutral; they encode the formative intentions, cultural assumptions, and design limitations of their creators. Just as formations set the stage for subsequent links in the Buddhist cycle, algorithmic architectures condition the range of possible outputs and ethical consequences.

5.3 Consciousness and Machine Learning Models

Vijñāna (consciousness) in Buddhism emerges in dependence upon conditions, marking the arising of awareness. While AI does not possess subjective consciousness, machine learning models represent a form of conditioned recognition. They "awaken" to patterns only insofar as they are trained upon structured inputs and iterative refinements. Their seeming “intelligence” is a contingent property, arising from data flows, parameter tuning, and continual feedback not from any intrinsic selfhood.

5.4 The Web of Interdependence

Dependent origination emphasizes that no phenomenon exists in isolation; each link is interwoven with others. AI systems, likewise, are products of a web of interdependence: datasets, hardware infrastructures, developer intentions, regulatory landscapes, and socio-political pressures (Hershock, 2021). An algorithm cannot be meaningfully assessed apart from the ecosystems in which it operates. Recognizing this networked causality challenges reductionist narratives that attribute AI outcomes solely to “technology,” instead framing them as emergent from interconnected human and non-human conditions.



6. Ethical Responsibility in Artificial Intelligence

Ethical responsibility in AI, viewed through dependent origination, is a distributed practice aimed at reducing harm, rejecting false autonomy attributions, and fostering compassion across sociotechnical networks for fair and sustainable outcomes.

6.1 Responsibility as Distributed

Dependent origination frames AI outcomes as products of interdependent causes data, design, deployment, and institutional incentives so accountability must span developers, deployers, users, regulators, and infrastructures, not a single actor. Governance should embed this interdependence via transparent data lineage, risk controls, human oversight, participatory feedback, and adaptive supervision for emergent risks. Contemporary regulations like the EU AI Act create layered oversight (AI Office, national authorities, EU database for high-risk systems), embedding accountability in conformity assessments, transparency, and post-market monitoring across the AI lifecycle (Mökander et al. 2022). A Buddhist lens emphasizes conditional responsibility: altering incentives and data practices upstream shifts harm profiles downstream, aligning ethical leverage with systemic points rather than end-stage blame. In practice, this includes co-design with affected groups, audit trails linking harms to causes, shared incident reporting, and escalation paths binding executives to technical governance.

6.2 Avoiding the Illusion of Autonomy

Buddhist thought warns against reifying independent selves; similarly, portraying AI as autonomous obscures human choices shaping its outputs, fostering anthropomorphism and diluting accountability. AI should be seen as moral objects toward which humans have duties not moral subjects with conscience or suffering. Thus, obligations rest on designers, sponsors, and operators. Governance requires transparency and human oversight for high-risk uses, ensuring decisions (e.g., credit, health) remain reviewable by qualified humans. Labelling AI interactions and synthetic media, as modern regulations mandate, reduces false agency attributions by clarifying system boundaries, enabling informed consent and contestability (Wittenberg et al. 2024). A middle-way approach avoids extremes of techno-utopianism and techno-fatalism, centering interdependence and preserving human deliberation.

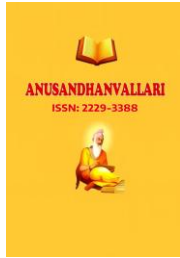
6.3 Compassion and Non-Harm

Compassion (*karuṇā*) and non-harm (*ahiṃsā*) guide AI design and policy toward reducing suffering for individuals, communities, and ecosystems, extending “safety” beyond technical robustness to include justice and sustainability. Practically, this means mindful data practices (*sati*) limiting collection, ensuring transparency, and anticipating downstream effects and context-sensitive measures (*upāya*) for vulnerable groups. Inclusive governance emphasizes participation of historically marginalized communities, aligning with global multi-stakeholder trust-building efforts. Ecological non-harm calls for lifecycle assessments, efficient procurement, and governance favoring sufficiency over scale, integrating sustainability into conformity assessments and monitoring (Stogiannos et al. 2023). Commitments include pre-deployment harm forecasting, red teaming for social and ecological risks, grievance channels, and continuous oversight that evolves with systems and societies, turning the ethical aim of reducing suffering into active institutional practice.

7. Dependent Origination and Complexity Science

7.1 Parallels with Systems Theory

Complexity science investigates how systems composed of many interacting elements produce emergent behaviors that are often non-linear and difficult to predict. This perspective closely mirrors the Buddhist concept



of dependent origination (pratītyasamutpāda), which asserts that phenomena arise only in dependence on multiple conditions. Just as in complex systems, where small changes in one part can ripple through and alter the whole, dependent origination emphasizes that no phenomenon exists independently every effect is contingent on a network of causes and conditions (Preece, 2025). In the context of artificial intelligence, this analogy becomes particularly salient: AI systems display behaviors that emerge from intricate interactions among algorithms, data, and environmental inputs. These behaviors cannot be fully anticipated by examining individual components in isolation, underscoring the system-wide interdependence central to both complexity science and Buddhist philosophy.

7.2 Buddhist Contribution to Complexity Studies

While complexity science traditionally analyzes systems in descriptive or mechanistic terms, Buddhist philosophy contributes a normative and ethical perspective. Dependent origination not only describes how phenomena arise interdependently but also encourages reflection on the consequences of these interconnections. For instance, in socio-technical AI systems, decisions made by algorithms can have cascading effects on social, economic, and ethical domains. By integrating Buddhist insights, researchers and practitioners are reminded to consider the moral dimensions of emergent behaviors, ensuring that the design and deployment of AI systems are guided by ethical awareness of interconnected outcomes (Yan, Y. 2024).

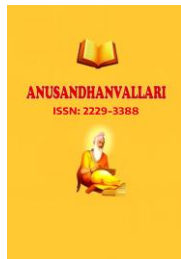
7.3 Toward a New Paradigm

The convergence of dependent origination and complexity science suggests a shift from linear, deterministic models of causality toward a relational, multiscale understanding. In AI, this paradigm encourages moving beyond simple cause-effect frameworks to approaches that recognize dynamic interdependencies, context-sensitive interventions, and emergent properties. Such a perspective not only improves our capacity to model and predict AI behaviors but also provides a conceptual foundation for responsible AI governance, where interventions are evaluated with attention to both system-wide effects and ethical implications.

8. Challenges and Future Directions

A conditional, multiscale view of AI causality faces several challenges. First, identifying stable variables and interventions in sociotechnical systems is difficult, as constructs are often context-dependent and may shift under intervention, challenging standard causal inference assumptions (Cobey & Baskerville, 2016). Second, multiscale causal emergence methods involve combinatorial complexity and demand principled ways to attribute causal contributions across scales, though recent axiomatic approaches show promise for more tractable heuristics. Third, aligning causal methods with governance remains inconsistent: advances in causal-XAI must pair with enforceable institutional practices and regulatory frameworks to have real impact. Future research should focus on four directions:

- (1) Developing multiscale causal diagnostics for AI auditing, identifying where macroscale governance offers unique control beyond microscale code-level fixes.
- (2) Advancing information-theoretic and nonparametric tools to monitor emergent risks and feedback during deployment.
- (3) Embedding stakeholder-informed, adaptive governance that treats ethics as a continual, context-sensitive process rather than static compliance.
- (4) Examining cross-cultural ethical models such as Buddhist conditionality that emphasize transforming conditions to reduce harm, integrating normative clarity with causal techniques.



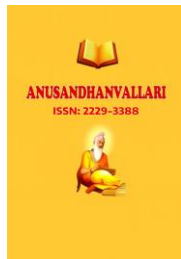
Such approaches can link interdependence insights with practical interventions to enhance AI safety, fairness, and robustness in complex sociotechnical systems.

9. Conclusion

Reframing AI through dependent origination clarifies that system behaviors are not intrinsic to models but arise from interdependent causes and conditions across data, design, deployment, and governance. This aligns with complexity-informed causality in which emergent properties and multiscale structures possess unique causal efficacy, best addressed through plural methods and adaptive oversight (Hoel, 2025). By combining Buddhist insights on conditionality and the ethical aim of alleviating suffering with formal causal and information-theoretic tools, practitioners and policymakers can better identify leverage points, distribute accountability, and design interventions that modify conditions to prevent harm (Keskin & Aste, 2020). The result is a more interdependent and nonlinear account of causality for AI, coupled with a more responsible approach to governance that can evolve with complex environments. Such integration does not conflate distinct traditions; rather, it enriches both, offering conceptual clarity and practical guidance for steering AI in an interconnected world (Encyclopedia of Buddhism, 2024).

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