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The Hidden Cost of Acceleration: A Conceptual Analysis of Time Compression in AI-Driven Materials Research

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Abstract

The integration of artificial intelligence (AI) into materials research has dramatically accelerated discovery processes, enabling rapid screening, prediction, and optimization of material properties through machine learning algorithms and data-driven simulations. This conceptual analysis examines the phenomenon of time compression in AI-driven workflows, where temporal efficiencies reshape research dynamics, often at the expense of deeper interpretive insights and systemic interactions. By synthesizing recent literature, the paper explores how accelerated paces influence epistemic structures, potentially diminishing opportunities for serendipitous findings and fostering over-reliance on algorithmic outputs. Conceptual interpretations reveal trade-offs in knowledge generation, where speed enhances productivity but compresses reflective cycles essential for robust understanding. Systems-level insights highlight feedback mechanisms between AI tools and human expertise, underscoring risks of narrowed exploration spaces and ethical concerns related to data biases and resource inequities. The proposed framework integrates these dynamics, offering interpretive lenses for balancing acceleration with sustainable research practices. This work contributes to applied AI in materials science by emphasizing interpretive and integrative reasoning over predictive claims and advocating mindful navigation of time compression to preserve the integrity of scientific inquiry in an era of rapid technological advancement.

Keywords Knowledge dynamics, Epistemic risks, Conceptual frameworks, AI in materials science, Time compression, Research acceleration

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Introduction

The advent of artificial intelligence (AI) has profoundly transformed materials research, shifting paradigms from traditional trial-and-error methods to sophisticated data-driven approaches that leverage vast datasets and computational power. In recent years, AI techniques such as machine learning (ML) and deep learning have enabled the prediction of material properties, inverse design of structures, and high-throughput screening, thereby expediting the identification of novel compounds with tailored functionalities [1, 2]. For instance, generative models have enabled the exploration of chemical spaces far beyond human capacity, identifying stable inorganic materials and optimizing alloys for specific applications such as energy storage and catalysis [3, 4]. This acceleration aligns with broader trends in scientific innovation, where computational tools integrate with experimental workflows to reduce development timelines from decades to months, fostering advancements in sustainable technologies such as advanced batteries and nanomaterials [5].

Yet, this surge in velocity introduces subtle yet significant alterations to the fabric of research practices. Time compression, defined here as the condensation of investigative phases through AI-mediated efficiencies, alters the temporal rhythms of inquiry. Traditional materials research often involved extended periods of iteration, allowing for reflective synthesis and unexpected insights during synthesis or characterization stages. In contrast, AI-driven pipelines compress these intervals, prioritizing rapid outputs over prolonged deliberation [6]. This shift raises interpretive questions about how such compression influences the depth of conceptual understanding and the interplay between human intuition and algorithmic logic. For example, while AI excels at pattern recognition in large datasets, it may overlook nuanced contextual factors that human researchers integrate through experiential knowledge, potentially leading to streamlined but superficial interpretations [7].

The motivation for this analysis stems from the growing recognition that acceleration, while beneficial, carries hidden costs that manifest in epistemic and ethical domains. Epistemic costs arise from altered knowledge-production dynamics, in which compressed timelines may constrain exploration of alternative pathways or interdisciplinary connections, fostering convergence toward data-optimized solutions at the expense of broader systemic insights [8]. Ethical dimensions emerge as inequities, as access to high-quality datasets and computational resources favors well-resourced institutions, exacerbating global disparities in materials innovation [9]. Recent studies highlight how AI integration amplifies these issues, with biases in training data perpetuating representational harms in material predictions, particularly in underrepresented chemical compositions [10].

This paper adopts a purely conceptual lens to unpack these implications, drawing on interpretive reasoning to elucidate interaction dynamics within AI-enhanced research ecosystems. By focusing on systems-level insights, it reveals feedback structures where acceleration reinforces certain logics—such as efficiency-driven metrics—while marginalizing others, like ethical reflexivity or epistemic diversity. The analysis avoids empirical validations, instead emphasizing conceptual integrations that bridge literature on AI applications with philosophical considerations of time in science [11]. In doing so, it contributes to the discourse on applied AI in materials science, where the allure of speed must be balanced with the integrity of knowledge formation.

Historically, materials science has evolved through waves of technological integration, from computational simulations in the 1990s to the Materials Genome Initiative's emphasis on data infrastructures in the 2010s [12]. The current AI era builds on this foundation, with frameworks such as integrated computational materials engineering (ICME) incorporating ML to simulate multiscale phenomena [13]. However, the acceleration afforded by AI introduces novel trade-offs. For instance, autonomous laboratories powered by AI can perform thousands of experiments iteratively. Still, this rapidity may compress the interpretive space for human oversight, leading to overlooked anomalies that could spark innovative breakthroughs [14].

Conceptual interpretations of time compression draw from broader scholarly reflections on technological acceleration in science. In materials research, time serves not merely as a resource but as a structuring element that enables the maturation of ideas through iterative cycles of hypothesis refinement and validation [15]. AI disrupts this by automating decision points, shifting the locus of agency from researchers to algorithms, and altering the ethical stewardship of knowledge [16]. This raises questions about accountability, as opaque AI models may embed unexamined assumptions into material designs, affecting downstream applications in critical sectors such as healthcare and energy [17].

Systems-level insights further illuminate these dynamics, portraying AI-driven research as an interconnected network where acceleration creates reinforcing loops. High-speed predictions encourage reliance on existing datasets, potentially entrenching biases and limiting ventures into uncharted material spaces [18]. Ethical reasoning underscores the need for inclusive data practices to mitigate such loops, ensuring that acceleration benefits diverse stakeholders rather than perpetuating epistemic silos [19].

This introduction sets the groundwork for a deeper synthesis of theoretical backgrounds, followed by a proposed conceptual framework that integrates these elements. By examining time compression through interpretive and integrative lenses, the paper invites reflection on how materials research can harness AI's potential while safeguarding the richness of scientific inquiry.

Theoretical Background and Literature Synthesis

AI applications in materials discovery

The application of artificial intelligence in materials science has expanded rapidly over the past decade, with machine learning models emerging as foundational tools for property prediction, materials screening, and design optimization. Recent methodological advances include graph neural networks that encode atomic structures as relational graphs, enabling accurate prediction of electronic, mechanical, and catalytic properties across diverse material classes [20]. When coupled with high-throughput computational pipelines, these models facilitate the rapid screening of extensive compositional spaces, accelerating candidate identification for applications such as photovoltaics, hydrogen storage, and functional coatings [21].

Beyond predictive modeling, generative approaches have further extended AI's role, moving it from evaluation to creative exploration. Generative adversarial networks and related architectures have been deployed to synthesize novel molecular and crystalline structures, blending learned chemical priors with algorithmic exploration to traverse previously inaccessible regions of materials space [22]. Collectively, these developments signal a shift toward hybrid discovery workflows in which AI systems absorb data-intensive analytical burdens, allowing human researchers to focus on interpretive synthesis, hypothesis formation, and strategic decision-making.

The literature consistently emphasizes the capacity of AI-augmented workflows to compress discovery cycles by reducing reliance on exhaustive trial-and-error [23]. However, this efficiency gain introduces interpretive challenges. AI outputs often require contextual decoding to ensure alignment with domain-specific constraints, theoretical assumptions, and experimental realities. As such, the literature increasingly highlights the interplay between computational speed and human discernment, positioning interpretation—not just prediction accuracy—alone as a central bottleneck in AI-driven materials research [24].

The phenomenon of time compression

Time compression emerges as a defining dynamic of AI-enabled materials research, fundamentally altering the temporal structure of experimentation, analysis, and validation. In traditional materials workflows, extended time horizons enabled layered interpretation, where preliminary observations informed successive refinements through iterative experimental feedback [25]. AI disrupts this temporal rhythm by enabling near-instantaneous simulations, including surrogate-based predictions of phase stability, mechanical response, and structure–property relationships [26].

While such compression markedly enhances productivity, it simultaneously reshapes interaction dynamics within research teams. Rapid iteration cycles tend to prioritize quantifiable, immediately optimizable metrics, potentially at the expense of qualitative insights that require prolonged observation or interpretive deliberation [27]. Conceptual analyses indicate that accelerated paces encourage data-centric decision-making, reducing tolerance for exploratory deviations that may yield unanticipated synergies or conceptual breakthroughs [28].

At the systems level, time compression operates as a reinforcing feedback structure. The speed of AI-mediated inference strengthens optimization-focused trajectories, producing path dependencies that progressively narrow investigative scope and methodological diversity [29]. Ethical reasoning adds further nuance, noting that compressed timelines can intensify cognitive and institutional pressures, increasing the likelihood that long-term considerations—such as environmental sustainability or lifecycle impacts of material production—are overlooked in favor of short-term performance gains [30].

Epistemic implications of accelerated discovery

AI-induced acceleration profoundly affects the epistemic foundations of materials research. Historically, knowledge generation relied on cumulative interpretation across temporal scales, allowing disparate experimental observations to be integrated into coherent explanatory frameworks [31]. Time compression disrupts this process by privileging predictive efficiency and rapid convergence, potentially fragmenting epistemic coherence [32].

Machine learning models trained on historical datasets may reinforce dominant paradigms, reproducing established assumptions while limiting exposure to anomalous or paradigm-challenging phenomena [33]. Interpretive analyses thus reveal a trade-off between epistemic breadth and depth. While acceleration expands the volume of accessible data, it compresses the reflective space required for conceptual integration and theoretical abstraction [34]. To synthesize these dynamics, **Table 1** summarizes the principal dimensions of time compression in AI-driven materials research, highlighting how accelerated workflows reshape temporal steering, epistemic practices, and ethical deliberation.

Table 1. Dimensions of time compression in AI-driven materials research

Dimension	Description	Primary effect of acceleration	Epistemic risk
Temporal steering logics	AI-mediated prioritization of short-cycle evaluations	Rapid convergence toward efficiency-optimized solutions	Marginalization of slow-emerging material phenomena
Iteration compression	Reduction of time between prediction, validation, and retraining	Increased throughput and optimization speed	Reduced reflective synthesis and anomaly recognition
Dataset reinforcement	Reuse of existing data under accelerated cycles	Stability of predictions within known regimes	Entrenchment of dominant paradigms
Human–AI interaction	Shift of interpretive authority toward algorithmic outputs	Lower cognitive load for routine tasks	Diminished human epistemic agency
Ethical temporal compression	Shortened deliberation and governance cycles	Faster deployment of innovations	Overlooked long-term societal and environmental impacts

Systems-level perspectives further identify feedback loops in which over-reliance on algorithmic outputs diminishes human epistemic agency, subtly recalibrating the balance between intuitive reasoning and computational authority [35]. Ethical dimensions intersect here, as unequal access to advanced AI tools introduces epistemic asymmetries, shaping whose interpretations gain prominence and whose material priorities are foregrounded in innovation trajectories [36].

Ethical and societal dimensions

Ethical considerations in AI-driven materials research extend beyond technical performance to encompass broader societal and distributive consequences. Acceleration through AI raises concerns regarding data stewardship, particularly when biases embedded in training datasets propagate inequities in downstream applications, including biomedical and environmental materials [37]. Time compression intensifies these risks, as expedited workflows may curtail opportunities for ethical vetting and long-term impact assessment [38].

Conceptual interpretations frame this challenge as an interaction between technological speed and societal values. Speed-driven research logics may undervalue delayed or diffuse ethical costs, such as the environmental footprint of large-scale computational modeling or the deployment of resource-intensive materials [39]. Systems-level analyses further reveal reinforcing structures in which accelerated discovery incentivizes proprietary data silos, limiting collaborative knowledge exchange and constraining collective epistemic progress [40].

Reasoning grounded in epistemic justice underscores the need for inclusive governance frameworks that address global disparities in AI access and interpretive authority. Such frameworks are essential to ensuring that acceleration in materials research serves diverse societal needs rather than entrenching existing inequalities [41].

Proposed conceptual framework

The proposed framework conceptualizes time compression in AI-driven materials research as a multifaceted systemic dynamic that integrates the benefits of acceleration with its interpretive, epistemic, and ethical costs. Rather than treating acceleration as a linear increase in efficiency, the framework adopts a systems-level perspective, viewing research as an interconnected ecosystem of data generation, model inference, experimental validation, and human interpretation. Within this ecosystem, AI functions as a catalytic force that reshapes temporal flows and interaction patterns, altering how knowledge emerges from human–algorithm–data relations. Time compression is thus interpreted as a compressive force that restructures feedback mechanisms, rather than a neutral byproduct of computational speed.

Four analytically distinct but interdependent elements organize the framework. First, temporal steering logics describe how AI's rapid processing capabilities orient research workflows toward efficiency-optimized trajectories. Accelerated screening and prediction pipelines preferentially direct attention toward parameters and material candidates that align with short-cycle evaluation, potentially creating bottlenecks in exploratory branches that require longer temporal horizons. Second, epistemic trade-offs capture the tension between speed-enhanced productivity and diminished interpretive depth. As iteration cycles compress, opportunities for conceptual maturation, theoretical integration, and reflective synthesis are constrained, increasing the risk that knowledge production becomes fragmented or overly optimization-driven.

Third, ethical feedback mechanisms address how acceleration amplifies existing biases and inequities embedded within data, models, and institutional infrastructures. In the absence of reflexive intervention, time compression intensifies these feedbacks, allowing skewed representations or exclusionary practices to propagate more rapidly through research pipelines. Fourth, dynamic resilience emphasizes the importance of adaptive system architectures that support periodic decompression. Such structures enable deliberate slowing at critical junctures, fostering epistemic diversity, serendipitous discovery, and holistic understanding without abandoning the advantages of AI-enabled speed.

Central to the framework is the interpretation of AI not as a standalone analytical instrument, but as an embedded component of a broader research system. Time compression manifests through reinforcing loops in which rapid predictions feed into accelerated validations and dataset updates, progressively narrowing investigative focus while increasing the risk of epistemic silos. Systems-level analysis identifies leverage points within these loops, particularly hybrid human–AI interfaces that introduce intentional pauses for interpretive synthesis. These pauses function as epistemic safeguards, preserving multiple knowledge pathways and mitigating premature convergence. Ethical reasoning is integrated by emphasizing inclusive data practices and governance mechanisms that counteract compression-induced exclusions and asymmetries in epistemic authority. **Table 2** maps the core components of the proposed conceptual framework to their associated reinforcing mechanisms and potential intervention leverage points, clarifying how time compression can be actively governed rather than passively endured.

Table 2. Framework components and intervention leverage points

Framework component	Core challenge	Reinforcing mechanism	Potential intervention
Temporal steering logics	Over-optimization toward short-term metrics	Efficiency feedback loops	Diversified evaluation horizons
Epistemic trade-offs	Loss of interpretive depth	Rapid convergence and path dependence	Structured decompression phases

Ethical feedback mechanisms	Bias amplification and inequity	Accelerated propagation of skewed data	Inclusive data governance
Dynamic resilience	Reduced adaptability to uncertainty	Narrowed exploration spaces	Hybrid human–AI interfaces
Systems integration	Fragmented oversight	Isolated optimization pipelines	Embedded ethical checkpoints

As illustrated in **Figure 1**, the framework conceptualizes AI acceleration as a system of three interdependent loops—efficiency, epistemic, and ethical—interacting around a shared core to capture the reinforcing and moderating dynamics of rapid innovation in materials research.

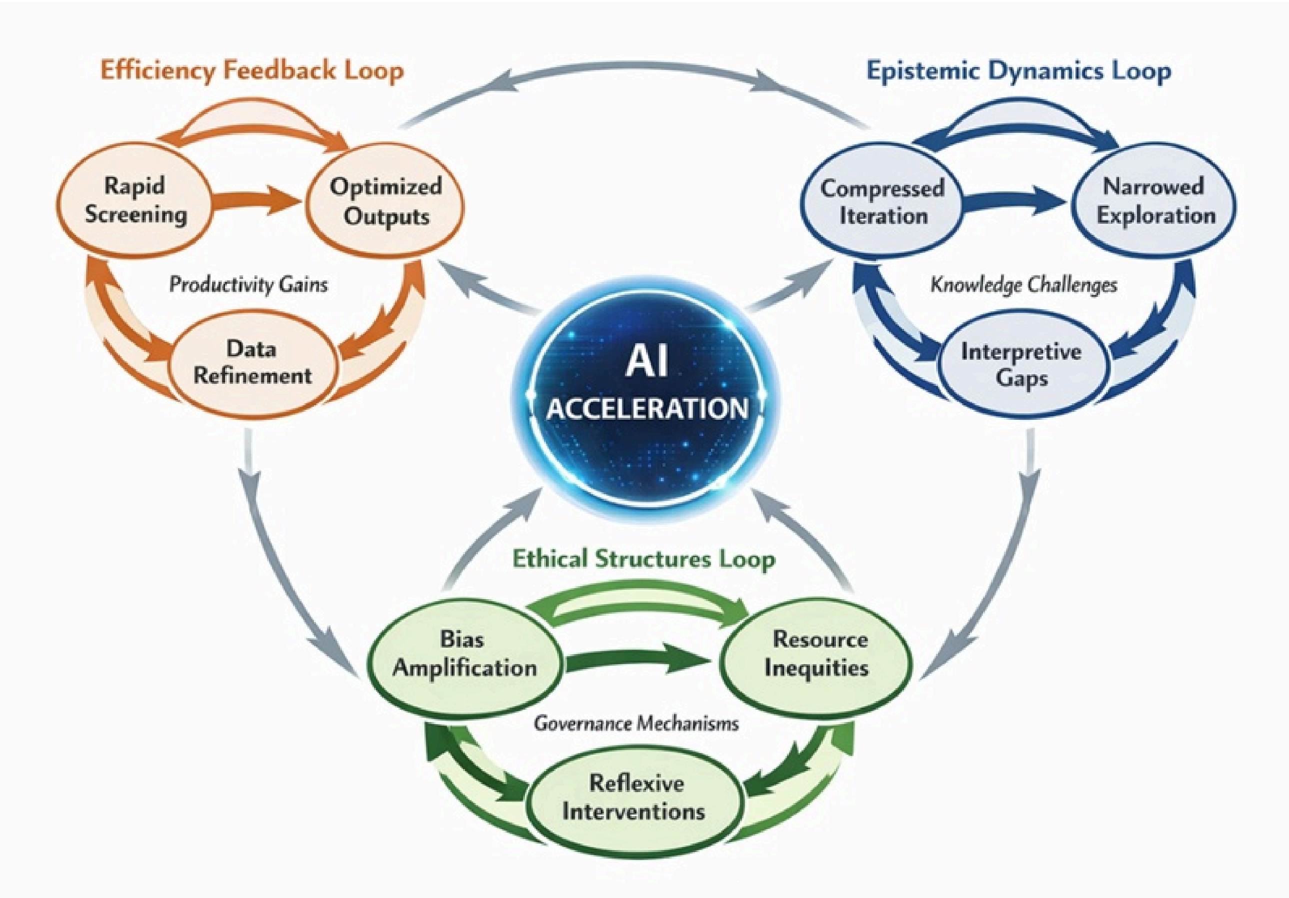

Figure 1. Conceptual framework illustrating the cyclical dynamics of AI acceleration in materials research.

Taken together, this framework offers an interpretive tool for diagnosing how time compression propagates through AI-driven materials research. By foregrounding interaction dynamics rather than isolated performance metrics, it enables researchers to identify points of intervention where acceleration can be modulated, ensuring that the pursuit of speed enhances rather than undermines epistemic robustness, ethical integrity, and long-term scientific value.

Analytical implications

1. Acceleration as structural reconfiguration rather than efficiency gain

The conceptual framework articulated earlier positions time compression not as a simple improvement in operational efficiency, but as a structural transformation of interaction dynamics within AI-driven materials research. Analytical implications arise most clearly when acceleration is examined as a reconfiguration of how computational predictions, experimental validations, and human judgment co-evolve. Accelerated AI screening pipelines generate tight efficiency feedback loops in which rapid predictions inform successive cycles of model retraining and candidate selection. While these loops substantially increase throughput, they simultaneously introduce steering effects that privilege readily optimizable descriptors, stable feature representations, and short-horizon performance metrics [4, 13].

Such steering biases can marginalize material behaviors that unfold over longer temporal scales, including slow phase transformations, degradation mechanisms, or kinetically constrained phenomena. The analytical implication is that acceleration subtly reshapes what counts as discoverable knowledge. Materials properties that resist rapid evaluation become structurally disadvantaged, not because of scientific irrelevance, but because they misalign with compressed computational–experimental tempos. Time compression, therefore, functions as an epistemic filter, selectively amplifying certain forms of material knowledge while attenuating others.

2. Redistribution of epistemic capacity through resource intensification

From a resource perspective, time compression systematically reorders investment priorities across materials research ecosystems. Compressed discovery cycles require sustained computational availability, scalable data infrastructure, and frequent model retraining to maintain predictive relevance. These demands disproportionately advantage institutions with access to high-performance computing, curated datasets, and technical personnel, while constraining participation by smaller laboratories or under-resourced research environments [9, 14].

Analytically, this redistribution of epistemic capacity highlights a critical trade-off: acceleration increases aggregate output but simultaneously narrows the pool of actors able to contribute meaningfully to frontier discovery. Rather than democratizing innovation, time compression may inadvertently centralize epistemic authority within a limited set of technologically privileged nodes. Interpreted through this lens, acceleration is not a neutral technological enhancement but a mechanism that reshapes access, influence, and visibility within the materials research landscape.

3. Reinforcement dynamics and the erosion of epistemic resilience

At the systems level, time compression exerts a profound influence on epistemic resilience—the capacity of research ecosystems to absorb uncertainty, adapt to failure, and sustain exploratory diversity. AI models trained predominantly on existing materials datasets tend to extrapolate dominant patterns, reinforcing incremental optimization trajectories rather than enabling disruptive conceptual shifts [1, 8]. As iteration cycles shorten, these reinforcement dynamics intensify, producing path dependencies that favor well-represented materials classes, canonical property regimes, and familiar compositional spaces.

Ethical and epistemic analyses intersect at this juncture. Underrepresentation within training corpora can propagate skewed assumptions regarding stability, feasibility, or performance, particularly for unconventional, emergent, or poorly characterized materials systems [7]. Time compression amplifies these effects by reducing opportunities for corrective exploration or counterfactual testing. The analytical implication is that acceleration may reduce a system's capacity to recognize its own blind spots, thereby undermining long-term scientific adaptability.

4. Decompression phases as epistemic counterbalances

Mitigating the epistemic risks associated with acceleration requires deliberate counterbalancing strategies. Interpretive analysis highlights the importance of hybrid human–AI research architectures that embed intentional "decompression phases" within accelerated workflows. These phases introduce structured pauses for critical reflection, reinterpretation of model outputs, and integration of tacit domain expertise that resists full automation [11, 12].

Rather than opposing acceleration outright, decompression reframes speed as a controllable variable—one that can be selectively relaxed to preserve epistemic diversity and conceptual breadth. Analytically, this positions time compression as a design parameter subject to governance rather than as an inevitable trajectory solely dictated by computational capability.

5. Ethical compression and the governance of responsibility

Ethical implications become especially salient when acceleration compresses deliberative cycles alongside experimental timelines. Rapid prototyping and deployment of materials innovations may curtail reflection on downstream societal and environmental consequences, including lifecycle sustainability, resource externalities, and long-term risk propagation [16]. Conceptually, this creates a tension between short-term innovation velocity and sustained epistemic integrity.

Analytical reasoning, therefore, supports governance approaches that integrate ethical checkpoints directly into AI-driven materials pipelines. Such mechanisms ensure that acceleration does not outpace responsibility, embedding reflexive oversight within the very structures that enable speed [24]. Collectively, these implications underscore the necessity of interpretive frameworks that treat time compression as a systemic force—one that must be actively governed to ensure that acceleration strengthens, rather than erodes, the foundational aims of materials science.

Results and Discussion

The examination of time compression in AI-driven materials research reveals a central paradox: while acceleration amplifies discovery capacity, it simultaneously introduces vulnerabilities within knowledge production and ethical stewardship. Synthesizing across computational, epistemic, and governance perspectives, it becomes evident that AI functions not merely as an analytical tool but as an ecosystem-shaping agent, restructuring feedback loops, incentives, and interpretive norms [3, 10]. Compressed iteration cycles, for example, tend to narrow exploration spaces, privileging trajectories aligned with existing datasets and established performance metrics. This effect echoes broader concerns about acceleration in contemporary science.

Systems-level insights derived from the framework indicate that addressing these vulnerabilities requires integrative design strategies. Modular AI architectures that incorporate intentional pause mechanisms for human-led synthesis offer one promising pathway, enabling researchers to interrogate assumptions, reassess objectives, and redirect exploration before biases become entrenched [13]. Ethical considerations further complicate the landscape, as unequal access to AI infrastructure and high-quality data risks deepening epistemic divides across institutions and regions. Inclusive policies aimed at democratizing data access and lowering technical barriers are therefore essential to sustaining equitable participation in accelerated discovery environments [9, 14].

The conceptual nature of this analysis constitutes a recognized limitation. The framework does not provide empirical quantification of time-compression effects; instead, it prioritizes theoretical coherence and interpretive depth. This limitation is consistent with the paper’s objective of articulating a novel conceptual lens rather than delivering performance benchmarks. Future research may extend this framework into specific subdomains—such as nanomaterials or generative materials design—to refine its applicability and empirically interrogate its propositions [21, 22]. Ultimately, mindful engagement with time compression reframes acceleration not as an inevitability but as a design choice, one that can be governed to transform hidden costs into opportunities for resilient, inclusive, and ethically grounded materials research.

Conclusion

This conceptual analysis has examined time compression as a defining yet under-theorized consequence of AI integration in materials research. While artificial intelligence has undeniably transformed discovery pipelines through unprecedented acceleration, this work demonstrates that speed is not a neutral gain. Instead, time compression operates as a systemic force that reshapes epistemic practices, redistributes interpretive authority, and alters the ethical contours of scientific inquiry. By foregrounding interaction dynamics rather than performance metrics alone, the analysis reveals how acceleration reorganizes the conditions under which material knowledge is produced, validated, and legitimized.

A central contribution of this study lies in reframing acceleration as a structural reconfiguration of research ecosystems. AI-driven workflows compress the iterative cycles of prediction, validation, and refinement, privileging forms of knowledge that support rapid evaluation while marginalizing phenomena that require extended temporal engagement. This compression subtly filters what becomes scientifically visible, favoring optimization-ready properties and well-represented material classes. As a result, the very criteria of discovery shift, not through explicit exclusion, but through temporal misalignment between algorithmic speed and material complexity.

At the epistemic level, the analysis highlights how time compression constrains reflective depth and conceptual maturation. Although accelerated workflows expand data access and predictive reach, they simultaneously reduce opportunities for integrative synthesis, anomaly recognition, and theoretical abstraction. The resulting tension between productivity and understanding underscores a fundamental trade-off in contemporary materials AI: gains in efficiency may come at the expense of epistemic resilience, defined here as the capacity of research systems to adapt to uncertainty, novelty, and failure. Without deliberate intervention, reinforcement dynamics may entrench dominant paradigms and narrow exploratory horizons.

Ethically, the study demonstrates that acceleration amplifies pre-existing inequities embedded in data infrastructures, computational access, and institutional capacity. Compressed timelines intensify this feedback, accelerating the propagation of biases and deepening asymmetries in epistemic authority. In this context, ethical concerns are not external constraints but integral components of accelerated systems, requiring governance mechanisms that operate within AI pipelines rather than alongside them.

The proposed conceptual framework integrates these insights by positioning time compression as a governable design parameter. By articulating temporal steering logics, epistemic trade-offs, ethical feedback mechanisms, and dynamic resilience, the framework offers researchers a structured lens for diagnosing where and how acceleration can be modulated. Importantly, it advances decompression not as resistance to innovation, but as a strategic intervention that preserves epistemic diversity, enables serendipity, and safeguards long-term scientific value.

Looking forward, this work invites a shift in how progress in materials AI is evaluated. Rather than equating success solely with speed or scale, future research should consider temporal balance as a criterion of scientific robustness. By treating time not merely as a resource to be minimized but as a constitutive element of knowledge formation, materials science can harness AI's transformative potential while preserving the integrity, inclusivity, and sustainability of discovery. In an era defined by acceleration, mindful governance of time compression emerges as a prerequisite for responsible and enduring innovation.

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