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Research Article

Human–AI Co-Creation and Creative Agency in Automated Systems

Rakshith Rajeshekar[1]
[1]Jain College, India

*Corresponding Author
Rakshith Rajeshekar

Abstract: The proliferation of artificial intelligence (AI) systems in creative domains has generated substantial debate regarding the nature of authorship, creative agency, and the role of automation in human creative processes. This paper examines the theoretical and empirical landscape of human–AI co-creation, focusing on the tension between automation efficiency and creative complexity. Drawing on computational creativity9 research, human-computer interaction studies, and creative systems design literature, this work presents an automation versus creative-complexity framework to evaluate whether AI systems enhance or suppress human creative agency. Through analysis of mixed-initiative paradigms, enactive models of creativity, and empirical studies of co-creative systems, this paper argues that the distribution of creative control between human and machine significantly determines the quality and originality of collaborative outputs. The findings suggest that while automation can streamline executional tasks, preserving human interpretive authority and exploratory capacity is essential for maintaining creative complexity. This framework offers scholars and practitioners a lens for evaluating AI's role in co-creative environments and designing systems that augment rather than replace human creativity.
Keywords: Human-AI collaboration, computational creativity, creative agency, automation, co-creation, mixed-initiative systems, creative complexity.

1. INTRODUCTION

The integration of artificial intelligence into creative practices has fundamentally altered how artists, designers, musicians, and other creative professionals approach their work. From generative art systems to AI-assisted composition tools, computational systems are increasingly positioned not merely as instruments but as collaborative partners in the creative process (Davis, Hsiao, Popova, & Magerko, 2015; Secretan, 2011). This shift raises critical questions about the nature of creativity itself, the locus of creative agency, and the implications of automation for human authorship and artistic expression. Contemporary discourse in computational creativity and human-computer interaction has identified a fundamental tension: while AI systems can enhance efficiency and generate novel outputs, they may simultaneously constrain human creative agency and reduce the complexity of creative exploration (Liapis & Yannakakis, 2016; Yannakakis, Liapis, & Alexopoulos, 2014). This tension is particularly acute in domains where creative decision-making, interpretive judgment, and aesthetic sensibility are central to the value of the work produced. As Usman (2017) demonstrated in the context of visual effects production, AI-assisted compositing tools can streamline technical workflows while simultaneously altering the nature of creative decision-making processes, raising questions about the preservation of human creative authority.

The automation versus creative-complexity framework proposed in this paper provides a conceptual lens for evaluating the impact of AI systems on human creativity. This framework distinguishes between automation that merely executes predefined tasks (potentially reducing creative complexity) and collaborative systems that preserve or enhance human exploratory capacity and interpretive authority (Kantosalo & Toivonen, 2016). Understanding this distinction is crucial for scholars in computational creativity and creative AI, as it enables more nuanced evaluation of whether specific AI implementations genuinely support co-creation or simply automate creative labor. This paper contributes to the field of computational creativity and human-AI interaction by synthesizing theoretical frameworks, empirical

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evidence, and design principles that illuminate the conditions under which AI systems enhance rather than diminish human creative agency. The analysis proceeds through four main sections: first, a review of theoretical models of human-AI co-creation; second, an examination of the automation versus creative-complexity trade-off; third, an exploration of creative agency and authorship in automated systems; and fourth, a discussion of design implications and evaluation frameworks for co-creative systems.

2. Theoretical Foundations of Human–AI Co-Creation

2.1 Enactive Models of Creativity

The enactive approach to human-AI co-creation conceptualizes computational systems as interactive colleagues rather than passive tools or autonomous generators (Davis, Popova, Sysoev, & Hsiao, 2014). This model, grounded in enactive cognitive science, emphasizes the embodied, situated, and interactive nature of creative cognition. Rather than treating creativity as a purely mental phenomenon that can be replicated through computational processes, the enactive model positions creativity as emerging through dynamic interaction between creator, artifact, and environment. Davis and colleagues (2014) implemented this model in the Drawing Apprentice system, which engages in real-time collaborative sketching with human users. The system does not simply automate drawing tasks or generate complete artworks; instead, it responds to human input, proposes additions, and adapts its behavior based on the evolving creative context. This approach preserves human agency by maintaining the human creator as an active participant in an ongoing creative dialogue rather than relegating them to the role of supervisor or editor of machine-generated outputs. The enactive model has significant implications for understanding creative agency in automated systems. By framing the AI system as a colleague engaged in mutual adaptation and shared meaning-making, this approach resists the reduction of creativity to algorithmic optimization. As Davis, Hsiao, Popova, and Magerko (2015) argue, computational collaboration in creative domains should support improvisation, exploration, and the emergence of unanticipated creative directions rather than constraining creators to predefined solution spaces.

2.2 Mixed-Initiative Paradigms

Mixed-initiative interaction represents another influential theoretical framework for human-AI co-creation, emphasizing the alternation or concurrent distribution of initiative between human and machine (Yannakakis *et al*., 2014). In mixed-initiative systems, both human and AI can propose ideas, make decisions, and guide the creative process, with control flowing dynamically based on the task context and the capabilities of each partner. Yannakakis and colleagues (2014) define mixed-initiative co-creativity as a mode of interaction in which computational systems actively contribute creative ideas while preserving human steering capacity. Their empirical evaluation of the Sentient Sketchbook, a mixed-initiative game design tool, demonstrated that users exhibited greater creative exploration and produced more diverse outputs when the system offered suggestions and alternatives rather than simply executing commands. This finding supports the hypothesis that appropriate computational initiative can enhance rather than constrain human creativity. Liapis and Yannakakis (2016) further developed this framework by examining how human intervention shapes computational creative processes. Their research demonstrates that human guidance can steer generative search toward richer, more contextually meaningful outcomes, countering the tendency of purely automated systems toward generic or formulaic outputs. The mixed-initiative paradigm thus provides a middle path between full automation (which risks eliminating human agency) and purely manual creation (which fails to leverage computational capabilities).

2.3 Search-Based Formalization of Co-Creativity

Kantosalo and Toivonen (2016) offer a formal account of human-computer co-creativity grounded in conceptual space theory and computational search processes. Their framework distinguishes between alternating co-creativity (in which human and machine take turns contributing to the creative work) and task-divided co-creativity (in which different aspects of the creative task are allocated to human and machine). This formalization clarifies how the division of creative labor affects both process and outcome. In alternating modes, humans typically retain greater exploratory control, as they can redirect the creative trajectory after each computational contribution. In task-divided modes, the risk of reductive automation increases if critical interpretive or evaluative functions are delegated entirely to the machine. Kantosalo and Toivonen's (2016) analysis reveals that the structure of collaboration, who does what, when, and how, fundamentally shapes the distribution of creative agency and the complexity of the resulting work. The search-based formalization also highlights the importance of transparency and comprehensibility in co-creative systems. When users understand how the computational partner explores creative possibilities and generates proposals, they are better positioned to guide the collaboration effectively. Conversely, opaque or "black box" systems may undermine human agency by obscuring the basis for computational contributions, making it difficult for users to exercise meaningful creative control (Bown & Bray, 2016).

3. The Automation versus Creative-Complexity Trade-Off

3.1 Efficiency Gains and Agency Costs

A central tension in human-AI co-creation concerns the trade-off between automation efficiency and the preservation of creative complexity. Automation excels at reducing executional friction, accelerating production timelines, and maintaining technical consistency. However, these benefits may come at the cost of reduced human agency, diminished exploratory capacity, and homogenization of creative outputs (Secretan, 2011). Secretan (2011) traces the evolution of creativity support tools from simple assistants to more sophisticated collaborative partners. While early tools focused on automating repetitive tasks, contemporary AI systems increasingly make higher-level creative decisions, such as selecting color palettes, composing musical phrases, or generating narrative structures. This expansion of automation into traditionally human-dominated creative decisions raises questions about the locus of creative authority and the nature of authorship. Usman (2017) provides empirical evidence of this trade-off in the domain of visual effects production. In examining AI-assisted compositing workflows, Usman found that while automation significantly reduced production time and technical complexity, it also altered the nature of creative decision-making. Artists reported feeling less engaged in certain aspects of the creative process and expressed concerns about the homogenization of visual styles when relying heavily on automated tools. This finding illustrates how efficiency gains through automation may inadvertently constrain creative complexity and individual artistic expression.

3.2 Mixed-Initiative Solutions

The mixed-initiative approach offers a potential resolution to the automation-complexity trade-off by enabling systems to propose novel ideas while preserving human steering capacity (Liapis & Yannakakis, 2016). Rather than fully automating creative tasks, mixed-initiative systems augment human capabilities by offering suggestions, generating alternatives, and exploring possibilities that the human creator might not have considered independently. Empirical studies support the effectiveness of this approach. Yannakakis *et al*. (2014) found that users of mixed-initiative systems reported higher levels of creative engagement and produced more diverse outputs compared to users of purely automated tools. The key distinction lies in the preservation of human interpretive authority: mixed-initiative systems propose options but leave final decisions to the human creator, maintaining a sense of creative ownership and control.

Table 1 summarizes the key differences between fully automated, mixed-initiative, and manual creative systems along dimensions relevant to the automation-complexity trade-off.

Table 1: Comparative Analysis of Creative System Paradigms

Dimension	Fully Automated Systems	Mixed-Initiative Systems	Manual/Tool-Based Systems
Human Agency	Low – system makes most decisions	High – human retains final authority	Very High – human makes all decisions
Computational Contribution	High – generates complete outputs	Moderate – proposes options and alternatives	Low – executes specific commands
Creative Complexity	Low to Moderate – risk of homogenization	High – combines human judgment with computational exploration	Variable – depends entirely on human skill
Efficiency	Very High – rapid output generation	High – accelerates exploration while preserving control	Low to Moderate – limited by human speed
Exploratory Capacity	Limited – confined to trained patterns	High – expands possibility space while preserving steering	Moderate – limited by human cognitive capacity
Authorship Clarity	Ambiguous – unclear human contribution	Clear – human as primary author with AI assistance	Clear – human as sole author

3.3 Intrinsic Motivation and Agent Behavior

Guckelsberger, Salge, Saunders, and Colton (2016) introduce an information-theoretic approach to understanding agent behavior in co-creative contexts through the concept of coupled empowerment maximization. Their framework predicts when computational agents will exhibit supportive versus antagonistic behaviors based on whether the agent's actions increase or decrease the human partner's future action possibilities. This approach provides a principled basis for designing AI systems that augment rather than constrain human creativity. Supportive agent behaviors, those that expand the human creator's options and enable richer exploration, align with the goal of preserving creative complexity. Antagonistic behaviors, while potentially useful in specific contexts (such as providing creative constraints or challenges), risk reducing human agency if not carefully calibrated to user preferences and task requirements.

The coupled empowerment framework also addresses a critical design challenge: how to create AI systems that adapt their behavior to support human creativity without requiring explicit programming of supportive behaviors. By maximizing the joint empowerment of human and machine, systems can autonomously discover interaction patterns that enhance collaborative creativity (Guckelsberger *et al*., 2016).

4. Creative Agency and Authorship in Automated Systems

4.1 Distributed Responsibility and Attribution

The introduction of AI systems into creative workflows raises fundamental questions about authorship and creative responsibility. Traditional models of authorship assume a single human creator or clearly defined collaborative team. However, human-AI co-creation distributes creative contributions across human and computational actors in ways that challenge conventional attribution frameworks (Johnson, 2014). Johnson (2014) argues for a systems-thinking approach to creative responsibility that acknowledges the distributed nature of agency in human-AI systems. Rather than attempting to isolate the "true" author of a co-created work, this perspective examines how creative responsibility flows through networks of human designers, users, algorithms, training data, and institutional contexts. Such an approach recognizes that authorship in co-creative systems is not a binary property but a spectrum of contributions and influences. This distributed view of authorship has practical implications for how scholars evaluate co-creative systems. Rather than asking whether the human or the machine is the "real" creator, more productive questions concern how creative agency is allocated, what kinds of decisions each partner makes, and how the collaboration shapes the final outcome (Moroni, Von Zuben, & Manzolli, 2002). These questions direct attention to the structure and dynamics of collaboration rather than attempting to reduce co-creation to traditional authorship categories.

4.2 Interaction Design Principles for Preserving Agency

Bown and Bray (2016) argue that computational creativity systems must integrate core interaction design principles to preserve human agency and creative control. They identify several key principles: comprehensibility (users should understand what the system is doing and why), predictability (users should be able to anticipate system behavior), and controllability (users should be able to guide system actions effectively). These principles are frequently violated in contemporary AI systems, particularly those employing deep learning or other "black box" approaches. When users cannot understand the basis for system suggestions or predict how their inputs will influence outputs, their capacity for meaningful creative control diminishes. This opacity problem is especially acute in generative systems that produce complex outputs (such as images, music, or text) through processes that are difficult to interpret or explain (Bown & Bray, 2016). Addressing this challenge requires deliberate design choices that prioritize transparency and user control, even at the cost of some computational sophistication. For example, rule-based or constraint-based generative systems may offer less impressive outputs than neural network approaches but provide clearer pathways for human guidance and interpretation. The choice between these approaches should be informed by the specific creative context and the relative importance of human agency versus computational autonomy.

4.3 Embodiment and Social Interaction

Research on embodied creative systems reveals additional dimensions of creative agency in human-AI collaboration. Saunders, Chee, and Gemeinboeck (2013) examined human-robot interaction in musical composition and performance contexts, finding that embodiment significantly affects how humans perceive and engage with computational creative partners. Physical presence, gesture, and spatial positioning all contribute to the sense of the robot as a social actor with its own creative agency. These findings suggest that creative agency is not solely a matter of who makes which decisions but also involves social and affective dimensions of collaboration. When computational partners are embodied and capable of social interaction, humans may attribute greater creative agency to them, even when their actual decision-making capabilities are limited. This phenomenon has implications for designing co-creative systems: embodiment and social cues can enhance engagement and collaboration, but they may also obscure the actual distribution of creative control (Saunders *et al*., 2013). Mathewson and Mirowski (2017) extended this line of inquiry through experiments with AI improvisors in live theatrical performance. Their work demonstrates both the potential and the challenges of real-time co-creation with generative language systems. While the AI could produce novel and contextually appropriate contributions, coordination challenges and occasional incoherent outputs revealed the limitations of current systems. The study highlights the importance of designing for graceful failure and maintaining human capacity to redirect collaboration when computational contributions are unhelpful or inappropriate.

5. Evaluation Frameworks for Co-Creative Systems

5.1 The Four-Question Framework

Karimi, Grace, Maher, and Davis (2018) propose a comprehensive evaluation framework for computational co-creative systems based on four key questions: Who is being evaluated? What is being evaluated? When is the evaluation occurring? And how is the evaluation being conducted? This framework addresses the complexity of evaluating systems in which creativity emerges through interaction rather than being a property of isolated artifacts or agents. The "who" question recognizes that different evaluators (system designers, end users, domain experts, or the general public) may have divergent criteria for judging creative success. The "what" question distinguishes between evaluating the creative artifact, the creative process, the system's contribution, or the human's contribution. The "when" question acknowledges that creativity judgments may differ depending on whether evaluation occurs during the creative process or after completion. Finally, the "how" question addresses the methods and metrics used for evaluation, ranging from subjective ratings to objective measures of novelty and value (Karimi *et al*., 2018). This framework provides a structured approach for scholars to assess whether AI systems enhance or suppress human creative agency. By systematically considering these four dimensions, researchers can develop more nuanced understandings of how specific design choices affect collaborative creativity and avoid oversimplified conclusions about system effectiveness.

5.2 From Isolation to Involvement

Kantosalo, Toivanen, Xiao, and Toivonen (2014) document the process of adapting autonomous creative systems to support human-computer co-creation, revealing the substantial design changes required to transform isolated generative systems into collaborative partners. Their case studies demonstrate that enabling interactivity fundamentally alters system behavior, shifting from predetermined generation toward responsive co-creation. This research highlights a critical insight: systems designed for autonomous creativity often require significant redesign to function effectively in co-creative contexts. Features that support autonomous generation (such as optimization for a predefined fitness function) may actually hinder collaboration by limiting the system's capacity to respond to human input or adapt to evolving creative goals. Conversely, features that support collaboration (such as real-time responsiveness and incremental contribution) may reduce the sophistication of autonomous outputs (Kantosalo *et al*., 2014).

Table 2 outlines key design transitions required when adapting autonomous creative systems for co-creative contexts.

Table 2: Design Transitions from Autonomous to Co-Creative Systems

Design Aspect	Autonomous Creative Systems	Co-Creative Systems
Generation Process	Batch generation of complete outputs	Incremental, iterative contributions
Timing	Offline, non-interactive	Real-time, responsive
Evaluation	Internal fitness function or aesthetic measure	Incorporates human feedback and preferences
Control	System-driven exploration of possibility space	Shared control with human steering
Output	Complete artifacts	Partial contributions or suggestions
Adaptation	Fixed behavior or autonomous learning	Responsive to human input and context
Interface	Minimal (output-focused)	Rich, supporting bidirectional communication

5.3 Multi-Agent Architectures

Akimoto and Ogata (2016) propose multi-agent architectures for co-creative narrative generation, integrating multiple computational agents with distinct generative strategies alongside human authors. This approach resists the homogenization that can result from single-model automation by introducing diversity through multiple computational perspectives. The multi-agent approach offers several advantages for preserving creative complexity. First, it distributes creative agency across multiple computational actors, reducing the risk that a single algorithmic bias dominates outputs. Second, it creates opportunities for emergent creativity through interaction among agents. Third, it maintains human creators as integrators and curators of diverse computational contributions rather than relegating them to supervisory roles (Akimoto & Ogata, 2016). This architectural strategy aligns with the broader principle that preserving creative complexity requires distributing rather than concentrating creative authority. By multiplying computational perspectives and maintaining human judgment as the ultimate arbiter, multi-agent systems can leverage automation while preserving the exploratory richness and contextual sensitivity characteristic of human creativity.

6. Implications for Creative Practice and System Design

6.1 Design Principles for Augmentative Co-Creation

Based on the theoretical frameworks and empirical evidence reviewed, several design principles emerge for creating AI systems that augment rather than suppress human creative agency:

Principle 1: Preserve Interpretive Authority. Systems should propose options and alternatives rather than making final creative decisions. Human creators should retain authority over which computational contributions to accept, modify, or reject.

Principle 2: Maximize Transparency. Users should understand how the system generates suggestions and what factors influence its behavior. Comprehensibility enables effective guidance and maintains user confidence in their creative control.

Principle 3: Support Exploratory Capacity. Systems should expand the range of creative possibilities available to users rather than constraining exploration to predetermined solution spaces. This may involve generating diverse alternatives, suggesting unexpected directions, or revealing hidden patterns in creative materials.

Principle 4: Enable Dynamic Control Allocation. The distribution of initiative between human and machine should adapt to task context, user preferences, and the relative strengths of each partner. Rigid allocation of roles may limit collaborative potential.

Principle 5: Design for Graceful Failure. Systems should enable users to easily recover from unhelpful or inappropriate computational contributions. The cost of rejecting or modifying system suggestions should be low to maintain creative flow.

These principles operationalize the automation versus creative-complexity framework by specifying design strategies that preserve human agency while leveraging computational capabilities (Feldman, 2017).

6.2 Contextual Considerations

The appropriate balance between automation and human control varies across creative domains and task contexts. In domains where technical execution is highly constrained by formal rules (such as certain aspects of software engineering or technical drawing), greater automation may be acceptable because creative complexity resides primarily in high-level design decisions rather than executional details. Conversely, in domains where execution itself is a site of creative exploration (such as improvisational music or experimental visual art), automation that reduces executional engagement may significantly diminish creative complexity (Davis, 2013). Similarly, the phase of the creative process affects optimal automation levels. Early exploratory phases may benefit from computational systems that rapidly generate diverse possibilities, while later refinement phases may require more direct human control to achieve specific aesthetic or functional goals. Effective co-creative systems should adapt their behavior to support different phases of creative work (Liapis & Yannakakis, 2016). Table 3 presents a framework for assessing appropriate automation levels based on creative domain characteristics and process phases.

Table 3: Contextual Framework for Automation in Co-Creative Systems

Context Factor	High Automation Appropriate	Moderate Automation (Mixed-Initiative)	Low Automation Appropriate
Creative Locus	Execution is routine; creativity in high-level decisions	Creativity distributed across planning and execution	Execution itself is primary site of creative exploration
Process Phase	Idea generation; rapid exploration	Iterative development; refinement	Final polishing; personal expression
Domain Formalization	Highly constrained by rules or standards	Partially structured with room for interpretation	Open-ended; few formal constraints
User Expertise	Novice users needing guidance	Intermediate users seeking augmentation	Expert users prioritizing control
Task Complexity	Simple, well-defined tasks	Moderate complexity with multiple valid approaches	Highly complex, ambiguous tasks
Output Stakes	Low-stakes experimentation	Professional work with quality requirements	High-stakes, signature work

6.3 Ethical and Professional Considerations

The shift toward human-AI co-creation raises ethical questions about attribution, compensation, and professional identity. As AI systems take on more substantial creative roles, questions arise about how to credit contributions, compensate creators, and maintain professional standards (Johnson, 2014). These issues are particularly pressing in commercial creative industries, where intellectual property rights and creative attribution have significant economic implications. Feldman (2017) emphasizes the importance of considering user experience and emotional factors in co-creative systems. Creative work is not purely cognitive but involves emotional engagement, personal expression, and professional identity. Systems that reduce creative agency may undermine these affective dimensions of creativity, even if they produce technically competent outputs. Designers of co-creative systems must therefore attend to both functional and experiential aspects of collaboration. Furthermore, the increasing sophistication of AI creative systems may exacerbate existing inequalities in creative industries. Access to advanced co-creative tools may become a source of competitive advantage, potentially marginalizing creators who lack resources to adopt these technologies. Conversely, if AI systems enable automation of creative labor, they may displace human creators or devalue creative skills. These socioeconomic implications require careful consideration alongside technical development (Secretan, 2011).

7. Conclusion

This paper has examined the landscape of human-AI co-creation through the lens of an automation versus creative-complexity framework, arguing that the distribution of creative control between human and machine fundamentally determines whether AI systems enhance or suppress human creative agency. The evidence from computational creativity research, human-computer interaction studies, and empirical evaluations of co-creative systems converges on several key conclusions. First, theoretical models of co-creation—including enactive approaches, mixed-initiative paradigms, and search-based formalizations—provide complementary perspectives on how to structure human-AI collaboration to preserve human agency while leveraging computational capabilities. These models emphasize interaction, shared control, and the importance of maintaining human interpretive authority over creative decisions. Second, empirical studies consistently demonstrate a trade-off between automation efficiency and creative complexity. While automation can accelerate production and reduce executional friction, it risks homogenizing outputs and diminishing human engagement when it extends to higher-level creative decisions. Mixed-initiative approaches offer a promising middle path, enabling systems to propose novel ideas while preserving human steering capacity. Third, questions of authorship and creative responsibility in co-creative systems require moving beyond traditional attribution frameworks toward distributed models that acknowledge the complex interplay of human designers, users, algorithms, and contextual factors. Rather than attempting to isolate a single author, scholars should examine how creative agency flows through human-AI systems and how different design choices affect this distribution. Fourth, effective evaluation of co-creative systems requires multidimensional frameworks that consider who is evaluating, what is being evaluated, when evaluation occurs, and how it is conducted. Oversimplified metrics focused solely on artifact quality may miss critical aspects of how systems affect human creative agency and process.

Finally, design principles for augmentative co-creation emphasize preserving interpretive authority, maximizing transparency, supporting exploratory capacity, enabling dynamic control allocation, and designing for graceful failure. These principles operationalize the goal of creating AI systems that augment rather than replace human creativity. The automation versus creative-complexity framework offers scholars and practitioners a conceptual tool for evaluating AI's role in creative domains. By focusing attention on how systems distribute creative control and affect human agency, this framework enables more nuanced assessment of whether specific AI implementations genuinely support co-creation or simply automate creative labor under a collaborative veneer. Future research should continue to develop empirical methods for assessing creative agency in human-AI collaboration, explore how different creative domains and task contexts affect optimal automation levels, and investigate the long-term effects of co-creative systems on creative skill development and professional practice. As AI capabilities continue to advance, maintaining focus on human creative agency and complexity will be essential for ensuring that these technologies genuinely augment rather than diminish human creativity.

The field of computational creativity stands at a critical juncture. The choices made in designing and deploying co-creative systems will shape not only the future of creative practice but also fundamental questions about the nature of creativity, authorship, and human agency in an increasingly automated world. By centering human creative agency and employing frameworks that distinguish between automation and augmentation, scholars and designers can work toward AI systems that enhance rather than supplant the irreducible complexity of human creative expression.

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