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Requiem for Sustainability Preaching: A Call for Embedded Green Innovation

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Abstract: The traditional paradigm of sustainability advocacy, characterized by awareness campaigns and ethical appeals "sustainability preaching", faces a crisis of relevance in an industrial landscape increasingly dominated by artificial intelligence (AI), automation, and robotics. These technologies prioritize quantifiable metrics like efficiency, speed, and cost-effectiveness, often sidelining sustainability initiatives unless they directly contribute to optimization goals. This article argues that the efficacy of sustainability preaching is diminishing, creating a disconnect between established environmental goals, particularly in green chemistry, and the operational imperatives of AI-driven systems. We analyze the rise and plateau of conventional sustainability discourse, contrasting it with the rapid technological takeover prioritizing performance and economic viability. We propose that for sustainability to remain impactful, it must transition from an external, preached ideal to an intrinsically data-driven, embedded reality within automated workflows. This involves reframing sustainability concepts like lifecycle assessment and circularity into quantifiable parameters compatible with AI optimization and advocating for an "invisible sustainability" built-in rather than bolted-on. Finally, we explore the significant opportunities this paradigm shift presents for chemists and scientists to make sustainability quantifiable, design automation-compatible materials and processes, and bridge chemical expertise with AI, machine learning, and digital twin technologies. The article concludes that sustainability's survival depends not on continued preaching, but on its evolution into a smarter, quieter, and deeply integrated component of future technological and industrial systems.

Keywords: sustainability; green chemistry; artificial intelligence; automation; robotics; data-driven sustainability; industrial optimization; chemical innovation

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1. Introduction

The discourse surrounding sustainability has, for decades, been characterized by what might be termed the "sustainability preaching" era. This period involved fervent advocacy, widespread awareness campaigns, and the development of numerous theoretical frameworks aimed at guiding environmental responsibility across academia, policy, and industry. Concepts like the Triple Bottom Line, Corporate Social Responsibility (CSR), and Environmental, Social, and Governance (ESG) criteria became central tenets, shaping corporate reporting and public perception [1]. Green chemistry emerged as a critical academic and practical field, offering principles to minimize environmental impact at the molecular level [2]. However, this era, while successful in raising awareness, often struggled to translate ideals into widespread, scalable action, frequently being perceived as more aspirational than operational.

We are now entering a distinctly different paradigm defined by the rapid and pervasive integration of artificial intelligence (AI), machine learning (ML), and advanced robotics into nearly every facet of industrial operation. From optimizing complex supply chains and automating manufacturing processes to accelerating materials discovery and enabling precision agriculture, these technologies are fundamentally reshaping industrial priorities [3]. The driving forces are no

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longer primarily ethical appeals or regulatory pressures, but the relentless pursuit of efficiency, speed, cost reduction, and data-driven decision-making. This technological wave represents a powerful, perhaps irresistible, force altering the landscape in which sustainability must operate.

This article posits a central thesis: in an age increasingly dominated by the logic of automation and optimization, the traditional model of sustainability advocacy, the "preaching", is losing its efficacy and relevance. Sustainability can no longer thrive merely as a moral high ground, or a separate initiative bolted onto existing processes. To survive and remain impactful, it must undergo a fundamental redefinition. It needs to be seamlessly integrated into the very fabric of AI-driven systems, articulated through the language of pragmatism, and measured by quantifiable performance metrics aligned with the new industrial imperatives of efficiency and economic viability. The challenge is not to abandon sustainability, but to evolve it from a preached ideal into an embedded, data-driven reality.

2. The Rise and Plateau of Sustainability Discourse

The concept of sustainability gained significant traction in the late 20th century, evolving from niche environmentalism into a mainstream global concern. The publication of reports like "Our Common Future" (the Brundtland Report) in 1987 formally defined sustainable development [4], setting the stage for decades of discourse [5]. This discourse expanded rapidly, encompassing environmental protection, social equity, and economic viability [6]. In the corporate world, this manifested initially as CSR, often driven by reputational concerns and stakeholder pressure. Over time, frameworks like the Global Reporting Initiative (GRI) and eventually ESG criteria emerged, attempting to standardize and quantify corporate sustainability performance [7]. Academic fields like industrial ecology and green chemistry provided the scientific underpinnings. Green chemistry, formally articulated through its 12 principles, offered a roadmap for designing chemical products and processes that reduce or eliminate the use and generation of hazardous substances [8]. These principles became pillars in academic research and influenced policy initiatives, such as the US EPA's Green Chemistry Challenge Awards [9].

Despite this proliferation of frameworks, research, and advocacy, the "preaching",the translation into widespread, transformative industrial practice often fell short. Several factors contributed to this plateau. Firstly, the scale and complexity of global supply chains and industrial systems made systemic change inherently slow and difficult. Implementing truly sustainable practices often required significant upfront investment, changes to established processes, and a long-term perspective conflicting with short-term financial pressures [10]. Secondly, sustainability initiatives were frequently perceived as idealistic or peripheral to core business operations, lacking integration into primary performance metrics and decision-making processes [11]. The emphasis often remained on reporting and compliance rather than fundamental redesign. Thirdly, the "preaching" model itself, relying heavily on moral suasion and voluntary adoption, struggled to compel action universally, particularly when economic conditions tightened or when greener alternatives presented performance trade-offs. The disconnect between academic ideals, such as those promoted by green chemistry [12], and the pragmatic realities of industrial adoption became increasingly apparent, highlighting a gap between potential and practice. While awareness grew, the momentum for deep, operational change seemed to stall, leaving the sustainability movement vulnerable to being overshadowed by more immediately impactful technological shifts or diluted through greenwashing [13].

3. The Technological Takeover: AI, Robotics, and Automation

The plateauing of traditional sustainability discourse coincides with, and is increasingly overshadowed by, an unprecedented wave of technological advancement driven by AI, ML, robotics, and widespread automation. Unlike the often value-laden appeals of the sustainability movement, the adoption of these technologies is propelled by tangible, quantifiable benefits: radical improvements in efficiency, speed, precision, cost reduction, and predictive capability [14]. Industries

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across sectors are aggressively prioritizing AI-driven optimization, not necessarily out of disregard for environmental concerns, but because these tools offer compelling solutions to immediate operational and economic challenges, fundamentally altering strategic priorities [15].

This technological takeover manifests in numerous ways. In materials science, AI algorithms can rapidly screen vast chemical spaces to discover novel materials with desired properties, potentially accelerating the development of sustainable alternatives but often prioritizing performance characteristics dictated by immediate application needs [16]. Supply chains are being transformed by AI-powered logistics optimization and robotic process automation (RPA), which streamline operations and reduce waste, primarily focusing on minimizing costs and delivery times [17]. In manufacturing, robotics combined with AI-driven quality control enables levels of precision and consistency previously unattainable, leading to reduced material waste [18] and energy consumption [19] as byproducts of efficiency gains, rather than as primary goals. The common thread is that sustainability benefits, when they occur, are often secondary consequences of optimization algorithms architected around performance and economic metrics.

The relentless focus on efficiency and economic survival, particularly in competitive global markets, means sustainability initiatives are increasingly sidelined unless they directly contribute to these core objectives. The logic of AI-driven systems inherently favors quantifiable inputs and outputs, making it easier to justify investments in automation that promise immediate returns compared to investments in greener processes whose benefits might be longer-term or less easily translated into direct cost savings or performance boosts recognized by optimization algorithms [20]. Consequently, the operational landscape is shifting towards one where technological prowess and data-driven efficiency are the dominant currencies, potentially leaving traditional sustainability paradigms struggling for traction.

4. The Crisis of Relevance: Where Does Green Chemistry Stand Now?

The ascendancy of AI-driven optimization creates a significant crisis of relevance for traditional sustainability approaches, particularly for fields like green chemistry. A fundamental dissonance emerges between the holistic, often qualitative goals of sustainability (e.g., minimizing hazard, using renewable feedstocks, designing for degradation) and the narrowly defined, quantitative objectives typically programmed into AI optimization algorithms (e.g., maximizing yield, minimizing cost, maximizing throughput) [21]. While AI can be programmed with sustainability constraints, the current industrial imperative often prioritizes immediate economic and performance gains, pushing environmental considerations down the list unless mandated by regulation or directly translatable into cost savings [22].

This leads to a growing industrial reluctance to adopt "greener" chemical alternatives or processes, even when scientifically sound, if they do not align seamlessly with automated systems or if they present even minor trade-offs in performance or cost compared to established, automation-compatible methods. For instance, a novel bio-based solvent developed following green chemistry principles might be ignored if an existing, less environmentally benign solvent performs marginally better within an automated high-throughput screening system optimized solely for reaction speed [23]. Automation favors predictability, consistency, and quantifiable metrics – characteristics that established, well-understood (though potentially less sustainable) processes often provide more readily than newer, greener innovations that may require process adjustments or have less predictable scale-up behavior.

Furthermore, the AI era exacerbates the long-standing disconnect between academic research in green chemistry and its real-world industrial adoption. Academia continues to produce a wealth of research on sustainable chemical pathways and materials [24]. However, much of this output struggles to bridge the gap to industrial application, a challenge now amplified by the need to integrate with complex, data-intensive automated workflows [25]. Industry demands solutions that are not just greener, but also robust, scalable, economically viable, *and* compatible with existing or planned automation infrastructure. The failure to frame green chemistry innovations in the language of data, efficiency, and automation compatibility risks rendering valuable academic contributions practically irrelevant in the new industrial landscape. Green chemistry, once a pillar of the sustainability movement, now faces the challenge of proving its value proposition within a system increasingly governed by the logic of AI and automation.

5. Toward a New Sustainability: Data-Driven, Embedded, Unpreached

The apparent conflict between traditional sustainability goals and the imperatives of the AI-driven industrial age necessitates a fundamental rethinking of how sustainability is approached and implemented. Instead of clinging to the "preaching" model, which often positions sustainability as an external constraint or a separate ethical layer, a new model must emerge: one where sustainability is intrinsically data-driven, deeply embedded within automated workflows, and largely "unpreached" because it becomes an inherent part of optimized performance. This requires translating sustainability principles into the quantitative language that AI systems understand and prioritize [26].

Reframing core green chemistry and sustainability concepts is crucial [27]. Atom economy, traditionally a measure of reaction efficiency in terms of incorporated atoms, needs integration into AI-driven process optimization algorithms alongside yield and throughput metrics. Lifecycle Assessment (LCA), often a complex and time-consuming offline analysis, must evolve towards dynamic, real-time LCA powered by sensor data and integrated into digital twins of production processes, allowing for continuous environmental impact assessment and optimization [28]. Circularity principles need translation into quantifiable parameters for material selection algorithms and supply chain logistics optimization, favoring materials designed for disassembly and reuse within automated systems [29]. The goal is to make sustainable choices the *result* of optimization, not an afterthought. For example, an AI optimizing a chemical synthesis pathway could be programmed to minimize not only cost and time but also a composite metric including energy consumption, waste generation (quantified E-factor), and hazard scores derived from databases, making the "greener" pathway the mathematically optimal one [30].

This leads to the concept of "invisible sustainability"—sustainability that is built-in, not bolted-on. It operates quietly within algorithms and automated systems, driving resource efficiency, minimizing waste, and reducing environmental impact as part of the core operational logic. It does not require constant advocacy because it aligns with the system's inherent drive for optimization. This embedded approach is more resilient to economic fluctuations and shifting priorities because it links environmental performance directly to operational efficiency and, potentially, long-term economic advantage. The focus shifts from convincing industry to *be* sustainable to providing the tools and frameworks that make sustainable operations the most efficient and intelligent choice within an automated context.

6. Opportunities for Chemists and Scientists in the New Age

This paradigm shift, while challenging traditional approaches, simultaneously opens significant new opportunities for chemists, materials scientists, and chemical engineers willing to adapt and engage with the tools and logic of the AI era. The need to make sustainability quantifiable and automation-friendly places chemists in a pivotal role. They possess the domain expertise required to translate complex environmental and safety considerations into the parameters and metrics that AI systems can process and optimize [31]. This involves developing robust quantitative structure-activity relationship (QSAR) models for toxicity and environmental fate [32], creating reliable databases of material properties relevant to sustainability (e.g., biodegradability, recyclability potential), and defining accurate metrics for lifecycle impacts that can be fed into optimization algorithms.

Furthermore, there is a critical need for designing novel materials and chemical processes conceived from the outset to thrive within AI-optimized ecosystems. This means prioritizing not only green chemistry principles but also factors like process robustness, amenability to automated control

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and monitoring, compatibility with robotic handling, and the generation of high-quality data suitable for ML model training [33]. Chemists can proactively design catalysts that are highly selective and efficient under conditions suitable for automated flow reactors, develop self-healing materials that reduce maintenance needs in automated systems, or create bio-based polymers with predictable degradation profiles that simplify end-of-life processing in automated recycling facilities [34].

The most significant opportunity lies in bridging the expertise of green chemistry with the power of AI, ML, digital twins, and smart factory concepts. Chemists can collaborate with data scientists and engineers to build predictive models for reaction outcomes, environmental impact, and material performance, reducing the need for extensive experimentation. They can contribute to the development of digital twins for chemical plants, enabling virtual process optimization that incorporates sustainability metrics alongside traditional economic ones. By actively participating in the development and deployment of these technologies, chemists can ensure sustainability considerations are embedded effectively, guiding AI towards genuinely greener and more efficient solutions. This shapes a future where chemical innovation and environmental responsibility are intrinsically linked within automated industrial systems.

7. Conclusion

The era of "sustainability preaching," characterized by advocacy and awareness-raising, is effectively drawing to a close. Its methods are increasingly misaligned with the operational realities of an industrial landscape being rapidly reshaped by AI, automation, and data-driven optimization. The relentless pursuit of efficiency, speed, and quantifiable performance inherent in these technologies creates a new imperative where sustainability, to remain relevant and impactful, cannot persist as a separate, morally-driven initiative. The traditional rhetoric has lost resonance in environments prioritizing algorithmic efficiency and automated workflows.

This necessitates a profound transformation, not an abandonment, of sustainability. The challenge is to move beyond advocacy towards integration. Sustainability must be redefined in the language of data, embedded within the core logic of AI systems, and measured through quantifiable metrics aligned with performance optimization. Concepts from green chemistry and lifecycle thinking need translation into parameters that AI can understand and incorporate into its calculations, making environmentally conscious choices the *result* of optimization rather than an external constraint. This calls for an "invisible sustainability" – one that is built-in, data-driven, and operates quietly within the automated systems governing production and innovation.

For chemists and scientists, this represents not an end, but a critical juncture demanding adaptation and engagement. The future lies in quantifying sustainability, designing materials and processes compatible with automation, and actively bridging the gap between chemical expertise and AI capabilities. By embracing this challenge, the chemical sciences can ensure the next wave of industrial innovation is not only efficient and powerful but also inherently more sustainable. The death of sustainability preaching does not mean the death of sustainability itself; rather, it signals the urgent need for its evolution into a smarter, quieter, more deeply embedded force, capable of thriving not through rhetoric, but through integration into the technological fabric of the future.

Conflicts of Interest: The author declares no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
CSR	Corporate Social Responsibility
ESG	Environmental, Social, and Governance
GRI	Global Reporting Initiative
LCA	Lifecycle Assessment
ML	Machine Learning

QSAR	Quantitative Structure-Activity Relationship
RPA	Robotic Process Automation

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