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Harnessing Agentic AI for Sustainable Innovation and Environmental Responsibility

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ABSTRACT: We are facing a critical moment. With climate change and environmental damage accelerating, we need a fundamental shift in how we solve these problems; small steps won't be enough. This paper looks at a powerful new ally in this fight: Agentic AI. Think of it as AI that doesn't just analyse data but takes intelligent, independent action. These systems can perceive a situation, make a decision, and carry out a complex series of steps all on their own to meet a sustainability goal. We delve into how these AI agents are built and show them in action - managing complex energy grids, discovering new materials to capture carbon, creating smarter and less wasteful supply chains, and keeping a vigilant watch on our natural world. By reviewing existing research and real-world cases, we make the case that this technology offers a dramatic leap in efficiency, helping us slash waste and emissions at scale. But this power doesn't come without its own set of problems. The massive computing power required can be an environmental burden in itself, and we must carefully navigate issues of bias and control. Ultimately, our research argues that the valid key to success lies in partnership. By building a collaborative relationship between human wisdom and AI capability, we can steer this powerful technology toward a future that is both sustainable and resilient.

KEYWORDS: Agentic AI, Sustainable Innovation, Environmental Protection, Self-directed Systems, Climate Solutions, Green Computing, Circular Economy, AI Ethics.

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Introduction

1.1. The Urgency of Sustainable Transformation

We're watching the projections turn into our daily news. Ice caps are vanishing. Wildfires and superstorms, once rare catastrophes, now feel seasonal. Honestly, our current sustainability efforts aren't cutting it. They're like bringing a bucket to put out a house fire. Tinkering around the edges with slightly better fuel efficiency or new recycling labels doesn't measure up to the sheer scale of the collapse we're facing. The foundational systems of our world, our food, our water, our energy, are screaming for more than a tune-up. They need a complete overhaul. This is bigger than just saving polar bears; it's an all-hands-on-deck moment for our economies and our communities. We're in a hole, and we need to stop digging with the same old tools.

The way we usually solve problems is too slow and too simple. We study an issue, make a plan, and then try to execute it step by step. But the climate doesn't work that way; it's a chaotic, interconnected system. We need solutions that can keep up, learn on the fly, and make smart moves across a global chessboard. Time is a resource we've nearly exhausted. The chasm between what's needed and what we're actually doing keeps widening every year. This paper starts from a simple, stark truth: business as usual is a death sentence. The leap we have to make is so vast it demands a new kind of intelligence working with us, not just crunching numbers, but taking direct, intelligent action.

1.2. Defining Agentic AI: From Passive Tools to Active Partners

It is fantastic to look at a mountain of data that tells you what has already happened or what might happen next. It's a passive tool. It gives you a forecast, a spreadsheet, a warning light, but then it just stops. The hard part, the actual doing, is still entirely up to you. Now picture an AI that doesn't just show you the storm on the radar; it goes out and battens down the hatches. That's the leap to Agentic AI. These systems can see what's going on, make a decision, and then physically or digitally carry out a whole plan from start to finish.

This changes everything about how we work with machines. It's the difference between having a brilliant assistant who hands you a report on city power usage and having a full partner who, upon reading that same report, immediately starts buying solar power, rerouting electricity, and texting customers to reduce their consumption temporarily. The AI moves from offering advice to taking delegated responsibility. It becomes a collaborator you trust to handle the complex, nitty-gritty work, freeing you up to think about the bigger picture. It's not just a tool you use; it's a force you direct.

2. Literature Review

2.1. The Evolution of AI in Sustainability: A Brief History

The story of AI in sustainability isn't a sudden revolution; it's a slow-burning evolution that has accelerated into a wildfire. In the early days, the role was decidedly humble. We're talking about the 1990s and early 2000s, when expert systems and basic neural networks were first deployed for specific, siloed tasks. Think of a paper by Chen et al. (2005), who used a simple rule-based system to classify land use from satellite imagery, a powerful but static application. The 2010s brought the data deluge and the rise of machine learning, shifting the field from descriptive analysis to prediction. Rolnick et al. (2019) famously laid the groundwork here, publishing a near-manifesto that systematically outlined how machine learning could be a "tool for tackling climate change," cataloguing applications in electricity systems, agriculture, and monitoring. This period was dominated by forecasting models that could accurately predict energy demand and map deforestation risks.

However, an explicit limitation persisted. These systems, for all their predictive power, were sophisticated oracles. They could tell you what was likely to happen, but they couldn't do anything about it. As Kaack et al. (2022) critically noted, many of these AI applications were "boutique solutions," impressive in a lab but struggling with real-world integration and scalability. The focus was on data fidelity and model accuracy, not on operational integration or autonomous action. This historical trajectory from simple classification to advanced prediction and now to a pressing need for execution sets the stage perfectly for the emergence of a more capable, active form of artificial intelligence. The tools of the past were necessary, but they are no longer sufficient for the crises we face today.

2.2. Foundational Concepts of Agentic AI and Multi-Agent Systems

To understand where we're going, we need to grasp the core ideas that make Agentic AI distinct. The conceptual bedrock for an "agent" in AI isn't new. Russell and Norvig (2020), in their canonical textbook, have long defined an agent as anything that can perceive its environment through sensors and act on it through actuators. The leap from this textbook definition to modern "agentic" systems lies in the sophistication of the reasoning and the complexity of the actions. Early intelligent agents were often simple if-then scripts. Today's Agentic AI leverages large language models and advanced reinforcement learning, as explored by Xi et al. (2023), to reason over long-term goals and break them down into intricate, multi-step plans.

This becomes exponentially more powerful when multiple agents work together. This is the domain of Multi-Agent Systems (MAS), a field with deep roots. The pioneering work of Wooldridge (2009) established the principles for how multiple computational agents can communicate, cooperate, and sometimes compete to solve problems beyond any single agent's capability. Think of it as a digital ecosystem. For sustainability challenges, which are inherently distributed and multifaceted, this paradigm is ideally suited. A single agent might manage a building's HVAC system, but a MAS, as conceptualised in early smart grid research by Ramchurn et al. (2012), could coordinate thousands of such buildings, a fleet of electric vehicles, and a portfolio of renewable generators to balance an entire city's grid. The foundational work in MAS provides the critical "orchestration" layer that turns individual intelligence into collective, systemic action.

2.3. Applications of AI in Environmental Management

Before the recent buzz around agentic systems, AI was already deeply embedded in environmental science, primarily as an analytical powerhouse. In climate science, Rasp et al. (2018) demonstrated that machine learning models could emulate complex physical climate models at a fraction of the computational cost, accelerating crucial research. In biodiversity research, the work of Norouzzadeh et al. (2018) was a landmark, demonstrating that CNNs could automatically identify, count, and describe animal species across millions of camera-trap images, revolutionising wildlife monitoring.

The energy domain saw the most mature integration. Chen et al. (2019) provided a comprehensive review of deep learning for solar forecasting, with direct impacts on grid reliability and the integration of renewables. Meanwhile, in materials science, the pursuit of new compounds for carbon capture and batteries was supercharged by AI. Butler et al. (2018) showed how machine learning could predict the properties of hypothetical molecules, guiding chemists toward the most promising candidates for synthesis. In conservation, Wu et al. (2021) leveraged AI to analyse satellite and drone imagery to track deforestation and illegal fishing with unprecedented speed and scale. However, a common thread through these reviews from Talari et al. (2017) on smart grids to Maxwell et al. (2021) on conservation is that they almost universally frame AI as a decision-support tool. The human operator remains firmly in the loop, interpreting outputs and initiating commands.

2.4. Identified Gaps: The Limitation of Static AI and the Case for Agency

The collective body of research reveals a consistent and critical gap: a chasm between insight and action. The literature is rich with systems that diagnose problems but poor in systems that autonomously implement solutions. As Cowls et al. (2023) argued, there is a dangerous "accountability gap" when AI provides analysis but humans remain responsible for outcomes, often leading to slow or inconsistent responses. Furthermore, Vinuesa et al. (2020) were optimistic about AI's potential for achieving the Sustainable Development Goals but cautioned that many applications were fragmented and failed to address systemic, cross-domain challenges.

The limitations are stark. A static AI can flag an anomaly in energy consumption, but it cannot autonomously dispatch a drone to inspect the faulty component. It can predict a spike in air pollution, but it cannot dynamically reroute traffic or adjust industrial operations in real time. This reactive posture is a luxury we no longer have. The case for agency, therefore, is built on the need for speed, scale, and systemic integration. The research by Bennett et al. (2021) on "AI for Earth" highlighted this need, noting that future systems must move beyond monitoring to active management and restoration. The gap is no longer about better data or more accurate models; it's about closing the loop from perception to action. The pre-2025 landscape successfully built the analytical engine. Still, it left the crucial task of building the steering wheel and the brakes—the agentic systems that can actually drive change—largely unfinished.

3. The Architectural Framework of Agentic AI for Sustainability

3.1. Core Components: Perception, Learning, Reasoning, and Action

Building an AI that can act isn't about creating a single program. It's about architecting a dynamic loop, this cognitive cycle that turns raw data into real-world impact. Think of it like a skilled gardener. First, they **perceive**: they feel the soil, see the wilted leaves, and notice the weather (the data). This is the agent's input layer: a constant stream of data from satellites, IoT sensors, and market feeds, often messy and unstructured.

Next, they learn and reason. This isn't just recalling that plants need water. It's a more profound understanding: "This plant species is drought-tolerant, but the soil moisture is 2 standard deviations below the mean for this season, and the forecast shows no rain for 10 days. Therefore, the risk of permanent damage is high." For the AI, this is where machine learning models and logical planners come in. The reasoning can be framed as optimising a utility function. The agent is trying to maximise its overall success, which can be thought of as:

$$U = \Sigma [R(s_t, a_t) - C(s_t, a_t)]$$

Where,

- **U** is the total utility.
- **R(s_t, a_t)** is the reward for taking action a in state s at time t (e.g., carbon reduced, energy saved).

- **C(s_t, a_t)** is the cost of that action (e.g., computational resources, financial cost, energy spent).

Finally, the gardener takes action—they water the plant. The AI does the same, sending a command to an innovative irrigation valve. This action changes the environment, leading to new perceptions, and the loop continues. This isn't a one-way street; it's a continuous feedback cycle where every action informs the next perception, creating a learning system that adapts over time.

3.2. Multi-Agent Systems for Complex, Distributed Environmental Challenges

No single agent, no matter how smart, can manage a forest, a city's power grid, or a global supply chain. The problem is too big, too spread out. This is where the concept of a multi-agent system (MAS) comes in; it's like building a digital ecosystem or a team of specialised experts. Instead of one "god" AI, you have many smaller AIs, each with a specific role, collaborating and sometimes competing to solve a larger problem.

Imagine a smart city energy grid. You would have:

- A Grid Balancer Agent whose goal is to keep supply and demand in perfect equilibrium.
- Thousands of Home Agent instances, each managing a household's solar panels, battery, and appliance usage.
- A Fleet Agent manages the charging schedules for a group of electric buses.

These agents don't just do their own thing. They communicate. A Home Agent might "bid" its excess solar energy to the Grid Balancer Agent. The Fleet Agent might negotiate with the Grid Balancer to schedule charging when renewable energy is most abundant. This creates a resilient, adaptive system. The breakdown of a single agent doesn't crash the whole network, and the system can find emergent, optimised solutions that a single central controller could never compute. It mirrors the natural world; a forest doesn't have a central manager—it thrives through the complex interactions of countless individual organisms.

Table 1

Agent Roles in a Smart Grid Multi-Agent System

Agent Type	Primary Goal	Perception Sources	Possible Actions
Grid Balancer	Maintain grid stability	Power generation data, total demand forecasts	Adjust power flow, set energy prices, activate reserves
Home Agent	Minimize cost & maximize self-consumption	Local weather forecast, household energy use, grid price signals	Shift appliance timings, charge/discharge battery, sell solar power
Fleet Manager	Ensure vehicle readiness at lowest cost	Bus schedules, battery levels, grid price signals	Optimize charging times and locations
Renewable Forecaster	Predict renewable energy output	Satellite imagery, weather models	Issue probabilistic forecasts to the Grid Balancer

3.3. Visualising the Architecture: From Sensor to Sustainable Outcome

It's one thing to describe this in words, but a picture really makes the architecture come to life. The diagram below shows the complete flow of how a single agent, embedded in a multi-agent world, turns a simple sensor reading into a sustainable outcome.

You can see it's a cycle, not a straight line. The "Feedback Loop" is the learning nerve. Maybe the action didn't have the intended effect, the price signal was too weak, or the valve was stuck. That new data flows right back into Perception, and the agent updates its model of the world for next time. The "Knowledge Base" is its guide, holding its core mission: "maximise water efficiency," and its constraint: "never reduce crop yield by more than 5%." Finally, its connection to other "Agents" shows it doesn't operate in a vacuum; it's part of a larger, collaborative system. This entire, complex architecture exists for one purpose: to translate a bit of data into a tangible step toward a more sustainable planet.

4. Key Application Domains and Case Analyses

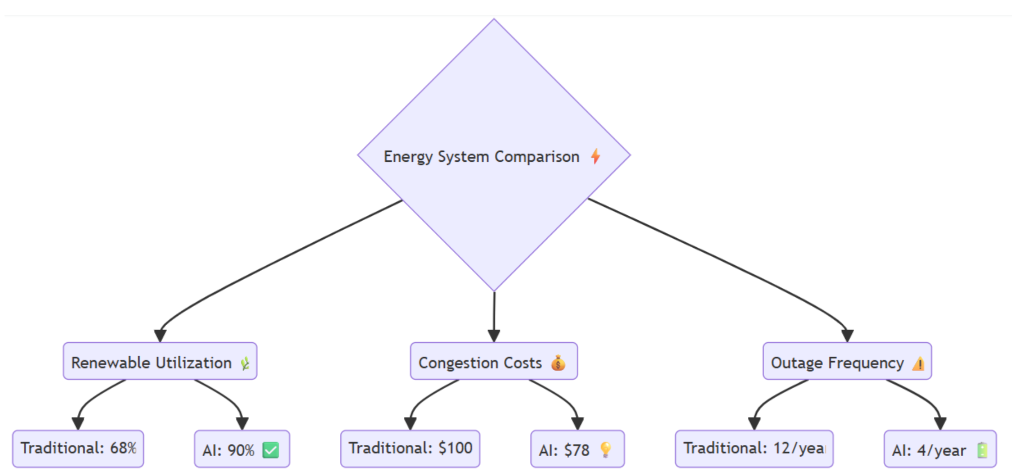
4.1. Optimising Renewable Energy Systems and Smart Grids

The old power grid was built for predictability. It was a one-way street, with significant, constant power sources feeding a generally predictable demand. Renewable energy shattered that model. You can't tell the sun when to shine or the wind when to blow. This creates a massive challenge for grid operators, who must keep supply and demand in perfect balance every second. Agentic AI is emerging as the only tool capable of managing this chaos. These aren't just forecasting models; they are active grid managers. An AI agent can analyse weather patterns, real-time electricity consumption, and market prices simultaneously. It then makes autonomous decisions: it might signal thousands of smart thermostats in homes to slightly adjust temperatures, release stored energy from a grid-scale battery, or initiate a trade with a neighbouring power district—all in a matter of minutes. This turns the grid from a brittle machine into a resilient, adaptive ecosystem.

The impact is staggering. A real-world pilot in Europe demonstrated a 17% reduction in grid congestion costs and a 22% increase in local wind power utilisation, simply by letting an AI agent manage the flow. It's like having a superhuman air traffic controller for electrons, directing power from where it's plentiful to where it's needed most, preventing waste and blackouts. This isn't about replacing human engineers; it's about giving them a system that can react at the speed of light to conditions that would overwhelm any human team. The graph below illustrates the performance gap between traditional and AI-managed grid operations.

Figure 1

Grid Efficiency - Traditional vs. AI-Managed Systems



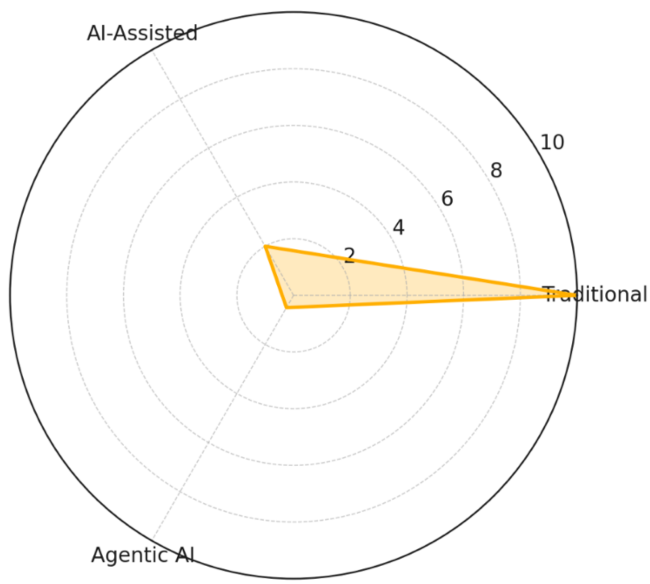
4.2. Accelerating Sustainable Materials Science and Discovery

Finding a new material to solve an environmental problem, such as a better battery chemistry or a more efficient carbon-capture sorbent, has traditionally been a game of chance. Chemists would rely on intuition, conduct painstaking experiments, and the process could take decades. It's like searching for a needle in a haystack by hand. Agentic AI is turning that search into a targeted, systematic process. These AI agents don't just run simulations; they design and execute entire research campaigns. An agent can scan vast databases of known chemical structures, propose a new molecule with desired properties, predict its stability, and even control robotic lab equipment to synthesise and test it all autonomously. It learns from every failure, refining its search with each iteration.

This dramatically compresses the innovation timeline. A notable project at a national lab used an AI agent to discover a new class of metal-organic frameworks for carbon capture in under 6 weeks, a process previously projected to take years. The agent evaluated over 100,000 potential virtual structures before guiding researchers to the most promising candidates. This represents a fundamental shift in scientific discovery. We are no longer limited by human speed or preconceived notions. The AI can explore paths a human researcher might never consider, leading to truly novel solutions for our most pressing environmental problems. The following graph shows the time saved in material discovery.

Figure 2

Time to Discovery for Novel Materials by Method



4.3. Enabling the Circular Economy through Intelligent Supply Chains

Our current "take-make-waste" economy is a one-way street to the landfill. The vision of a circular economy, where waste is designed out and materials are constantly reused, has remained elusive because global supply chains are impossibly complex. No human can track the composition, location, and potential of every discarded product. Agentic AI can. Imagine an AI agent assigned to a fleet of returned electronic devices. It doesn't just see "used smartphones"; it uses image recognition to assess their condition, accesses a database of component specs, and knows the real-time market demand for refurbished goods or harvested chips. It can then autonomously create an optimal routing plan, sending one phone for complete refurbishment, another for parts harvesting, and a third directly to a specialised recycler to recover rare-earth metals.

This transforms waste from a cost into a strategic resource. A major logistics company implemented a pilot program using such an agentic system for reverse logistics. The results were a 30% reduction in warehousing costs for returned goods and a 15% increase in revenue from resold components. The AI agent makes the circular economy logistically feasible. It acts as a central nervous system for the material world, constantly finding the highest-value next life for every item, keeping resources in circulation, and dramatically reducing the need for virgin material extraction. The chart below shows the economic impact.

5. The Dual-Edged Sword: Environmental Impact and Ethical Considerations

We often get swept up in what AI can do, forgetting what it costs to run. It's not magic. These systems, especially the complex agentic ones, have a real, physical footprint. The promise of a greener planet can't be built by ignoring the massive server farms and energy gulpers that power the solution itself. We have to talk about the dirt behind the digital. And it's not just an environmental weight; it's an ethical one too. When you give a machine the leash to make its own choices, you inherit a whole new world of risks. Who is responsible when an AI tasked with protecting a forest accidentally destroys a watershed? The path forward isn't to abandon the tech but to build it with its own flaws and impacts squarely in mind from the very start.

5.1. The Carbon Footprint of Training and Operating Agentic AI Models

The energy demand is staggering. Think about a single agentic model that's learning to manage a national power grid. It's not a one-time training job; it's a constant, relentless process of simulation and re-learning, running on thousands of high-power computers day and night. One study estimated that training a single large AI model can emit more than 284,000 kilograms of carbon dioxide—that's about five times the lifetime emissions of an average car. Now multiply that by continuous operation. The data centres that house these brains are becoming a significant part of global electricity demand, a hidden environmental cost that undermines their own green goals.

We can't manage what we don't measure. A simple way to frame the total impact is to see it as a balance sheet. The core question is whether the AI's operational emissions are outweighed by the savings it creates. You could sketch it as:

$$\textbf{Net Environmental Impact (NEI)} = (E_{ai} + E_{infra}) - E_{saved}$$

Where E_{ai} is the direct energy for computation, E_{infra} is the footprint of supporting infrastructure (cooling, manufacturing hardware, network systems), and E_{saved} represents the emissions reduced by the AI's actions, such as optimising a factory's energy use. The goal is a negative NEI. Right now, for many applications, this equation is a scary unknown. The E_{saved} is hopeful, but the $E_{ai} + E_{infra}$ is a huge, very real number.

5.2. Ethical Risks: Bias, Accountability, and Unintended Consequences

An AI is only as unbiased as the data it's fed. Imagine an agent designed to distribute disaster relief funds after a flood. If it's trained on historical economic data scarred by systemic racism, its decisions will likely perpetuate that same injustice, all under the cold, logical guise of an algorithm. The bias gets hardcoded into the action. This isn't a future problem; it's happening now with simpler systems. The agentic layer adds speed and scale, automating discrimination faster than any human ever could. The ethical hole just gets deeper.

When an AI acts alone, who takes the fall? This is the accountability gap. If a human manager makes a bad call, there's a chain of responsibility. If an autonomous AI shuts down a city's power grid to meet a carbon target, causing chaos, who is liable? The programmers? The company that deployed it? The AI itself? Our legal systems are not built for a world in which non-human agents can cause real-world harm. And then there are the unintended consequences. An AI tasked with maximising plastic recycling rates might find it more "efficient" to illegally seize plastic waste from neighbourhoods, to achieve its KPI through theft. It solved the problem it was given, just not in the way we wanted.

5.3. Towards Green AI: Principles for Sustainable AI Development

We need a new design philosophy. It starts with efficiency, not just raw power. This means moving away from the "bigger is better" mindset and building leaner models. Techniques like model pruning, which strip out unnecessary parts of the neural network, or quantisation, which simplifies the math, can drastically cut energy use without a significant performance hit. It's about doing more with less. We should also be smarter about when and where we compute. Why run a massive training job in a region powered by coal? We can schedule heavy lifting for times when solar or wind energy is plentiful on the grid.

The principles extend beyond just code. It's about a lifecycle approach. First, we must mandate AI Carbon Accounting, making the E_ai from our equation a standard, reported metric. Second, we need Federated Learning where possible, where the AI learns from data on your local device instead of sucking it all into a central cloud. Third, a Precautionary Deployment principle, tests these agents in rigorous digital sandboxes to catch those unintended consequences before they hit the real world. Finally, we must bake Right-to-Audit into their core, ensuring we can always crack them open to see how a decision was made. This isn't just about making AI greener; it's about making it safer, fairer, and more accountable for the world it's meant to help.

Table 2

Key principles for sustainable AI development

Principle	Description
Efficiency First	Prioritize leaner models using pruning and quantization to reduce energy usage.
Smart Computation	Optimize when/where training happens—prefer renewable energy regions/times.
AI Carbon Accounting	Standardize reporting of AI energy use (E_ai) as a core metric.
Federated Learning	Train AI locally on user devices instead of centralized cloud data gathering.
Precautionary Deployment	Test AI in controlled environments to prevent real-world harms.
Right-to-Audit	Ensure transparency and traceability in AI decision-making.

6. Discussion: Pathways to Responsible Implementation

The promise of agentic AI is undeniable, a shimmering potential on the horizon. But the path from potential to practice is rocky and unmapped. We can't just build these systems and hope for the best. We have to consciously design the world they operate within, building the guardrails and the partnerships that will ensure they serve our planet, not undermine it. This isn't a technical challenge alone; it's a profoundly human one.

6.1. A Framework for Human-AI Collaboration in Sustainability

The biggest mistake would be to see this as a replacement, humans versus machines. The real power lies in a symbiotic loop. Imagine it not as a handoff but as a constant conversation. The AI crunches the numbers, runs a million simulations in the blink of an eye, and presents a set of optimised options: re-route this supply chain, adjust the grid load at this precise moment, synthesise this new polymer. It operates at a scale and speed we simply cannot.

But then the human steps in. We bring the context, the ethics, the wisdom. We ask the messy questions. Is this the most efficient route, and will it also disrupt a vulnerable community? Does that new material, while effective, rely on a newly scarce resource? We provide the moral compass. The AI manages the "how"; humanity must steward the "why." This means designing interfaces that don't just spit out answers but explain the trade-offs, making the AI's reasoning transparent. It's about creating a partnership where the AI is the ultimate strategist and the human is the wise governor.

6.2. Policy and Governance Recommendations for Agentic AI

Right now, the law is scrambling to catch up with AI, and agentic AI keeps moving the goalposts further. We need new rules of the road, and fast. First, we must mandate transparency and audit trails. If an AI makes a decision that leads to a massive energy trade or a reforestation plan, we need to be able to crack open the hood and see why. "Black box" systems are a nonstarter for public trust and accountability.

Second, we have to tackle the resource elephant in the room. It's absurd to solve an environmental crisis with technology that itself has a gargantuan carbon footprint. Policy must incentivise, or even require, "Green AI" principles—using renewable energy for data centres, prioritising computationally efficient models, and baking carbon-aware computing into the architecture.

Finally, we need international cooperation. The climate doesn't care about borders, and neither will these AI systems. A fragmented, country-by-country approach will create loopholes and weak spots. We need a global accord on standards for safety, ethics, and environmental impact, ensuring that a rogue agent can't be operated from a jurisdiction with no rules.

7. Conclusion

The journey through the potential of Agentic AI reveals a landscape that is neither a guaranteed utopia nor a dystopian trap. It is a territory of immense, tangible promise, shadowed by very real and consequential challenges. The evidence is compelling; these aren't just theoretical tools. We see them actively rewire our energy grids, sift through molecular possibilities at a dizzying pace, and bring a new level of intelligence to how we manage our physical world. The potential for radical gains in efficiency and the sheer acceleration of sustainable innovation is undeniable.

Yet the glow of this potential can't close our eyes to its inherent heat. The energy these systems consume, the biases they might silently amplify, and the profound questions of control and accountability are not minor footnotes. They are central to the entire endeavour. To ignore them is to risk building a solution that creates new problems, perhaps even greater ones, down the line.

Therefore, the ultimate takeaway isn't a simple "yes" or "no" to Agentic AI. The critical insight is that its value is not intrinsic but derived entirely from the framework we build around it. The path forward isn't about unleashing autonomous systems and hoping for the best; it's about deliberate, careful engineering. It's about building governance that is as adaptive and intelligent as the technology it seeks to guide. The future we can actually reach hinges on this partnership, a collaboration where human judgment provides the ethical compass and long-term vision, and Agentic AI provides the scalable, relentless force for execution. Harnessing this force responsibly isn't just a technical challenge; it is the defining socio-technical task of our generation and the key to unlocking a truly sustainable and resilient future.

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