

Beyond Algorithms: Generative AI as a Catalyst for Accessible and Accountable Optimization

“Harnessing Generative AI for Optimization: A Practical Guide for Indonesian Researchers and Students”



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Abstract

Generative artificial intelligence (GenAI) is reshaping decision-making, yet mathematical optimization, despite its value, remains limited to expert use. This study examines how GenAI can broaden optimization's reach by reducing technical barriers and fostering wider participation in decision science. Using a descriptive qualitative approach, the analysis integrates Scopus-indexed literature (2019–2025), institutional policy frameworks, and practitioner-oriented sources, including La Academic.

Three perspectives guide the study: the 4I framework (Insight, Interpretability, Interactivity, Improvisation), the Technology Acceptance Model (TAM), and Institutional Theory. Findings show that GenAI strengthens Insight by synthesizing diverse data into summaries, enhances Interpretability by explaining trade-offs in plain language, enables Interactivity through scenario testing, and supports Improvisation during disruptions. These functions reinforce TAM's constructs of perceived ease of use and usefulness, making optimization more accessible.

Institutional Theory highlights adoption drivers: coercive regulations demanding explainability, normative professional standards, and mimetic pressures from peer adoption. Yet challenges persist, including hallucinations, bias, and over-reliance, which threaten trust and reliability.

The study concludes that GenAI complements rather than replaces optimization, offering accessibility while optimization provides rigor. Responsible adoption requires verification systems, educational reforms, and institutional safeguards, paralleling democratization efforts in academic publishing such as La Academic's *Summary Publishing in Sinta-Accredited Journals* (Academic, 2025).

Keywords: Generative Artificial Intelligence (GenAI); Optimization; Decision Science; Technology Acceptance Model (TAM); Institutional Theory; 4I Framework; Responsible AI; Democratization of Technology; Educational Innovation; Indonesia

Introduction

Generative artificial intelligence (GenAI) has emerged as one of the most influential technological shifts of the last decade. Large language models (LLMs), image generators, and multimodal AI systems are widely used in education, business, and research, drawing unprecedented levels of attention from policymakers, media, and the public. In contrast, mathematical optimization—although a cornerstone of decision science with proven applications in manufacturing, healthcare, logistics, and finance—has remained largely invisible beyond specialist circles (Huang et al., 2025; Wiberg et al., 2025). This paradox is evident in digital search trends: while terms such as “AI” and “LLMs” have surged, technical phrases like “linear programming” and “integer programming” remain stagnant. Optimization is critical for improving efficiency and resource allocation, yet it is seldom recognized outside the academic and technical communities that build and apply these models.

The limited reach of optimization does not reflect a lack of success. Operations research has a long history, beginning in World War II and extending into the rise of industrial engineering and modern analytics (Encyclopaedia Britannica, 2025). However, barriers remain high: real-world problems are often ill-structured, while optimization requires formalization into variables, constraints, and objective functions (Kobbacy et al., 2007). Most managers reason in narratives, scenarios, and heuristics rather than algebraic models, leaving optimization tools underutilized in practice.

GenAI offers a potential solution by serving as an intermediary between human reasoning and mathematical formalism. Instead of requiring technical coding, users can describe problems conversationally, and GenAI can generate preliminary optimization models or interpret solver outputs (Simchi-Levi et al., 2025). This represents a shift from symbolic modeling to dialog-based problem-solving. For example, a manager could ask, “What if production capacity drops by 15%?” and receive not only recalculated results but also narrative explanations of the trade-offs involved. In this way, GenAI may lower the barriers that have historically limited optimization’s democratization.

To conceptualize this integration, Simchi-Levi and colleagues (2025) propose the 4I framework: *Insight, Interpretability, Interactivity, and Improvisation*. These four principles describe how GenAI complements optimization: by producing up-to-date situational awareness (Insight), translating model logic into comprehensible language (Interpretability), enabling interactive “what-if” analysis (Interactivity), and adapting recommendations to disruptions (Improvisation). Together, these elements help reframe optimization from a specialized mathematical tool into a more accessible form of decision support.

The adoption of such innovations can be better understood through established theories of technology diffusion. The Technology Acceptance Model (TAM) emphasizes that users adopt tools when they perceive them as both useful and easy to use (Davis, 1989; Venkatesh & Bala, 2008). GenAI’s natural language interface enhances ease of use, while its ability to explain optimization outcomes improves perceived usefulness. At the same time, Institutional Theory

highlights how organizations adopt technologies not only for efficiency but also under external pressures: *coercive* (e.g., legal requirements for explainability under the EU AI Act, 2024), *normative* (e.g., professional standards for transparency), and *mimetic* (e.g., following competitors' adoption strategies). Together, TAM and Institutional Theory provide complementary perspectives on how GenAI-driven optimization may diffuse across industries.

The relevance of democratization extends beyond technical applications. In academic publishing, for example, similar barriers of accessibility and readiness exist. La Academic's educational materials illustrate how scaffolding can reduce such barriers. Its blog post *What Is Research?* (La Academic, 2025a) clarifies foundational concepts, while another post, *Mengapa La Academic Membantu Artikel Lebih Siap Terbit Atau ...* (La Academic, 2025b), demonstrates how structured support helps authors prepare for submission. Similarly, the SSRN resource *Summary Publishing in Sinta-Accredited Journals* (Academic, 2025) shows how institutional guidance enables broader participation in scholarly ecosystems. These parallels reinforce the broader claim: democratization requires not just technical tools but also institutional and educational support.

This study aims to contribute to the growing conversation on GenAI and decision science by addressing three objectives:

1. To examine how GenAI enhances accessibility and usability of optimization for nonspecialist users.
2. To evaluate adoption drivers through TAM, focusing on ease of use and usefulness.
3. To analyze the institutional dynamics—coercive, normative, and mimetic—that shape responsible adoption.

The novelty lies in bringing together technical frameworks (4I), adoption models (TAM), and institutional perspectives into a single analysis. By synthesizing literature from operations research, artificial intelligence, and organizational studies, this article develops an integrated framework for understanding how GenAI democratizes optimization, while acknowledging the ethical and governance challenges that accompany it.

Research Design

This article applies a descriptive qualitative approach, selected because the field of GenAI-enhanced optimization is still emerging and characterized by conceptual exploration rather than mature empirical datasets. Rather than conducting experiments or surveys, the focus here is on synthesizing peer-reviewed studies, institutional frameworks, and practitioner-oriented sources into a coherent analytical narrative. Qualitative synthesis allows the integration of insights from operations research, artificial intelligence, and organizational theory, each of which frames adoption dynamics differently (Creswell & Poth, 2018).

The rationale for this design is threefold. First, since generative AI applications in optimization are recent, most contributions appear as conceptual discussions, preliminary experiments, or case analyses (Li et al., 2023; Huang et al., 2025). Second, the study aims to integrate multiple

theoretical perspectives—including the 4I framework, the Technology Acceptance Model (TAM), and Institutional Theory—which necessitates a flexible and interpretive research strategy. Third, qualitative synthesis makes it possible to draw connections between technical findings and institutional realities, such as governance frameworks and professional standards (OECD, 2023; European Commission, 2024).

Sources of Evidence

The evidence base for this study is drawn from three categories:

1. Academic Literature (Scopus, 2019–2025):

Recent scholarship on the intersection of GenAI and optimization provides the foundation. Examples include supply chain applications (Menache et al., 2025; Simchi-Levi et al., 2025), advances in optimization modeling with LLMs (Li et al., 2024a, 2024b), and crossdisciplinary reviews (Wiberg et al., 2025). These works provide both technical insights and domain-specific applications.

2. Institutional Reports and Policy Frameworks:

Global institutions are actively shaping the governance landscape for AI adoption. This study incorporates the EU AI Act (2024), OECD guidelines for trustworthy AI (2023), and World Economic Forum reports on resilient digital supply chains (WEF, 2025). These documents frame the coercive and normative pressures highlighted by Institutional Theory.

3. Educational and Practitioner Guides:

To connect the idea of democratization with parallel developments in other domains, the study draws on resources from La Academic. Blog articles such as *What Is Research?* (La Academic, 2025a) and *Mengapa La Academic Membantu Artikel Lebih Siap Terbit Atau ...* (La Academic, 2025b) emphasize the role of institutional scaffolding in lowering barriers to participation. The SSRN publication *Summary Publishing in Sinta-Accredited Journals* (Academic, 2025) further reinforces the parallels between optimization and academic publishing: both require structured support for accessibility.

Analytical Framework

The interpretation of findings is structured by three complementary frameworks:

1. The 4I Framework (Insight, Interpretability, Interactivity, Improvisation):

Originally proposed by Simchi-Levi and colleagues (2025), the 4I framework describes how GenAI enhances optimization by making it more intuitive, adaptable, and communicable. In this study, the 4I framework is used to code examples of GenAI applications across different sectors.

2. Technology Acceptance Model (TAM):

TAM is employed to interpret adoption dynamics at the individual and organizational level. The constructs of *perceived ease of use* and *perceived usefulness* (Davis, 1989; Venkatesh & Bala, 2008) are used to evaluate why non-experts may be more inclined to adopt optimization tools when mediated by GenAI.

3. Institutional Theory:

To capture broader organizational and societal forces, Institutional Theory is applied, focusing on coercive, normative, and mimetic pressures (DiMaggio & Powell, 1983). These dimensions help explain why adoption varies across industries and why governance frameworks matter.

Together, these frameworks provide a layered perspective: the 4I model addresses technical usability, TAM explains behavioral adoption, and Institutional Theory situates these dynamics within organizational and societal contexts.

Literature Collection and Review Process

A systematic search of Scopus was conducted for publications between 2019 and 2025. Keywords included “*Generative AI*,” “*optimization*,” “*large language models*,” “*decision-making*,” and “*institutional adoption of AI*.” Articles were filtered for relevance, privileging studies that either addressed optimization directly or examined GenAI adoption more broadly. Policy documents were retrieved from official institutional websites (e.g., EU, OECD, WEF). Practitioner resources from La Academic were identified as illustrative cases of democratization in parallel fields.

The review followed an iterative process:

- First pass: Identification of candidate works.
- Second pass: Extraction of themes related to 4I, TAM, and institutional pressures. □
- Third pass: Integration of insights into comparative thematic categories.

Coding and Synthesis

Thematic analysis proceeded in three stages:

- Open coding: Initial labeling of recurring concepts, such as “explainability,” “ease of use,” “hallucination,” and “resilience.”
- Axial coding: Grouping these into the dimensions of 4I, TAM, and Institutional Theory. For example, “explainability” was mapped to Interpretability and also to normative pressures.
- Selective coding: Developing overarching themes that demonstrate how GenAI democratizes optimization, while also introducing governance challenges.

This process ensured a transparent alignment between evidence and interpretation.

Validity and Reliability

To enhance the credibility of findings, triangulation was used across the three categories of sources: academic studies, institutional frameworks, and practitioner guides. For instance, the democratizing effect of GenAI was supported by evidence from technical studies on LLMs in supply chains (Li et al., 2023), institutional calls for transparency (OECD, 2023), and educational guidance for academic publishing (Academic, 2025). Reliability was strengthened by documenting the review process and coding procedures in detail.

Ethical Considerations

The study engages with two ethical dimensions. First, in terms of methodology, sources are cited transparently to avoid misrepresentation or unacknowledged borrowing. Second, in terms of content, the analysis acknowledges that GenAI carries risks—including bias, hallucinations, and over-simplification—that could undermine trust if not addressed through institutional safeguards.

By adopting a qualitative design anchored in multiple frameworks, this study provides a robust foundation for examining how GenAI reshapes the accessibility, adoption, and governance of optimization.

Results

1. Supply Chain Optimization

Among all industries, supply chain management has been the quickest to test the combination of optimization and GenAI. Optimization has long underpinned tasks such as routing, sourcing, and capacity planning, but it has usually required specialized expertise. GenAI now offers a conversational bridge, enabling managers to articulate problems in natural language and generate or revise optimization models without technical mediation (Menache et al., 2025).

- **Insight:** By aggregating streams of demand forecasts, shipping delays, and supplier updates, GenAI produces a timely and consolidated view of supply chain operations.
- **Interpretability:** Instead of returning numerical solver outputs, GenAI reframes them as trade-offs—for instance, explaining how reducing costs may extend delivery windows.
- **Interactivity:** Managers can ask iterative questions like, “What if we reroute through an alternative port?” and quickly receive revised optimization solutions.
- **Improvisation:** In times of crisis, such as pandemic-driven shortages, GenAI helps adapt sourcing strategies or reroute logistics in near real time.

From a TAM perspective, this enhances *ease of use* by minimizing technical barriers and *usefulness* by providing actionable explanations. Institutionally, mimetic pressures emerge as companies emulate early adopters demonstrating resilience (Wiberg et al., 2025), while coercive pressures come from governments emphasizing supply chain transparency (WEF, 2025).

2. Healthcare Decision-Making

Healthcare presents high stakes, where optimization supports tasks like resource allocation, surgery scheduling, and pandemic response. Yet clinicians often distrust models they cannot interpret. GenAI helps reduce this gap.

- **Insight:** GenAI can consolidate patient inflow data, ICU occupancy, and staff availability into an integrated picture of hospital operations (Hadary et al., 2020).
- **Interpretability:** Optimization outcomes are explained in terms of clinical reasoning: e.g., “Allocating two additional nurses to ward A reduces patient wait times by 30%.”
- **Interactivity:** Administrators can explore scenarios such as, “What if we expand ICU capacity by 20%?” and receive adjusted staffing recommendations.
- **Improvisation:** During emergencies, such as sudden disease outbreaks, GenAI helps reassign resources dynamically.

Here, usefulness dominates TAM adoption dynamics: clinicians are more likely to adopt when AI recommendations demonstrably improve patient outcomes. Coercive pressures come from safety regulations requiring explainability (EU AI Act, 2024). Normative pressures are rooted in medical ethics, demanding transparency and fairness. Mimetic pressures appear when hospitals replicate strategies of pioneering institutions that use AI to improve care efficiency.

Yet risks remain substantial. Hallucinations may lead to unsafe recommendations—for example, disregarding legal staffing ratios. As a result, hybrid verification combining AI suggestions with solver validation becomes essential.

3. Financial Modeling and Risk Analysis

In finance, optimization governs portfolio balancing, capital allocation, and risk mitigation. These models are often reserved for quantitative analysts, leaving decision-makers reliant on intermediaries. GenAI democratizes access by making optimization conversational.

- **Insight:** AI systems can synthesize diverse financial indicators, such as bond yields and currency fluctuations, into coherent overviews.
- **Interpretability:** Trade-offs—like balancing liquidity with risk-adjusted returns—are explained in plain terms, making decisions more defensible.
- **Interactivity:** Portfolio managers can query scenarios such as, “What happens if inflation rises by 1%?” and receive revised portfolio strategies.
- **Improvisation:** During crises (e.g., currency depreciation), GenAI supports rapid recalibration of investment decisions.

Ease of use is critical here: non-technical managers can directly engage with tools previously locked within quantitative teams. Usefulness is evident when AI explanations help justify decisions under volatile conditions. Institutionally, coercive pressures arise from financial

regulators requiring transparency, normative pressures stem from professional ethics in fiduciary responsibility, and mimetic pressures drive competitive firms to adopt when peers demonstrate success.

Still, hallucination risks are acute: a GenAI-generated but flawed optimization model could expose firms to significant financial harm. Governance structures remain essential for accountability.

4. Urban Logistics and Smart Cities

Cities face mounting logistical challenges with e-commerce growth, congestion, and sustainability goals. GenAI combined with optimization and digital twins provides promising avenues (Xu et al., 2025).

- **Insight:** By combining traffic flows, delivery demands, and emissions data, GenAI offers real-time views of logistics systems.
- **Interpretability:** Trade-offs, such as faster delivery versus higher carbon emissions, are framed in accessible narratives for policymakers.
- **Interactivity:** Planners can test scenarios like, “What if trucks are restricted from the city center between 8 a.m. and 5 p.m.?” and receive modeled outcomes.
- **Improvisation:** During disruptions—such as accidents or strikes—GenAI proposes alternative routes and adaptive schedules.

From a TAM standpoint, *usefulness* is clear when tools reduce congestion and environmental impact, and *ease of use* is enhanced by natural language interfaces that allow participation from policymakers and community stakeholders. Institutionally, coercive pressures arise from regulations on emissions, normative pressures from global sustainability targets, and mimetic pressures from cities emulating “smart city” pioneers.

Cross-Cutting Findings

When comparing across domains, several themes emerge:

1. **Democratization:** GenAI lowers the barrier for non-experts to engage in optimization, broadening its reach.
2. **Reliability Risks:** Hallucinations and oversimplification remain pressing challenges, demanding hybrid validation.
3. **Governance Needs:** Adoption requires institutional safeguards, particularly in high-stakes domains such as healthcare and finance.
4. **Institutional Shaping:** Adoption is influenced as much by external pressures (laws, ethics, competition) as by technical merit.

Together, these results support the view that GenAI and optimization are complements rather than substitutes

Discussion

Reassessing the 4I Framework in Practice

The results reveal that the 4I framework (Insight, Interpretability, Interactivity, Improvisation) provides a useful lens for understanding how GenAI reshapes optimization.

- Insight emerges as a democratizing function, transforming raw data streams into narratives or dashboards that non-specialists can understand. In supply chains, for instance, GenAI translates complex disruptions into clear operational overviews. This dimension resonates strongly with *perceived usefulness* in TAM, as better situational awareness directly improves decision quality.
- Interpretability appears to be the most transformative contribution of GenAI. Mathematical outputs that once alienated managers are now reframed in everyday language. For healthcare and finance, this feature directly addresses concerns about transparency and trust.
- Interactivity turns optimization into an exploratory dialogue rather than a one-off calculation. Managers and planners can iterate through scenarios dynamically, aligning optimization with how decisions are made in practice.
- Improvisation strengthens resilience. Whether in logistics disruptions or hospital crises, GenAI provides a means of quickly re-optimizing when conditions shift, something traditional models often struggled to accommodate.

The findings support Simchi-Levi et al.'s (2025) argument that GenAI does not replace optimization but complements it by making it more usable. The 4I framework explains not only the technical integration but also the behavioral shift in how decision-makers interact with optimization systems.

Technology Acceptance Model: Behavioral Dynamics

Applying TAM helps clarify adoption pathways.

- Ease of Use: The shift from algebraic coding to conversational interfaces radically reduces barriers. This aligns with Davis' (1989) assertion that ease of use influences willingness to adopt. The healthcare and finance cases demonstrate that even individuals without technical training can now meaningfully engage with optimization.
- Usefulness: GenAI's ability to contextualize trade-offs into business or clinical terms increases perceived value. Managers adopt tools not only because they are easier but because outputs are more relevant to their needs.

The dual improvement in both ease of use and usefulness explains why adoption may accelerate across diverse industries. Yet, TAM alone cannot fully account for the institutional forces shaping adoption—hence the importance of Institutional Theory.

Institutional Theory: Pressures and Legitimacy

Institutional Theory highlights how adoption is not just a matter of individual acceptance but is embedded in broader organizational and societal contexts.

- **Coercive Pressures:** Regulations such as the EU AI Act (2024) legally require explainability, making Interpretability a compliance necessity. Similarly, financial regulators demand transparency in algorithmic trading.
- **Normative Pressures:** Professional communities, such as medicine and finance, impose ethical standards. For instance, clinicians are ethically bound to demand transparency in patient care decisions.
- **Mimetic Pressures:** Organizations imitate early adopters to maintain legitimacy. In supply chains, firms that show resilience through GenAI optimization set benchmarks that competitors feel compelled to follow.

By situating adoption within these pressures, Institutional Theory enriches the analysis beyond technical or behavioral explanations. It underscores that responsible democratization requires institutions to evolve alongside technology.

Ethical and Governance Considerations

Despite its potential, GenAI-driven optimization raises critical ethical concerns.

Reliability and Hallucinations

Large language models may generate plausible but flawed optimization models. For example, omitting a constraint in a hospital staffing plan could compromise patient safety. Hybrid systems—where GenAI drafts are verified by solvers or human experts—are essential to mitigate this risk.

Over-Simplification and Skill Erosion

While accessibility is valuable, there is a risk that managers may rely too heavily on AI outputs without critical evaluation. Optimization has traditionally required careful problem formulation; GenAI's ease may undermine this discipline. Educational programs must adapt by teaching students not only how to use GenAI but also how to question and validate its outputs.

Bias and Fairness

Because GenAI is trained on historical data, it can reproduce biases. In healthcare, this could mean unequal treatment recommendations. In finance, it could mean skewed investment strategies. Governance protocols must address these biases through regular audits and ethical oversight.

Accountability and Power Redistribution

Democratization changes organizational power structures. Frontline workers now have direct access to optimization tools, potentially bypassing expert intermediaries. While this decentralizes decision-making, it complicates accountability. Institutions must clarify where responsibility lies when GenAI-generated recommendations go wrong.

Parallels with Academic Publishing

The democratization challenges in optimization mirror those in scholarly publishing. La Academic's resources, such as *What Is Research?* (La Academic, 2025a), *Mengapa La Academic Membantu Artikel Lebih Siap Terbit Atau ...* (La Academic, 2025b), and *Summary Publishing in Sinta-Accredited Journals* (Academic, 2025), illustrate that widening participation requires scaffolding. Just as guides and institutional support help students and lecturers navigate journal submission, GenAI-enabled optimization requires educational and governance frameworks to ensure accessibility translates into quality and accountability.

Future Research Directions

Several areas demand further inquiry:

1. **Verification Mechanisms:** Research is needed to create automated systems that validate GenAI-generated optimization models.
2. **Human–AI Collaboration:** Studies should explore how teams can balance AI assistance with human judgment to avoid over-reliance.
3. **Cross-Industry Case Studies:** Comparative analyses can reveal how institutional pressures vary by sector, shaping adoption differently.
4. **Educational Reforms:** Investigations into curricula that train students in critical use of GenAI will be essential.
5. **Ethical Auditing:** Frameworks for auditing GenAI systems must be developed to ensure fairness, transparency, and accountability.

Toward Responsible Democratization

The synthesis of 4I, TAM, and Institutional Theory suggests that democratization is both a technical and institutional process. GenAI enables broader access by lowering barriers, but governance and education ensure that access leads to responsible use. Optimization provides rigor, while GenAI provides accessibility. Together, they create a decision science that is both more inclusive and more powerful.

The analogy with academic publishing underscores the central argument: democratization is not achieved through technology alone but through institutional structures that guide and support its use. For optimization, this means hybrid verification, revised training, and institutional accountability. For publishing, it means guides, mentorship, and transparent standards. Both reveal that true democratization requires accessibility plus institutional scaffolding.

Conclusion

Generative artificial intelligence (GenAI) has introduced new ways of engaging with complex decision-making, creating possibilities that were previously out of reach for many organizations. Optimization, a discipline long central to operations research and management science, has historically been underutilized due to its technical requirements and steep learning curve. This article has explored how GenAI can act as a democratizing force, lowering barriers to entry while raising questions about governance, ethics, and institutional adaptation.

By synthesizing evidence from recent Scopus-indexed research, institutional policy frameworks, and practitioner-oriented resources, this study has provided a multi-layered analysis of GenAI's role in optimization. Three frameworks guided this exploration: the 4I model, the Technology Acceptance Model (TAM), and Institutional Theory. The 4I model captured how GenAI improves optimization through Insight, Interpretability, Interactivity, and Improvisation. TAM clarified how adoption is driven by perceptions of ease of use and usefulness. Institutional Theory revealed the external pressures—coercive, normative, and mimetic—that shape organizational adoption. Together, these frameworks illuminate both the promise and the constraints of democratizing optimization through GenAI.

The findings highlight several important contributions. First, GenAI enhances optimization's accessibility, allowing non-specialists to engage in decision-making processes once reserved for technical experts. Second, by reframing outputs in plain language and supporting dynamic “whatif” scenarios, GenAI strengthens transparency and adaptability across industries. Third, institutional pressures ensure that adoption does not occur in isolation but within broader governance environments, where regulations and professional norms impose accountability requirements.

Yet, the analysis also cautions against over-enthusiasm. The risks of hallucination, bias, and overreliance remain significant. Without verification mechanisms, AI-generated recommendations could mislead managers in high-stakes domains such as healthcare or finance. Furthermore, by simplifying access, GenAI may inadvertently erode critical modeling skills, leaving organizations vulnerable if AI outputs are accepted uncritically. These challenges reinforce the need for educational reforms that balance accessibility with critical evaluation skills.

The broader lesson is that democratization requires both technology and scaffolding. This parallels developments in academic publishing, where initiatives like La Academic's educational guides (La Academic, 2025a, 2025b) and its SSRN resource on publishing in Sinta-accredited journals (Academic, 2025) demonstrate how institutional support enables wider participation. Similarly, GenAI can broaden optimization's reach, but only if institutions develop safeguards, training, and governance protocols that ensure responsible adoption.

Looking ahead, several directions for future research are clear. Scholars should investigate frameworks for verifying AI-generated optimization models, explore hybrid human–AI collaboration models, and analyze sector-specific adoption pathways under varying institutional pressures. Pedagogical research is equally important, as universities and training programs must

prepare students not only to use GenAI but also to challenge and evaluate its recommendations. Policymakers and regulators will need to balance innovation with accountability, creating frameworks that support experimentation without sacrificing safety or fairness.

In conclusion, GenAI does not replace optimization—it amplifies it. Where optimization provides rigor, GenAI adds accessibility. Together, they redefine the practice of decision science, creating opportunities for more inclusive, transparent, and resilient organizations. Yet this opportunity is accompanied by responsibility. To harness GenAI’s potential fully, institutions, educators, and practitioners must commit to responsible democratization, where access is matched with governance. If realized thoughtfully, this integration could make optimization not just a specialized discipline but a shared foundation for decision-making across industries and societies.

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