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Mathematics & Artificial Intelligence for Industry from Small Business to Large Enterprises

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Abstract- The convergence of mathematics and artificial intelligence is fundamentally transforming how industries operate; however, the pace and nature of this transformation vary considerably across organizations of different sizes. This article explores how mathematical optimization techniques, machine learning algorithms, and AI systems can generate competitive advantages, while critically examining the asymmetric barriers hindering their adoption in organizations. We propose a conceptual framework demonstrating that while large enterprises possess the resources to develop customized AI solutions, small and medium-sized enterprises (SMEs) are increasingly leveraging available alternatives, such as AI service subscriptions, conversational interfaces that mask mathematical complexities, and open-source optimization engines. Based on contemporary research and emerging industry practices, the analysis underscores that mathematical accuracy embedded in AI infrastructure remains essential for reliable industrial deployment. The study concludes that increased accessibility to mathematical AI resources, coupled with system designs that clearly distinguish between cognitive reasoning and numerical processing, represents a viable path toward widespread industrial modernization.

Keywords— Artificial intelligence, mathematical optimization, small and medium enterprises, industrial mathematics, AI adoption, digital transformation, machine learning, decision support systems.

I. INTRODUCTION

The Fourth Industrial Revolution ushered in an era where mathematical science and intelligent systems converge to revolutionize production methodologies. Whether the goal is to optimize assembly line operations or predict consumer demand, algorithmic decision-making and AI-powered analytics have become cornerstones of corporate competitiveness. Despite this momentum, adoption patterns reveal striking disparities: large, well-funded companies have aggressively pursued customized AI solutions, while smaller firms are often constrained by limited budgets, insufficient technical expertise, and inadequate digital infrastructure.

This research is based on a fundamental question: What strategies enable the effective deployment of mathematical and artificial intelligence (AI) tools across various organizational levels, from small family businesses to global industrial giants? The research begins with the premise that successful implementation depends on two interconnected factors: first, a solid understanding of the mathematical principles that ensure the reliability of

AI, and second, the strategic use of innovative tools designed to overcome barriers to entry . This research delves into this discussion through three key contributions. First, we present a systematic map of mathematical AI applications in industrial environments, categorized by operational scale and solution complexity. Second, we identify the obstacles faced by small and medium-sized enterprises (SMEs) and analyze the innovative responses that have emerged to mitigate these challenges. Finally, we outline an adoption roadmap that enables organizations to identify appropriate mathematical AI approaches that align with their unique structural characteristics and strategic requirements.

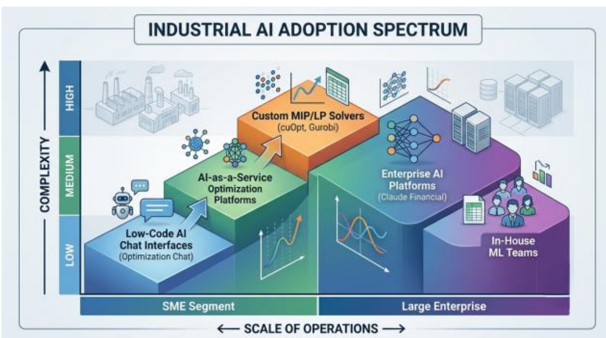

Figure 1: Scope of AI adoption in mathematics at the industrial level

Objectives

This research examines precisely how mathematical science and artificial intelligence can be meaningfully integrated into industrial processes across the organizational spectrum, from modest local workshops to multinational conglomerates, recognizing that prescriptive approaches are fundamentally inadequate for the heterogeneous realities of AI adoption.

Specific research objectives

- Explore the mathematical foundations that make artificial intelligence trustworthy.
- Documenting the obstacles faced by small and medium-sized enterprises in adopting artificial intelligence.
- Identifying and evaluating emerging solutions that democratize mathematical artificial intelligence for small and medium-sized enterprises.
- Compare the capabilities, resources, and methods of artificial intelligence in small and medium-sized enterprises versus large companies.

Research questions

- The research addresses the following questions:
- What are the core mathematical disciplines that underpin industrial artificial intelligence , and why is mathematical accuracy important for reliable implementation?
- What are the specific obstacles preventing small and medium-sized enterprises (SMEs) from adopting artificial intelligence and mathematical optimization tools, and how important are these obstacles in practice?
- What emerging solutions, such as natural language interfaces, AI-as-a-service platforms, and open-source tools , are effectively enabling access to mathematical AI for small businesses?
- How do AI capabilities, resource requirements, and implementation methods differ systematically between small, medium, and large enterprises?

II. THE MATHEMATICAL FOUNDATIONS OF ARTIFICIAL INTELLIGENCE

1. Basic Mathematical Disciplines

The architecture of industrial AI relies on several fundamental mathematical fields. Linear programming (LP) and mixed integer programming (MIP) form the structural foundation for decision optimization, facilitating resource allocation, production planning, and logistics optimization. These methodologies address problems with linear constraints and objective functions, with MIP extending its capabilities to include discrete decision variables, such as binary options or integer quantities. Combinatorial optimization tackles problems with discrete configurations whose potential solutions expand exponentially with the problem's size. Classical formulas like the traveling salesman problem, vehicle routing challenges, and task sequencing difficulties are examples of this category. Despite their high computational demands, these problems are common in industrial logistics and supply chain management. Statistical learning, along with machine learning, provides predictive capabilities that complement optimization frameworks. Methodologies ranging from ARIMA time series analysis to neural networks enable demand forecasting, quality control, and anomaly identification. The choice between statistical and machine learning approaches depends on data availability and problem characteristics.

Table 1. Artificial intelligence mathematical methods by application field.

Area of application	Basic mathematical methods of artificial intelligence	Typical applications	Business suitability
Production plan	Mixed Linear Programming (MIP)	Resource allocation, production scheduling, and capacity planning	Suitable for companies of all sizes with the appropriate optimization tools.
Supply chain improvement	Vehicle routing problem (VRP), linear programming (LP)	Logistics planning, transportation optimization, and distribution network design.	Large companies primarily; small and medium-sized enterprises can adopt it through cloud computing-based optimization services.
Demand forecasts	ARIMA, Artificial Neural Networks (ANNs), Deep Learning	Sales forecasting, inventory management, demand planning	Small businesses with limited historical data can use the ARIMA model; all businesses benefit from AI models that have complete datasets.
quality control	Classification using machine learning, and extracting	Defect detection, process monitoring, and predictive quality assurance.	Suitable for companies of all sizes.
	correlation rules		
Financial risk management	Mathematical optimization and machine learning	Creditworthiness assessment, fraud detection, investment portfolio optimization, risk assessment	Large companies and financial institutions primarily
Energy Management	Internet of Things (IoT), Mathematical Optimization	Energy efficiency, predictive maintenance, and improved sustainability	Suitable for companies of all sizes.

2. The Mathematical Accuracy Challenge

Contemporary research has revealed a fundamental limitation: large-scale language models, despite their impressive capabilities, are unreliable at performing computations. These systems function as probabilistic textual predictors, excelling in annotation, syntax, and pattern recognition, but lacking the internal precision required for accurate calculations. The SOLID framework (Synergic Optimization of Large-Scale Language Models for Intelligent Decision Making) addresses this limitation by integrating mathematical optimization models with large-scale language models through iterative coordination. Within this architecture, optimization operators perform accurate calculations, while large-scale language model operators provide contextual understanding and strategic guidance, with each component operating within its domain. The architectural solution to this challenge separates cognitive reasoning from computational execution: AI systems determine what requires computation and delegate the calculations to deterministic environments, such as code, databases, and mathematical equation solvers. This principle governs the effective implementation of industrial AI, regardless of the size of the organization.

III. ARTIFICIAL INTELLIGENCE IN SMALL AND MEDIUM-SIZED ENTERPRISES

1. The environment for small and medium-sized enterprises

Small and medium-sized enterprises (SMEs) constitute the vast majority of businesses globally. In the European Union, they represent 99% of all businesses and employ nearly two-thirds of the workforce. In developing economies, they contribute 40% of GDP and employ 60% of the workforce. Despite their economic importance, SMEs face specific obstacles in adopting artificial intelligence (AI). A systematic review of 78 peer-reviewed articles, using a technology-regulatory-environment framework, identified ten critical dimensions affecting AI adoption, with significant differences between SMEs and large enterprises. These challenges are categorized into six main groups:

Table 2. Barriers to AI adoption in small and medium-sized enterprises

Barrier category	Specific challenges	Level of risk
Financial constraints	High initial investment in software, hardware, cloud infrastructure and qualified AI staff; limited access to financial resources.	High
human capital	There is a shortage of data scientists, machine learning engineers, and professionals with industry experience and artificial intelligence skills.	High
Technical infrastructure	Reliance on outdated systems, poor data quality, fragmented databases, and limited digital infrastructure.	High
Conscience and knowledge	A limited understanding of the capabilities, benefits, and strategic value of artificial intelligence; and a lack of awareness that data represents a highly important business asset.	Half
Organizational and cultural resistance	Preference for making decisions based on intuition, resistance to organizational change, and distrust of "black box" AI models.	Half
Regulatory concerns and privacy concerns	Compliance with data protection regulations (such as the General Data Protection Regulation), cybersecurity risks, and concerns related to privacy and data management.	Half

Research examining the obstacles to implementing artificial intelligence (AI) in the manufacturing sector has revealed that a lack of knowledge, implementation timelines, difficulty in selecting applications, and time constraints are among the most significant challenges. Interestingly, the findings suggest a shift in priorities, with organizations now placing greater emphasis on cost-benefit analysis rather than focusing on a general lack of AI knowledge as the primary skills gap.

2. Applications with an impact on small and medium-sized enterprises

Despite some challenges, certain applications offer significant value to small and medium-sized enterprises (SMEs). AI-powered demand forecasting shows particular promise. By incorporating external variables such as macroeconomic indicators, consumer search behavior, and market trends, SMEs can achieve more accurate forecasts than traditional methods allow. Improving production through the integration of the Internet of Things (IoT) presents another opportunity. Even without meeting the "five elements" of big data (volume, velocity, variety, reliability, and value), SMEs can implement successful machine learning and AI initiatives in manufacturing environments. Sensor-based cost models, which calculate unit manufacturing costs based on actual machine utilization rates, provide SMEs with dynamic cost visibility and pave the way for the adoption of Industry 4.0 technologies.

3. Emerging solutions for SME access

The market responded to the challenges facing small and medium-sized enterprises (SMEs) with innovative solutions designed to simplify mathematical complexity. Three main models emerged:

- AI-as-a-S (AI-aaS) optimization platforms provide pre-built optimization models accessible via APIs. Platforms like DcisionAI combine AI-driven problem formulation with mathematical optimization powered by operations research tools, eliminating infrastructure costs. These platforms offer workflow templates covering manufacturing, healthcare, retail, logistics, and energy, making advanced optimization accessible to non-specialist users.

- Natural language interfaces represent a significant advance in making mathematical optimization accessible to everyone. Hybrid AI architectures now allow operators to interact with complex decision support systems through dialogic interfaces. Research on agent-based architectures supporting natural language modeling in batch industrial production processes shows that operators can naturally query enriched datasets and receive data-driven diagnostic responses with average numerical errors of less than 3 %. This eliminates the traditional need for costly expertise in mathematical modeling .
- Open-source optimization tools reduce financial barriers. NVIDIA cuOpt , an open-source GPU-accelerated optimization engine released under the Apache 2.0 license, enables organizations to solve large-scale linear programming, hybrid programming, and vehicle routing problems with unprecedented speed and scalability.

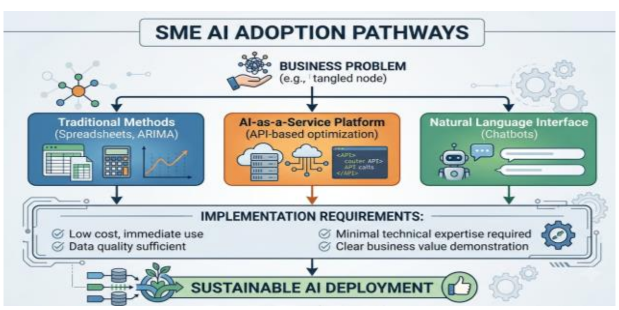

Figure 2: AI adoption pathways in small and medium-sized enterprises

IV. ARTIFICIAL INTELLIGENCE AND MATHEMATICS FOR LARGE COMPANIES

1. Advantages and Strategic Location

Large companies possess advantages that enable them to implement advanced artificial intelligence and mathematical optimization, including substantial financial resources, dedicated data science departments, extensive and structured data assets, and the ability to develop customized solutions precisely tailored to their business contexts. However, research indicates that 44% of studies on AI adoption focus on small and medium-sized enterprises (SMEs), reflecting a growing recognition of the importance of understanding the dynamics of AI adoption within these companies . The distribution of studies (44% on SMEs, 15% on large companies, 9% on both categories, and 32% unspecified) demonstrates that while large companies have been at the forefront of AI adoption, academic focus is increasingly on bridging the gap in SMEs.

2. Enterprise-level applications of artificial intelligence in sports

Table 3. Enterprise AI capabilities versus SME AI solutions.

Capacity dimension	AI solutions for small and medium-sized enterprises	AI solutions for enterprises
The size of the problem	Designed for small and medium-sized operations (up to approximately 1000 sites or operating units).	Designed for complex and large-scale operations (between 10,000 and over 15,000 sites or operating units).
Allocation	Predefined AI models with limited configuration and customization possibilities.	Fully customized AI models and algorithms designed specifically to meet the unique needs of each company.
Systems integration	Cloud platforms with API integration and low-code/no-code connectivity.	Local, cloud, or hybrid infrastructure with dedicated data lines and enterprise-level integration.
Technical expertise is required.	Low; AI capabilities are stripped away through user-friendly interfaces.	High level; requires internal teams specializing in artificial intelligence, data science and engineering.
Cost structure	Prices are determined on a subscription or pay-as-you-go basis with a low initial investment.	Large capital expenditures (CapEx) plus ongoing operating expenses (OpEx)
Computer resources	A shared cloud computing infrastructure with scalable resources	Dedicated high-performance computing environments,

Capacity dimension	AI solutions for small and medium-sized enterprises	AI solutions for enterprises
		including GPU clusters and AI clusters.
Data requirements	It works with relatively limited, incomplete, or moderately structured datasets.	This requires large, high-quality, well-organized datasets that are constantly updated.
Solution performance	They provide cost-effective solutions that are "good enough" to meet common business needs.	It provides highly efficient, scalable, and high-performing artificial intelligence solutions for strategic decision-making.

Portfolio optimization and risk management are leading applications. Advanced optimization frameworks, such as SOLID, demonstrate how to combine mathematical optimization and linear language models to improve portfolio performance. Empirical evidence suggests that hybrid approaches combining optimization models with contextual inference from linear language models achieve higher annual returns and better risk-adjusted performance compared to any single approach. Large-scale supply chain optimization enables the streamlining of procurement, production, and delivery processes to reduce costs and improve efficiency across value chains. Multi-agent systems, including linear language-based agents, provide strategic coordination and adaptive inference, complemented by rule-based agents and microlanguage models that perform efficient, domain-specific tasks at the edge.

3. Hybrid AI Systems Single-Agent and Multi-Agent

Recent advances in agent-led AI are fundamentally transforming the enterprise manufacturing sector. Hybrid agent-led AI and multi-agent frameworks enable heuristic maintenance, with linear learning model (LLM)-based agents providing strategic coordination and adaptive inference, while specialized agents handle perception, preprocessing, analysis, and optimization. These frameworks employ layered architectures that coordinate perception , preprocessing , analysis, and optimization through an LLM-based planning agent that manages workflow decisions and maintains context. Specialized agents independently handle schema discovery, intelligent feature analysis, model selection, and heuristic optimization.

VI. COMPARATIVE ANALYSIS AND ADOPTION FRAMEWORK

1. Key differences in AI adoption

Studies reveal methodological differences in how organizations of different sizes approach mathematical artificial intelligence. These differences extend beyond resources to include organizational culture, decision-making processes, and implementation methodologies.

Research using the TOE framework has identified ten thematic groups that organize the factors for AI adoption: technological readiness, personalization/flexibility, AI tools and needs, data requirements, skills and competencies, resources and financial readiness, management commitment and support, market dynamics and competitive pressure, external support and collaboration, and regulatory and ethical compliance.

Table 4. Comparative analysis of AI adoption in small and medium-sized enterprises and large companies.

Dimensions	Small and medium-sized enterprises (SMEs)	large companies
Main motive	Improving operational efficiency, reducing costs, and increasing productivity.	Achieving a competitive advantage, market leadership, and long-term strategic growth.
Speed of decision making	Faster thanks to centralized decision-making by owners or managers.	It is slower due to multiple levels of management, governance processes, and stakeholder approvals.
Risk tolerance	In general, they tend to avoid risks due to limited financial and operational resources.	Risk management through diversified investment portfolios and structured governance frameworks.
A source of innovation	Driven primarily by external technology	Driven by a combination of internal

Dimensions	Small and medium-sized enterprises (SMEs)	large companies
	providers, consultants, and strategic partners.	research and development, innovation teams, and technology providers.
Data maturity	Emerging capabilities for handling data with fragmented or unstructured datasets.	Mature data systems that include structured, managed, and integrated business data.
Implementation schedule	It is usually accomplished within a few months using cloud-based AI solutions.	It often takes from one year to several years due to organizational complexity and extensive integration.
Success metrics	Return on investment (ROI), cost savings, operational efficiency, and payback period.	Creating strategic value, positioning in the market, the ability to innovate, customer experience, and long-term business growth.
The impact of failure	This could significantly impact business continuity due to limited resources.	It can generally be managed within a diversified project portfolio and a regulatory risk management framework.
Talent strategy	This depends on outsourcing, consultants, managed services, and supplier expertise.	This approach focuses on developing internal AI capabilities through specialized teams in data science, AI engineering, and analytics.

2. Performance of the mathematical model on different scales

Research on the performance of mathematical models offers valuable insights for their widespread application in organizations. One key finding is that simpler approaches often produce more accurate results for small and medium-sized enterprises (SMEs) with limited data. Business time series, particularly for SMEs, tend to be short or imprecise, limiting the generalizability of complex AI models, which require reliable and large datasets to function effectively. However, when SMEs accumulate high-frequency data that includes additional variables such as prices, weather, and internet traffic over extended periods, machine learning approaches leverage this information more effectively than traditional models. This suggests that the transition from an SME to a large enterprise requires both financial resources and a gradual accumulation of data.

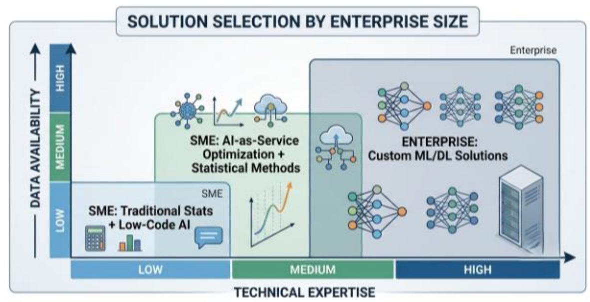

Figure 3: Company size and choice of AI solutions.

3. Hybrid methods and the "analyst" pattern

The emergence of hybrid architectures, which combine AI's reasoning capabilities with the reliability of mathematical solutions, is one of the most promising developments bridging the gap between small and medium-sized enterprises (SMEs) and large corporations. The SOLID framework exemplifies this approach, where a linear learning model (LLM) interprets problems in natural language and then generates formal mathematical models that are processed by deterministic solutions through iterative coordination. This pattern AI for abstraction, solutions for computationis evident across various sectors. In large enterprises, multi-agent systems with LLM-based schemas enable business operations teams to interact with complex supply chain data through dialogic interfaces. The system uses LLM to understand the planners' intentions and then coordinates deterministic optimization models for actual computation. For SMEs, this pattern becomes accessible through AI-as-a-Service platforms, which provide ready-made optimization models without requiring the configuration of a complex environment. Research on hybrid architectures for batch industrial production processes shows that fine-tuned system architecture, data conversion pipelines, and integration patterns enable reliable AI-enhanced decision support in production environments.

VII. DISCUSSION AND FUTURE PROSPECTS

1. Implications of the practice

The results point to numerous practical implications for organizations of all sizes:

For small and medium-sized enterprises (SMEs): Making mathematical AI tools accessible to everyone opens up unprecedented opportunities. Natural language interfaces facilitate access to specialized knowledge, while AI-as-a-service models eliminate infrastructure costs. Success requires: (1) starting with well-defined problems that deliver a clear return on investment, (2) employing AI for reasoning and deterministic tools for computation, and (3) gradually building data quality and digital infrastructure. Research suggests that entrepreneurs should begin with simple, low-cost applications rather than pursuing overly sophisticated evaluation methods.

Large companies, despite possessing the resources for sophisticated solutions, still face a critical challenge of organizational agility. Maintaining a competitive edge can be achieved by establishing AI centers of excellence, developing hybrid AI architectures, and keeping pace with trends in making AI accessible to small and medium-sized enterprises (SMEs). The emergence of hybrid AI, encompassing both agent and multi-agent systems, paves the way for a scalable, explainable, and cost-effective industrial AI.

Policymakers: Supporting AI adoption among small and medium-sized enterprises (SMEs) requires addressing knowledge gaps related to available technologies and government funding. Research confirms that these companies need additional support to fully leverage AI technologies, and policymakers must develop approaches tailored to both SMEs and large corporations. Entrepreneurs should be encouraged to participate in AI knowledge sharing with similarly sized businesses.

2. Search Trends

This analysis gives rise to several research opportunities:

Moving from small and medium-sized enterprises (SMEs) to large enterprises: How do SMEs successfully expand their AI capabilities in mathematics as they grow? What are the thresholds that stimulate the transition from statistical methods to machine learning and personal optimization? Research indicates that the ongoing differentiation between SMEs and large enterprises is crucial, and even the traditional division between them may not be sufficient, calling for a more nuanced distinction.

Reliability of Mathematical AI : As the generation of automated systems using linear logic models evolves, how can we ensure and verify the accuracy of mathematically generated systems? The SOLID framework provides theoretical guarantees of convergence under convexity assumptions, but real-world systems often deviate from these assumptions. Therefore, research is needed on how to maintain reliability in non-convex environments.

Data quality frameworks: Research is needed on the underlying data quality issues and data readiness assessment frameworks for companies of all sizes. Small and medium-sized enterprises (SMEs) often face limited access to external data, and the data access and volume required to run AI predictive analytics vary considerably depending on company size.

Hybrid AI architecture: Best practices for designing systems that combine linear logic and deterministic computations deserve further investigation. The integration of directed linear reasoning (SLM) for lightweight, privacy-preserving peripheral reasoning with linear logic reasoning (LLM) for comprehensive reasoning and coordination represents a promising area of research.

VIII. CONCLUSION

Mathematics and artificial intelligence are transforming industry, but at uneven paces. Large companies have been quick to develop customized solutions and build dedicated teams, while small and medium-sized enterprises (SMEs) have often been left behind due to costs, expertise, and infrastructure barriers. This paper demonstrates that this gap is narrowing. Three key trends —natural language interfaces (NLIs) that simplify mathematical complexity, AI-as-a-service platforms that eliminate infrastructure costs, and open-source optimization tools that mitigate financial barriers —are helping to make the potential of mathematical AI accessible to everyone. It is crucial that the mathematical foundations of artificial intelligence remain fundamental. Recognizing that language models analyze logically without performing calculations, and that reliable numerical operations require deterministic systems, provides the architectural principle for effective implementation in organizations of all sizes. The emergence of hybrid frameworks like SOLID, which coordinate optimization factors and language models through iterative collaboration, demonstrates how the strengths of both approaches can be combined. The adoption framework provides guidance for organizations of all sizes. For small and medium-sized enterprises (SMEs), the optimal approach is to leverage publicly available tools and hybrid structures. For large enterprises, maintaining a competitive edge requires balancing customized development with organizational agility, while also recognizing the trend toward making solutions accessible to everyone. The mathematical AI revolution appears to be within everyone's reach. As the theme of the 2025 Mathematics for Industry Forum, "The Challenges of Mathematics for Industry in the Age of Artificial Intelligence," emphasizes , fostering collaboration between academia and industry is essential to advancing the prospects of industrial mathematics.

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