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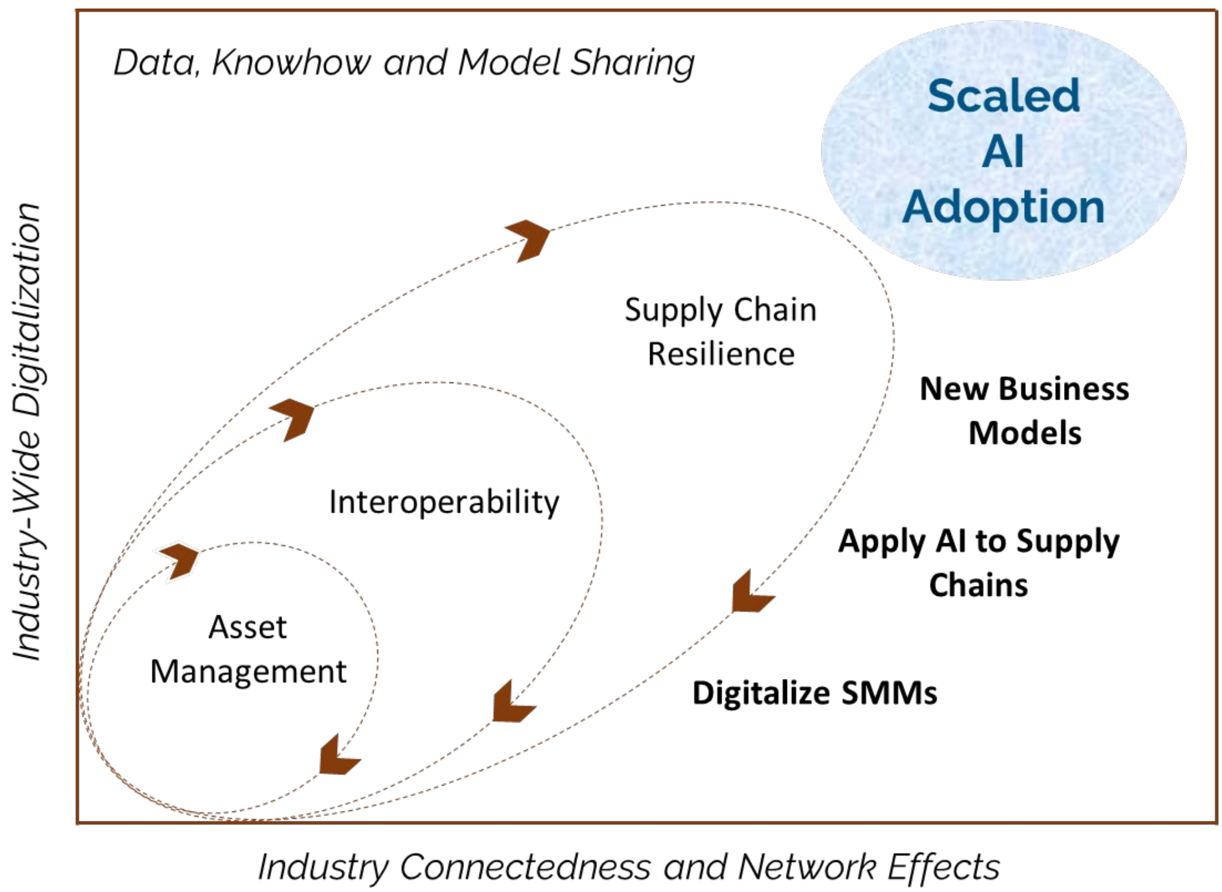
Towards Resilient Manufacturing Ecosystems Through Artificial Intelligence – Symposium Report



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Towards Resilient Manufacturing Ecosystems Through Artificial Intelligence – Symposium Report

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September 2022

U.S. Department of Commerce
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National Institute of Standards and Technology
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Abstract

In 2020, the National Science and Technology Council (NSTC) Subcommittee on Advanced Manufacturing and Subcommittee on Machine Learning and Artificial Intelligence articulated cross-agency interest in organizing a symposium to outline benefits of AI adoption in manufacturing and identify issues that inhibit widescale adoption. In response, the National Science Foundation (NSF) and the National Institute of Standards and Technology (NIST) sponsored a three-workshop Symposium entitled “Strategy for Resilient Manufacturing Ecosystems Through Artificial Intelligence (AI)” to seek input from industry, academia, and government experts. The workshop focused on potential roles of each sector in performing research and development (R&D) and on the implementation ideas for AI in manufacturing that could inform the development of the U.S. Advanced Manufacturing strategic plan.

The pervasive application of AI in manufacturing can provide a world-leading advantage to the U.S. manufacturing industry. However, much faster pace of development of the skills and tools needed to accelerate industry adoption is needed. The Symposium addressed factory and intercompany solutions in conjunction with industry strategies for scaling access to data and expertise, which are largely available only through collaboration to take advantage of the value of AI. To support industry scaling and deployment, R&D is required to push these capabilities to manufacturing. However, technology R&D from concept through pre-production is not sufficient to initiate AI deployment at scale. Symposium recommendations address this issue with a roadmap organized to overcome the current lack of industry tools, trust, confidence, and experience. Guidance is provided for industry R&D focused on the barriers to AI scaling and deployment. There are eight specific recommendations for collaborative actions by industry, government, and academia:

1. Establish new and/or expanded Public Private Partnerships (PPPs) to facilitate a broad range of R&D.
2. Research, develop, and demonstrate advanced software tools, models, and infrastructure for AI implementation and scale-up in manufacturing.
3. Establish programs that achieve industry collaboration on an integrated and trusted set of shared capabilities.
4. Initiate R&D to enable industry-wide scaling and deployment of AI applications in manufacturing.
5. Educate and train a digital-savvy manufacturing workforce with software and hardware tools needed to deploy and scale the use of data and AI with trust and confidence.
6. Enable digital capabilities at small and medium-sized manufacturers (SMMs).
7. Incentivize AI adoption throughout established supply chains.
8. Promote new business models for AI adoption.

As this adoption cycle takes hold, the market-driven forces of entrepreneurship and investment capital will ultimately lead to industry-wide adoption of AI technology. As a direct result, the U.S. manufacturing industry will progress towards achieving global leadership and resilient supply chains.

Keywords

Manufacturing; Advanced Manufacturing; Intelligent Manufacturing; Smart Manufacturing; Digital Manufacturing; Artificial Intelligence; AI; Machine Learning; ML; Education and Workforce Development; Supply Chain.

Glossary

Artificial Intelligence (AI) in manufacturing refers to software systems that can recognize, simulate, predict, and optimize situations, operating conditions, and material properties for human and machine action.

Machine Learning (ML, generally seen as a subset of AI) refers to algorithms that use prior data to accurately identify current state and predict future state, with the goal of improving productivity, precision, and performance.

Models are digital, software representations (quantitative, qualitative, pattern, causal, inference, etc.) of real-world events, systems, or behaviors, which can use data to simulate or predict future results.

Network Effects are the incremental benefits gained by existing users for each new connection that joins the network through expansion of available information and accessible knowledge.

Networking creates digital connections among devices, machines, equipment, databases, computer programs, and users, to exchange information, make decisions, and take actions.

Predictive Modeling is the use of data, AI, ML, simulation, and digital twins to assess, predict, and anticipate process, product, and operational behaviors for control, design, optimization, health, and failure prevention and mitigation.

Scale means readily accessible, easy to use, and cost effective for manufacturers of all sizes.

Standard Data Format refers to the organization of information (protocol) according to agreements on preset specifications that describe how data should be stored or shared for consistent collection and processing across different systems and users.

Tools refer to software platforms that support the availability of data, knowhow, and models for use in business and operations.

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1. Introduction

Artificial Intelligence (AI) refers to a rich spectrum of data and knowledge driven technologies that have been applied to many industries in many countries, including the United States. A global competition is underway to achieve economic leadership through the development and application of artificial intelligence (AI) technology in key industries.

AI technology promises to be a powerful tool for expanding knowledge, increasing prosperity, and enriching the human experience. Such advanced technologies are the foundation of the innovation economy and a source of enormous power for countries that harness them.

As AI moves from scientific research to mainstream tools, engineering will be as important as the research breakthroughs. Many of the most important real-world impacts will occur after deciding how to employ existing AI algorithms and systems, some more than a decade old. However, adoption of AI in manufacturing will require development of new AI tools and algorithms. The integration challenge is immense. Harnessing data, hardening, and packaging algorithms for field implementation, and adapting AI software to legacy equipment and rigid organizations, all require time, effort, and patience. Integrating AI often necessitates overcoming substantial organizational and cultural barriers, and it demands top-down leadership.

The full potential of AI accrues from orchestrated industry-wide actions that encourage adoption. However, realizing this potential also requires the adoption of new business practices that enable the industry to become networked and interconnected. Innovative technologies, services, infrastructure, and software tools are needed to provide manufacturers assurance that their valued data will be protected when data is aggregated industry wide to provide the scaled, enhanced benefits of AI methods. Those benefits include new network-based business models that provide faster process development and increased productivity, quality, and environmental sustainability. It is also critical to ensure that strong collaborations between the AI and manufacturing communities are fostered (including overcoming cultural and language barriers) to achieve the goals identified by the Symposium.

Manufacturing is important to global competitiveness because it impacts jobs, national security, energy and material consumption, climate change, environmental sustainability, and societal health and safety. Because advanced manufacturing operations depend on experience and knowhow, in addition to codified technical and scientific knowledge, the potential to use AI to enhance production discovery and apply implicit knowledge incorporated in the industry's extensive and rich data sources is high.

The U.S. research and development (R&D) priorities for federal investment in AI, and strategic importance of AI and machine learning (ML) in advanced manufacturing, are summarized in several government reports.[1] Given the complexity of the issues, the current state of the manufacturing industry, and the broadly scoped definition and spectrum of AI possibilities, a comprehensive symposium was conducted under the auspices of the National Science and Technology Council, Subcommittees on Advanced Manufacturing (SAM) and Machine Learning Artificial Intelligence (MLAI).

[1] https://www.ai.gov/

In building on these previous reports, the National Science Foundation (NSF) and the National Institute of Standards and Technology (NIST) sponsored a symposium titled the "Strategy for Resilient Manufacturing Ecosystems Through Artificial Intelligence." The aim of the symposium was to define opportunities for leveraging AI in the U.S. advanced manufacturing sector. The Symposium, comprised three workshops, brought together over 100 industry, academic, and government experts in the advanced manufacturing and AI communities.

The first workshop, held in December 2020, identified four key areas for adoption of AI in manufacturing that are synergistic with the growing foundations of manufacturing digitalization. The second workshop consisted of a series of four roundtable discussions held in June and July 2021, resulting in three defined goals as focal points to overcome the greatest barriers to AI adoption. The third and final workshop consisted of three roundtables held in February 2022. Using the results of the prior two workshops, Workshop 3 produced an actionable roadmap and recommendations for specific R&D strategies, government programs, and industry actions that can initiate and accelerate the adoption of AI in advanced manufacturing. The reports of these three workshops are included in the Appendices.

The purpose of this report is to analyze the discussions and findings of the three workshops and provide key recommendations for adoption and scaling of AI in advanced manufacturing. These efforts aim to maintain U.S. global leadership in this technology, and thus reap the benefits of economic prosperity and national security. The individual workshop reports are included in the Appendices for reference.

2. Symposium Summary

AI in manufacturing operations includes software systems that can recognize, simulate, predict, and optimize situations, operating conditions, and material properties for human and machine action that impact the production process. These functions are widely applied for production objectives that include operational control and management, diagnostics, quality assurance, equipment and operational health monitoring, and production optimization from factory to supply chain to ecosystem. AI also plays important roles with chain of custody for cross factory, supply chain, and ecosystem items of interest such as materials, energy, emissions, carbon, contamination, and defect tracing. AI systems offer capabilities to learn and scale data accumulated from years of experience and provide opportunities to derive new insights for continuous improvement of factory operations and products.

AI in manufacturing also includes systems that support the application of AI in manufacturing operations. These systems address human-computer interfacing, validate interactions, validate and verify data, select data and models, manage contracts, exchange data within and between companies, and enhance security, privacy, and protection of confidential information. Further, AI in manufacturing includes software systems that address the ability to *search, discover, access, and use* widely distributed networked, industry resources, including data sets, models, tools, training, application playbooks, and market opportunities. The value of AI goes hand-in-hand with digitalization of the manufacturing industry (a.k.a. Smart Manufacturing), which entails the advancement towards the use of data and modeling as key factory, supply chain, and ecosystem assets in concert with physical assets.

Data and information technology (IT) capabilities in non-manufacturing industries are evolving at an increasingly rapid pace, and other countries are investing in digitalization of manufacturing significantly. Following 40 years of progress with digital data in the U.S. manufacturing industry, industry digitalization has been building in interest and adoption for 15 years. Typically, the U.S. industry has pursued digital transformation with an incremental, risk averse posture and pace comparable to that of the past 40 years—not the rapid pace of change needed to realize the future. Digital transformation has been slowed by legacy business practices and market drivers that have increased implementation complexity. Furthermore, potential benefits that can be derived from collected and transmitted data are largely untapped. These actions have widened the gap between small and medium-sized manufacturers (SMMs) and large manufacturers, and have failed to capture the greatest, available benefits from factory implementation that are the result of integrating across supply chains and ecosystems. At present, the most successful use cases for AI in manufacturing are heroic efforts that require advanced education and training, and these efforts do not scale to other equipment, facilities, or companies.

Realizing the full potential of AI will require innovative technologies, services, and infrastructure for manufacturers to provide trusted data and access to software tools. It will also require expertise to build and use AI for greater industry-wide interoperability, supply chain resiliency, new business models, and environmental sustainability. The roadmap developed in Workshop 3 centers on the need for industry-wide strategies for 'data sharing' (in many forms) and collaborative application development to broaden access, lower cost, and speed up industry adoption of AI on the factory floor. It identifies the need for networked intercompany operations that optimize supply chains, address resiliency, enable new business models, and open new revenue sources. Sharing data and resources for manufacturing operations and supply chain management require protecting intellectual property, trade secrets, and confidential data and information. Substantial changes in organizations, markets, culture, technology risk management, and business management are required to facilitate these strategies. The manufacturing industry is not fundamentally opposed to the adoption of AI technology, or the basic changes in business models the technology will inevitably create. On the contrary, many large corporations and a few SMMs are currently working to incorporate AI technology into their operations. It is important to build on these successes and scale the adoption process.

Because AI derives additional power from data found outside of any one company, there are significant, potential benefits to companies in exchanging data for supply chain and ecosystem opportunities. This is similar to health care in which sharing data among facilities and health care ecosystems can improve patient care and outcomes. However, the adoption of AI is complicated by limitations in capabilities at SMMs, the significant need for R&D, a lack of scalable successes, and the need to build business trust. Longstanding industry practices on how data and operations are valued and compartmentalized currently work in opposition to these opportunities. If current industry practices remain unchanged, the competitive benefits of intra- and inter-company (operational) interoperability, and data sharing that comes with scaled AI adoption, are expected to move forward incrementally and slowly at best. Competitiveness that comes from speed of adoption is already stalling.

An accelerated adoption strategy focuses, first and foremost, on financial value as a driver. Three categories of monetization were identified, and then used to distinguish three primary AI applications: (1) asset management on the factory floor, (2) interoperability between operating assets within factories and supply chains, and (3) intercompany interaction for supply chain resiliency. These groupings of AI applications describe the manufacturing hierarchy in three dependent layers. These dependencies imply that manufacturers must act individually on factory strategies, contractually on interoperability strategies, and as a connected industry on resilient supply chain strategies. Being able to demonstrate the financial gains that can be achieved by radically leveraging networks and manufacturing interconnections (that are not largely used today) will significantly accelerate AI adoption. Industry-wide asset management capabilities can be increased via sharing of accessible data, expertise, and applications within a brokerage of easy discoverable targeted application solutions. Operational interoperability focuses on connecting data across operating assets within factories and across supply chains for greater operational coupling of processes. Intercompany business interactions drive supply chain resilience and depend on the visibility and analysis of shared business data, as well as the ability of manufacturers to act in concert.

Tools to preserve privacy and security and manage data sharing must be integrated in each of the three primary AI applications mentioned above, and for each form of data and model sharing. Furthermore, these tools need to be seamless so manufacturers can grow and readily move among the three layers of monetization. All these tools depend on carefully building and managing trust in interactions between businesses, people, and machines. The human role in AI adoption is essential. For each manufacturer, business and operating tools, mechanisms of business exchange, and acquisition of skills through training and education need to align in a process that can only proceed when trust and risk management are strengthened.

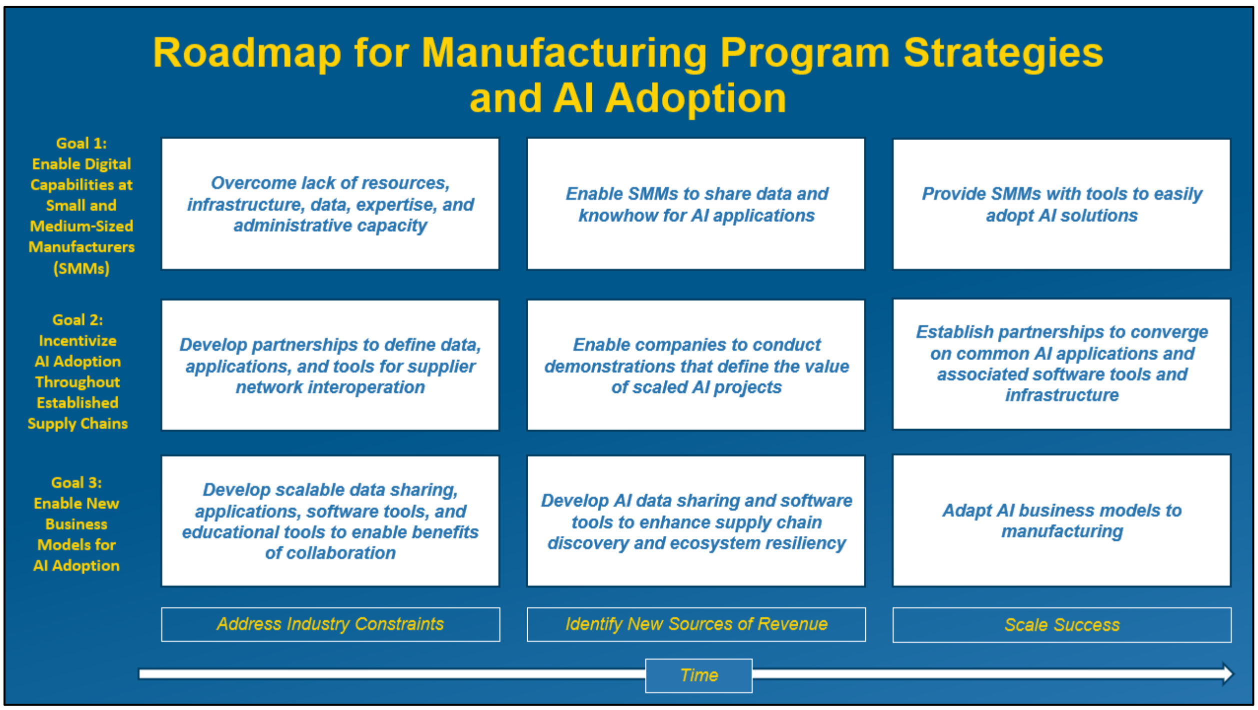
Scaling and integration of these operational and business tools encompass a large area of foundational R&D that becomes industry focused to accelerate adoption and go beyond incremental change. In addition to AI methods that extend beyond image recognition and gain access to the time-dependent data in manufacturing, the industry needs methods and tools that move toward automated algorithm development. There is also a need to deal with the complexities of collecting data and applying solutions at the location of deployment, when those solutions employ machine learning models generated from the aggregated data of many manufacturers.

There is also a need to appropriately balance the proprietary interests and the benefits related to improving capabilities with data sharing. This becomes more complex when sharing data and models across companies and deploying them locally for specific applications. Security, validation, verification, privacy preservation, and expertise need to be integrated with scaled data exchange, to establish a trustworthy, assured, and usable environment for industry deployment. R&D is needed to bring these business components together into a system, and to create the software and communications framework needed to enable a trusted and dependable AI service provision infrastructure.

This report offers a roadmap of nine interrelated program areas, summarized in **Figure 1**. Some aspects of these program areas are currently being worked on by industry, government, and academic organizations. However, the existing R&D must be expanded and orchestrated in the broader framework to address risks and barriers, building on each other to progress over time. The roadmap explicitly addresses overcoming key barriers and industry risk areas, building and aligning tools and training, immediate and longer-term monetization, and scaling capability throughout the small, medium, and large manufacturers that form the industry supply chains and ecosystems.

As shown in **Figure 1,** the roadmap forms a 3x3 matrix that charts goals vs. acceleration drivers against a series of interrelated subgoals that constitute the program strategies, including the use of ongoing development cycles that build on activities and experience. The roadmap organizes national program strategies as a combination of industry, academic, and government activities all intended to accelerate the adoption of AI throughout the U.S. manufacturing industry. The subgoals in the white boxes are highly interrelated and each box represents a strategy that needs to be accomplished to implement the roadmap. As a result, the chart can be read from left to right and top to bottom.

Figure 1: Roadmap for Manufacturing Program Strategies and AI Adoption



With respect to execution, the roadmap reflects strong input from Symposium participants that scaling adoption in the industry will ultimately need the shared network as an engine. Scaling occurs because of network effects in which simple-to-use tools, aligned with training resources and solution resources, are all discoverable, accessible, usable, and affordable. However, an execution strategy needs to start top down with existing supply chains to build the tools and resources as well as the trust and experience. SMMs need the means to establish digital capabilities. Initializing adoption through existing supply chains will likely be incremental and will not scale, but it does set the stage with tools, training, and resources to transition into networked models.

Given the Roadmap, the Symposium participants were strongly concerned that an accelerated adoption cycle could not even get started without R&D that demonstrates pre-production or first production industry runs. These preliminary outcomes that showcase industry scalability and value are possible with industry, academia, and government collaboration. The Symposium identified structural start-up constraints and recommended there be one or more demonstrations on first pass actions to address these distributed barriers simultaneously. A first pass action is an agreement on an approach that is sufficient to validate integration without the deep development of an individual constraint. The actions needed to address structural start-up constraints include:

- Establish standardized data formats and repositories to store data securely
- Create an exchange platform for access to AI data, tools, models, and information
- Provide financial incentives for SMMs to upgrade their digital capabilities
- Build educational programs at academic institutions and fund training programs at SMMs
- Demonstrate value with use cases and providing blueprints for solutions at manufacturers of all sizes
- Enable data collection from legacy equipment that still has useful life, especially at SMMs
- Allow 'in-kind' cost share for the value of the data provided by industry participants in government programs and public-private institutes/centers and making that data available to researchers

Multidisciplinary and multi-stakeholder collaboration among industry, academia, and government must undertake start up demonstrations to implement the industry-wide strategies embedded in the roadmap that follows. Public Private Partnerships (PPPs), for which there are many successful models, are the most appropriate coordinating structures. An opportunity exists to build on past PPP successes by expanding them or building new PPPs to fit the industry R&D requirements for AI adoption in U.S. manufacturing. PPPs will need to involve all stakeholders in defining programs and funding requirements, distributing best practices, supporting the implementation of programs and distribution of funds, and coordinating initiatives. The successes demonstrated by PPP coordination will reduce the risk of applying AI technologies in manufacturing operations, making it easier for entrepreneurs and private investors to visualize innovative operational products and business models.

3. Recommendations

There are eight specific recommendations for collaborative actions by industry, government and academia:

1. <u>Establish new and/or expanded Public Private Partnerships to facilitate a broad range of R&D.</u>

   Given the multi-disciplinary and multi-stakeholder collaborations needed among industry, academia, and government, Public Private Partnerships (PPPs) are the most effective coordinating structures for AI adoption by U.S. manufacturing companies. There are many successful PPP models that can be leveraged and expanded upon to produce demonstrations of scalable AI solutions for a wide range of manufacturing problems. Based on the success of previous models, the establishment of new and/or expanded PPPs are recommended.

2. Research, develop, and demonstrate advanced software tools, models, and infrastructure for AI implementation and scale-up in manufacturing.

   Existing AI and data analytics technologies provide value in limited applications, but additional R&D is required to develop AI methods, implementation software, and data collection and protocols specifically suited to manufacturing operations. An infrastructure needs to be developed to source data from multiple manufacturers, build algorithms, and continuously update algorithms as additional data becomes available. Development of low cost, easily accessible, networked software tools that can be easily distributed on the web is recommended. This will allow SMMs to realize the efficiency gains that will drive AI adoption.

3. Establish programs that achieve industry collaboration on an integrated and trusted set of shared capabilities.

   Clear demonstrations of the ability of AI methods to derive improved solutions from cross-company collaborations are required. Successful business collaborations that prove the power of AI to deliver productivity gains can overcome the reluctance of manufacturers to transfer data off the shop floor, thus expanding the resources available for producing AI solutions for the entire manufacturing industry.

4. Initiate R&D to enable industry-wide scaling and deployment of AI applications in manufacturing.

   Research is needed to develop an interoperating set of software and hardware tools to enable and deploy data sourcing, aggregation, classification, and service delivery infrastructure for manufacturing solutions at network scale. That model has flourished in other industries by providing experts and entrepreneurs business opportunities to capture network effects and provide competitive advantage to their customers.

5. Educate and train a digital savvy manufacturing workforce with software and hardware tools needed to deploy and scale the use of data and AI with trust and confidence.

   It is critical to educate and train a diverse workforce on the implementation tools needed to deploy and scale AI for manufacturing. AI adoption and workforce development can be accelerated by linking development tools and training.

6. Enable digital capabilities for small and medium-sized manufacturers (SMMs).

   AI adoption and scaling requires that SMMs expand digital capabilities, especially considering SMMs comprise the vast majority of U.S. manufacturing companies. The U.S. manufacturing industry will benefit from SMMs having the resources, infrastructure, and expertise needed to adopt AI solutions, and share data and knowhow for AI applications.

7. Incentivize AI adoption throughout established supply chains.

   Focusing on AI adoption through established supply chains is a logical first step toward building trust and confidence in working collaboratively. Supply chains offer an established foundation of trust and a critical mass for developing partnerships that define data, applications, and tools for supplier network interactions. These partnerships provide opportunities to demonstrate the benefits of enabling companies to converge on common AI applications using shared software infrastructure.

8. <u>Promote new business models for AI adoption.</u>

   Realizing the full value of AI in manufacturing will require new business models centered around the value of data and AI. In other industries, data is collected and used to sell services that support manufactured products and operations, creating a continuous cycle of improvements. Additional capabilities that need to be explored include repositories for critical manufacturing data, secure methods for making relevant data available at network scale, and incentives for entrepreneurs to establish new data aggregation, algorithm building, and service delivery businesses. With appropriate data sharing and software tools, new business models also can enhance supply chain discovery and ecosystem resiliency.

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Caption for Cover Graphics:
Accelerating AI adoption in U.S. manufacturing for global competitiveness, a world-leading workforce, supply chain resilience, and environmental sustainability.

Symposium: Strategy for Resilient Manufacturing Ecosystems Through Artificial Intelligence

Report from the First Symposium Workshop

Aligning Artificial Intelligence and U.S. Advanced Manufacturing Competitiveness

December 2 and 4, 2020

Facilitated by

UCLA

Supported by the National Science Foundation and the National Institute of Standards and Technology

March 2021

Executive Summary

Artificial Intelligence (AI) refers to a rich spectrum of data and knowledge driven technologies that have collectively taken on a “silver bullet” status in many countries, including the United States. A global competition is underway to achieve economic leadership through the development and application of AI technologies in key industries, often supported by large government investments.

The U.S. priorities for federal investment in AI R&D are summarized in several reports from government agencies. These reports highlight the strategic importance of AI in advanced manufacturing, but they do not present a broad, actionable strategy for applying AI in the manufacturing industry.

In building on these previous reports, the National Science Foundation (NSF) and the National Institute of Standards and Technology (NIST) have sponsored a symposium titled the “Strategy for Resilient Manufacturing Ecosystems Through Artificial Intelligence.” The symposium will define opportunities for leveraging AI in the U.S. advanced manufacturing sector and has been organized into a series of three workshops. The first workshop (Workshop 1), “Aligning Artificial Intelligence and U.S. Advanced Manufacturing Competitiveness,” was held on December 2 and 4, 2020. This workshop was unique in bringing together experts in advanced manufacturing, AI, IT, and computer science from industry, universities, federal agencies, and national laboratories.

Workshop participants were enthusiastic about both the near term and long term benefits of applying AI to manufacturing. These included far better use of industry data and scaled use of domain knowlege throughout the industry, noting that AI is not a replacement for domain knowledge. They identified priority opportunities, challenges, and collaboration points for accelerating the implementation of AI in manufacturing, and used the span of economic value as the topmost driver – market share, productivity, energy and material consumption, national security, and climate, environmental, and ecosystem impacts. A key observation was that manufacturing has derived little benefit from the *network effects* that have transformed other industries, even though the potential is high for *AI*, *machine learning, predictive modeling, and networked data centric analytics* and solutions to enable such a transformation.

> **Artificial Intelligence (AI)** in manufacturing refers to software systems that can recognize, simulate, predict, and optimize situations, operating conditions, and material properties for human and machine action.
>
> **Machine Learning** (generally seen as a subset of AI) refers to algorithms that use prior data to accurately identify current state and predict future state, with the goal of improving productivity, precision, and performance.
>
> **Networking** creates digital connections among devices, machines, equipment, databases, computer programs, and users, to provide the **connectedness** needed to exchange information, make decisions, and take actions.
>
> **Predictive Modeling** is the use of data, AI, machine learning, simulation, and digital twins to assess, predict, and anticipate process, product, and operational behaviors for control, design, optimization, health, and failure prevention and mitigation.
>
> **Network Effects** produce increased benefits for network users as the number of connected user nodes increases by expanding the availability of information and knowledge accessible to all.

In assessing AI in manufacturing, it was noted that current AI applications are almost *exclusively* for machine and operational units, i.e., component levels within individual company operations, and rarely extend to line operations, intracompany systems, or intercompany supply chains. This fact focused workshop discussions on the transformational opportunities afforded by the application of AI methods and tools to support manufacturing operations beyond the component level. The participants stressed that, with broad industry adoption, AI and machine learning systems have the potential to transform the prevailing manufacturing business model, which emphasizes the proprietary nature of data. This transformation, which is essential for the successful implementation of AI solutions, can also be enabled by AI tools for data privacy, discovery, and reuse, essentially using AI to enable AI. The workshop identified seven key principles for realizing full value and wide adoption of AI in manufacturing:

1) The entire manufacturing industry, including small, medium, and large manufacturers, suppliers, and R&D collaborators, must approach digital transformation at the industry level. There are significant benefits to adopting highly connected industry business practices that involve shared data and knowhow, in addition to scaling the customary contractual exchange of data.
2) AI must focus on untapped opportunities within and across all operations, but within the span of economic benefit. Access to routine industry data and the right tools for putting these data to use for economic benefit is the key requirement for wide industry adoption of AI.
3) There is a need for appropriate methods and tools to provide assurances that critical proprietary data will be protected, while allowing noncritical data to be shared for the training of AI systems. Such tools must provide the guarantees on security and control for data access that manufacturing companies require for the full benefit of network effects to be realized on a national scale.
4) Agreements and de facto standards for data formats, timing, and sharing will be needed, along with the implementation tools needed to apply them to produce value.
5) Important lessons for building industry-wide data and cross-industry modeling networks critical for AI can be learned from other industries that have gained competitive advantages by doing so.
6) AI tools that link supply chains can improve manufacturing resilience by increasing supply chain visibility and coordination, decreasing duplication of productive capacity, improving productivity management across companies, and providing individual manufacturers with the flexibility to re-tool and re-specify operations to change product type and production volume.
7) AI tools and networked, data centric modeling approaches are actively researched and rapidly evolving, making it difficult to predict the skills that tomorrow's manufacturing workforce will need, but we cannot wait for tomorrow's tools to be available. There is an urgent need to configure educational programs that provide the foundational knowledge that today's engineers and technicians will need, using existing data centric methods as a bridge to the AI tools of the future.

Workshop 1 identified four primary areas of joint AI and manufacturing R&D that provide an industry-wide framework for development and implementation. Importantly, the framework was designed to provide benefits both to individual manufacturers and industry-wide by creating a virtuous cycle of expanding capability and adoption. The four areas are:

- AI for Industry-Wide Data Sharing
- AI for the Factory Floor
- AI for Discovery of Capabilities and Solutions
- AI for Building Resilient Supply Chains

The seven principles, the AI opportunity areas, and the implementation framework identified in Workshop 1 provide the basis for Workshop 2, which will address how to bring AI and manufacturing communities together to create, develop, and implement new tools to enable a cycle of research, development, and adoption. Critical issues that will be addressed in Workshop 2 are the foundational requirements for interconnectedness, including the ability to manage, exchange, and share data with trust; the availability of shareable data for building new AI tools and applications; and the ability to access and reuse data and application capabilities and knowhow throughout the industry. These broad-based tools can enable new foundational tools to address hoped-for advances in manufacturing productivity, precision, and performance, particularly by providing increased capabilities to assess and predict at affordable cost. The expected overall impact will be to enable AI solutions for search, discovery, and reuse at scale. Workshop 3 will produce a roadmap for advancing AI to increase the resilience and competitiveness of advanced manufacturing.

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Introduction

Manufacturing is important to global competitiveness because it impacts jobs, national security, energy and material consumption, climate change, environmental sustainability, and societal health and safety. Because advanced manufacturing operations depend on experience and knowhow, in addition to codified technical and scientific knowledge, the potential for using AI to enhance production by accessing the implicit knowledge incorporated in the industry's extensive and rich data sources is high.

The U.S. priorities for federal investment in AI R&D are summarized in the *National AI Research and Development (R&D) Strategic Plan, 2019 Update,*[1] which calls out manufacturing as one of several sectors that can be transformed by AI. The *Strategy for American Leadership in Advanced Manufacturing*[2] specifically highlights the importance of AI implementation as a priority R&D area. *Recommendations for Strengthening American Leadership in Industries of the Future*[3] proposes the establishment of an Industry of the Future (IotF) Institute on Generative Design in Advanced Manufacturing to coordinate the R&D required to advance AI and machine learning tools. These reports all emphasize the strategic importance of AI in advanced manufacturing.

Given the complexity of the issues, the characteristics of the manufacturing industry, and the broadly scoped definition and spectrum of AI possibilities, a comprehensive symposium comprised of a series of three workshops has been planned to examine manufacturing competitiveness and produce a strategy for realizing resilient manufacturing ecosystems through AI. The progression of workshops has been planned to reflect a logical flow of discussion that results in an implementation roadmap:

1) Workshop 1, to identify priority opportunities and key challenges;
2) Workshop 2, to address the R&D and establish an implementation framework for applying AI to address the opportunities and challenges identified in Workshop 1; and
3) Workshop 3, to produce a roadmap for advancing the use of AI in manufacturing and provide recommendations for its implementation.

Workshop 1 benefitted from the opinions and experience of experts in manufacturing and AI from academia, industry, and government and was unique in bringing together communities that have not extensively interacted previously. The participants in the workshop sessions included: (1) industrial leaders in manufacturing operations and manufacturing information technology (IT), (2) researchers in schools of engineering, business, and computer science, (3) commercial manufacturing IT and AI service providers, and (4) technical program personnel from across the federal agencies and laboratories. Appendices A through D provide details on the workshop and the symposium organization, leadership, and participants.

Industry-wide Strategies

The diversity of experience and organizations represented in the workshop resulted in lively discussions about the breadth of opportunities for the near and long term adoption of AI technology in manufacturing. The current strategy for implementation can be characterized as largely "bottoms up," a reference to focusing on the high cost development of applications in individual factories, mostly for machine and

[1] https://www.nitrd.gov/pubs/National-AI-RD-Strategy-2019.pdf
[2] https://trumpwhitehouse.archives.gov/wp-content/uploads/2018/10/Advanced-Manufacturing-Strategic-Plan-2018.pdf
[3] https://science.osti.gov/-/media/_/pdf/about/pcast/202006/PCAST_June_2020_Report.pdf?la=en&hash=019A4F17C79FDEE5005C51D3D6CAC81FB31E3ABC

operational units producing high-value products. This bottoms-up strategy implicitly assumes that industry data collaboration will occur, and market forces will drive needed investment in development of new infrastructure, technology, and supply chain collaboration, including small, medium, and large manufacturers. This view of factory floor applications through the lens of existing practice fails to consider the largely unrealized potential of industry-wide strategies that require collaboration, new standards, and methods for securely exchanging data.

There was also a strong collective sense that manufacturing presents a promising problem space with abundant opportunities for collaboration for the AI community. The dimensions of this disciplinary opportunity encompassed the need to enable individual manufacturers to identify and safely provide access to non-proprietary data, information, and capability, and the ability to locate, access, and use relevant resources for a particular manufacturing problem. These capabilities would allow individual manufacturers to be informed by the extensive body of non-proprietary manufacturing knowledge accumulated industry-wide through experience and scientific investigation, rather than relying primarily on their own limited experience.

More specifically, the potential for sourcing and using operational data and domain knowhow in industry-wide strategies emerged from the cross community perspective of the workshop. It was emphasized that proprietary, product specific data must be maintained secret, but that most data from widely used machines, processes and operations could be shared to provide generalized solutions that improve industry-wide productivity. While other industries have gained competitive advantages by exploiting the network effects that interconnectedness generates around common needs, manufacturing companies linger in established business models emphasizing the acquisition of assets, control of curated supply chains, and business to business transactional or contractual relationships. These are linear business relationships that sacrifice the potential for exponential scaling that interconnected businesses enjoy.

Today's access to data management and computational capabilities simply did not exist a decade ago and an unprecedented capacity to collect and manage massive amounts of data is now commonplace with network based cloud services. Breakthrough IT infrastructure, data science, and other methods now exist to apply data analytics, machine learning, digital twins, and other predictive, reactive and discovery modeling approaches to amazingly large data sets that can encompass cross-industry modeling. Networked industry-wide modeling and the exploitation of network effects are not new concepts; many other industries have already been transformed by the competitive advantages they provide. Manufacturing has different constraints and risks than other industries, but there is no compelling reason that the manufacturing industry could not derive increased benefit from these advances.

While the interest in industry-wide strategies was high, there was, at the same time, the practical consideration that digital innovations to unleash the potential of AI must align with the ongoing digital transformation of manufacturing operations, making it essential that AI innovations result in increased profitability to incentivize manufacturers to adopt them. Any associated product quality and operational performance improvements provide significant benefits to manufacturers, but only to the extent that they increase sales due to product and service differentiation, increase productivity, and/or reduce costs due to reductions in time, waste, and defective product. Profitability is the overriding driver. While a growing number of demonstrations of the use of AI in manufacturing can be identified in large, well-financed companies, individual, independently developed solutions are typically expensive, do not generalize easily, and have proven difficult to scale. Therefore, it is likely that the widespread adoption of AI in manufacturing will be paced by the availability of AI solutions that can be implemented at reasonable cost and by a manufacturing workforce that mostly lacks specialized AI expertise. This concept of needing scaled access to cost effective solutions and a skilled workforce to implement solutions for cost improvement is also not new. What is new is the potential for AI to be a strategic enabler of industry-wide approaches that benefit individual manufacturers. Because companies will use profitability as a key metric, broad industry adoption, from factories to supply chains, will be driven by cost, with the cost of acquiring a workforce that can implement the tools an important factor.

It is important to note that the benefits derived from industry-wide actions can enable vastly increased opportunities for the small and medium size businesses that constitute about 98% of all U.S. manufacturers. In this regard, it is likely that different innovations initially will provide benefits to different segments of the industry and sizes of companies. Just as the early adopters of web-based commerce were small businesses that tolerated quirky software to gain market access, new AI tools may allow small manufacturers to acquire new customers outside established supply chains and small companies to source manufacturing services domestically.

The consideration of industry-wide AI strategies also stimulated significant discussion on cultural and educational barriers to AI adoption. In manufacturing, legacy practices, cultures, real and perceived risks, and a lack of transparency and trust are challenges to expanding the role of AI that are at least as great as the technical challenges. Discussions centered on the potential for homomorphic encryption, federated learning, and synthetic data methods to provide access to data needed for machine learning without revealing sensitive trade secrets or production status information. These methods are active areas of AI research that should be expanded to include manufacturing relevant applications. Business sensitive data i.e proprietary data, needs to be identified and separated from data about commonly used machines, operations, processes, and materials that can be safely and securely shared only with the intended recipient. Finally, there is a need for applications and associated industry datasets to be identified and prioritized and to make the relevant data from these available to university researchers who can more robustly research and develop new AI, machine learning, predictive, and networked modeling methods. It is instructive to draw an analogy with the annual ImageNet competition, which made several million labeled images publicly available to researchers. A competitor in the 2012 edition featured the advent of deep learning, which smashed every previous record for image identification and ushered in the age of commercial machine learning.

Finally, and importantly, implementation of AI in manufacturing requires a dramatically expanded and technologically capable advanced manufacturing workforce, but AI tools are rapidly evolving, making it difficult to predict the skills that tomorrow's manufacturing workforce will need. History has shown that it is impossible for workforce training to drive technology adoption. Rather, benefits to individual companies will drive workforce needs as companies adopting AI technologies accrue accelerating advantages. It is in this context of technology adoption that the workforce is tied to an industry-wide strategy. Just as a shortage of HTML programmers did not prove to be an impediment to the explosive growth of the Internet and web based commerce, an AI based economy is expected to grow and accelerate with the development of accessible tools and methods that enable the application of AI by non-specialists at dramatically reduced costs.

AI for Industry-Wide Data Sharing

The manufacturing sector generates more measured, observational, operational, modeled and experience-based data than any other sector of the economy, even surpassing the financial sector. These data offer an industry base that could be contextualized and made available to enable radical innovations by AI in business practices, process engineering, product and system design, scalability, and sustainability, going far beyond improving the efficiency of manufacturing methods at individual sites. On the other hand, few companies generate enough of the right data internally to apply AI, even for narrowly focused applications on process or machine units. This contrast of a data rich industry with data poor individual manufacturers drove the conclusion that the entire manufacturing industry can benefit from innovative AI tools and methods that aggregate data across manufacturers, while protecting critical intellectual property and preserving data privacy and provenance. Since the capabilities of and confidence in the anticipated data infrastructure can be expected to increase with additional users and contributors, the benefits of participation are expected to increase with time, fulfilling the fundamental requirement for a viable, self-sustaining, and self-financing network. In a virtuous cycle, the contributions of individual manufacturers enable broad, new industry-wide capabilities that provide productivity benefits to the contributing companies. Furthermore, the accompanying opportunities for researching new methods should provide opportunities for founding new businesses to deliver solutions to manufacturers.

A major discussion point concerned the tight grip manufacturing companies maintain on intellectual property, often extended to all production relevant data and information. This culture of secrecy emerged from a craft culture that placed high value on expertise and is as old as the industry itself. It has caused few problems to date because the culture is pervasive worldwide, and until now there has been little or no opportunity for firms to benefit financially from sharing manufacturing data. However, as indicated in this report, AI has the potential to radically increase the value of manufacturing operational and product data by harvesting the implicit knowledge incorporated in it and harnessing its predictive, reactive and discovery capacity, again through data centric modeling, machine learning, simulations, and digital twins. Since the value of this implicit knowledge almost certainly exceeds the value of explicit manufacturing knowledge, this information must be made accessible to unlock its value.

Workshop participants highlighted some specific observations related to shareable, trusted data:

- There is potential for federated learning, homomorphic encryption, and synthetic data methods to provide assurance of data protection. These methods are under active investigation by the AI community, but there is little investigation in the manufacturing domain. Fair and consistent methods are also needed for the valuation of data. Methods for ensuring data integrity, security and privacy are critical.
- Some suggested the need for repositories of curated and labeled data, and others observed the potential for self-curation by grouping production data across companies by machine model number, since each machine model is typically produced in large numbers. Participants also cited web-based, vendor-provided machine tool thermal error compensation services as an emerging model for providing services with secure data sharing.
- The IT industry has pioneered best practices that can be adopted by the manufacturing sector to begin taking advantage of the benefits of shared data, while still retaining a company's competitive advantage.
- Participants noted the burden of data cleaning and conditioning, lamenting the fact that highly trained data scientists must be pressed into service as "data janitors." What is particularly important is the ability to identify, assemble and curate data that is relevant to solving an particular problem while enabling the reuse of that data in addressing related problems. Such generalization and reuse of non-proprietary data allows the applications to scale.
- In addressing the critical interactions of humans with manufacturing equipment and systems, the workshop participants looked for direction from AI applications in intelligent, autonomous robotics. These efforts include automation of tasks that require humanlike manipulation, robots with greater autonomy and flexibility, and integration of humans and machines to perform tasks.
- Participants stressed the need to determine and tune the level of decision making authority an AI system has to each use case.

Appendix A: Workshop 1

AI for the Factory Floor

The benefits of employing real time sensing with modeling, in particular predictive modeling, to control production quality in-process have been recognized almost since the advent of digital computation. This concept lies at the core of Industry 4.0, Smart Manufacturing, Digital Manufacturing, etc. and is fulfilled in the notion of a digital twin (recognizing that definitions of digital twin vary widely). Over the past half century of computational modeling, manufacturing science has progressed to the point where almost any manufacturing process can be brought under computer control but the solutions are expensive, time consuming, and often require the capabilities of highly trained professionals. Worse, they lack generality and often can be applied only to a limited range of processes or machines and are not easily maintained. This has limited the penetration of solutions to expensive, difficult to produce products, such as jet engines, or very high volume production as in semiconductors, automotive components, and materials in the process industries.

Computational modeling challenges for harnessing mountains of data from factory operations led to a focused discussion on machine learning methods and their potential to provide the generality and the associated dramatic cost savings that computational modeling methods have so far failed to achieve. This potential was reinforced by representatives from the Manufacturing USA Institutes who stressed the importance of data enabled AI solutions. Many of the Manufacturing USA Institutes already have a wide spectrum of AI and ML applications underway.

Workshop participants highlighted some specific observations related to modeling and production control:

- There was much discussion about merging AI and physicochemical modeling methods to reduce the amount of data needed to train machine learning systems. While highly desirable, such methods still need to address the high development cost and narrow application range of most physicochemical models.
- Data centric methods have a potential to reduce implementation time and cost, and increase generality, but they need to be explainable and carefully validated to be used with confidence. These methods must be investigated.
- Participants discussed the current success of applications that apply data analytics and statistical and parametric modeling. These data centric approaches are important precursors to the richer capabilities of AI and machine learning and can provide effective solutions today.
- AI for predictive maintenance and for quality assurance were offered as quick wins for every manufacturer to explore.
- AI and machine learning have the potential to provide the capability to automatically locate, configure, and install the data driven process control approaches that are appropriate to particular setups.
- The need for data standards was highlighted. One participant reported acquiring two machine tools with identical model numbers, one domestically produced and the other produced abroad by the same company. However, the control code and sensor outputs on the two machines were incompatible. At a minimum, all machine tools with the same model number need compatible outputs.
- Participants discussed concepts of portable AI models and open source code/tools/data to bridge the development gap.

AI for Discovery of Capabilities and Solutions

Once data, information, and application knowhow have been made accessible, they must be made discoverable. In this regard, manufacturing can take inspiration from the world wide web, where information holders voluntarily post information for users, often in the hope of deriving income. A series of discussions focused on prior attempts to automate the digital translation of design data, as represented in a Computer Aided Design (CAD) file, to manufacturing instructions with acceptable guarantees on the successful execution of those instructions. The key reference was with generative manufacturing, the prevailing model. In essence, the generative method employs software that incorporates explicit knowledge about manufacturing processes and machine capabilities to generate a process plan, thereby making process selection and planning accessible to non-experts.

The most successful application of the generative method has been in automating the generation of cutting paths for computer controlled machine tools. Commercial software designed for this purpose is available and widely used today. However, in spite of the widespread use of such programs, a significant fraction of software generated cutting paths fails to execute successfully. This requires intervention by human experts, and those interventions represent a major portion of the engineering cost of producing many machined parts. Similar attempts to automate the generation of process plans for other manufacturing processes have been notably less successful, including attempts to organize expert manufacturing knowledge to make it accessible to non-experts.

AI has the potential to identify manufacturers who already have the equipment, process plans, and expertise needed to manufacture a needed part by searching for similar parts, materials, machines, or processes manufacturers have previously produced or used. Of necessity, manufacturers collectively hold a vast library of three dimensional, geometrical representations of the parts they have produced in standard CAD formats. Because each part has already been produced, its manufacturer has an associated process plan, tooling, and the other specialized expertise required to produce it. Like case-based reasoning and retrieval, if a CAD library of these parts were accessible, indexable, and searchable, it could serve as the basis for an open marketplace for manufacturing services that would be particularly useful for small- and medium-sized companies that are frequently driven to seek offshore manufacturing sources. A search-based marketplace does not require the customer to possess any process expertise or require the manufacturer to disclose any information to the customer except price and delivery, making it attractive to small- and medium-sized manufacturers with concerns about intellectual property.

A similar search function might also allow manufacturers to reuse the data and modeling configurations and setups for commonly used process operations or machines. In general, there are levels of detail in specifying configurations. Several levels of detail could be relatively open without affecting proprietary concerns, but as configuration information becomes more specific and proprietary, sharing would need to become a business transaction. The issue becomes one of recalibrating intellectual property. CESMII[4] has been tackling this kind of approach through a concept named “Profile” that acts within a standard based data infrastructure stack. What is missing is a way to make the distributed library or capability accessible, indexable, and searchable.

The evolution of a networked system for the discovery of manufacturing resources might evolve along similar lines to the evolution of software tools for searching, browsing, and webpage creation on the Internet. Web-based tools evolved explosively to more powerful versions in a few short years in the mid-1990s from Lycos to Google, Mosaic to Internet Explorer, and Front Page to Word under the driving force

[4] Clean Energy Smart Manufacturing Innovation Institute, one of sixteen Manufacturing USA Institutes

of accelerating web-based commerce. The potential exists for new software tools to promote a similar expansion of web-based commerce in manufacturing.

Workshop participants highlighted some specific observations related to the discovery of manufacturing data and modeling application resources:

- A manufacturing web could provide the framework for greater interconnectedness and increasing a network effect for application resources.
- At the operations level, machine learning methods gain power with more data. This provides the potential for creating a data marketplace in which solution providers can purchase and aggregate data from multiple firms and charge them for process control services. But this solution is only viable if the data providers feel confident that their data will be protected.

The points above are about the distribution of AI tools, application capability, and knowhow, but their successful adoption is fundamentally dependent on people. The economics of AI ultimately depend on a close coupling of AI and human centric operations. The roles of people encompass the development of the tools, the development and sustainment of applications, and execution of the solution implementations. Publicly, AI has been associated with job loss, but the reality is that there is significant opportunity in thinking systematically about people, process and technology, especially when scaled across the industry to change the actual work content of manufacturing jobs.

What is urgently needed are educational programs that provide the foundational knowledge and skills that today's engineers and technicians need to be able to use and contribute to the AI tools, capabilities, and solutions that are emerging. Workshop discussions generated some potential approaches to move forward:

- AI programs could be developed that evaluate manufacturing companies, identify priority training areas, and offer customized training. As new technologies are incorporated into more factories, the need for workforce training will become more urgent.
- There is a need to create new ways to generate educational and training content, distribute that content to potential operators, and certify the operators' content knowledge.
- Just-in-time training, cross training, and "snackable" content need to be developed, and distribution of the content could include the creation of workforce standards to highlight the "personas" of operators in their functional positions.
- Whatever the form and function of training content, the resulting instructional materials must be configured to ensure economies of scale.
- While new forms of content are being created, it is imperative to advance and harness the coming generations' fluency with information technology.

AI for Building Resilient Supply Chains

The supply chain disruptions created by the Covid-19 pandemic have elevated manufacturing resilience to a national imperative by demonstrating the impossibility of managing national scale supply disruptions through company specific supply chains without vastly increased information sharing and coordination. Current efforts in applying AI methods to supply chain management are almost exclusively implemented in the proprietary supply chains of individual companies.

The workshop participants associated manufacturing resilience with the ability to adjust, reconstruct, and link supply chains to provide better management of productivity at a national scale, across companies and industries. This further implies that each manufacturer has the flexibility to change product lines and/or

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adjust product specifications. AI tools can improve manufacturing resilience by increasing supply chain visibility and coordination, decreasing duplication of productive capacity, and improving productivity management across companies by linking supply chains at a national scale. AI tools also support individual manufacturers with the complementary capability and flexibility to re-tool machines and re-specify operations to provide greater flexibility in product lines and volumes. Supply chains and individual manufacturers will need to act in concert, requiring the day-to-day availability of appropriate data, data interconnectedness, and decision support for industry-wide operational management, with full understanding that supply chain data is among the most sensitive data that manufacturers hold.

As discussed in previous sections, AI can play a transformational role in allowing manufacturers to securely exchange supply chain data and experience in a business to business, operation to operation sense. In addition to their work on AI production applications, the Manufacturing USA Institutes have stressed the industry-wide role of data in manufacturing competitiveness. The Institutes have collectively advocated for a digital supply chain data infrastructure involving small, medium, and large enterprises. This is part of comprehensive proposal that includes the concept of a Manufacturing Guard, a network of subject matter experts on manufacturing and production, a national supply chain data exchange, a Technology Corps to build an agile manufacturing workforce, and a Resilient Manufacturing Advisory Council. Together these form a public-private advisory for the national orchestration of supply chains, a function especially important in times of disruption[5].

Principles for Adoption of AI in Manufacturing

As discussed previously, an important reference of Workshop 1 are the benefits that have been realized in other industries from a scaled, networked, and interconnected infrastructure. The workshop identified seven key principles (also listed in the Executive Summary) to spur the adoption of AI in manufacturing:

1) The entire manufacturing industry, including small, medium, and large manufacturers, suppliers, and R&D collaborators, must approach digital transformation at the industry level. There are significant benefits to adopting highly connected industry business practices that involve shared data and knowhow, in addition to scaling the customary contractual exchange of data.
2) AI must focus on untapped opportunities within and across all operations, but within the span of economic benefit. Access to routine industry data and the right tools for putting these data to use for economic benefit is the key requirement for wide industry adoption of AI.
3) There is a need for appropriate methods and tools to provide assurances that critical proprietary data will be protected, while allowing noncritical data to be shared for the training of AI systems. Such tools must provide the guarantees on security and control for data access that manufacturing companies require for the full benefit of network effects to be realized on a national scale.
4) Agreements and de facto standards for data formats, timing, and sharing will be needed, along with the implementation tools needed to apply them to produce value.
5) Important lessons for building industry-wide data and cross-industry modeling networks critical for AI can be learned from other industries that have gained competitive advantages by doing so.
6) AI tools that link supply chains can improve manufacturing resilience by increasing supply chain visibility and coordination, decreasing duplication of productive capacity, improving productivity management across companies, and providing individual manufacturers with the flexibility to re-tool and re-specify operations to change product type and production volume.
7) AI tools and networked, data centric modeling approaches are actively researched and rapidly evolving, making it difficult to predict the skills that tomorrow's manufacturing workforce will need, but we cannot wait for tomorrow's tools to be available. There is an urgent need to configure educational

[5] see https://www.mfgguard.com

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programs that provide the foundational knowledge that today's engineers and technicians will need, using existing data centric methods as a bridge to the AI tools of the future.

A Framework to Stimulate Demand for Digitalization

The chart below groups the resonant workshop comments[6] in a graphic that came together as an implementation framework for driving demand for digitalization and the adoption of AI.

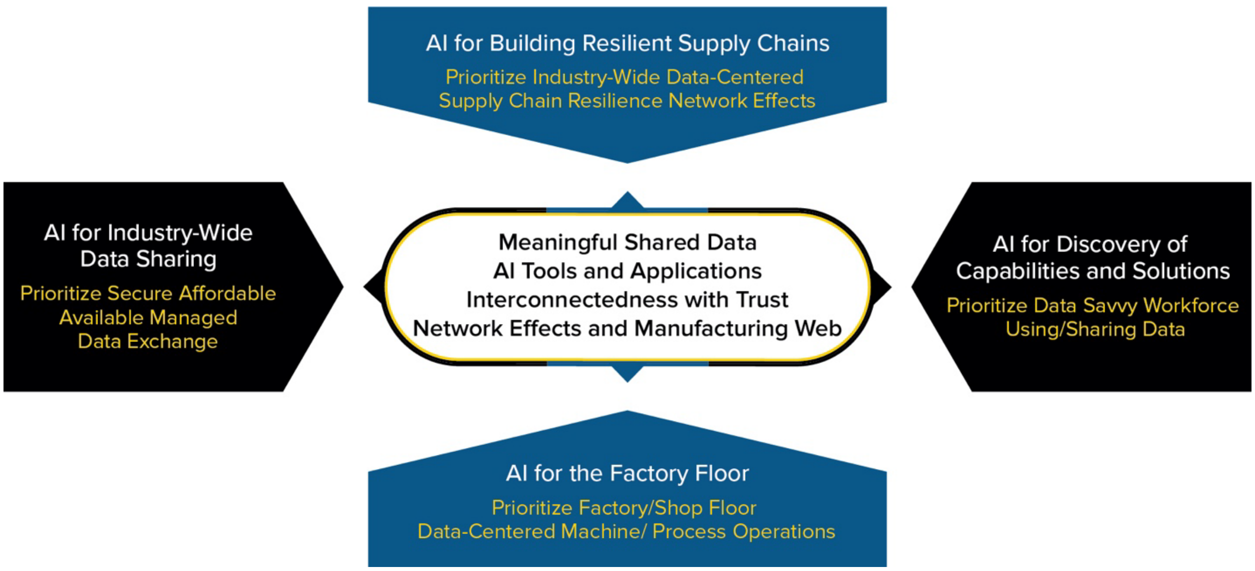

Figure 1: Framework to stimulate demand for digitization

The blue regions at the top and bottom define the need to use industry-wide and factory specific AI strategies to link supply chains with the factory operations. This linkage is essential to providing benefits that directly impact operations on the factory floor, where the data needed to provide further benefits, is generated. Workshop participants, however, also identified high priority opportunities for AI at the supply chain level that included increasing yield, decreasing waste, preventing single source failure, providing supply chain as a service, shared inventory and capability data, and signals for real time supply and demand changes. Opportunities also included business to business interoperability, open source data for building AI tools, and machine/operations benchmark data. At the factory level, priority AI opportunities include augmenting human involvement, automated product testing and quality assurance, machine/operation monitoring and control, and providing higher quality information to human workers.

The black regions on the left and right address the need to establish industry-wide adoption of collaborative AI infrastructure and workforce strategies. As shown on the left, infrastructure, tools, and practices are needed to enable data sharing with trust. Workshop participants emphasized the need for data that is meaningful, available, accessible, affordable, reusable, sharable, secure, and trusted. The region on the right addresses the need for a workforce that can find and apply AI tools, data and modeling configurations and

[6] Resonant comments are those that arose in more than one source – workgroups, chat, email and panel notes

application knowhow in factory operations, and have the direction and capability to contribute data, information, and knowhow relative to a redefined value proposition for intellectual property.

The objective of the framework is to depict the key elements needed to secure the critical mass of industry commitment necessary for sustained use of AI and data centric solutions. A cycle of collaboration can start now using proven AI methods to produce tools for today's workforce and to define workforce training programs that can be updated with industry participation at a pace consistent with technology innovation and industry demand. This is also consistent with a general position taken by the workshop participants that the industry needs to start working with data now with a line of site to what is needed to enable AI in the future.

There are currently significant federal investments of an industry-wide nature. The Manufacturing Extension Program, the Manufacturing USA Institutes, and several federal agency and state programs are addressing pieces of an industry-wide approach through public-private partnerships. These efforts are directionally significant for data centric solutions, but they need augmentation and orchestration to be able to speed up adoption to address and scale AI for industry-wide impact. As overviewed in the body of this report, further research, development, and demonstration are needed on every aspect of the technology and educational supply chains. R&D on the specifics of a collaboration and business model for government, academic, and commercial business to work together would have a profound impact.

Next Steps

The workshop set the stage by explaining how AI can transform manufacturing competitiveness by enabling industry-wide collaboration, provided specific suggestions for opportunities to implement AI in advanced manufacturing, and framed perspectives that can inform the discussions in the future Workshops. The items enumerated below offer further context to be vetted with Workshop 1 participants and additional domain experts for framing the discussions in Workshop 2:

1) The broad proposition is to use AI methods to benefit manufacturing from factory level machine and process operations to supply chain operations by facilitating industry-wide strategies that overcome or circumvent industry-wide barriers.

2) One of the foundational truths about AI technology is that AI methods increase in power with increasing availability of the "right" data.

3) Workforce training cannot drive the need for AI adoption, rather competitiveness and industry benefit will drive workforce needs as AI technologies start to achieve industry-wide application.

4) It is essential to work within the current state of the manufacturing industry to find actions that incentivize companies to accelerate the pace of digitalization in an orchestrated manner for all four areas in the above chart together.

5) The key metrics in manufacturing companies are throughput, quality, on-time delivery, resilience, and cost; and cost is the overriding metric.

6) The AI adoption cycle must start with existing data analysis techniques, tools, and training that initially align with the ongoing digital transformation of manufacturing operations, which will provide the data for development of new AI tools and define workforce training needs.

7) Three technical foundations are required for interconnectedness and benefits of network effects:

    a. The ability to manage and share data with trust;

b. The availability of shareable data for building new AI tools and applications; and
c. The ability to access and reuse AI data and application capabilities throughout the industry.

8) There is a business need for distinguishing critical intellectual property from data that can be safely shared.
9) While a few companies are exploring the potential for search based methods to supplement and enhance generative methods in manufacturing, the subject requires more investigation and research.
10) Better coordination across many siloed efforts, especially with those that are publicly funded, could be a major accelerator for addressing national goals. Federal government incentives are essential for facilitating the formation of public/private partnerships to overcome collaboration barriers and encourage R&D in AI technologies and applications that support the full range of AI's interconnectedness potential.

In general, Workshop 1 set the stage for considering much broader roles for AI in achieving transformational manufacturing competitiveness than just factory level applications. Drawing from the experiences of other industries, the potential of industry connectedness and the resulting network effects is significant for manufacturing. These broader roles, however, were expressed in the context of the practical reality that the manufacturing industry does not have a history with or a culture that is conducive to industry-wide strategies. Furthermore, the risk posture, supplier and manufacturer interdependencies, and the supplier market have grown and thrived on vertical optimization and compartmentalization for many years. While the broader benefits of AI are tied to connectedness, moving forward in the near term will heavily depend on factory machine, and process level applications with immediate economic benefit for individual manufacturers to begin building a foothold in investment interest. It is AI's predictive capacity across the range of data centric modeling, and ultimately digital twins, that was emphasized.

The expectation for Workshop 2 is to provide a more detailed evaluation of the opportunities and challenges in applying AI for the wide ranging roles that formed the basis of this report:

- Industry-Wide Data Sharing
- Factory Floor Application
- Discovery of Capabilities and Solutions
- Building Resilient Supply Chains

The Implementation Framework offers an interrelated and interlinked R&D approach in which each of these four areas of AI opportunity can be further defined, aligned, and developed for each of the four areas of manufacturing implementation, but they must also be linked in an orchestrated development process at pace with continuous economic benefit. The objective is a virtuous research and development cycle that produces an AI development and implementation engine for manufacturing that drives manufacturing competitiveness.

Appendix A: Workshop 1

Appendix A: Symposium and Workshop Plans

In early 2020, the National Science and Technology Council (NSTC) Subcommittee on Advanced Manufacturing and Subcommittee on Machine Learning and Artificial Intelligence articulated cross-agency interest in the strategic and timely value of organizing a symposium on a U.S. strategy for resilient manufacturing ecosystems through AI. Co-chairs, an organizing committee, and an advisory committee (please see Appendix B) were established and engaged in a process with both subcommittees to frame, shape, focus, and plan the symposium.

Considering the nature and complexity of the topic and with the aim of providing a comprehensive perspective, a three-workshop symposium was designed. The symposium brings together two communities: the advanced manufacturing community that is focused on the digitalization of manufacturing and the AI/ML community that is focused on applications, information technology, and computer science.

The overall goals of the symposium are to:

- Generate a cross-stakeholder consensus on AI for achieving U.S. manufacturing resilience, economic competitiveness, reduced energy consumption, and cyber/data security, and
- Set the stage for the two communities to collaborate on a roadmap that lays out a national strategy for a three-year horizon that places R&D needs in a comprehensive context.

The following three workshops were planned:

Workshop 1: Aligning Artificial Intelligence and U.S. Advanced Manufacturing Competitiveness

- What is resilience for manufacturing ecosystems balanced with competitiveness, resource consumption, demand and supply shocks, and national cyber and data security?
- What U.S. resilience elements are strong, weak, or missing in a digitalization context? Which are near term priorities? What about advanced manufacturing drives value for AI?

Workshop 2: AI Technologies, Practices, Workforce Needs, and National R&D Priorities for Manufacturing

- What are the enabling solutions for integrating resilience with all national manufacturing priorities? Where is AI the right solution and where is it not? What R&D is needed?
- What workforce capabilities are needed and what else or what other factors need to be addressed for AI R&D to be implemented successfully? What are the challenges?

Workshop 3: Comprehensive Roadmap for a Three-Year Horizon

- What are the dimensions of a comprehensive plan for implementing AI in U.S. advanced manufacturing that make up a national workforce, technical, practice, and operational strategy and roadmap?

Each workshop is standalone with respect to important objectives and reportable outcomes but connected to the others to achieve a fuller, more comprehensive outcome. A list of the symposium and workshop organizers is provided in Appendix B. The organization and the workshop program are included in Appendix C. A list of Workshop 1 participants is provided in Appendix D.

Appendix B: Symposium Leadership

Co-Chairs

Jim Davis: Vice Provost IT, Office of Advanced Research Computing, UCLA, and Program Oversight, Clean Energy Smart Manufacturing Innovation Institute (CESMII)

Stephan Biller: CEO & President, Advanced Manufacturing International, Inc.

Charles Romine: Director of the Information Technology Laboratory, NIST

Organizing Committee

Said Jahanmir: Assistant Director for Federal Partnerships, Office of Advanced Manufacturing, NIST

Faisal D'Souza: Networking and Information Technology Research and Development (NITRD) Program of the NSTC

Lisa Fronczek: Associate Director, Advanced Manufacturing National Program Office, NIST

John Roth: Assistant Director for Research Partnerships, Advanced Manufacturing National Program Office, NIST

Don Ufford: Advanced Manufacturing Policy Fellow, Advanced Manufacturing National Program Office, NIST

Interagency Advisory Committee

Mike Molnar, Frank Gayle: Advanced Manufacturing National Program Office, NIST

Sudarsan Rachuri: Advanced Manufacturing Office, DOE

John Vickers: NASA

Bruce Kramer: Directorate for Engineering, NSF

Andy Wells: Directorate for Engineering, NSF

Astrid Lewis, Aubrey Paris: Department of State

Kim, Young Ah: Department of Homeland Security

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Appendix A: Workshop 1

Appendix C: First Workshop Organization

The first workshop was sponsored by the National Science Foundation and the National Institute of Standards and Technology, and hosted by the University of California, Los Angeles (UCLA). The virtual workshop was convened on December 2, 2020 and continued on December 4, 2020.

The workshop had two specific goals:

1. Construct a scan of priority opportunities, challenges, and collaboration points for AI/ML for U.S. advanced manufacturing competitiveness
2. Generate a table of opportunities, challenges, and collaboration points to be considered in depth in a future workshop

This workshop emphasized four overarching manufacturing areas of emphasis related to digitalization so that the workshop participants could consider the relative impacts and roles for AI and ML in advanced manufacturing:

1. Facilitating the manufacturing ecosystem and supply chain restructuring, connectedness, visibility, interoperability, and agility for global competitiveness, and preparing for and responding to global and national disruptions;
2. Envisioning greater performance and precision in advanced process and machine operations as assets in resilient manufacturing ecosystems;
3. Building a broadly skilled, data-savvy workforce that can be more flexibly deployed; and
4. Enabling industry data flow and exchange, cyber opportunity, and national cyber and data security.

To achieve the goals of the symposium as outlined in Appendix A, the first workshop comprised four distinct parts: introductory remarks, panels, workgroup sessions, and report-outs. These parts involved a multi-stakeholder group of participants from across many sectors. Utilizing a public-private partnership model, this workshop gathered input from participants to understand the unique nexus of AI and the manufacturing sector.

Introductory remarks on Day 1 of the workshop were made by the co-chairs. These remarks set the stage for the entirety of the workshop. The co-chairs focused on the task ahead for the participants to define the challenges of the manufacturing sector as well as potential opportunities for AI to meet those challenges. Day 2 introductory remarks were made by UCLA's Executive Vice Chancellor and Provost Emily Carter, who focused on the importance of bringing together industry, academia, and government partners to tackle the challenges of tomorrow.

The workshop included two panels, one focused on the challenges of the manufacturing sector, and one focused on the opportunities presented by AI. An invited panel of manufacturing experts discussed the definition of resilience for manufacturing ecosystems considering economic competitiveness, energy and material consumption, demand and supply shocks, and national cyber and data security, using the lens of digital transformation. An invited panel of experts from the AI/ML community reflected on the discussion of the first panel and how manufacturing challenges and opportunities are viewed from an AI/ML perspective by addressing overarching questions.

Panel 1. Manufacturing Challenges

Susan Smyth (co-moderator), SME President, U.S. Army Science Board, GM Chief Scientist for Manufacturing (Retd)

Stephan Biller (co-moderator), CEO & President, Advanced Manufacturing International, Inc.

Jeff Kent, Vice President, Smart Platforms Technology & Innovation, Procter & Gamble

Michele C. D'Alessandro, Vice President and CIO, Manufacturing IT, Merck & Co., Inc.

Çağlayan Arkan, Vice President, Manufacturing Industry, Microsoft Corp.

John Dyck, CEO, CESMII – The Smart Manufacturing Institute

Panel 2. Artificial Intelligence/Machine Learning (AI/ML) Opportunities

Lynne Parker (moderator), Deputy Chief Technology Officer of the United States, and Assistant Director for Artificial Intelligence (AI), White House Office of Science and Technology Policy

Ed Abbo, President and CTO, C3.ai

Jayant Kalgnanam, Director, AI Applications (Asset Mngt & Supply Chain), IBM Research; Distinguished Industry Leader (2020), Chemicals & Petroleum & Industrial Products

Daniela Rus, Director, Computer Science and AI Laboratory (CSAIL); Andrew (1956) and Erna Viterbi Professor of Electrical Engineering and Computer Science; and Deputy Dean of Research, Schwarzman College of Computing, MIT

Reid Simmons, Research Professor in Robotics and Computer Science, Carnegie Mellon University

With the topics introduced by the co-chairs and panels, the workshop turned to the participants to provide feedback in three facilitated breakout sessions. These sessions were designed to gather perspectives from both the manufacturing and AI/ML sectors into what opportunities and challenges exist in leveraging AI in the advanced manufacturing sector. Below are the three session topics with their respective questions.

Breakout Sessions

Session 1: National/global scale considerations for manufacturing ecosystems, supply chains, and data flows

a. What U.S. ecosystem and supply chain elements are strong, weak, or missing?
b. What impacts has the Covid-19 pandemic revealed for U.S. advanced manufacturing resilience?
c. How do national and global considerations impact the manufacturing ecosystem and data flow considerations?
d. Where do AI/ML versus other approaches stand as solutions, and why?
e. Why would the AI community be interested in these problems, and what would they need to understand about the problems?

Session 2: Local factory operation and workforce considerations where solutions are ultimately implemented

a. What U.S. factory and workforce elements are strong, weak, or missing in a digital transformation context?
b. What have the Covid-19 impacts revealed for factory and workforce considerations?
c. How do national and global considerations and ecosystem and data flow considerations come together in local factory and workforce considerations?
d. Where do AI/ML versus other data and modeling approaches stand as solutions, and why?
e. What needs to be true for the new data and modeling tools to be accessible to the workforce and for the workforce to use them?
f. Why would the AI community be interested in these problems, and what would they need to understand about the problem?

Session 3: Bringing ecosystems, data flow, factory operations, and workforce together; addressing priorities and cross-cutting AI/industry opportunities and challenges; and collaboration points

a. What are the priority AI opportunities and challenges?

Appendix A: Workshop 1

b. What are categorical use cases that showcase opportunities and challenges?
c. What needs to be true for AI opportunities in advance manufacturing to scale?
d. What does the manufacturing community need from the AI community, and why would the AI community be interested?
e. What structural changes are needed in the industry and its stakeholders?
f. What collaboration points between and among industry, academia, and government are needed?
g. What is in the opportunity table after the scan?

Following each breakout session, moderators shared brief reports that contained the salient points discussed at the sessions they moderated. These reports served as a transparent way to leverage all information across the breakout sessions among workshop participants.

Appendix D: Workshop 1 Participants

CO-CHAIRS

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Appendix A: Workshop 1

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Appendix A: Workshop 1

Symposium:
Strategy for Resilient Manufacturing Ecosystems Through Artificial Intelligence

Report from the Second Symposium Workshop

R&D Strategies to Scale the Adoption of Artificial Intelligence for Manufacturing Competitiveness

Facilitated by

UCLA

Supported by

National Science Foundation
and
National Institute of Standards and Technology

October 2021

Executive Summary

The National Science Foundation (NSF) and the National Institute of Standards and Technology (NIST) are sponsoring a three workshop Symposium entitled, "Strategy for Resilient Manufacturing Ecosystems Through Artificial Intelligence." Workshop 1, held in December 2020, identified four key areas of artificial intelligence (AI) adoption that are synergistic with and build on a growing foundation of manufacturing digitalization (a.k.a. Smart Manufacturing, Industry 4.0, Digital Manufacturing, and Manufacturing 4.0). Workshop 2, conducted as a series of four roundtable discussions held in June and July 2021, focused on identifying the most important research, development, and workforce education and training priorities for the industry-wide adoption of AI, with the goal of dramatically improving the competitiveness, efficiency, and resilience of US manufacturing. Both workshops emphasized the potential of AI to increase the performance and productivity of manufacturing operations and observed that realizing the full potential of AI will require new, industry-wide modalities for securely developing and providing manufacturing services to manufacturers of all sizes.

Manufacturing companies currently view AI as a new tool for implementation across a wide spectrum of business and operational interests. The current company centric approach ensures maximum protection of intellectual property and has not generally led to considering different ways data can increase value and market share, and ways data can be exchanged both technically and contractually. This approach leads each manufacturer to develop its own solutions in-house, which increases the cost and complexity of AI adoption for all manufacturers and limits AI's potential. Eliminating a massive duplication of effort represents a major cost saving opportunity in applying AI across all manufacturers. Limiting AI development to in-house data also ignores the proven benefit of commercializing AI systems and the ability to extract cost saving and profit producing insights for individual companies from huge quantities of data gathered across multiple sources, often on an industry-wide basis. Numerous industries have been transformed by using AI methods to harvest solutions at scale, but the manufacturing industry poses special challenges. Workshop 2 roundtables highlighted strategies and research and development (R&D) opportunities to address these challenges. The result was identification of four overall program goals for achieving industry-wide adoption of AI:

Goal 1: Support small and medium-sized manufactures (SMMs) to digitalize their operations. AI methods build on digital data, but few SMMs have the resources or experience to acquire, process, and analyze production data in digital form. A bottom-up approach takes advantage of the network connectedness of the industry to scale access to tools, training, and capability for SMMs to start the process of digital transformation and monetization of their data. Established curricula at US community colleges and universities are available to provide training and deliver digital savvy employees, but low cost, secure digital tools also need to be available. Incentives should be established to vastly expand academic curricula in collaboration with SMMs and other industry partners, and subsidies created to support SMM adoption of digital tools. The Manufacturing USA Institutes, the Manufacturing Extension Partnership (MEP) Program, and the Advanced Technological Education (ATE) Program all have key roles in AI training and implementation for US manufacturing companies.

Goal 2: Incentivize large companies to work within their established supplier networks to implement AI methods. A top-down approach minimizes data security risks and allows access to large volumes of data generated by major companies and their suppliers. Sharing data is essential for the development of practical AI methods to improve supply chain resilience. While a top-down approach does not scale, by demonstrating the benefits of successful implementation, companies build confidence in AI tools and trust to overcome fear of data sharing. Early successes at the top can be transferred down within established supply chains to SMMs and used to engage university researchers to the maximum extent possible to support development of new AI methods.

Goal 3: Enable new business models. Most manufacturing companies, especially SMMs, will never have the resources and capability to develop AI solutions in-house. In other industries, digital transformation has created new companies (often referred to as aggregators) that purchase data, and sell the services and solutions derived by using AI methods. Manufacturers need minimal risk, "safe" ways to sell their process level data and an economical way to purchase process level solutions. Trust issues loom large, but privacy preservation methods spanning encryption and federated learning hold potential to reduce the risks associated with sharing data, and research should be funded to apply these methods in manufacturing. Similarly, individuals can easily search the internet for products and information, but companies searching for manufacturing capability face daunting challenges that often drive them to look abroad, which increases supply chain complexity and disruption risk. A major strength of AI is its ability to index and categorize information for effective search. This capability can play a significant role in discovering US manufacturers, especially SMMs, with the capability to produce specific products or parts at reasonable cost.

Given these goals, small, medium, and large companies alike are seeking guidance on where to start AI adoption and find resources to help implement specific projects. As a result, the deliberations in Workshop 2 defined an AI adoption cycle by categorizing areas of AI monetization, application, industry-wide strategies, and risks into a hierarchy of three industry operating layers. Moving up the hierarchy involves moving through operations of increasing complexity, starting at the bottom layer with factory floor machine/process asset management, then to entire factory and supply chain interoperability, and at the top supply chain ecosystem resilience. This layered breakdown suggested staged strategies could be developed for each goal to safely unlock the profit-making potential of AI from factory floor to supply chain ecosystems. R&D programs should be focused on industry-wide education, tools, collaboration, and risk mitigation at each layer so progressive strategies can be pursued to build industry trust and confidence. Workshop 3, which is currently being planned, will produce an actionable roadmap including recommendations for specific R&D strategies and federal government programs that address the need for new technology, business policies, and infrastructure. The organization of the workshop is being planned around primary workstreams that include R&D programs, industry-wide infrastructure, industry adoption, government policy, and integration of these activities.

Table of Contents

Introduction

The National Science Foundation (NSF)/National Institute of Standards (NIST) Symposium entitled "Strategy for Resilient Manufacturing Ecosystems Through Artificial Intelligence" is drawing uniquely upon expertise in manufacturing, along with machine learning (ML) and artificial intelligence (AI) to address the questions: (1) What are the strategic roles of AI for US manufacturing competitiveness, (2) What would comprise a national strategy to accelerate and scale adoption, and (3) What are the research and development (R&D) areas, investment strategies, and roadmap workstreams needed to achieve this. Workshop 1, conducted in December 2020, emphasized the importance of connected industry strategies. It also identified AI for the Factory Floor, AI for Resilient Supply Chains, AI for Data Sharing (and sharing data for AI), and AI for Discovery of Capabilities and Solutions as four key areas of opportunity within an AI adoption cycle that is synergistic with manufacturing digitalization (a.k.a. Smart Manufacturing, Industry 4.0, Digital Manufacturing, and Manufacturing 4.0).

In Workshop 2, each AI opportunity area was explored in a dedicated roundtable to further delineate the nature of deploying AI in each area and what strategies exist or are needed. These deliberations were assimilated and merged into an integrated set of R&D priorities. A detailed summary of the discussion in each roundtable is included in the Appendices B through E. As an overview, the key questions addressed in each roundtable were as follows:

Roundtable 1: AI for the Factory Floor (June 15, 2021)
Define the benefits AI can bring to current manufacturing operations, determine how solutions can be developed, and identify a strategy for sharing data and AI/ML models from the factory floor.

Roundtable 2: AI for Building Resilient Supply Chains (June 29, 2021)
Determine if AI can provide visibility across proprietary supply chains and motivate large manufacturers and small and medium sized manufacturers (SMMs) to work together to improve supply chain resilience and achieve national coordination.

Roundtable 3: AI for Industry-Wide Data Sharing (July 7, 2021)
Determine if AI tools could provide industry-wide access to data in a prevailing manufacturing culture that emphasizes protection of intellectual property.

Roundtable 4: AI for Discovery of Capabilities and Solutions (July 19, 2021)
Determine how AI tools can enable a manufacturing business model that sources data from and provides solutions to firms on a national scale.

Workshop 2 focused on identifying the most important research, development, and workforce education and training priorities for industry-wide adoption of AI. When the deliberations of all roundtables were assimilated, AI was seen as having the potential to penetrate every aspect of the manufacturing industry. Dramatic improvement in manufacturing competitiveness centered on development and adoption of both predictive AI for shifting the industry from reactive to predictive control and management, and scaled interoperability for end-to-end optimization of operations at the factory floor, factory, supply chain, and ecosystem levels. These discussions highlighted strategies and R&D opportunities to address the challenges of AI adoption in manufacturing. The result was identification of three overall goals that can support strategy development for achieving industry-wide adoption of AI:

Goal 1: Support small and medium-sized manufactures (SMMs) to digitalize their operations. AI methods build on digital data, but few SMMs have the resources or experience to acquire, process, and analyze production data in digital form. A bottom-up approach takes advantage of the network connectedness of the industry to scale access to tools, training, and capability, and is required for SMMs to

Appendix B: Workshop 2

start the process of digital transformation and monetization of their data. Established curricula at US community colleges and universities are available to provide training and deliver digital savvy employees, but low cost, secure digital tools also need to be available. Incentives should be established to vastly expand academic curricula in collaboration with SMMs and other industry partners, and subsidies created to support SMM adoption of digital tools. The Manufacturing USA Institutes, the Manufacturing Extension Partnership (MEP) Program, and the Advanced Technological Education (ATE) Program all have key roles in AI training and implementation for US manufacturing companies.

Goal 2: Incentivize large companies to work within their established supplier networks to implement AI methods. This is a top-down approach that minimizes data security risks, but also allows access to large volumes of data generated by major companies and their suppliers. Sharing this data is essential for the development of practical AI methods to improve supply chain resilience. While this top-down approach does not scale, by demonstrating the benefits of successful implementation, companies build confidence in AI tools and trust to overcome fear of data sharing. Early successes at the top can be transferred down within established supply chains to SMMs and used to engage university researchers to the maximum extent possible to support development of new AI methods.

Goal 3: Enable new business models. Most manufacturing companies, especially SMMs, will never have the resources and capability to develop AI solutions in-house. In other industries, digital transformation has created new companies (often referred to as aggregators) that purchase data, and sell the services and solutions derived by using AI methods. Manufacturers need minimal risk, "safe" ways to sell their process level data and an economical way to purchase process level solutions. Trust issues loom large, but privacy preservation methods spanning encryption and federated learning hold potential to reduce the risks associated with sharing data, and research should be funded to apply these methods in manufacturing. Similarly, individuals can easily search the internet for products and information, but companies searching for manufacturing capability face daunting challenges that often drive them to look abroad, which increases supply chain complexity and disruption risk. A major strength of AI is its ability to index and categorize information for effective search. This capability can play a significant role in discovering US manufacturers, especially SMMs, with the capability to produce specific products or parts at reasonable cost.

Given these goals, small, medium, and large companies alike are seeking guidance on where to start AI adoption and find resources to help implement specific projects. As a result, the deliberations in Workshop 2 defined an AI adoption cycle by categorizing areas of AI monetization, application, industry-wide strategies, and risks into a hierarchy of three industry operating layers. Within these three layers, large companies and SMMs have vastly different operating constraints and perceptions of risk that must be addressed with distinct strategies to initiate the use of AI technology. With SMMs, these strategies can include large company requirements on their suppliers, regulatory actions by the government, and incentives that create financial benefits.

Industry-wide adoption was defined as commercial use at scale, across small, medium, and large companies to the benefit of each manufacturer and the whole industry. The framework for industry-wide adoption reported in Workshop 1 remains the foundation of the strategy, but with AI opportunities further delineated in Workshop 2. The application of AI focused on approaches for contained and selective sharing of contextualized **Data**, **Knowhow** in the form of capturing the steps, selections, and configurations of an engineered solution, and **Models** in the form of proven problem statements, which encapsulate data and knowhow as implemented solutions. Workshop 2 also focused on the monetization of AI applications which is essential to a competitive strategy. In the context of monetization and competitiveness, R&D needs where defined for tools to drive both bottom-up and top-down growth of AI applied to factory floor, factory, supply chain, and ecosystem. Equally important is the R&D to address business, operation, and risk requirements that need to be factored into the tools to build trust and confidence. Trust and confidence were defined in terms of simultaneous operational success, protection of intellectual property, adequately developed AI applications, and sharing of data and knowhow within acceptable windows of risk.

Adoption Cycle for Scaling Predictive AI and Industry Interoperability

Adoption Cycle Framework

Workshop 1 set the stage for considering broad roles for AI in transforming manufacturing competitiveness. The result was an implementation framework for AI in manufacturing that also expressed the opportunity for joint AI and manufacturing R&D initiatives. These areas of opportunity are shown in the blue and black sections of **Figure 1** below (from the Workshop 1 report). As shown, four primary areas of opportunity for joint AI and manufacturing R&D were identified. Industry-Wide Data Sharing and Discovery of Capabilities and Solutions (black sections) take advantage of industry connectedness and network effects. AI for these two areas facilitate scaling the ability of individual manufacturers to share and find resources to engineer and implement AI applications for performance, precision, productivity, and quality assurance.

Factory Floor and Building Resilient Supply Chains (blue sections) encompass predictive AI applied across physical operations. Factory floor opportunities for AI involve intracompany unit process operations and machines using advanced instrumentation and predictive, real-time modeling. These individual units are often working in operational isolation from each other within upstream and downstream portions of factory line operations and supply chains. As AI adoption expands, individual operations can be restructured for comprehensive, end-to-end performance, precision, productivity, and quality assurance optimization. End-to-end can be further extended to supply chain visibility of factory capability and capacity to support the management of factories, resolution of disruptions, and identification of new market opportunities. AI-oriented data sets and embedded knowledge can be structured to scale AI-based search and distribution so the entire industry (small, medium, and large enterprises) can derive and contribute value to end-to-end objectives. AI's predictive capability supports visualization, automation, robotics, and autonomous operations in which the workforce is used in smarter ways.

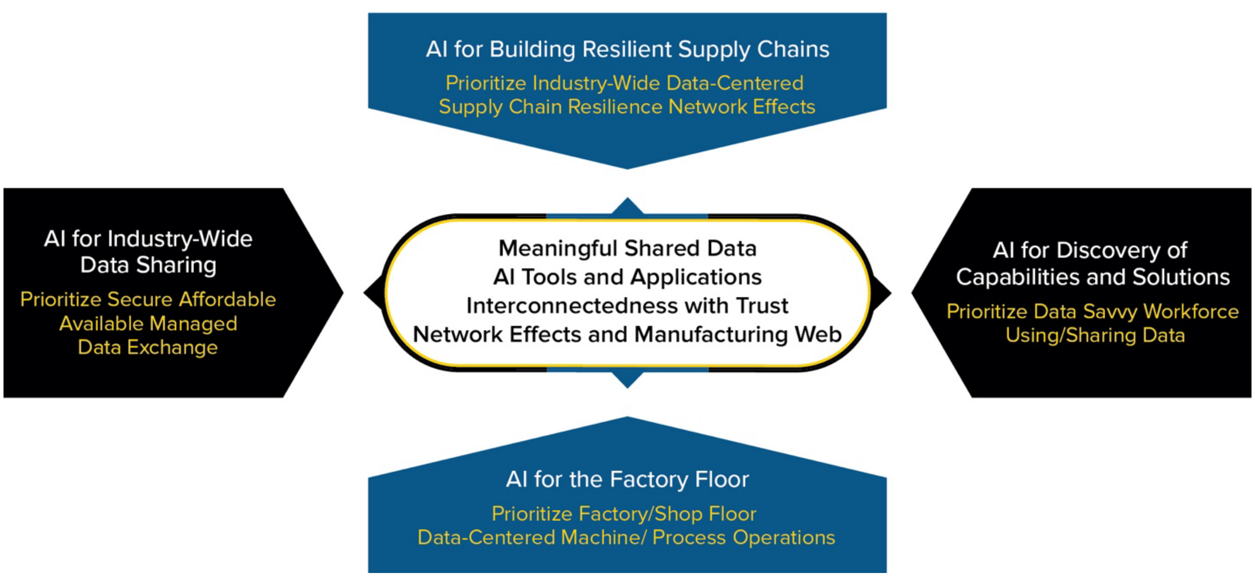

Figure 1: The Adoption Cycle Framework from Workshop 1

AI Monetization and Starting Small with Low Risk

The concept of "AI Monetization" spun out of a key discussion on hard dollar and soft dollar monetization, setting the stage for progressive monetization of AI starting with individual machine/process operations (unit operations). Economic value was stressed as a necessary condition and was defined as hard dollar savings or revenue that could be reinvested. Monetization, however, was raised from multiple perspectives reflecting industry segment, machine and process, and large and small manufacturers. Quality assurance, predictive maintenance, and asset performance were linked together and emphasized. These discussions naturally expanded to an entire factory or system of individual units, and ultimately across multiple intercompany factories in multiple locations and the supply chain feeding these factories. Large manufacturers often focus on their supply chains and drive AI application top-down, but this approach that does not scale. Scaling AI industry-wide requires a bottom-up, network approach driven by readily accessible tools, solutions, and a digital savvy workforce addressing the unique constraints at SMMs.

While scaling AI technology across the manufacturing industry is a long-term goal, the adoption of AI has already started in numerous applications that have demonstrated improvements in performance and competitiveness. Some practical examples of the use of AI technology are as follows:

- An oil and gas application increased unit performance, reduced energy waste, and monetized the application as increased product productivity and sales.
- A steel mill detected product quality problems in the upstream casting process to save hard dollar energy costs and improve facility maintenance in downstream hot rolling, which increased productivity and performance by reducing maintenance and downtime.
- A large metals fabrication factory showed substantial hard dollar energy savings across a line operation by integrating forging, heat treatment, and downstream machining.
- A small manufacturer increased productivity and sales and reduced consumption of raw materials with the addition of a single sensor.
- A food manufacturer managed energy usage without instrumentation across multiple units within a factory and could use the same system to monitor for equipment asset problems.
- Assembly-based industries, like aerospace and automotive, benefitted from preventive maintenance for reducing maintenance costs, machine failures, and production downtime.

There was clear recognition that in the context of end-to-end manufacturing, quality, waste, and operational issues affecting supplied parts and materials at one factory trace upstream to significant energy and materials costs and carbon intensity. Large companies with consumer facing products want better management of the source, quality, flow, and timeliness of materials and parts in their supply chains. Manufacturers of products currently in field operation (pumps, filters, or engines) are monetizing field maintenance services for these products by monitoring and improving in service performance and maintenance.

However, it became clear there is not much industry experience with successfully monetized AI applications beyond individual operations. Concerns about AI increasing financial, operational, and product performance risks in poorly implemented projects were emphasized as well as concerns about ensuring the protection of intellectual property. It was also uniformly clear that initially, AI should be used to aggregate information into dashboards that inform the decision process for human management. Dashboards for human involvement are far from new but their use represented a tolerable risk level for starting the development and scaling of AI operational management systems. Successes with individual machine/process operations can improve confidence in AI capabilities and allow the technology to grow into deeper and broader analyses of operations. This opens the door to make more automated decisions with less direct human interaction, which in turn leads to automation including robotic systems in highly mechanized facilities, and finally autonomy and self-directed decision making by machines.

However, all the roundtable deliberations returned repeatedly to a position that the starting point for AI adoption in manufacturing is at the individual machine/process operation with human management based on a simple display of information on dashboards intended for use by operators on the factory floor.

AI Monetization Layers

With reference to the blue Factory Floor and Building Resilient Supply Chains sections in **Figure 1**, the manufacturing industry can be characterized as a hierarchy of three operating layers. Moving up the hierarchy involves moving through operations of ever-increasing complexity, starting at the bottom layer with factory floor machine/process asset management, then to entire factory and supply chain interoperability, and at the top supply chain ecosystem resilience. With reference to the black areas of **Figure 1** for Industry-Wide Data Sharing and Discovery of Capabilities and Solutions, there are different data needs at each operating layer. When considering the monetization of the manufacturing layers together with data, knowhow, and modeling needs, three primary monetization layers emerge. Monetization at each operating layer represents expanded opportunity, but remains foundationally tied to individual asset performance, precision, productivity, and quality assurance. These operating layers are defined as follows:

- **Layer 1 -- AI Applied to Factory Floor Machine/Process Asset Management**: Predictive analytics at the unit asset management layer were discussed most often in terms of preventive maintenance and improved asset performance, precision, productivity, and quality assurance. Monetization took the form of reduced maintenance costs, machine failures, and production downtime, but also included currently aspirational benefits of in-situ quality management. Key AI tools that need to be developed and scaled included: (1) **feature modeling** with camera, vibration, and acoustic sensors such as see, feel, and hear capabilities in addition to point sensors, (2) **predictive modeling** (digital twin) using these key features, and (3) **data/model-based processing and visualization** for human machine interaction. Maximizing the predictive benefits of AI for individual assets, with verified and sustained confidence, requires maximizing focused data, knowhow, and models on commonly used assets and service categories. Often the data needed is greater than what can be generated in any one factory or company.
- **Layer 2 -- AI Applied to Entire Factory and Supply Chain Interoperability**: In this layer, AI is extended to maximizing performance, precision, productivity, and quality assurance for individual assets that are more tightly orchestrated in end-to-end operations. Included are factory (intracompany) management and interoperability of individual assets in line and factory operations. Because of the interoperability similarities, this includes business-to-business (B2B) intercompany interoperability. Given that end-to-end optimization relies on greater interoperability and coordination among the individual assets in the supply chain, the ability to monetize with management control and actions depends on the individual assets where "data and cyber" meet the physical operations in which parts and materials are produced. AI applications to drive interoperability and monetization include: (1) analytics for the discovery and identification of productivity opportunities, (2) data and modeled systems implemented across line/factory operations, (3) supply chain B2B interoperability (contract peer-to-peer data exchange), and (4) supplier/customer products-as-services (factory agreements with product users).
- **Layer 3 -- AI Applied to Supply Chain Resilience**: Optimizing product and material availability, quality assurance, and resilience require ecosystem visibility to manage variability and disruption,

and to promote and find new opportunities for manufacturers across supply chain ecosystems. Monetization accrues at individual manufacturers from supply chain visibility, predictive industry analysis, and opportunities with new supply chains and new products.

The relationships among monetization layers, data sharing needs, and R&D goals are shown in **Figure 2**.

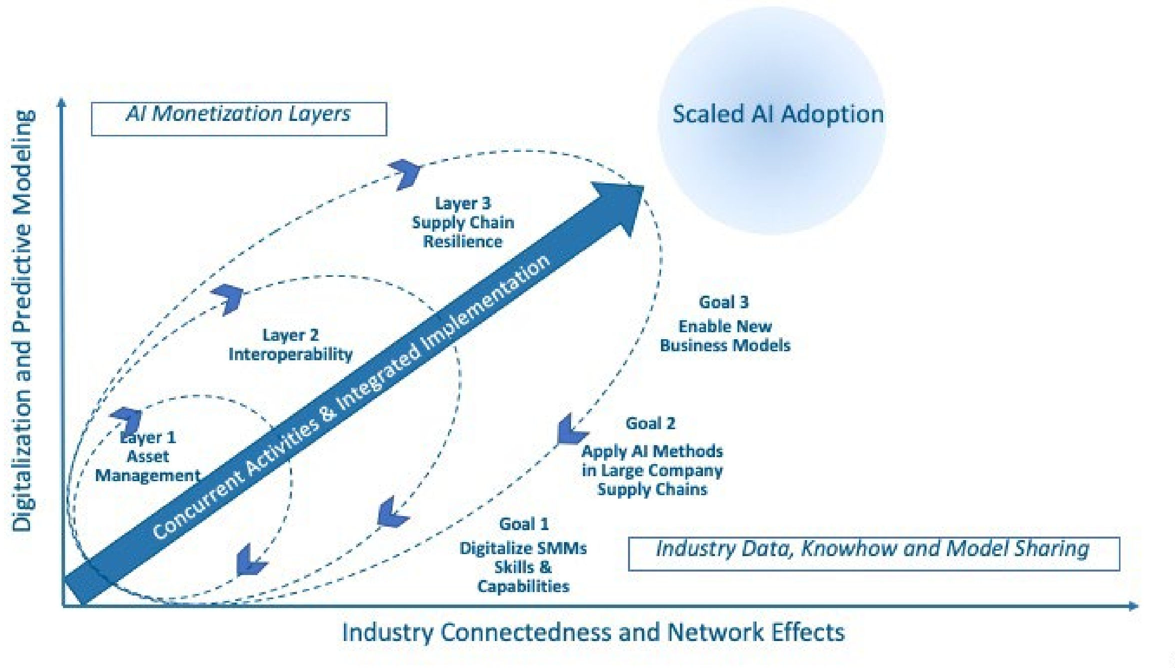

Figure 2: Layering AI Applications and Connected Industry Sharing

As illustrated in **Figure 2**, the three monetization layers are shown within three, nested ovals reflecting the distinct kinds of data, knowhow, and model sharing discussed above. The chevrons on each oval reflect data sharing for both contribution and use. The ovals are nested with the large block arrow indicating layers of monetized opportunity that act progressively from foundational action in Layer 1 where individual assets make products. By associating the monetization of AI applications and categories of data/knowhow needs with the operating layers in the manufacturing hierarchy, it is possible to combine actions in the layers into plans that are most likely to drive achievement of the three AI adoption goals shown on the right of the diagram. The diagram also shows how addressing these layers of AI implementation build digitalization and predictive modeling from the factory floor to supply chain ecosystems with increasing connectedness and leveraged network effects. Activities that are targeted toward achievement of a specific goal will likely impact certain operating layers more than others. How these operating layers map to the three goals is shown in **Figure 2** and summarized in the key points below. The end game is shown in **Figure 2** in the shaded circle as Scaled AI Adoption from broadly available digital skills, ecosystem trust and sharing, connected industry capability and benefits, and scaled access to US manufacturing capabilities

- **Goal 1**: Support small and medium-sized manufactures (SMMs) to digitalize their operations
  - Layer 1: Factory floor machine/process asset management
- **Goal 2**: Incentivize large companies to work within their established supplier networks to implement AI methods
  - Layer 2: Entire factory and supply chain interoperability
- **Goal 3**: Enable new business models

- Layer 3: Supply chain ecosystem resilience as a result of scaled access to US manufacturing capabilities

Top-Down/Bottom-Up Connected Industry Strategies

The layering of the adoption cycle framework in **Figure 2** helped organize the potential roles of multiple scaling strategies. In general, the roundtable discussions concluded that industry needs to "experiment" by combining business and operational tools, shared capability, and integrative platform mechanisms as top-down and bottom-up networked approaches. Both involve recalibrated definitions of what kinds of data, knowhow, and models are/or are not within a companies' intellectual property and trade secrets. If these are within company IP or trade secrets, then the recalibration takes the form of addressing ways of sharing and exchange when there is value. In general, individual companies stand to benefit greatly if there can be industry-wide strategies that facilitate extensive, but managed and secure, sharing. A key conclusion was that full economic potential of predictive AI and scaled interoperability stems from merging and scaling both top-down and bottom-up connected industry strategies.

Top-down supply chain interoperability strategies are facilitated by a business-driven exchange of operational data between companies and their supply chains. Similarly, top-down ecosystem visibility strategies are facilitated by an even wider business-driven exchange of data about factory inventory, capability, capacity, and availability. At the same time, selective sharing of contextualized data, knowhow, and models for individual assets across all companies can be facilitated with bottom-up strategies involving searchable data, models, and application resources. Similarly, supply chain resilience is enhanced with the ability to promote and search for factory opportunities across supply chain ecosystems, but in the context of agreed upon data exchanges.

Acceptable Windows of Risk

Broad AI adoption depends on demonstrated economic benefit, but due to the highly technical nature of AI, manufacturers see operational risks in the likelihood of success, impact on product performance, and exposure of trade secrets or the inability to manage intellectual property. How to address many legacy and serviceable AI applications without affecting well established operational systems remains a major concern. Additionally, top-down interoperability is naturally understood by the manufacturing industry compared to scaling from the bottom up. With no industry tools, trust, confidence, or experience, starting an interconnected AI adoption cycle is a hard problem that requires industry-wide R&D. The roundtables spent considerable time on risks and trust. These discussions were captured as the areas of risk shown in the axis titles of **Figure 3** as People and Machine Decision Making, and Trusted Data, Knowhow, and Model Sharing. These were considered in terms of risk that can be addressed progressively with the trust and confidence that are built from successful AI implementations. All these factors were blended to help define places where connected industry strategies could be initiated within acceptable windows of risk.

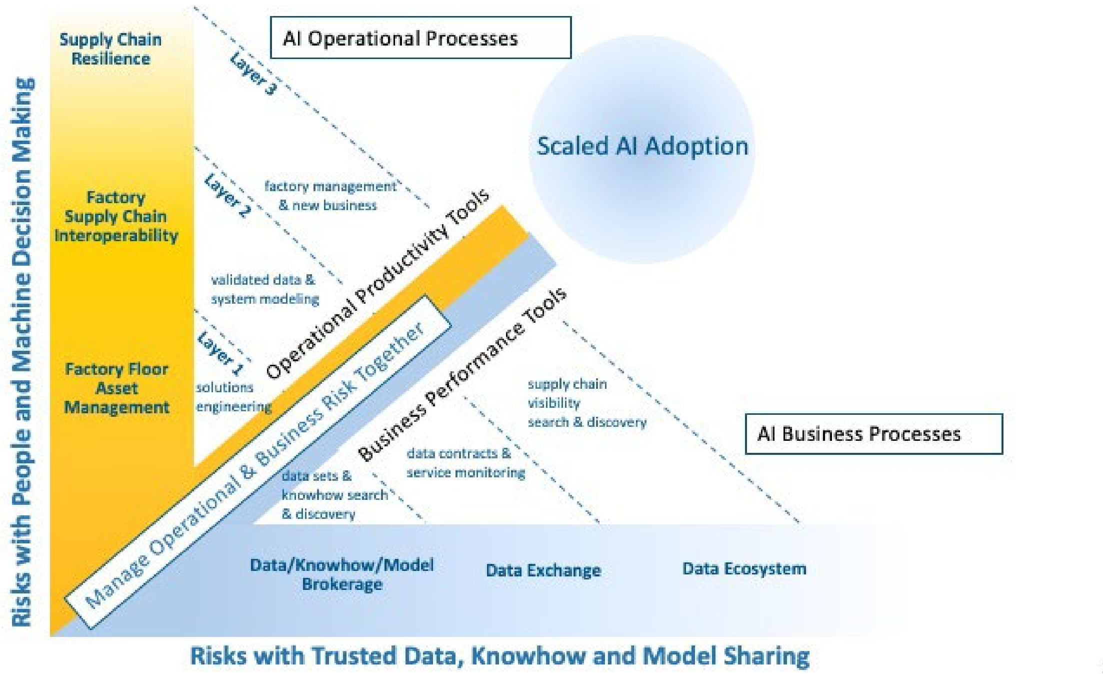

Figure 3: Aligning Tools with Connected Industry Risk Areas

The three monetization layers from **Figure 2** are again shown vertically in yellow in **Figure 3**. However, with reference to **Figure 2**, nested sharing is now associated with three types of industry data, knowhow, and model sharing. These are shown horizontally in blue as Data/Knowhow/Model Brokerage, Data Exchange, and Data Ecosystem drawing upon terminology used in the roundtables. The terminology describing the three types of 'sharing' is illustrative and not prescriptive of any one approach, be it centralized or distributed, market or policy driven. Notably, these paired areas of monetization and areas of industry sharing combine into business and operational requirements that form integrated business and operational tools that each manufacturer needs the access and skills to use. As one example shown for Layer 1, operational productivity tools for solutions engineering are combined with the business performance tools to search for and discover data sets and knowhow relevant to a particular need. These tools are needed to share and use data/knowhow with trust and to lower and manage risk. Similar pairings for Layers 2 and 3 also lead to combinations of tools that manage operational and business risk together as shown in the center yellow and blue areas. Business and operational roles for AI can be delineated. Each of the layered business tools need to support operations as they progress from dashboards with human-in-the-loop control to automation, robotics, and autonomy. A description of approaches that create this alignment is as follows:

For Layer 1, primarily a bottom-up, networked approach through which the industry contributes to and has access to data, knowhow, and models, and to tools such that non-experts and new businesses can engineer solutions for a specific operation or service application. These tools are paired with an educational infrastructure geared to training a data-savvy workforce to engineer solutions using implementation infrastructure that supports search, discovery, and use of data sets, knowhow, and models relevant to an application. While important to large companies, this layer heavily addresses the needs of SMMs whether they are in large supply chains or not.

For Layer 2, a Data Exchange to support top-down B2B and supply chain interoperability. From an operational standpoint, factory and supply chain interoperability are much the same. However, from a business standpoint, B2B and supply chain interoperability require specialized business agreements, service level agreements, and secure management and exchange of data, knowhow, and models between two or more entities. Layer 2 is therefore primarily associated with a top-down strategy driven by the large companies through their supply chains, but successful AI applications will require the capability, tools, and training described in Layer 1.

For Layer 3, ecosystem data trust refers to industry-wide agreement to share visibility into factory inventory, capability, capacity, etc. To be effective, sharing of data needs to be much broader across supply chain ecosystems than for Layer 2 interoperability. Benefits will be derived from industry-wide models that can predict changes and disruptions in supply chains for better factory management, but to act on changes and disruptions factories need the tools to promote and find new capabilities. Again, network search capability becomes important. This layer brings SMMs, large companies, supply chains, and multiple supply chain ecosystems together around industry opportunity.

For Trusted Data, Knowhow, and Model Sharing, Figure 3 considers not only top-down approaches but also bottom-up approaches that depend on building and scaling tools, capabilities, and opportunities using the web to search for the most relevant solutions. Companies need access to data to build models and multiple methods to monitor models for application validity and retraining. Data, knowhow, and models need mechanisms for verification and their use needs to accommodate business and operational requirements.

For People and Machine Decision Making, Figure 3 supports tools for production testing and evaluation in moving from human-in-the loop, to automation, to robotics, and to autonomy.

Each of the application layers benefits from shared data about asset services. The ability to scale monetization, especially for SMMs, requires data sets, tools, and infrastructure to implement seamlessly for a succession of assets. People and machine decision making, and trusted data, knowhow, and model brokerage are viewed as direct manufacturer risks which need to start safe with minimal risk and progress as confidence builds with successful implementations. The paired layers and tools are viewed as new shared industry capabilities that need to be developed based on general industry acceptance. Risks are indirect and associated with business trust, confidence, and incentives to collaborate. Overall, acceptable windows of risk need to be defined to support early AI adoption projects that demonstrate and build trust and confidence.

Blending these risks begins to shape one or more industry starting points. Layer 1 stands out for many manufacturers in that it involves pre-competitive, lower risk data sharing for solutions on commonly used assets, but with less product critical applications. Preventive maintenance and asset performance projects are also viewed as low-risk staring points. To manage risk, applications will start out with a human-in-loop, but this approach needs to be consistent with a critical mass of manufacturers and is particularly important for developing and building trust in the bottom-up strategies that are new to the industry. Layers 2 and 3 are important in starting an adoption cycle because the top-down nature of supply chains helps coordinate and push the technical and business solutions forward. However, all functions do not scale equally, and layer 1 asset management solutions remain foundational to future adoptions. Each layer does need to be paired with shared industry tools that facilitate business and operations together and start to scale training.

As has been strongly expressed, any form of intercompany sharing presents numerous barriers with trust and the protection of the data, knowhow, and modeling that have been developed and generated often over years of experience. However, there are digitalized components of these experiences that can lead to significant value. Therefore, the data, knowhow, and modeling used to build an application will originate in the business and operational environment in which a solution is being applied. How to start the data, knowhow, and model brokerage within an acceptable window of risk still needs to be defined. Challenging questions remain with building and implementing shared industry platform tools that accommodate both top-down interoperability and scaling effects for bottom-up networked strategies. Successful integration of top-down and bottom-up operations can create many solutions to problems across many industries.

With respect to people and machine decision making, building confidence in software based operational management systems will begin with full human involvement in operational actions that are based on a data and modeling system. The industry will want to do initial production testing and application with the human in the loop. Automation is sparingly applied only after significant confidence has been built. While automation for frontline control is well established, the interest in predictive AI is for higher level management of operations. There are clear breakthroughs in certain operations in which robotics have been used to monetize performance and precision. Autonomy remains at the far end of the operating risk progression with expectations that AI can enable this operating capability in the future.

Workshop 3

Workshop 1 set the stage for considering much broader roles for AI in transforming manufacturing competitiveness than just factory level applications. However, to achieve full AI benefit, all of industry needs to be part of the transformation. This produced an emphasis on the importance of connected, industry-wide strategies centered on an adoption cycle that spans factory to supply chain applications.

Workshop 2 has focused on how to address industry-wide strategies, clarified the roles of AI, and provided insights for executing an adoption cycle. The result was identification of four overall goals and a characterization of the manufacturing industry as a hierarchy of three operating layers. The following points provide an overall summary of the interaction of the three goals with operating layers.

- **Goal 1**: Support small and medium-sized manufactures (SMMs) to digitalize their operations
    - Layer 1: Factory floor machine/process asset management
- **Goal 2**: Incentivize large companies to work within their established supplier networks to implement AI methods
    - Layer 2: Entire factory and supply chain interoperability
- **Goal 3**: Enable new business models
    - Layer 3: Supply chain ecosystem resilience

From this interaction, staged strategies can be developed for each goal to safely unlock the profit-making potential of AI from factory floor to supply chain ecosystems. R&D areas can be focused on industry-wide education, tools, collaboration, and risk mitigation at each layer so progressive strategies can be pursued to build industry trust and confidence. With SMMs, unique strategies are required to address their operating constraints.

The three operating layers of the manufacturing industry will be assessed in Workshop 3 to identify specific implementation needs and strategies to address these needs. The organization of the workshop is being planned around primary workstreams that include: R&D, industry-wide infrastructure, industry adoption, government policy, and their coordination and/or integration. The results of Workshop 3 will be recommendations for specific R&D strategies, both centralized and distributed, and market and policy driven, and the federal government programs that address the need for new technology, business policies, and infrastructure. The ultimate end game is industry-wide of adoption of AI systems based on broadly available digital skills, ecosystem trust and sharing, connected industry capability and benefits, and global competitiveness.

Appendix A
Roundtable 1 Summary - June 15, 2021
AI for the Factory Floor

The goals for **Roundtable 1** were to define the benefits AI can bring to current manufacturing operations, determine how solutions can be developed, and identify a strategy for sharing data and AI/ML models from the factory floor.

The Benefits of AI

As is evident from the Workshop I report, the potential benefits of industry-wide AI adoption in manufacturing are well recognized. The discussions in this roundtable were focused on the benefits AI could bring to applications on the factory floor. The discussions covered a wide range of industry sectors represented by the participants, included examples spanning from the chemical process industry, to control or automation of machines or robots, to development of advanced materials. The participants recognized the importance of data collection, sharing in the application context, data integrity, security and intellectual property, and suggested approaches to pave the way to broadly apply AI to improve performance across the entire manufacturing industry.

It was noted that AI strategies will vary significantly for different company sizes and a company's position in the supply chain. SMMs ("Small to Medium Sized Manufacturers") frequently choose a tactical approach to focus on using AI to solve specific problems, while big companies often have a broader strategic approach to pursue AI deployment at the system level for significant gains in market competitiveness. Both scenarios are valid and can be expected to coexist, with advances in one area providing benefit to the other area. In general, the need to recognize and address the differences between large companies and SMMs in any AI/ML adoption project became a common theme in all four workshop roundtables.

Building out AI-enabled facilities and the associated workforce can require substantial capital investments, meaning profits and competitiveness are corporate drivers for AI adoption, and for financial institutions to invest. These investments can be loosely grouped into two types: investments with direct, or highly correlated returns, and investments with multi-faceted, indirect, or long-term benefits. Examples of direct returns include reduced product scrap or savings in labor cost. In the post COVID-19 era, an indirect example might be a facility enabled to operate with remote management of processes and workers. Regardless of the type of investment, to be viable in the manufacturing industry an AI project must result in benefits with a measurable return on the investment.

One driving factor for AI adoption in manufacturing is significant improvement in quality assurance, which is a top priority across all industry sectors. Pursuing quality assurance is comprehensive in that it naturally leads to improvements in preventive maintenance, throughput, utilization, reliability, and cost, with end-to-end supply chain applicability. For example, instead of using traditional statistical sampling to assess defect rates in products, a vision-based AI system could inspect every product to identify and remove defective products, producing near perfect output. A focus on quality assurance projects was viewed a good starting point for initial AI adoption.

How AI Solutions Can Be Developed

A successful AI factory floor project must start with a well-defined problem statement, including an estimate of the return on the investment required to implement the project. A well-formed problem statement is an essential success factor, and it is required to communicate the value proposition. In practice, any AI project requires a precise problem formulation that can be cast into a computational/mathematical structure. A concrete statement will ease the process of computational translation, and potentially increase the success rate of solving the problem by existing methods.

It was agreed that all aspects of data need to be managed and shared (in multiple forms) to build the models (tools and algorithms) for successful AI adoption. However, manufacturers traditionally do not share data, knowhow, and models out of fear that some "secret sauce" or competitive edge will be lost. This is unlike the open source approach frequently used in the computer software industry over the last decade. It may be argued that data sharing in manufacturing is more challenging than open sourcing in the software industry. Manufacturing typically involves specialized physical components or equipment that are harder to generalize than software systems.

Acknowledging these differences, limited data sharing still leads to several drawbacks in the context of AI adoption including: (1) companies within the same industry sector cannot benefit from the industry-wide data collected or produced by other companies, (2) the manufacturers of the machines often do not (with exceptions) have access to the production data from the machines, now installed in the buyers' plants that they made. (3) researchers in academic institutions, normally not being the direct competitors to the companies, do not have easy access to manufacturing data for AI research. The opportunity of industry academia collaboration is easily lost.

In addition, modern AI methodology is based on data-driven predictive modeling, ML, and computational methods. Data of good quality, with the right contexts, is of paramount importance in the success of any AI methodology. In terms of data availability, however, it has been recognized that accessing good quality data, at least for AI development purposes, proves to be challenging in manufacturing companies where floor operators often do not know how to read data, and are not incentivized to collect and log data.

The considerations of data sharing in manufacturing AI go beyond simply making the database or files available online. Different data-driven algorithms used in AI require different data attributes or forms, even for solving the same problem. Different data is needed at distinct stages of building the required AI models. Therefore, in addition to data, the associated AI algorithms or models also need to be shared for maximum utilization or benefits. Other practical issues such as data format, data structure, and the association between data sets and AI algorithms can be challenging without industry-wide coordination.

Even when data is shared and intellectual property concerns addressed, there are practical matters of data quality, biases, and security that can discourage companies from sharing their data. For example, corrupt (but still readable) data can result in "bad" AI models causing unintended consequences including physical harms or legal issues.

There was recognition that academic institutions have significant untapped capability in AI R&D and application adoption. This includes the capability to educate and train a workforce from floor operators, to engineers, to data and knowledge workers, to legal professionals, to new ways to transfer learning. This includes the capability to develop and benchmark scaled tools, methods, and algorithms; automate and contextualize data formulation; build secure models; demonstrate standards; and build algorithms for common applications. The lessons and great success of AI adoption resulting from academic-industry partnerships in other areas, such as computer vision and medicine, can be learned and applied to the manufacturing industry.

Strategy for Sharing Data and AI/ML Models

As a proposed solution to address the data access problem, participants discussed creation of a Data Exchange Platform (DEP) as a source of relevant data and models that are curated, searchable, and accessible. To create trust in the information available on the DEP, the content would be certified by experts in the field and protected from unauthorized use. The DEP would use a supply and demand model that would appropriately incentivize providers to share data, algorithms, and models to benefit all, including academic researchers. The DEP could also provide a platform for researchers from academic institutions to make contributions to the DEP, such as benchmark datasets and models that could directly benefit the industry. Creating the marketplace would naturally address several practical matters associated with data sharing such as standardization of data formats, and legal structures to protect the rights of those participating in the DEP.

Appendix B
Roundtable 2 – June 29, 2021
AI for Building Resilient Supply Chains

The goal for **Roundtable 2** was to determine if AI can provide visibility across proprietary supply chains and motivate large manufacturers and SMMs to work together to improve supply chain resilience and achieve national coordination.

The concept of lean manufacturing has been around since the 1930s and has driven large gains in efficiency in manufacturing. Starting in the 1970s, development of just-in-time delivery of goods assumed optimistically that the supply chain will always operate at capacity and not experience bottlenecks, shocks, cyberattacks, or other disruptions. Offshoring activities in the 1990s were thought to improve supply chain resilience by insulating manufacturers from labor disputes, allowing for global production, eliminating single points of failure, and creating access to emerging markets. While the downsides of offshoring included the shuttering of some large US-based manufacturing plants, trade agreements and access to technology also enabled the domestic growth of SMMs and real manufacturing output in the US has grown over the last 30 years. Today, 95% of US manufacturers are SMMs and 85% of SMMs have less than 20 employees, and their vital role in US manufacturing cannot be ignored.

While the US has a large base of manufacturing capacity, that capacity is fragmented and fragile to shock. These points of weakness have been accumulating for decades and remain unresolved to this day. The Covid-19 pandemic in 2020 created an edge of the bell curve supply chain disruption that will require several years to achieve full recovery. The Covid-19 crisis, as well as other potential disruptions like ransomware attacks and extreme weather events, have demonstrated that past assumptions about supply chain stability can no longer stand and that a strategy to create a resilient US supply chain is an issue of national security.

One way to insulate US manufacturing from supply chain shock is through AI-enabled supply chain visibility. Supply chains are designed to make-to-stock or make-to-order business models. Currently, most US manufacturers, even those who use make-to-order, have little visibility into their suppliers or their customers. For make-to-stock, forecasting is the main method for determining demand and visibility is even more limited. In both cases, if a disruption occurs, manufacturers have little or no advance warning. To the extent that there is visibility, it is thought to be tactical because SMMs lack the resources to operate strategically and are often focused on trying to solve day-to-day problems. In addition, large manufacturers often take a strategic view to exploit opportunities across the chain.

As a result, there was broad agreement among attendees that AI-enabled supply chain visibility has the potential to improve resilience and provide real benefits for all players. The imperative of AI visibility is to create benefits that address the needs of both tactical and strategic players. There was also agreement that many benefits can be extracted through sharing and scale. Nevertheless, AI is seen primarily as a cost item, so the benefits of AI-enabled supply chains need to be made clear and quantifiable to attract first movers and early adopters.

Motivating Manufacturers to Participate

As noted in Workshop 1, secrecy in manufacturing arose from a craft culture that placed high value on expertise, and that culture of secrecy is still pervasive today. As such, a culture shift in manufacturing is at least as difficult as a technological shift and at their core both require a high-level of trust. The Amazon Marketplace is a good example of how to create trust. In general, to be a vendor in the Amazon Marketplace, a company or individual must subject themselves to reviews, ultimately providing transparency to the buyer and incentivizing competition among sellers, i.e., the more positive reviews a supplier gets the more they will sell, while poor reviews work as an incentive to produce better results. In general, the best suppliers/products get the most and best reviews, and there is trust on the part of buyers and sellers because of transparency.

A trusted marketplace like Amazon will be necessary to motivate manufacturers to participate in AI adoption. A salient concern among attendees was that information a manufacturer shares with a customer may be used against them, and information a manufacturer accepts from outsiders may be intentionally misleading to harm their operations. However, most participants agree a trusted Marketplace that includes a data sharing facility containing certified information, perhaps supported by a public/private partnership, could create the digital assurance required to incentivize participation. This platform would allow manufacturers to consume factory floor profiles from a marketplace much the same way that enterprise IT professionals download infrastructure images from Amazon Web Services (AWS), or smartphone users download applications from app stores like the Apple Store and the Amazon Marketplace. This could produce the beginning of a sharing culture and the much-needed network effects in manufacturing.

As a public/private partnership, the Clean Energy Smart Manufacturing Innovation Institute (CESMII) is an example of an organization that could support this initiative. CESMII is one of the Manufacturing USA institutes that is currently developing a platform where manufacturers can share information and use advanced technologies and AI to improve performance. CESMII would manage and provide the guidance and leadership for the digital transformation required to create a resilient supply chain precisely because they are neither a manufacturer nor a vendor.

Supporting SMM Engagement

As important as creating trust in the resilient supply chain, is the creation of low barriers to entry for SMMs. The currently fragmented data systems are a cost burden to SMMs and simplifying their participation in supply chains is required for broad engagement. While individual SMMs may be data poor, in aggregate, they are data rich and so freeing SMM data in exchange for participation is one way to keep the barrier to entry low and motivate participation. Also, identifying which data is useful for SMMs will be key since sharing that data among SMMs will be the seed to create the required network effects for AI adoption to grow.

SMM engagement, however, will also rely on identifying large manufacturers who are first movers and who are willing to share their technology. Data with no modeling is like oil with no refineries, it is only valuable when you can turn it into something useful. Large manufacturers who are successful early movers in AI supply chain adoption have access to that refining capacity in the form of data models. For example, Intel in conjunction with their communication alliance partners, has created machine vision models for defect detection in chip manufacturing and also sells that technology in the form of *ready-to-run machine vision solutions* through their marketplace to other manufacturers and industries. Siemens manufacturers gas turbines with hundreds of sensors that feed AI models to smartly manage fuel consumption and emissions. Like Intel, Siemens has leveraged that internal expertise and monetized it in the form of AI professional services that they offer to the manufacturing sector, enabling other players to create industry specific AI models in the areas of predictive maintenance and generative design. So, while SMMs may share data to participate, a few large manufacturers could share data models as part of their entry burden and trade that for access to the data rich SMM community creating the seed for network effects to grow.

Approaches for Large Companies and SMMs to Work Together

The digital transformation so badly needed in manufacturing will be like lifting houses in vulnerable coastal areas. Lifting houses is a slow and costly process, but it hardens vulnerable areas against storm surges and informs construction practices moving forward. The most successful implementations of AI in manufacturing have occurred in a similar way. They are not rolled out as massive enterprise initiatives but rather piece by piece and following a roadmap so that they can scale slowly along a trajectory and avoid the pitfalls of disjointed solutions.

True motivation to participate in the resilient supply chain will require trust and patience and a long-term commitment to making the US a 21st century world leader in manufacturing and a leader in a resilient national and global supply chain. SMM engagement or a bottom-up approach to seeding a unified DEP will be where most of the initial growth will happen, but some top-down participation in the form of models from large manufacturers will be crucial to the creation of an AI enabled resilient supply chain.

Appendix C
Roundtable 3 – July 7, 2021
AI for Industry-Wide Data Sharing

The goal for **Roundtable 3** was to determine if AI tools could provide industry-wide access to data in a prevailing manufacturing culture that emphasizes protection of intellectual property.

With the overarching objective centered around finding solutions and knowledge to inform a national strategy to advance manufacturing processes, a mix of academic, government, and industry participants held an illuminating conversation for the third in the series of roundtables. In general, the lack of shared information is a pacing item for the adoption of AI and ML in manufacturing, making the topic of AI for Industry-Wide Data Sharing particularly relevant in Workshop 2. The session sought to solicit commentary from industry experts from Lockheed Martin, Microsoft, NSF, NIST, IBM, DOE, along with various higher education academics.

Why Data Should Be Shared

The concept of why data should be shared provoked a prolonged discussion on its merits. Panelists were quick to note the perils of data sharing, such as confidentiality and competitive risks, accuracy and quality of data, lack of curation and context, and legal issues, while hesitating on acknowledging the upsides or identify specific benefits. The unintended consequences of data sharing resounded loudly, with industries seeking to secure and privatize data to maintain their competitive advantage and to keep ownership of their intellectual property. Data was regarded as the "bread and butter," or the "secret sauce" that allows manufacturers to be competitive. To this regard, sharing data was met with trepidation and caution: how can we share data without losing our competitive advantage?

Admittedly, there is still much to learn and many ways toward improvement in data sharing protocols. A common way to describe manufacturing processes is necessary to maximize production capacities in coordination with suppliers, customers, and other departments within the same company. Manufacturers need a shared body of definitions, and especially important in SMMs where day-to-day operations can benefit by having a common dictionary. For this, an industry-wide ontology (semantic tools that formalize concepts and relationships) seems necessary to express standardized formal languages (like XML), thus ensuring shareability and interoperability. These standards could allow the use of AI to extract knowledge from disparate data sources. An example of this approach was shop floor maintenance logs. These logs were identified as a source of data to improve machine performance, especially in small businesses. Currently, extracting meaningful analytics from these logs requires human intervention to "tidy" the logs that often encompass a local vernacular that is not shared across industries. By taking a large dataset of maintenance logs, using Natural Language Processes and statistical analysis to optimize language understanding, and going through an iterative process to "train" the machine could lead to performance optimization.

Standardizing a process to use AI to extract knowledge could then have wide ranging implications that could positively impact the industry's performance. Having multiple "niche" operations build knowledge in this way, from the bottom up, encourages a groundswell of activity that uses data analytics to solve problems, a more likely scenario in data sharing than relying on giant companies that tend to be more risk averse. With more use cases like this, the entire manufacturing industry can benefit from scalable innovative AI tools and methods.

How Data Can Be Shared

Given the disparities between industry sectors, building use cases, and setting clear benchmarks from a manufacturing perspective are imperative. The healthcare industry is a clear example of an obvious use case for successful and impactful data sharing. Here, the goals and stakes are high. If you can enable a new treatment for a rare cancer, who wouldn't want it? In manufacturing, however, this incentive is not as crystal clear. Resources are typically referred to as "machines," and "jobs" are tasks done on a machine. A "model" may thus consist of a job that is a single operation, or a collection of operations that are conducted on multiple machines. Models and algorithms are used to improve performance on production lines (uptime) and minimize downtime. Improving throughput is often an important performance indicator that is directly related to a company's profit margin. Data can therefore enable much more by identifying best practices, improving product and system design, and advancing innovations, but having a clear example of why to do so is critical.

One impediment to sharing data comes in the realization that many SMMs have yet to collectively embrace the cloud. This issue could be driven by fear of exposing information that would endanger a business model, or lack of resources to implement and maintain the required computer system. The trust in cloud technologies, security concerns, and the vulnerability of networks all seem to come to play, and it is well known that SMMs are often devoting all their limited resources to solving day-to-day problems. In either case, there is a lack of appreciation for the need, benefit, and value of data sharing. Manufacturers need ways to make more data accessible, doing so in a manner that protects data privacy. Two approaches were discussed in the roundtable. A *trust model* where the creation and preservation of data is curated by subject experts. The data stays local with algorithmic models in place to protect knowledge. The second option was the use of *federated learning*, a paradigm for collaboration and partnership between companies using common, powerful ML models that build knowledge without exchanging data samples. An example could be a federation between machinery suppliers and machinery operators that provides ongoing improvements in predictive maintenance. This would enable collaboration between industries for learning models and ML explorations.

What Incentives Encourage Data Sharing

In an industry draped in a culture of secrecy and systems designed to increase competitive advantage, what incentives will encourage data sharing. Building use cases where manufacturers benefit from sharing data is a crucial step in setting priorities and understanding what is at stake. There is value in collecting data, doing it right, and extracting knowledge that can benefit an entire industry without infringing on the competitive advantages of individual entities. However, these values are not clearly defined. At this point, a global consensus among participants formed around the need for SMMs to get involved in sharing data to start addressing mutual problems. For example, crashes or physical injuries through machine tool usage can be avoided through the federation of machine tool documentation. Vendors can tailor their models using pooled data resources to avoid crashes. In either scenario, the curation of data is of critical importance. Another example comes in the form of government funded programs that are designed to make knowledge and research available in order to grow a specific area of research. And as mentioned previously, there is mutual consensus to share medical data between hospitals as long as privacy concerns are addressed appropriately.

One solution to prevent derivatives of work that may compromise competitive advantages is to bring in trusted third parties. They could help resolve potential liability issues by validating and verifying models to certify products. Furthermore, manufacturers may be more willing to share data with a trusted third party (rather than directly to the public) that can oversee the curation and protection of data.

Another idea, in an industry marked by being data rich but with data poor individual manufacturers, comes in the creation of synthetic data. With the need for big data to drive AI exploration for deep learning and data analytics, models to create synthetic or "fake" data can generate information that would add dimensionality and context to evaluate algorithms.

The widespread adoption of data sharing faces many challenges. Understanding the context of data is important. How data is used operationally, how it is annotated, and what it means should all be curated by experts in a particular field. With more successful use cases, more organizations will be willing to share data. Ultimately, the tremendous potential to advance knowledge through a collective ability to learn from data will take hold in the manufacturing industry.

Suppliers, for example, may choose to federate their data to build better predictive models of overall supply chain performance, resulting in mutually beneficial management.

Appendix D
Roundtable 4 – July 19, 2021
AI for Discovery of Capabilities and Solutions

The goal of **Roundtable 4** was to determine how AI tools can enable a manufacturing business model that sources data from and provides solutions to firms at national scale.

Roundtable 4 explored whether AI can be used to discover capabilities and solutions in the manufacturing industry. Its participants also tried to determine if AI tools can enable a business model that sources data from manufacturers and provides solutions to firms via a platform at a national level. The discussion led to many applications of AI tools that may lead to better performance, better quality of products, increased production, and reduction of downtime in manufacturing plants.

AI adoption in the manufacturing industry has significant challenges. People in the industry do not feel comfortable with adopting new technology. One primary reason for resistance is that computer science terms (jargon) can be intimidating and condescending to many people working in the manufacturing industry. Therefore, there is a need to translate AI jargon into a common English language customized for the manufacturing industry. Also, it was pointed out that advocates of AI technology do not offer a clear problem statement that reveals what issues within the industry could be resolved using AI tools.

The participants brainstormed many usages of AI in the industry. The following are some of the potential applications discussed during the roundtable.

1 One crucial issue for any manufacturer is that human skills and experience go away when an expert from the factory floor either retires or leaves the job. The industry lacks resources to stop the drainage of valuable knowledge. AI can help tackle this issue. AI, along with augmented and virtual realities (AR/VR), can capture and retain the knowledge base and train new staff to fill skill gaps. Thus, it can help the industry improve its knowledge management systems.

2 AI can work as a tech partner in the manufacturing industry. A combination of AI and human skills can work together to make operations more efficient, improve quality, and reduce human-based observations to cut down time to the finished products. An ambitious goal of the partnership can be a true artificial general intelligence (AGI), which can imitate a human mind for any task in most circumstances.

3 One important feature of AI models is their ability to predict. AI models can be used to predict the capabilities of manufacturers based on their historical data. This feature may hold the key to incentivize manufacturers to share their data because of their interest in marketing their capabilities to gain new contracts and possible financial benefits. On the other hand, model developers' interests are getting data from manufacturers and developing AI models that can be hosted at a marketplace. Another possibility is that manufacturers open controls of their machines to developers and invite them to create models predicting the capabilities of the machines. These new capabilities can increase visibility, encouraging SMMs to come forward and share their data.

Participants pointed out that the roadmap to the abovementioned possibilities of AI applications in the manufacturing industry has many challenges. The most important element is the development of a Data Exchange Platform (DEP) allowing manufacturers to share their data. The proposed DEP's framework should provide a roadmap to an organized aggregation point (e.g., marketplace) that allows the searching of its contents. A user should be able to sort the search results as per measurable features of the contents. The potential content of the DEP was questioned by the participants. For example, what abstractions of data are valuable that can be shared and aggregated, and could the data include CAD models (or graphics) of parts already being produced? Participants emphasized that more information, such as tolerances, bills of material, hierarchy, process plans, and material and engineering specifications, would make the data on the DEP more valuable. Another level of data abstraction for sharing could be the recipes that relate to instrumenting the experts and include information about machine configurations. The possibility of AI models as data abstraction was an interesting idea. AI models, a few participants referred them as skills, will allow developers to customize the models and provide manufacturers with the ability of information exchange without compromising their intellectual property (IP). In other words, no sharing of the actual data. Simulation models depicting manufacturing capabilities are also an option. The advantage of such simulations is that these will contain the real environment of factory floors. A futuristic idea of platforms where non-experts can customize AI models as per their needs was also discussed.

Participants agreed that most of the abovementioned data forms are viable options for data sharing through a DEP for the manufacturing industry. However, they emphasized that the industry would need standard definitions and units for measurements for the chosen abstraction(s) to enable the search of the contents and use search results for modeling, analysis, or decision-making purposes. Search engines will need to be developed to deal with the new structure of the data gathered. Further, to develop a DEP with data content from various manufactures, one will need to gain trust so that the manufacturers are comfortable with sharing their data. On the other hand, any user or developer would like to believe that the hosted data on the DEP is valid. Therefore, aggregating the contents on a DEP will also need an authority who can authenticate and certify the contents and its sources. Whether it will be the aggregator itself or certification authority, the community will need to decide upon an entity that can be trusted across the industry. These are hard pressed questions that need further investigation.

Overall, the participants agreed that the technology is available to develop a DEP. They concluded that the development of the DEP is a significant R&D effort and further investigations are required in the following areas:

1 Options for the data abstraction to be shared:
   - Geometry of products (e.g., CAD models) as the basic unit of data.
   - A recipe that relates to instrumenting human experts and includes information on machine configuration.
   - Skills or trained models with no need to share the data.
   - Process environmental models customized for a particular scenario.
   - A system to produce models where a non-expert can customize and train models for a specific operating environment.

2 Tools, infrastructure, and decisions required for realizing the platform:
   - Defining standards for measurements for the probable abstraction of information.
   - Aggregation model, aggregators, and roles of aggregators.
   - Ways to incentivize manufacturers.
   - Authentication, verification, or certification of the information.
   - Technology to search and compare different pieces of information at the aggregation gateway.

Appendix E

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Appendix B: Workshop 2

Appendix B: Workshop 2

Symposium: Strategy for Resilient Manufacturing Ecosystems Through Artificial Intelligence

Report from the Third Symposium Workshop

National Program Strategies and Roadmap to Scale the Adoption of AI in Advanced Manufacturing

Facilitated by

UCLA

Supported by

National Science Foundation
and
National Institute of Standards and Technology

June 2022

Executive Summary

The National Science Foundation (NSF) and the National Institute of Standards and Technology (NIST) sponsored a three-workshop Symposium entitled, "Strategy for Resilient Manufacturing Ecosystems Through Artificial Intelligence." **Workshop 1**, held in December 2020, identified four key areas for adoption of AI in manufacturing that are synergistic with the growing foundations of manufacturing digitalization. **Workshop 2**, conducted as a series of four roundtable discussions held in June and July 2021, defined three goals as focal points to overcome the greatest barriers to AI adoption. **Workshop 3** consisted of three roundtables held in February 2022. Using the results of the prior two workshops, Workshop 3 produced an actionable roadmap and recommendations for specific R&D strategies, government programs, and industry actions that can initiate and accelerate the adoption of AI.

Following 40 years of progress in digital data in the manufacturing industry, Smart Manufacturing/ Industry 4.0 has been building in interest and adoption for 15 years. Unfortunately, the U.S. manufacturing industry is pursuing digital transformation with an incremental approach, risk posture, and pace comparable to that of the past 40 years. The Symposium emphasized the potential for the application of AI in manufacturing to provide a world-leading advantage to the U.S. manufacturing industry that justifies a much faster pace of research and development, skills and tools development, and industry adoption. Such a broad transformation will encompass structural business change that accommodates industry-wide strategies to apply AI and achieve its full competitive value. With data and IT capabilities changing at an increasingly rapid pace, and other countries investing in digitalization and competitiveness, the workshops tackled a fundamental question of how to accelerate both technology change and market-driven business models in the U.S. The manufacturing industry is not fundamentally opposed to the adoption of AI technology, or the basic changes in business models the technology will inevitably create. On the contrary, many large corporations and a few Small and Medium Manufacturers (SMMs) are currently working to incorporate AI technology into their operations. However, the adoption of AI is complicated by limitations in capabilities at SMMs, the significant need for R&D, a lack of scalable successes, and the need to build business trust in new ways. Unless several key challenges can be overcome, the benefits of advanced AI systems in the hierarchy of manufacturing operations will remain incremental at best.

The roadmap presented in this report derives from the deliberations in all three workshops. It identifies multiple roles in which government programs have a key role to play in ensuring that the U.S. manufacturing industry leads the transition to an AI driven, digital future. Given the need for multi-disciplinary and multi-stakeholder collaboration among industry, academia, and government to take on industry-wide strategies, Public Private Partnerships (PPPs), for which there are many successful models, are the most appropriate coordinating structures. An opportunity exists to build on past PPP successes and adapt them to fit the requirements for AI adoption in U.S. manufacturing by involving all stakeholders in defining programs and funding requirements, supporting the implementation of programs and distribution of funds, and coordinating initiatives. The successes demonstrated by the actions of PPP coordination will reduce the risk of applying AI technologies in manufacturing operations, making it easier for entrepreneurs and private investors to visualize innovative operational products and business models. As this adoption cycle takes hold, the market-driven forces of entrepreneurship and investment capital will ultimately lead to industry-wide adoption of AI technology, and the U.S. manufacturing industry will be on its way to achieving global competitiveness and resilient supply chains.

Appendix C: Workshop 3

Introduction

The National Science Foundation (NSF) and the National Institute of Standards and Technology (NIST) sponsored a three-workshop Symposium entitled, "Strategy for Resilient Manufacturing Ecosystems Through Artificial Intelligence." This report and its recommendations are a compilation of inputs from all three workshops in the Symposium, including key areas for the use of AI in manufacturing, goals to overcome the greatest barriers to AI adoption, important priorities for research, development, and workforce education, an actionable roadmap, and recommendations for specific R&D strategies, government programs, and industry actions that can initiate and accelerate the adoption of AI. To obtain this information, the workshops brought together representatives from manufacturing companies, AI researchers and application developers, university faculty with manufacturing and AI expertise, government agencies, labs and programs, and the Manufacturing USA Institutes to address the essential requirements for broad, industry-wide adoption of AI technology in U.S. manufacturing. The questions discussed during the workshops included:

- Key roles for AI in manufacturing and how they can be monetized;
- Primary barriers to accelerating and scaling AI adoption;
- Software tools, training, and R&D required;
- Organization of the identified elements as programs in a national roadmap; and
- Requirements for implementing and coordinating a national research, development, and adoption cycle for AI in U.S. manufacturing.

Artificial Intelligence (AI) in manufacturing refers to software systems that can recognize, simulate, predict, and optimize situations, operating conditions, and material properties for human and machine action.
Machine Learning (generally seen as a subset of AI) refers to algorithms that use prior data to accurately identify current state and predict future state, with the goal of improving productivity, precision, and performance.
Models are digital, software representations (quantitative, qualitative, pattern, causal, inference, etc.) of real-world events, systems, or behaviors, which can use data to simulate or predict future results.
Scale means readily accessible, easy to use, and cost effective for manufacturers of all sizes.
Standard Data Format refers to the organization of information (protocol) according to agreements on preset specifications that describe how data should be stored or shared for consistent collection and processing across different systems and users.
Tools refer to software platforms that support the availability of data, knowhow, and models for use in business and operations.

Workshop 1 set the stage for the discussion by identifying seven key principles and the primary functions that need to be integrated to support an industry-wide strategy for realizing full value from and wide adoption of AI in manufacturing.

Workshop 2 brought full clarity to the potential for AI to penetrate nearly every aspect of the manufacturing industry and identified three goals for AI adoption that can overcome key barriers. The goals provided critical direction for Workshop 3:

- **Goal 1**: Enable Digital Capabilities at Small and Medium-Sized Manufacturers (SMMs)
- **Goal 2**: Incentivize AI Adoption Throughout Established Supply Chains
- **Goal 3**: Enable New Business Models for AI Adoption

Workshop 3 used these three goals as the basis for recommending an AI adoption roadmap. During each roundtable, the moderators reviewed one main goal and its subgoals with the participants and requested feedback to validate the completeness of the draft roadmap, steps to accomplish the goals and subgoals, and actions for implementation by government, industry, and academia. The resulting Roadmap provided a matrix of interrelated programs for accomplishing the three goals in efforts focused on addressing industry constraints, identifying new sources of revenue, and scaling success.

In validating the roadmap, four common themes emerged across all three goal discussions:

- Improved digital capability at SMMs was viewed as an absolute prerequisite for industry-wide adoption of AI and achievement of its full benefits.
- Structural business and technological limitations are inhibiting implementation of AI systems and execution of the roadmap.
- Broad adoption of AI will require new industry business models that accommodate widespread aggregation of data across manufacturers and access to advanced software tools with appropriate scale and cost for manufacturers of all sizes (i.e., software-as-a-service).
- Technologies required for robust, scaled, trustworthy AI in manufacturing are at a nascent stage and require continued R&D investment and coordination with existing research programs.

Within these common themes, roundtable discussions focused on the current barriers to AI adoption, and significant input formed around seven structural constraints. Participants recommended that execution of the AI adoption roadmap should start with actions to address these constraints, with a particular focus on SMMs, R&D, trust, and scalability. The following constraints and associated actions emerged:

1) Agree on establishing standardized data formats and repositories to store data to get started
2) Create an exchange platform for access to AI data, tools, models, and information
3) Provide financial incentives for SMMs to upgrade digital capabilities
4) Build educational programs at academic institutions and fund training at SMMs
5) Show value with use cases and provide blueprints for solutions at manufacturers of all sizes
6) Data enable legacy equipment that still has useful life, especially at SMMs
7) Allow 'in-kind' cost share for the value of the data provided by industry participants in government programs and institutes and make that data available to researchers

These constraints emerged as core barriers preventing many individual companies and their supply chains from participating in AI implementation programs. In practice, the seven structural constraints are linked together, and actions to address them require interrelated solutions. Targeted actions by government, industry, and academia are therefore required to address these interrelated problems and to coordinate the interaction of existing AI programs with new initiatives. While the immediate actions required will largely produce incremental progress in the use of AI, workshop participants suggested that incremental improvements will enable entry points for AI implementation and stimulate progress on the roadmap.

Execution of roadmap programs will necessarily begin with currently available technologies, which can provide immediate value. The Symposium stressed the importance of executing the roadmap with industry use cases and recommended starting an industry adoption cycle with a program that demonstrates that diverse manufacturing challenges can be addressed with an integrated set of 'first pass' actions on the

seven constraints to demonstrate how business collaborations can succeed and produce value. A successful 'first pass' industry collaboration entails identifying initial use cases that apply AI to common manufacturing problems, provide demonstrations of the economic benefit of data sharing, produce first sharable "blueprints," and bring training together with basic tools. Expanding the execution of the roadmap in more complex use cases will require more advanced software tools, models, and infrastructure to enable the new business models required for scaling SMM digitalization and supply chain resilience.
Recognizing these needs, the roundtables also identified four key R&D areas for future development programs:

- AI methods and data aggregation tools for manufacturing's dynamic data types
- Automation of algorithm building and continuous tuning
- Going beyond incremental industry change
- Scaling data and operational interoperability

Results from Workshops 1 and 2

Workshop 1, held in December 2020, identified four key areas of priority AI adoption that are synergistic with and build on a growing foundation of manufacturing digitalization (a.k.a, Smart Manufacturing/ Industry 4.0). The workshop emphasized the potential for untapped *productivity*, *precision*, and *performance*. Realizing the full potential of AI will require innovative technologies, services, and infrastructure for manufacturers to provide, with trust, the non-proprietary or protected domain data and knowhow needed to build and use AI for greater industry-wide interoperability, supply chain resiliency, new business models, and environmental sustainability. These strategies center on 'data sharing' (many forms), and application building, but also require substantial changes in organizations, markets, culture, technology risk, and business management. AI derives its power from more data than found in any one company. This is combined with industry learning how to scale and address AI to obtain significant benefits from intercompany data and operational interoperability. Longstanding industry practices on how data and operations are valued and compartmentalized currently work in opposition to these opportunities and need to change. If current industry practices remain unchanged, the competitive benefits of intra and intercompany (operational) interoperability and data sharing that comes with scaled AI adoption are expected to move forward slowly at best. Competitiveness that comes from speed of adoption is already stalling.

Workshop 2, conducted as a series of four roundtable discussions held in June and July 2021, focused on identifying the most important research, development, and workforce education priorities for industry-wide adoption of AI. It provided two important framing perspectives from which to build a Roadmap.
First, three categories of monetization were identified and then used to distinguish three primary kinds of AI applications: (1) asset management on the factory floor, (2) interoperability between operating assets within factories and supply chains, and (3) intercompany interaction for supply chain resilience. These groupings of AI applications form three layers that also depend on each other: asset management depends on exploiting data; operational interoperability depends on asset management but also line operations and intercompany data interoperability; and supply chain resilience depends on data and operational interoperability as well as intercompany business visibility. These dependencies imply that manufacturers must act individually and together on resiliency strategies.

With respect to the role of industry interconnectedness: Layer 1, asset management, depends on industry data, knowhow, and application sharing in a brokerage of solutions targeted and discoverable for specific applications; Layer 2, interconnectedness, focuses on connecting data across operating assets within factories and across supply chains for greater operational interoperability; Layer 3, supply chain resilience, depends on the visibility and analysis of shared business data and in turn on the ability of individual manufacturers to act in concert. The workshop participants defined the functional requirements to be satisfied for each layer and identified three goals as areas of focus to guide development of an implementation roadmap.

Workshop 2 also categorized data in three different forms associated with each of the layers: data brokerage (sharing data to build software models for asset management), data exchange (exchanging data to increase operational interoperability), and supply chain data ecosystem visibility (exposing capacity and capability data for greater supply chain responsiveness). Operational technology and business technology performance tools to preserve privacy and security must be integrated in each of the three primary kinds of AI applications and for each form of data sharing. Furthermore, those tools need to be seamless across the layers so manufacturers can grow and readily move among the three layers of monetization. All of these tools depend on carefully building and managing trust in interactions between businesses, people, and machines. The human role in AI adoption is essential. For each manufacturer, business and operating tools, mechanisms of business exchange, and acquisition of skills through training and education need to align, a process that can only proceed at the pace of trust building and risk mitigation. These integrated operational and business tools encompass a large area of foundational R&D.

Workshop 2 identified a critical area of R&D associated with the complexities of collecting data and applying solutions at the location of deployment and source data when those solutions employ machine learning models generated from data aggregated from many manufacturers. A complex process is associated with the continuous learning that occurs as additional data is generated. There is also the need to appropriately partition that learning between the proprietary interests of the user and the shared interest of that same user in improving the capabilities of the underlying generic software model. This created a long-term R&D goal to create the software and communications framework needed to enable a trusted and dependable AI service provision infrastructure.

Workshop 3 Methodology and Roundtable Results

Workshops 1 and 2 both emphasized the potential of AI to penetrate every aspect of the manufacturing industry and produce significant economic impact. Numerous discussions highlighted strategies and R&D opportunities to address the challenges of using AI technology. Three primary goals were identified as foundational in addressing the most critical barriers impacting each of the three layers of monetization.

Workshop 3 used these three goals as the basis for recommending an actionable, AI adoption roadmap, including recommendations for specific R&D strategies, federal government programs, and industry initiatives that address the need for innovative technology, business policies, applications, software tools, training, and infrastructure to support AI adoption. Three roundtables were organized for Workshop 3 with one roundtable devoted to each goal. To stimulate roundtable discussions, a set of subgoals gleaned from Workshops 1 and 2 were developed for each of the three overall goals as follows:

Goal 1: Enable Digital Capabilities at SMMs

1. Overcome lack of resources, infrastructure, data, expertise, and administrative capacity
2. Enable SMMs to share data and knowhow for AI applications
3. Provide SMMs with tools to easily adopt AI solutions

Goal 2: Incentivize AI Adoption Throughout Established Supply Chains

1. Develop partnerships to define data, applications, and tools for supplier network interoperation
2. Enable companies to conduct demonstrations that define the value of scaled AI projects
3. Establish partnerships to converge on common AI applications and associated software tools and infrastructure

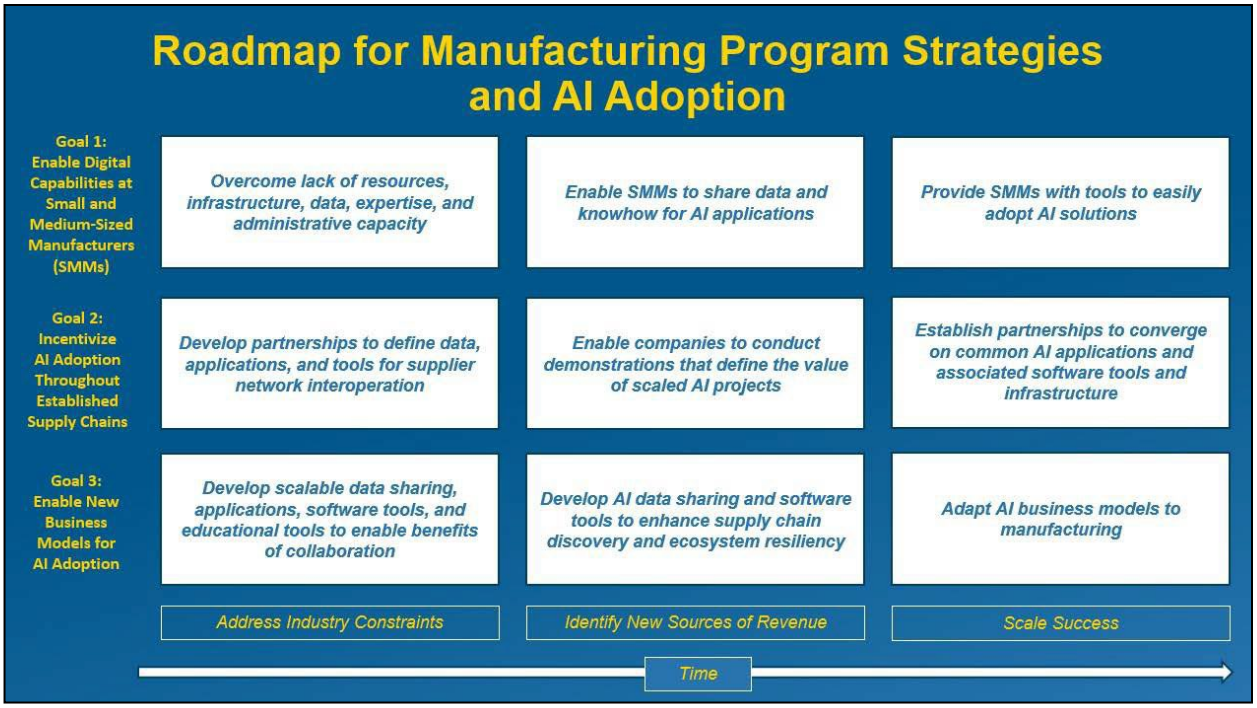
Goal 3: Enable New Business Models for AI Adoption

1. Develop scalable data sharing, applications, software tools, and educational tools to enable benefits of collaboration
2. Develop AI data sharing and software tools to enhance supply chain discovery and ecosystem resiliency
3. Adapt AI business models to manufacturing

The Workshop 3 roadmap was envisioned as a set of systematic recommendations for R&D, tools, training, and the distribution and coordination of industry, university, and government roles to overcome AI adoption barriers, accelerate the use of AI, and build a wave of momentum based on operational benefits. The roadmap addresses recommendations for AI adoption, not just within an individual factory, but across all operations of the industry and its supply chains. Importantly, the workshop focused not only on what should be included in a national roadmap, but also the roles of various key stakeholders, how they come together, and the execution and coordination of the roadmap. In acknowledging the U.S. preference for market-driven approaches, Workshop 3 raised questions around the aspects of the roadmap that require coordination, and the forms the coordination must take to best facilitate market-driven AI adoption.

Figure 1 charts the recommended goals and subgoals that constitute a logical roadmap and the program strategies, including the use of ongoing development cycles that build on activities and experience. The roadmap organizes national program strategies as a combination of industry, academic, and government activities all intended to accelerate the adoption of AI throughout the U.S. manufacturing industry. The subgoals in the white boxes are highly interrelated and each box represents an outcome or strategy that needs to be accomplished to implement the roadmap. As a result, the chart can be read from left to right **and** top to bottom.

Figure 1: Roadmap for Manufacturing Program Strategies and AI Adoption
(Figure can be read left to right **and** top to bottom)



During each roundtable, the moderators reviewed one main goal and its subgoals with the participants and requested feedback on (1) completeness of the information in the draft roadmap, (2) how to accomplish the goals and subgoals, and (3) specific actions to be considered by government, industry, and academia. The participants in each of the roundtables engaged in detailed discussions of the goals and actions that could contribute to achievement of the three primary goals. A summary of each roundtable follows:

Goal 1 Roundtable: Enable Digital Capabilities at SMMs

A vast majority of U.S. manufacturers are SMMs, representing approximately 300,000[1,2] manufacturers and another 300,000 manufacturing related businesses. A core group of about 25,000 companies represents most of the economic output from this segment. Roundtable participants noted SMMs have been slow to convert to digital operations, let alone adopt AI systems, yet they are not only vital, but they are also the largest segment of the manufacturing ecosystem (albeit distributed) with a large share of operational data and knowhow. Having data in digital forms and starting to adopt AI solutions using the current state of the art requires a level of expertise and financial resources SMMs do not have.

Options to reduce these barriers include tools for easy digitalization and networking of data, and the formation of a platform environment where data, tools, applications, solutions, and use cases can be shared, offering incentives for sharing data and applications, and creating small scale demonstrations that

[1] Manufacturing Extension Partnership (MEP) at the National Institute of Standards and Technology (NIST) of the U.S. Department of Commerce, Gaithersburg, Maryland (Apr 2015 –Jan 2021)

[2] National Association of Manufacturers

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quantify the value of digital operations. Participants noted that SMMs will naturally gravitate toward advanced technologies if they are ready-to-use (high Technology Readiness Levels – TRLs), affordable, and create value. While low cost, easily deployable solutions do not yet exist in manufacturing, analogous software solutions enabled the digital transformations of many other industries long ago. With development of the appropriate software tools, the successes in industries such as financial services and retail distribution could be examples of how to approach AI adoption at SMMs.

Enabling initial digitalization in the core group of SMMs was considered a prerequisite to AI adoption and achievement of a resilient supply chain. For SMMs to develop digital capabilities, and resilient supply chains to manifest, simple, low cost, easy to use solutions, and tangible demonstrations of value are essential to accelerate AI adoption.

Goal 2 Roundtable: Incentivize AI Adoption Throughout Established Supply Chains

This discussion focused on approaches to incentivize AI adoption throughout established supply chains with an emphasis on building trust, sharing value, and overcoming resource differences. Participants described the flow of information, including data sharing among supply chain partners, and propagating defined applications from large companies down the supply chain to SMMs, a process which is usually managed by contractual agreements. However, there are numerous business and technical challenges in the process that make sharing information and data inefficient, especially when applied in advanced digital systems. Participants discussed these challenges and approaches to address them.

1. Many SMMs are not using digital sensors in their operations and do not have the resources to respond to the requirements of large companies. Development of small-scale demonstrations that highlight the value of digital systems could be used to stimulate SMMs interest in digital operations and AI systems. Community colleges were identified as regional locations for these demonstrations.
2. The data generated by machines and process operations is highly variable and difficult to use in AI applications. Standards for data and data formats would make information processing more efficient and support development of customized applications and analytics. Large corporations were identified as leaders that could support agreement on formats and the use of often existing standards throughout a supply chain. Machine and equipment builders could implement formats and standards to ensure compatibility of data streams for machine learning, at least for identical machine models.
3. Of the machines and process equipment currently in operation in the U.S., most in use, especially by SMMs, do not have digital capability. The development and distribution of “black boxes,” i.e., ready-to-go, hardware units for connecting wired and wireless sensors and for ingesting and transmitting data, was discussed as an important way to enable digital capability on legacy machines.
4. The “cost share” and the associated administrative requirements in various government programs and manufacturing institutes was cited in the roundtable as a barrier to participation by SMMs with limited resources.

Goal 3 Roundtable: Enable New Business Models for AI Adoption

This roundtable explored strategies to enable new AI business models in the manufacturing industry. A standard and secure way to selectively share or provide data in useful forms was viewed as essential to convince manufacturers to use digital methods both inside and outside their organizations. Other important topics included expanded business models using digital methods to provide AI educational opportunities, and the need for a national repository for critical manufacturing data especially test results. In summary, the participants agreed on the following needs to enable these new business models:

1. Organizations that can provide AI expertise, support, infrastructure, and a repository for manufacturing data and publishing use cases to SMMs.
2. A set of tools for privacy preserving encryption, categorizing, integrating, uploading, and making data available for generating AI/ML solutions.
3. A Platform with a subscription-based model where resources and data can be shared, exchanged, or purchased, and solutions provided for a fee. The Platform should also include search engines for finding capabilities and matchmaking between problems and experts.

Workshop 3 Actionable Roadmap and Recommendations

The objective for Workshop 3 was development of an actionable roadmap to accelerate digitalization and the adoption of AI in U.S. manufacturing, and promote global leadership in productivity, quality, resiliency, and environmental sustainability. During the roundtables, four common themes emerged from all the discussions:

- Improved digital capability at SMMs was identified as a prerequisite for industry-wide adoption of AI.
- Structural business and technological limitations are inhibiting AI adoption.
- Broad adoption of AI will require widespread, technician-friendly access to sophisticated software tools that are broadly applicable and provided on a software-as-a-service basis at a modest cost.
- Technologies required for robust, scaled, unbiased, and trustworthy AI in manufacturing are largely at a nascent stage and require continued R&D investment.

In reading **Figure 1** from left to right, the first column is focused on addressing industry constraints. Somewhat predictably, most roundtable discussions involved descriptions of these constraints, and participants suggested taking actions to address them with a particular focus on SMMs, R&D, and scalability to stimulate a pathway to start building solutions. There was a strong theme that a focus on SMMs would result in the easy-to-use tools, infrastructure, and training that large companies can also use to great benefit.

The roundtables provided focus and substance around the actions to address seven structural constraints that are impeding AI adoption in manufacturing and need to be overcome to start. Although addressing these is likely to produce incremental progress in the beginning, the knowledge and benefits from successful AI adoptions can be used to reshape programs and accelerate the application of AI technologies in manufacturing operations. Also, addressing these as an integrated set refers to reaching sufficient industry agreement across all of them at acceptable rudimentary levels to demonstrate an overall capability that does not currently exist. The seven structural constraints and actions to address them are as follows:

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1) **Agree on preliminary standardized data formats**
   - Define and reach agreement on standardized data formats (metadata) to get started on some demonstrations of problems, as well as a repository to store data, especially for test results. These agreements should demonstrate how multiple companies in the manufacturing industry could benefit by facilitating the capability of machines to execute machine learning solutions and developing customized apps for specific segments and applications.
2) **Create a business platform**
   - Develop and implement a managed and searchable business marketplace platform where companies can upload and download software tools, models, education programs, and benchmark data sets and results, success stories, and other information.
3) **Financial incentives for digital upgrades**
   - Provide financial incentives with reduced administrative requirements for SMMs to buy digital capable equipment, software tools, etc. For example, if government funds were available, qualified SMMs could apply for funding to acquire the hardware and software required to digitize their operation. An exchange platform could operate as a trusted source of information for SMMs to identify appropriate hardware and software.
4) **Build educational programs**
   - Provide funding for digital training at SMMs.
   - Fund AI, data acquisition, and digital literacy educational programs at universities and colleges, especially community colleges.
   - Document the results of these activities, especially solutions to specific problems, for publication on the business platform.
5) **Show value with use cases and blueprints for solutions**
   - Develop multiple operational, re-usable cases for specific applications and industry segments to demonstrate the value of AI and the value of reusable blueprints. For example, use case demonstrations might be available in the aerospace industry, automotive industry, Department of Defense (DOD), and Manufacturing USA institutes.
   - For SMMs, the use cases should demonstrate value at a scale consistent with their capabilities and be mobile to allow regional operation and encourage participation. Essentially carry a “live” demonstration to an SMMs’ home base.
   - Large organizations with significant digital capabilities could develop blueprint solutions to complex use case challenges and openly share the results in the business platform. Examples of complex use cases include intercompany data transfer and analysis (i.e., data exchange for interoperability), coordination across a supply chain, or a solution set involving the interaction of several of the key structural constraints identified in Workshop 3.
6) **Data enable legacy equipment**
   - Develop cost effective Internet of Things (IoT) edge devices that can data-enable legacy manufacturing equipment that still has useful life, especially for SMMs. Some existing examples of this approach were discussed in the roundtables.
7) **Encourage use of in-kind contributions as “cost share”**
   - Existing cost share requirements in government programs, competitive funding solicitations, and membership in manufacturing institutes can be a major barrier to participation, especially for SMMs with limited resources and experience with digital operations. Cost share requirements

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should be revised to prioritize in-kind contributions, particularly for data. For example, convert a financial requirement for participation in a program or an institute to a data sharing requirement.

Figure 2: Interrelated Structural Constraints Inhibiting AI Adoption

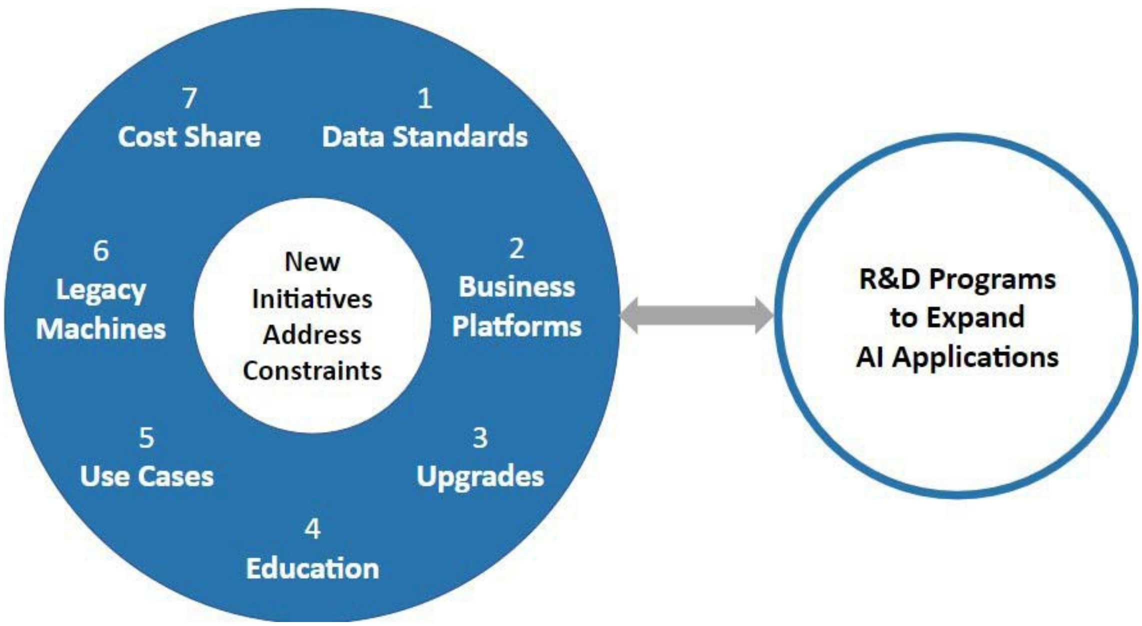

Figure 2 is a graphic display showing the seven structural constraints linked together in a ring. The ring represents the continuous linkage among all the constraints and the need for interrelated solutions.
Developing new prerequisite programs to address the constraints will require action across multiple constraints, industry consensus, coordination with existing programs, and innovations in R&D. Beyond incremental progress, the roadmap for AI adoption involves significant R&D challenges that can influence and shape all roadmap activities. The full potential of AI will require continued R&D and development of innovative services for manufacturers of all sizes, including unique approaches to market-driven agreements for industry collaborations. Four categories of cross roadmap R&D were also summarized in Workshop 3:

1. **AI methods, tools, and data aggregation for manufacturing's time-centered data types**: While existing AI and data analytics technologies in the industry are sufficient to provide value in limited applications, considerable R&D work is required to develop more robust AI methods, tools, and data collection protocols that are suited for the time-sensitive data relevant to manufacturing. Those methods are likely to require cutting edge research since they will differ substantially from established deep learning methods, which were generally developed to perform well in applications involving image recognition.
2. **Data to automate algorithm building and continuous tuning:** The fundamental advantage of AI technologies is learning from data. However, the infrastructure does not exist to aggregate data from multiple operations and manufactures, provide access to proven data, build algorithms, and

continuously update data and the algorithms as additional information becomes available. Significant R&D is required to develop this infrastructure and set the stage for the long-term achievement of wide access to machine learning solutions tailored to specific industrial applications that can execute locally, and fine-tune with continued acquisition of local data.

3. **Going beyond incremental change:** The roles of networks and industry interconnectedness in manufacturing operations are largely untested. The network approach tends to be outside the prevailing appetites of large companies that favor incremental, top-down solutions. R&D is needed to develop low cost, easily accessible network tools that can be widely distributed on the web (i.e., data-as-services or manufacturing-as-services) allowing SMMs to create immediate value and drive AI adoption from the bottom up. The tools required for aggregating data and building algorithms at scale in a networked environment are significantly different than top-down centralized approaches.
4. **Scaling data and operational interoperability:** Products-as-services is a new business model with traction in large companies that produce end-use products. In these companies, in-service product data is used to sell services to buyers that support the product, and the manufacturer can use data to improve the product, which creates a continuous cycle of improvements. By recognizing that every supplier is a manufacturer, and every manufacturer is a supplier, this concept can be extended to entire supply chains and facilitate interoperability and resiliency. The R&D challenge is to develop tools and business models that enable suppliers and manufacturers to access measurements and exchange data to act together to improve operations up and down the supply chain.

Executing the Roadmap: Formulating National Program Strategies

The seven structural constraints defined in the Workshop 3 roundtables are impacting all aspects of AI adoption across all sectors of the manufacturing industry and impeding the start of a cycle of industry adoption. As a result, individual companies or supply chains are not suited to implement industry-wide programs to address them. Roundtable participants shared the view that targeted government actions are required to address these interrelated problems, and to coordinate the interaction of existing AI programs with new initiatives to start the adoption cycle identified in the roadmap. An examination of the seven integrated actions shows that these enable an entrée into each of the primary goals driving the roadmap. The four R&D areas start with the current state of the industry and how to use current technologies, but are defined to look forward to all areas of monetization.

Although the immediate actions required to address these constraints will initially produce incremental progress in the use of AI, participants agreed that incremental improvements with these directional changes could stimulate a pathway toward broad AI adoption. Increased use of AI can lead to the availability of open data sets which are a prerequisite for the R&D programs needed to innovate advanced AI methods and associated tools. As more powerful software tools become accessible to industry, they will drive the value that powers the propagation of new business models that employ the tools. Some of the new business models will be implemented by existing companies, but many will be implemented by new entrants who see profit potential and have the risk appetite and expertise to enter the market. This is the likely path to the emergence of AI-fueled data aggregation and a solutions infrastructure for manufacturing.

The roadmap is premised on Public Private Partnerships (PPPs) to coordinate the preparation of the U.S. manufacturing industry for an AI-enabled future, and foster the fundamental research needed to make that future possible. The federal government has successfully created this type of organization in the past and many existing programs can serve as component elements or models for component elements. An opportunity exists to build on past PPPs successes and adapt them to fit the requirements for AI adoption in U.S. manufacturing companies. Additional reference activities that could inform or provide direct support include:

- In the financial accounting industry, the Financial Accounting Foundation (FAF), an independent, private sector, not-for-profit organization, operates for the purpose of supporting efficient, robust capital markets. The FAF administers the Generally Accepted Accounting Principles (GAAP) standards and its use by companies, not-for-profits, governments, and other organizations to prepare their financial statements.
- The Manufacturing USA Institutes are models of successful PPPs that already include some elements of AI business and operational infrastructure and application technologies. Notably, CESMII, MxD, and CyManII are three PPPs focused specifically on manufacturing digitalization.
- Most recently, the National Cybersecurity Center of Excellence (NCCoE) was formed as part of the National Institute of Standards and Technology (NIST). NCCoE brings together experts from industry, government, and academia to address the real-world needs of securing complex IT systems and protecting the nation's critical infrastructure. NCCoE publishes example solutions that provide organizations the details needed to recreate the solution in part or in full.
- The National Science Foundation's (NSF) National Artificial Intelligence Research Institutes bring together collaborators from universities, industry, and government agencies to perform foundational AI research that goes beyond applying known techniques to discover new methods with new applications. This creates a virtuous cycle where foundational results are applied, and applications can be generalized and made foundational.

Figure 3 is a graphic representation of how the PPPs could be structured, with an overall goal to accelerate innovation and the rate of AI adoption. These PPPs organizations would need to be chartered to pursue a collaborative process with industry that defines a scope of work to solve pressing AI challenges, assemble teams from industry, government, and academia to address all aspects of the challenge, and build practical, repeatable, reusable demonstrations of solutions. Rather than attempting to create a broad, unified solution to all seven structural constraints, or conduct deep R&D on individual constraints, the PPPs need to address the technical and business challenges of integrated solutions associated with specific use cases in real-world AI applications in manufacturing. To accomplish this mission, the PPPs could focus on the following activities:

- Organize and fund industry demonstrations of the interaction of the seven structural constraints to define points of entry for initial AI adoption in the roadmap
- Fund targeted technical and business R&D and publish solutions
- Bring industry, government, and academic resources together, including manufacturing experts and AI experts
- Identify problems and develop solutions
- Coordinate with multi-agency programs
- Document and promote adoption of solutions
- Educate the workforce at all corporate levels

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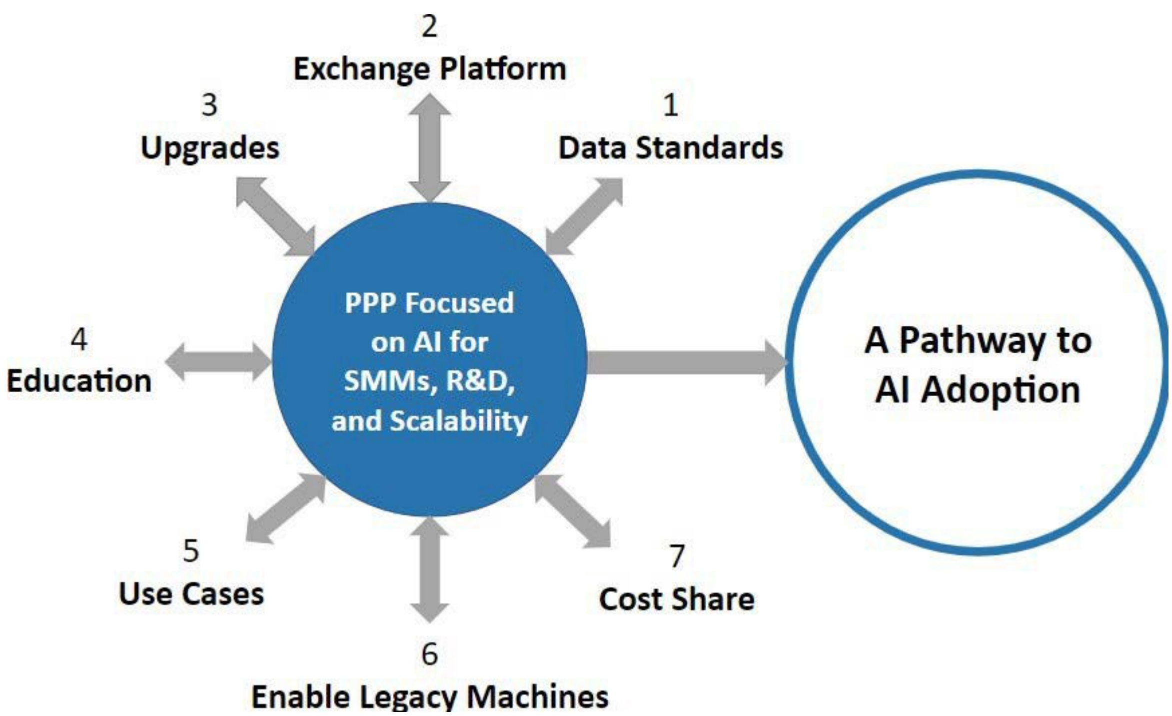
- Provide and manage a repository for exchange of information
- Support adoption of new business models

Figure 3: PPPs Focused on SMMs, R&D, and Scalability to Accelerate AI Adoption



Concluding Statement

The roadmap presented in this report is a compilation of inputs from all three workshops in the Symposium. It recognizes that industry awareness of AI and digitalization is growing, and that U.S. manufacturing companies are genuinely interested in adopting AI technology. Many large corporations and a few SMMs are currently working to incorporate AI technology into their operations, but the pace of adoption is limited by the slow pace of digital transformation in the U.S. manufacturing industry. At present, most successful use cases for AI in manufacturing are heroic efforts that require advanced education and training and do not scale to other equipment, facilities, or companies. Because of the seven structural constraints, the gap in capability between large and small companies for AI implementations continues to widen, slowing impact and exacerbating challenges. It has already proven difficult to overcome these structural constraints through incremental improvements on individual shop floors.

Broad, overarching programs with a systematic view of the power of AI methods to provide industry-wide benefits through network effects are needed to stimulate, accelerate, and scale the adoption process. The U.S. is the world leader in most of the industry sectors that have adopted that approach and no country has better capabilities to bring a similar transformation to manufacturing.

The Symposium recommendations also include a roadmap execution strategy that starts with a program that demonstrates that diverse manufacturing challenges can be addressed with an integrated set of 'first pass' actions on seven constraints to demonstrate how business collaborations can succeed and produce value. A successful ‘first pass’ industry collaboration demonstrates value and how an industry wide AI adoption can proceed. Given the multi-disciplinary and multi-stakeholder collaboration among industry, academia, and government that is needed to start, nurture and grow industry-wide strategies, Public Private Partnerships (PPPs), for which there are many successful models, are the most appropriate coordinating structures. An opportunity exists to build on past PPPs successes and adapt them to fit the requirements for AI adoption in U.S. manufacturing companies. However, the actions being recommended in this report will require expansive PPPs to pursue the collaborative processes required to define programs that identify pressing AI challenges and the teams from industry, government, and academia to address them. The PPPs must be structured to facilitate practical, repeatable demonstrations of solutions, and focus on solutions involving a wide range of tools and products that address scalability. Rather than attempting to create a broad, unified solution to all seven structural constraints, or conduct deep R&D on individual constraints, the PPPs need to address the technical and business challenges of multiple approaches to integrated solutions associated with specific use cases in real world AI applications in manufacturing.

Additionally, PPPs collaborations of industry, government, and academia are needed to provide industry-wide coordination through a governance and execution structure that involves all stakeholders in defining programs and funding requirements, supports the implementation of programs and distribution of funds, and coordinates initiatives. The successes demonstrated by the actions of PPPs will reduce the risk of applying AI technologies in manufacturing operations, making it easier for entrepreneurs and private investors to visualize innovative operational products and business models. As this process takes hold, the U.S. manufacturing industry will be on its way to achieving global competitiveness and resilient supply chains.

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Appendix

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*Through Workshop 2

Appendix C: Workshop 3