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

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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.

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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

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.
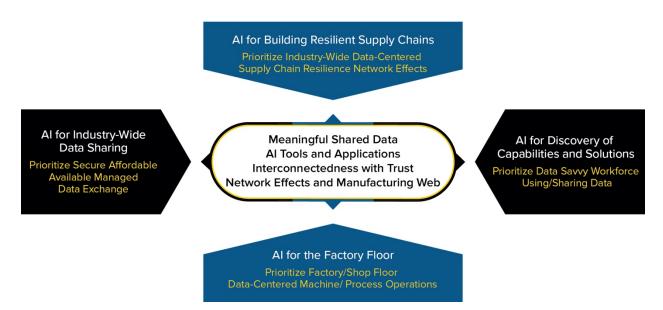

Figure 1: The Adoption Cycle Framework from Workshop 1

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**.
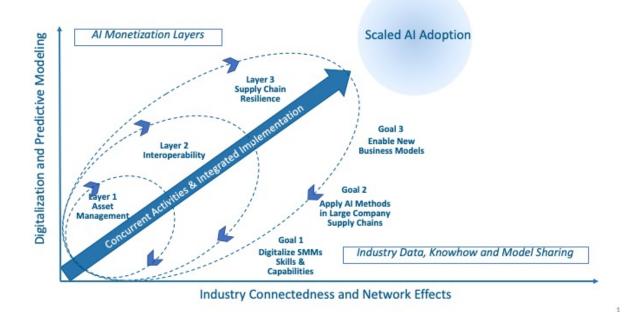

Figure 2: Layering AI Applications and Connected Industry Sharing

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.
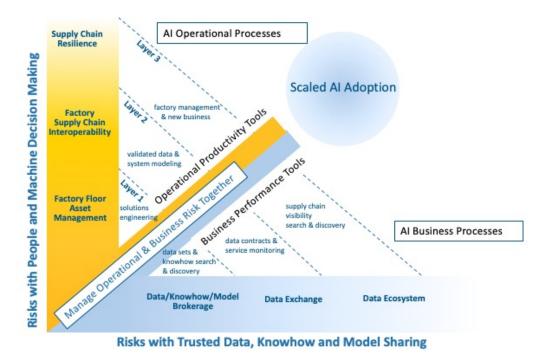
Figure 3: Aligning Tools with Connected Industry Risk Areas

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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