CASE WESTERN RESERVE UNIVERSITY
Institute for Smart, Secure and Connected Systems

A Manufacturing Technology Roadmap

for AI-Enhanced Multimodal Sensing of Materials and Processes for Complete Product Lifecycle Performance

JANUARY 2024

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About this Roadmap

Digital manufacturing technologies are critical in accelerating product development and commercialization, enhancing sustainability and optimization of manufacturing processes, enabling new products and revenue streams, and boosting economic productivity and national output. Significant advancements in the development and deployment of distributed sensing, imaging, closed-loop controls, and Edge Computing are now driving the motivation to combine artificial intelligence/machine learning (AI/ML) with physical domain knowledge to integrate multiscale, multimodal data streams over the entire product lifecycle. This will result in improvements to energy and materials efficiencies of manufacturing and enhancements in the performance and lifetime of products from design to service to end-of-life management.

Case Western Reserve University (CWRU) received one of seven (7) awards from the National Institute of Standards and Technology (NIST) to develop a manufacturing technology roadmap to strengthen U.S. innovation and productivity across entire industry sectors. The CWRU-led roadmap is specifically focused on a comprehensive approach to future manufacturing and advanced materials by integrating sensing, data analytics, and AI/ML tools with traditional materials science and manufacturing process domain knowledge over the entire product lifecycle. The integration of these tools with human domain knowledge holds the potential to dramatically improve full product lifecycle performance including but not limited to shorter time-to-market implementation; greater product recyclability and circularity; improved sustainability and lower environmental impact of products and processes; greater resource efficiency, higher product yield, and reduced pressure on critical materials and natural resource markets; longer product lifespans; higher product quality; optimized manufacturing processes and streamlined operations; and better supply chain visibility of product data.

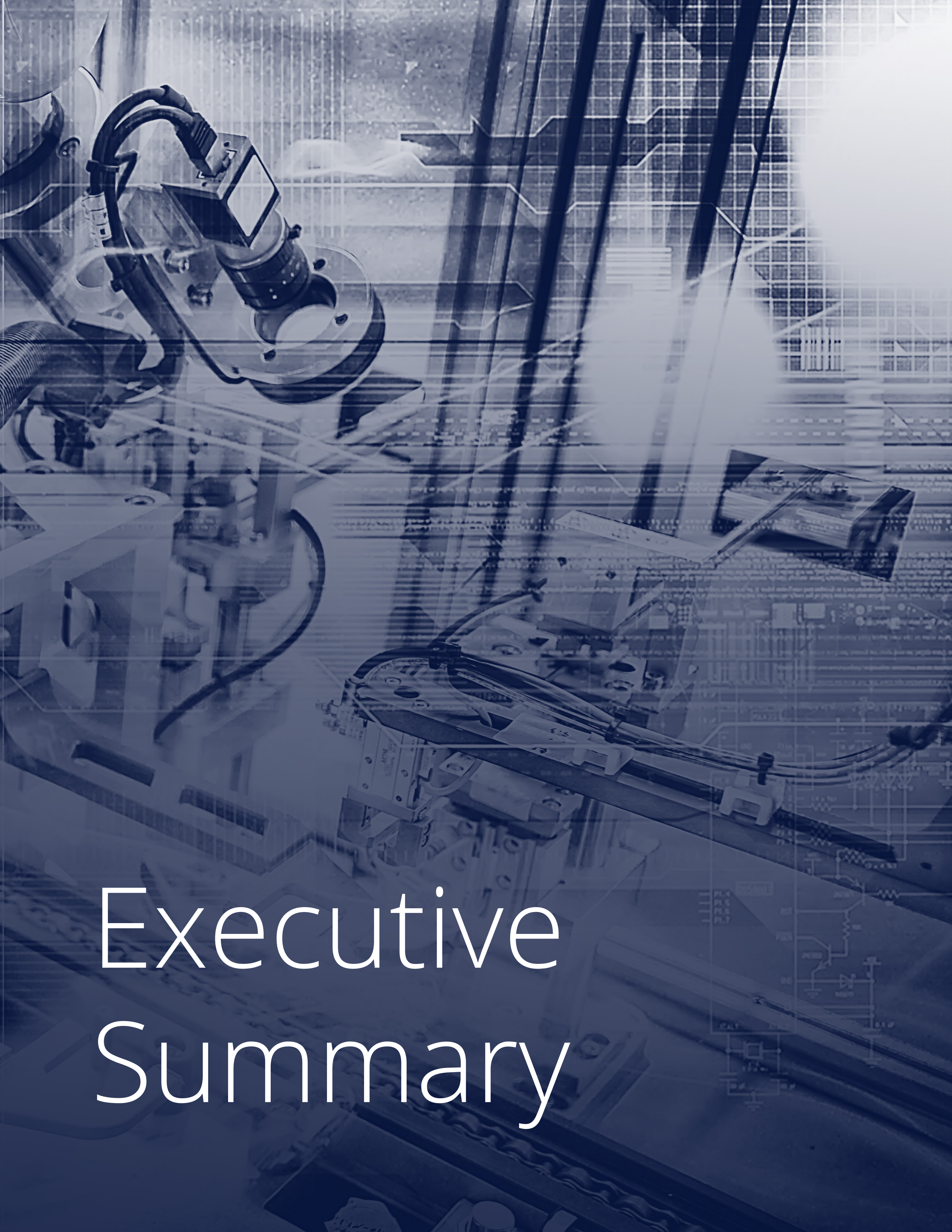
The roadmap's development is led by CWRU's Institute for Smart, Secure and Connected Systems (ISSACS) which serves as the connector for regional and national collaborators and partners across the university's schools, particularly in engineering, science, and management. ISSACS will leverage the combined strengths of sensing, edge processing, AI/ML, networking and communications, augmented reality, metal and polymer materials science and engineering, and mechanical evaluation and material forensic capabilities at CWRU in pursuing the opportunities outlined in this technology roadmap.

The roadmap draws upon a diverse pool of expertise in sensing, materials science, artificial intelligence and advanced data analytics, process control and automation, and other areas related to digital manufacturing and improving the lifecycle performance of materials and products. The technical experts who contributed to this roadmap identified the challenges to the development of manufacturing capabilities through applications of AI-enhanced multimodal sensing, data harmonization, and closed-loop process control, and proposed a series of research and development activities that aim to help manufacturers apply these tools and technologies to enhance the performance of products across all stages of lifecycle: from design through end-of-life management. ISSACS and the primary contributors in this effort recognize that several of the research and development activities proposed in this roadmap are beyond the scope, funding level, and capabilities of any single organization, and will likely require the coordinated efforts of a multistakeholder consortium to deliver new manufacturing capabilities in multimodal sensing and AI/ML-driven closed-loop control. Further, this roadmap represents a momentary snapshot of the most critical implementation challenges and opportunities for AI-enhanced multimodal sensing and closed-loop control capabilities; it must be continually updated based on the changing requirements of the U.S. manufacturing sector.

This roadmap was developed under the direction of Nicholas Barendt, Executive Director of ISSACS, and other Case School of Engineering faculty members at CWRU including Robert Gao, John Lewandowski, and Kenneth Loparo. The digital manufacturing experts who made essential contributions through interviews and workshop attendance are also identified in Appendix C of this report. Nexight Group supported the overall roadmapping process and helped to prepare the content in this document.

This work was performed under financial assistance award #70NANB22H049 from U.S. Department of Commerce, National Institute of Standards and Technology.

Contents



Executive Summary

Artificial intelligence and machine learning (AI/ML) are playing an ever-increasing role in the development of technology strategies that support a comprehensive vision of future manufacturing in which data, automation, and materials science and manufacturing domain expertise are blended to ensure highly efficient production of world-class quality products for United States manufacturers. Combining AI/ML with physical domain knowledge can enable the integration of multiscale, multimodal data streams over the entire product lifecycle, resulting in substantial improvements in manufacturing efficiencies and product performance: from design to service to end-of-life management.

These capabilities offer numerous pathways for users to pursue manufacturing sustainability and circularity goals and have the capacity to bring products to market faster with greater reliability. For example, the ability to better track the lifecycle of products and their constituent materials would help recyclers produce cleaner feedstocks. However, the ability to use data insights from AI/ML to drive improvements across product lifecycles is hindered by limitations in accessing and accurately and appropriately curating large datasets across manufacturing processes and supply chains, modeling and simulating complex physics and materials behavior, and interpreting or trusting the results of AI/ML and data analytics.

The Materials Genome Initiative (MGI)[1], launched in 2011, has significantly accelerated the development and deployment of new materials. AI-driven materials R&D was not initially a key component of MGI but has since become an essential pillar in its most recent Strategic Plan. **Despite significant advances made through the support of the MGI, more efforts are needed to address the challenges limiting the use of AI-enhanced multimodal sensing, data harmonization, and closed-loop process control to enhance complete product lifecycle performance.**

Case Western Reserve University (CWRU) sought funding from the National Institute of Standards and Technology (NIST) to develop this roadmap under the direction of the Institute for Smart, Secure and Connected Systems (ISSACS) which is focused on developing AI-enhanced multimodal sensing and closed-loop control capabilities for improving product performance, but with the specific imperative of driving these performance improvements across the product lifecycle. **The roadmap offers an array of recommended high-impact, cross-cutting research and development priorities—or Implementation Plans—to enable new AI-driven capabilities for U.S. manufacturers** by providing pre-competitively developed software tools and equipment, standards and techniques, and training and educational resources.

The opportunities outlined in this roadmap are designed to help interested parties of the U.S. manufacturing sector unify data streams across stages of product development lifecycles, use AI- and data-driven methods to uncover insights around products and manufacturing domains, and employ feedback strategies for improving specific aspects related to the design, synthesis, processing, service use, and end-of-life management of materials and products. The ISSACS roadmap is intended to be a dynamic document that requires periodic updates to reflects evolving business needs and requirements of the U.S. manufacturing sector.

1 Materials Genome Initiative. 2023. Accessed October 20, 2023. https://www.mgi.gov/.

In addition to the opportunities, challenges, and recommended implementation plans, **four overall conclusions resulted from the roadmap development effort:**

Exemplar products, use cases, and pilot programs are needed to drive R&D progress and demonstrate value.

Exemplar products, use cases, and pilot programs are crucial mechanisms for driving collaborative R&D activities and demonstrating the value of adopting tools for improving performance across the product lifecycle.

These mechanisms can support R&D progress in various ways. For example, they can be useful educational tools that show how to integrate lifecycle management and improvement methods into manufacturing operations to support decision-making, predictive design and maintenance, and sustainable product development. Additionally, exemplar products, which can be based on retired components, could help offer invaluable lessons on successfully applying multimodal sensing, AI/ML, and process control and automation to a unique manufacturing product, process, or operation. The business community can also provide unique insights and experiences for defining business cases, driving the choices of exemplars, and proposing strategies for setting and meeting specific roadmapping goals across different time horizons.

Workforce development initiatives to build skillsets in multimodal sensing and AI-driven process control techniques must maintain pace with the rapid development of core technologies.

Multimodal sensing and AI-driven process control techniques are relatively nascent but rapidly evolving; to maintain the pace of technological innovation, R&D activities must be pursued in a manner that supports developing a robust talent pipeline through education and training.

To achieve this, it will be important to increase opportunities to train educators who can then train the incumbent workforce with the skills needed for the adoption of these technologies and methods. Academic curricula should be updated to help prepare engineers and managers to utilize data in ways that improve the flexibility, agility, and resilience of their organizations. In addition, the ecosystem must develop worker training programs on the use of AI/ML-driven software/tools to facilitate a shift from traditional experimental methods to high-throughput computational-experimental methods for developing new materials and products faster and more efficiently.

A public-private advisory council is needed to establish an overarching AI strategy, align the roadmap's opportunities with ongoing R&D initiatives, and leverage existing assets and investments in related topic areas.

To avoid redundancies or duplicative efforts with ongoing R&D efforts, the roadmap should build on the successes of previous manufacturing initiatives and leverage existing investments and capabilities including facilities, talent, and equipment. Specifically, the ISSACS roadmap is not intended to provide a comprehensive overview of numerous industry-driven initiatives that are actively developing novel advanced materials, manufacturing technologies, software tools, best practices and standards, and educational resources in analogous topic areas.

An advisory council or board, composed of industry leaders and Federal agency representatives from across the fields of AI/ML, data science, and product lifecycle management, **should be established to advise on matters related to R&D activities, workforce development, and policy.** This includes aligning with the U.S. National and Federal Agency AI Strategic Goals set by the National Artificial Intelligence Initiative Office (NAIIO) to ensure the Manufacturing USA Institutes and related manufacturing innovation ecosystem initiatives (e.g., National Science Foundation [NSF] Engines and Engineering Research Centers [ERCs], Economic Development Administration [EDA] Regional Technology and Innovation Hubs [Tech Hubs], etc.) are working in close coordination to prioritize where and how AI should be applied to maximize economic and national security.

The advisory council's functions should also include: carefully examining the landscape of ongoing manufacturing-related initiatives by industry sector, processing equipment, and materials types; building on the successes of existing workforce skills development initiatives that provide learning management systems and manufacturing certifications; and harmonize the general requirements across manufacturing sectors in the use of multimodal sensing and AI/ML-driven process controls to improve performance across the product lifecycle.

Consortium-based R&D provides long-term funding needed to convene industry around pre-competitive research challenges across manufacturing sectors and disciplines.

R&D programs require continuous support and long-term funding without interruptions, as funding gaps that halt progress in technology development can be detrimental to product development timelines as well the recruitment and production of an educated workforce. Consortium-based solutions can address this need by providing continuous, long-term funding commitments.

Consortia can also help to address pre-competitive research challenges by fostering a culture of sharing data and lessons learned while protecting the intellectual property interests of the manufacturing community. In addition, consortia help to improve overall cooperation and harmonization within the broader community by unifying the requirements for general standards and practices across disparate manufacturing sectors and coordinating interdisciplinary teams that represent the complete value chain of product development. Consortia-based activities and technical sponsorships must also gauge the needs of the business community to define the business drivers necessary to attract and secure funding commitments.

Summary of High-Impact R&D Implementation Plans

Figure 1 outlines high-impact, cross-cutting R&D priorities to enable new AI-driven capabilities for U.S. manufacturers through pre-competitively developed software tools and equipment, standards and techniques, and training and educational resources.

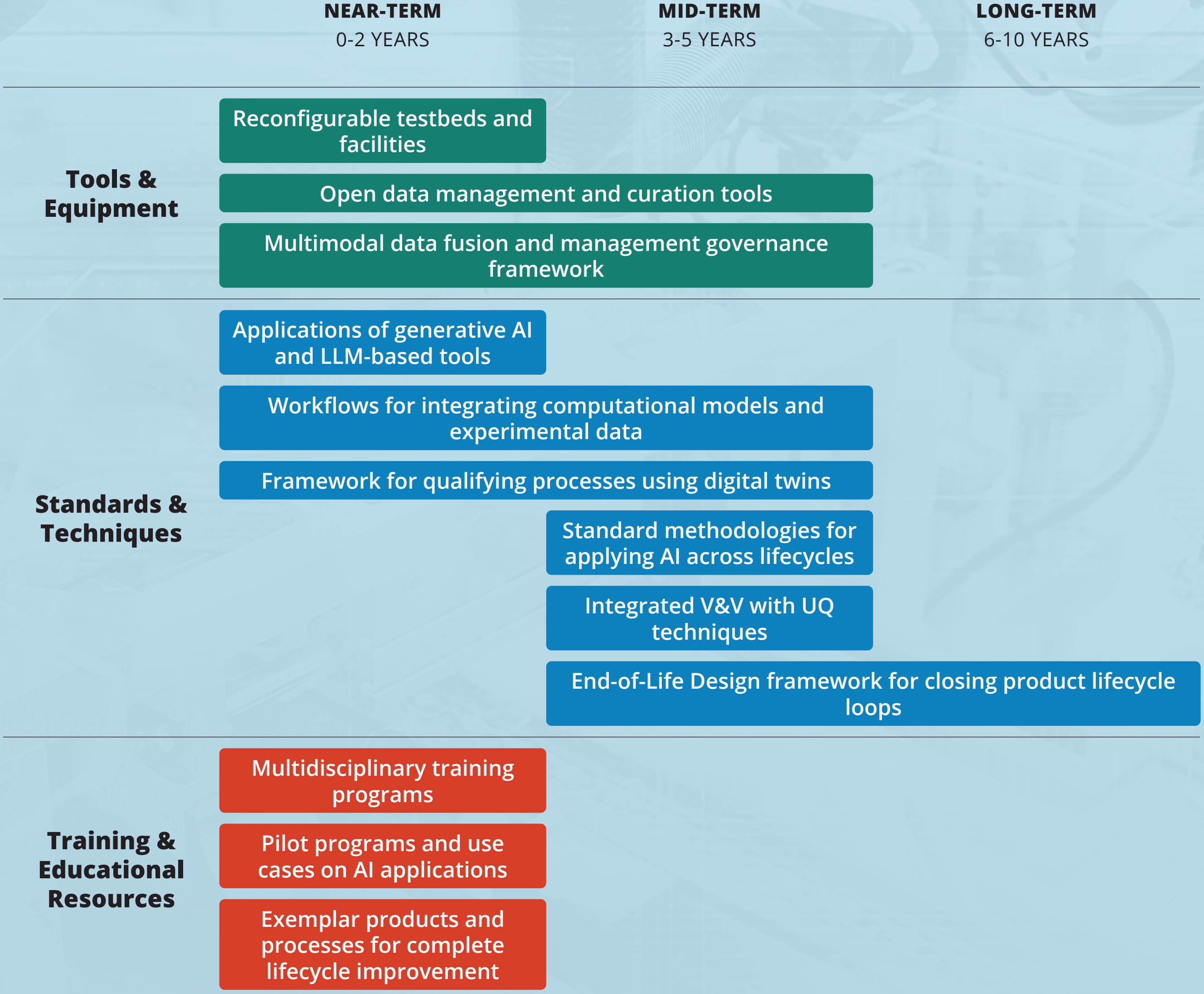


Figure 1: *Overview of the key opportunities (i.e., Implementation Plans) and the estimated timeframes for which R&D activities are estimated to have a significant impact in enabling new AI-driven capabilities for U.S. manufacturers through the provision of pre-competitively developed software tools and equipment, standards and techniques, and training and educational resources. See detailed Implementation Plans in Appendix B.*

Roadmap Strategy

With recent advances in artificial intelligence (AI) and machine learning (ML) over the past few years, alongside improvements in distributed sensing, Internet of Things (IoT), and Edge Computing, there is a tremendous opportunity to combine AI/ML with physical domain knowledge (materials, processes, etc.) for manufacturing. This integration would make it possible to leverage the multi-scale, multimodal data streams from across a product's service life to achieve significant improvements at each stage in its lifecycle, from materials synthesis and selection, to product design, manufacturing, deployment, and eventual retirement and/or recycling.

This roadmap sets out a vision for this desired future state, identifies major challenges and opportunities related to achieving the vision, and provides a set of implementation plans for overcoming the challenges and realizing the benefits of AI-enhanced multimodal sensing of materials and processes for complete product lifecycle performance.

Vision Statement

Data harmonization methods will **establish causal relationships in product lifecycle data** and allow manufacturers **to interpret meaningful insights for robust decision-making and enhanced performance** throughout all stages of a product's lifecycle.

Figure 2 presents the goals of the roadmap and its connection to the core focus areas and impact on the key aspects of the product lifecycle.

Roadmap Goal and Objectives

This roadmap establishes a plan to develop multimodal sensing and AI/ML-driven closed-loop control capabilities and data insights to help manufacturers improve full product lifecycle performance. There are four key objectives to enable this goal:

1. Integrate Multimodal Data Over Multiple Timescales (throughout the product lifecycle)
2. Capture Domain Insights from Materials Science and Manufacturing to guide Core Technology Developments
3. Develop Feedback Strategies over Multiple Timescales that impact Materials Synthesis and Selection, Product and Process Design, Process Control, Product Service Life, and Retirement
4. Develop Core Technologies necessary to achieve the vision (AI/ML, Multimodal Sensing and Imaging, Process Control and Automation, Physics-based Computational Models)

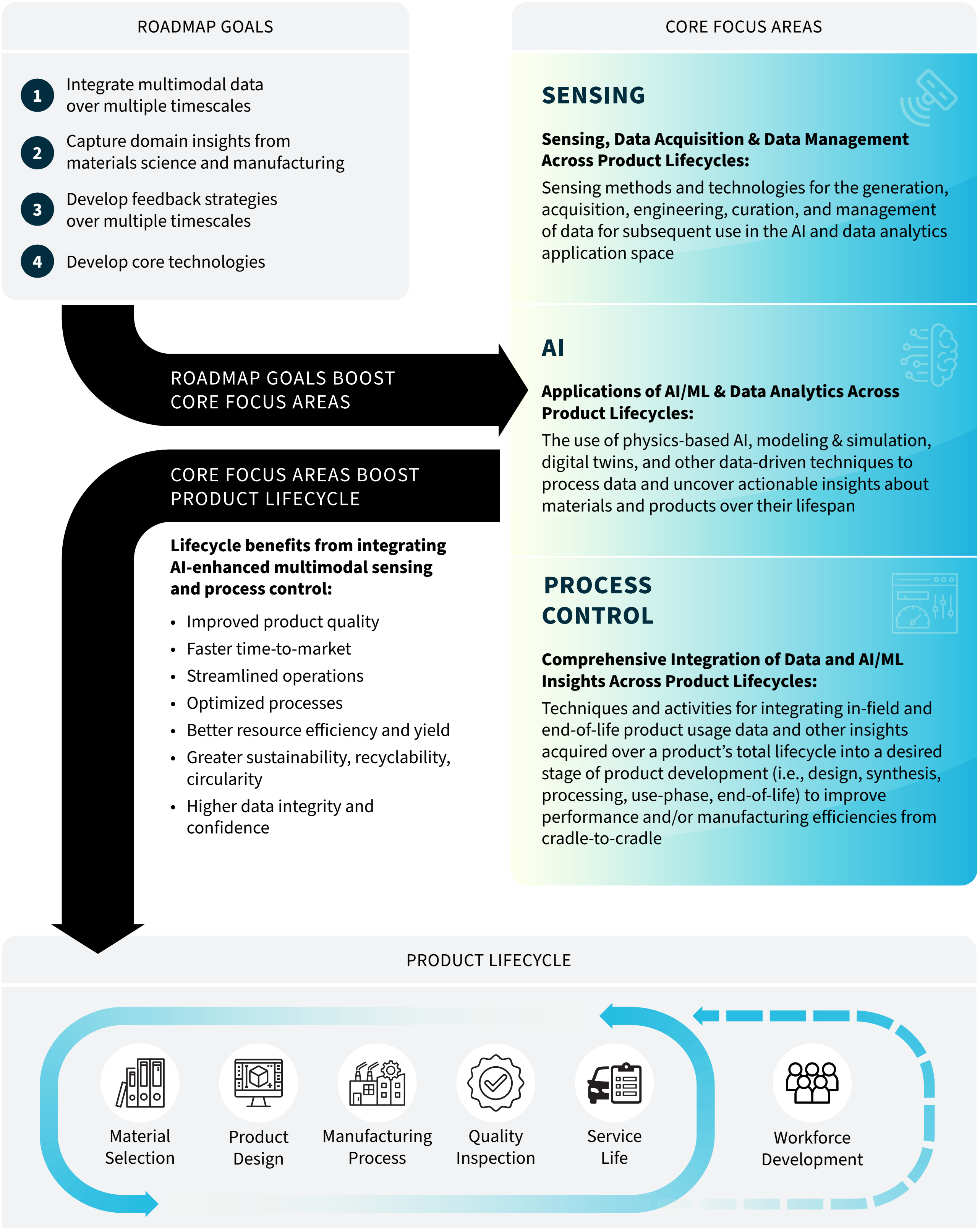


Figure 2: *Overview of the Roadmap Strategy including benefits of increased capabilities in AI-enhanced multimodal sensing of materials and processes for complete product lifecycle performance.*

Core Focus Areas

Table 1 contains three core topics that are essential to improving full lifecycle performance: sensing, AI, and process control. These foundational elements generally correspond with the roadmap's three distinct focus areas:

Table 1: *Description of the scope and list of relevant subtopics for each of the roadmap's core Focus Areas.*

Focus Area	Subtopics/Scope
Sensing, Data Acquisition & Data Management Across the Product Lifecycle: Sensing methods and technologies for the generation, acquisition, engineering, curation, and management of data for subsequent use in the AI and data analytics application space	• Deployment of sensing/imaging methods and technologies across the stages of the product lifecycle including materials synthesis, materials experimentation, materials selection, manufacturing processes, in-field use, and end-of-life management • Interoperability standards for data curation, engineering, management, tagging, and contextualization (e.g., conditions/settings for data collection) across the stages of a product's lifecycle • Fusion of multimodal, multi-temporal, multi-fidelity datasets • Building training datasets to improve AI robustness • Data acquisition from high-throughput experiments
Applications of AI/ML & Data Analytics Across the Product Lifecycle: The use of physics-based AI, modeling & simulation, digital twins, and other data-driven techniques to process data and uncover actionable insights about materials and products over their lifespan	• Using data analysis techniques including AI/ML, statistical approaches, and physics-based models to identify patterns and trends in datasets and across timescales • Digital twin concepts including modeling and physics-based understanding of digital twins • Using reduced-order modeling techniques to reduce the computational complexity of numerical simulations • Classification, image recognition • Decision-making (e.g., end-of-life management of materials) • Predictive design & predictive analytics
Comprehensive Integration of Data and AI/ML Insights Across the Product Lifecycle: Techniques and activities for integrating in-field and end-of-life product usage data and other insights acquired over a product's total lifecycle into product development (i.e., design, synthesis, processing, use-phase, end-of-life) to improve performance and/or manufacturing efficiencies from cradle-to-cradle	• Using insights to apply changes in design tools, materials selection processes, QA processes • Using lifecycle data to design products for sustainability, end-of-life management, circularity (e.g., recycling, reuse), etc. • Interfacing with and automating instrumentation, process control and automation, and robotics • Enabling machine/software interoperability • Real-time process control/parameter tuning • Applying feedback strategies across timescales • Robotics • Automation • Human-robot interaction

Challenges

To achieve the vision of applying data insights from AI/ML to drive improvements across the product lifecycle, a set of challenges must be addressed. This section provides a summary of these challenges, including challenges specific to the roadmap's three core focus areas as well as overarching, foundational challenges.

Overarching Challenges

There are three broad, cross-cutting challenge areas that cut across all of the roadmap's core focus areas and are critical to address in order to achieve the roadmap vision. These challenges are described in Table 2.

Table 2: *Description of the overarching key challenges limiting the development of manufacturing capabilities for improving full product lifecycle performance*

Ability to curate big data (with respect to volume, velocity, variety, veracity)	**Ability to simulate** complex physics and materials behavior	**Ability to interpret and trust** results
The advent of big data can significantly complicate the data curation process to ensure quality in data analysis, given the high volume, streaming velocity, broad variety, and often low veracity that is sometimes characteristic of big data	Increased complexity of manufacturing processes demand better sensing technologies and methods to provide access to measurements that comprehensively reveal the underlying physics	The data-driven nature of AI/ML techniques, while competent in analyzing complex manufacturing systems and products throughout their lifecycle, are generally difficult to interpret from a physical point of view, thereby raising an issue of trustworthiness for widespread acceptance

Sensing, Data Acquisition, & Data Management

Challenges specific to sensing and data include the proper organization and labeling of large volumes of measured data, gaps in organizations' understanding of data, and willingness to share their data to achieve broader industry goals.

Users lack a framework to determine which data are most valuable for ML and AI.
Users do not have standard methods or frameworks to prioritize datasets most needed for training ML and AI algorithms. It is often difficult for a non-expert to discern or predict which data may be most valuable for a specific end-use application.

Data engineering, preparing, and querying data can be time-consuming and costly.
Solving problems of interest may take significant time and effort due to factors such as the volume and disparate nature of the data. This is particularly the case for manufacturing data, which may have a low signal-to-noise ratio as well as duplicative and extraneous information. Technological improvements are needed to provide more effective ways to query/question data in manufacturing environments.

Organizations are resistant or unable to share data.
Data sharing has many benefits, including helping to improve the accuracy of AI/ML models, asset optimization, tracking/tracing products and product data through the product lifecycle, and exchanging product information for process automation and digital twin development. Shared data can also play a vital role in validating computational modeling results, generating new insights, or being applied by other researchers in innovative or unanticipated ways—all of which can lead to improved R&D outcomes. However, organizations and research institutions are often unwilling or unable to share data due to concerns with privacy, potential losses of competitive advantage, and other issues such as missing context or metadata, and nonamenable file sharing formats. Many industries are also collecting data from production environments rather than research-based environments which often results in data that lacks the appropriate context or metadata to make it useful and valuable. These barriers to sharing data vary by industry; data sharing is particularly challenging for some industries such as semiconductor and defense manufacturing.

Source data are often heterogenous and inconsistent, leading to difficulty with feature identification and extraction.
Traditional data sources are not type-safe, are semantically inconsistent, and are ontologically indeterminate. As a result, feature identification is difficult and cannot be uniformly applied across even similar manufacturers or manufacturing processes. Feature extraction is often accomplished via brute force methods with zero reproducibility.

Stakeholders often lack understanding of the appropriate computational tool to solve different types of problems.
While data analytics and algorithmic problem solving are important and powerful problem-solving methods, many product marketing groups mistake such tools for AI. Different types of ML are also often poorly defined to prospective end users. As a result of confusion about AI/ML definitions and concepts, sensing and data collection efforts are often scoped incorrectly based on applying the wrong tool.

Computing infrastructure is not keeping pace with the increasing volume of sensor data.
The increased volume of data enabled by the widespread deployment of advanced sensors leads to problems with storing, managing, and querying large amounts of collected data, particularly for organizations that have not made the transition to digital manufacturing. Addressing this challenge may require approaches such as on-the-fly data reduction, which could intersect with the work being done on related problems such as edge computing.

Applications of AI, ML, & Data Analytics

Challenges in AI, ML, and data analytics applications include technical hurdles such as a lack of standards for raw data collection and conversion, as well as organizational challenges including distrust of AI, lack of interdisciplinary expertise, and uneven access to resources for advancing AI, ML, and data analytics technologies.

Many stakeholders are skeptical about the near-term usefulness of AI technologies.
Stakeholders lack confidence in the ability of AI- and ML-based approaches to reliably identify manufacturing defects. This issue may be compounded by potential public backlash toward ChatGPT and other related large language model (LLM) deployments that can provide inaccurate results when acting beyond the realm of the training dataset, on faulty data, or even on intentionally malicious data. It is currently unclear which entity will be responsible for declaring that a new manufacturing technology is acceptable—especially if AI plays a role in decision-making.

AI/ML technologies are often difficult to generalize.
Most AI/ML techniques require a significant variety and volume of labeled data for training; in practice, it is difficult to collect enough data to train a generalizable AI/ML model. Transfer learning entails adapting pre-trained models to solve new but similar issues and with less burdensome data collection requirements. In either case, a trained model may work well in a lab setting but not outside a controlled lab environment. Data science teams need to be more integrated with process control engineering teams, and the model development lifecycle should be more integrated with plant-scale data to prevent issues such as overfitting and lack of generalization.

There is a lack of experts with knowledge of both manufacturing and AI/ML.
More experts are needed with expertise in both AI/ML and diverse manufacturing topics such as industrial or mechanical engineering in order to adequately address the issues that arise in combining these disciplines. Multidisciplinary curriculum development at the undergraduate level offers a potential approach in helping to bridge the gap, though this comes with its own challenges (e.g., rigid course requirements required for program accreditation).

There are no standard methods to convert raw data from sensors to a format suitable for AI/ML tools.
Data captured in manufacturing environments, especially with small-to-medium manufacturers, is often gathered by third-party companies with different data collection, storage, and management approaches. The work required to acquire the correct data, and the data engineering that is required to properly format, label, integrate, pre-process, and prepare the data so that it can be readily used for the appropriate AI/ML tools is significant. There is currently no standard way to convert raw data to an ML/AI-friendly format, and no standards to determine which data is useful for which AI/ML methods. Typically, these activities rely on human judgements and efforts that are difficult to replicate at scale. Other institutions, such as the NSF-funded Engineering Research Visioning Alliance (ERVA), also recognize the need for "common, effective, and affordable standards for data collection, analysis, and communication" to enable more efficient and secure ways to collect, storage, analyze, and collect data while addressing proprietorship and privacy concerns.[2]

Capabilities for enhancing full lifecycle performance (e.g., resources, manpower, expertise) often differ across the supply chain.
Differences across the supply chain (e.g., company size and sector type), affect what might be realistic for various organizations regarding AI/ML investments (talent, process, equipment, etc.), timeframes, and complexity. In addition, smaller manufacturers are often required to

2 Engineering Research Visioning Alliance. 2023. Engineering the Future of Distributed Manufacturing: A Visioning Report. Columbia, SC: SSRN. dx.doi.org/10.2139/ssrn.4512398.

adopt processes and technologies as part of a larger supply chain, which may be burdensome with their often limited technical and financial resources.

There is a lack of modeling standards or frameworks for determining the required level of granularity in physics-based process models.
It is difficult to capture the real-world complexities and materials behavior in physics-based models. This challenge arises primarily from the difficulties in formulating the non-linear and/or non-stationary dynamics of the equipment and materials as well as the associated uncertainties when applied in real-world settings. It can be further rooted in a lack of communication between modelers developing computational models and digital twins and process engineers dealing with the full complexity of the manufacturing process. The information must be effectively communicated throughout the entire system to properly develop computational models and digital twins, including the raw materials, the process, the product, the factory or factories producing the product, and the factory equipment. Additionally, there is a digital thread that enables the manufacturers to centralize their data into one standardized hub, providing all manufacturing elements with access to the same data, so that the digital twin can then use this data to create a virtual copy of the desired products, environments, and processes.

Comprehensive Integration of Data and Insights

Challenges related to integration of data and insights are varied and include a need for standard approaches to improve lifecycle performance and validate results, incompatibility between advanced manufacturing techniques and traditional post-processing manufacturing methods, and a need for more pre-competitive data, among other issues.

Standardized approaches are needed for performing verification and validation (V&V) with uncertainty quantification (UQ).
Standardized approaches will be needed to enable UQ for AI and ML-driven models. However, the development of standards is challenging due to the complexity and computational intensity of UQ compounded with the novelty and lack of integration of AI/ML models into the broad manufacturing sector, as well as the need to create standard UQ approaches that can be applied to multiple sectors/applications, lifecycle metrics, and levels of rigor. Industry-wide benchmarks and the participation of key standards development organizations (SDOs) could potentially address this issue by offering a common framework for evaluating and comparing the performance of different AI/ML models across industry sectors and applications.

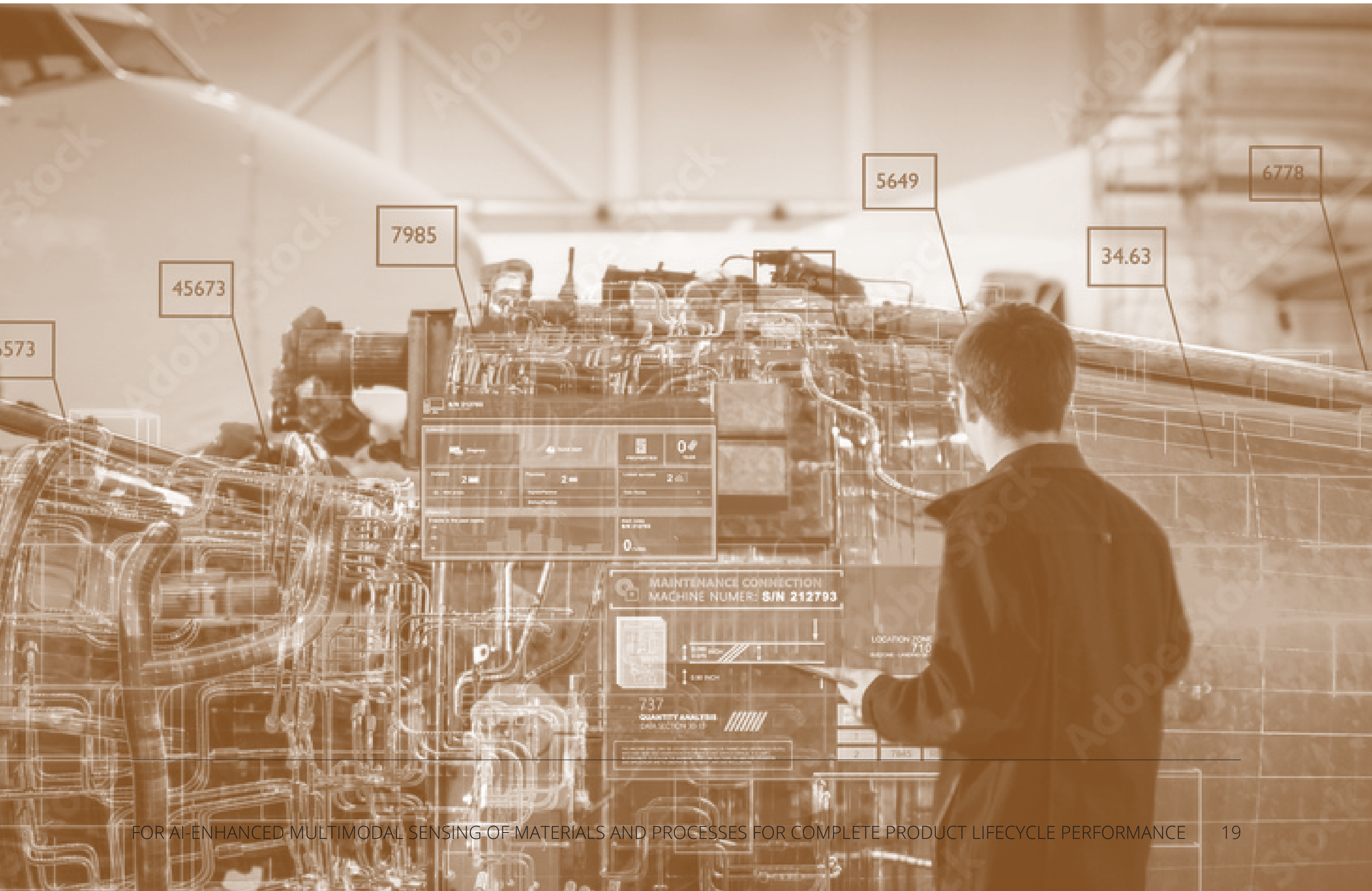
There is low predictability of behavior of AI/ML systems and products over the whole lifecycle.
It is difficult to predict real-world performance based on how a tool behaves during the development phase, and there is currently no standard that can be applied to aid in estimating how performance during the development and operational phases of a product will differ. In addition, performance characterization ontologies for AI/ML-based tools do not yet exist. These issues are especially prevalent for systems that continuously update their models based on current data. There is a need to generate robust and trustworthy high-performance models and develop reduced-order models (ROMs) that are less expensive and time-consuming.

Traditional post-processing manufacturing techniques are often incompatible with advanced manufacturing methods.
Post-processing techniques that are used as a means of tweaking processes for traditionally manufactured components may not work for advanced manufacturing methods (e.g., heat treating of additive manufactured components may not respond similarly to conventionally processed components/materials). Data and sensing required for 3D printing also differ from the data/testing/sensing methods that is traditionally done with manufactured components. Understanding of the unique needs for novel processes must be built into new models and tools in this space.

There is a need for standardized methods to improve lifecycle performance.
Standards, which are important for legal purposes and manufacturers' liability, are currently not set up to ensure confidence in terms of the ability to improve product lifecycle performance.

There is a lack of non-sensitive, pre-competitive exemplars for the exploration of AI/ML techniques.
Industry sectors may have different lifecycle needs (e.g., recycling or recertifying versus retirement), and the effectiveness of models and validation data is not often shared across different stakeholders. As a result, it is unclear how best to access existing data from industry or generate new data that are broadly applicable. The development of low-priority exemplars that are shared and agreed upon by stakeholders within an industry sector would support the development, commercialization, and standardization of AI/ML techniques in this space.

Environmental interactions with products in the field are an important consideration that can be challenging to assess.
The environmental impacts on components throughout their lifecycles are essential to understand, particularly to enable continued updates of digital twins. While upfront characterization is common, it often lacks follow-through to capture such environmental changes. In addition, failures are not typically published, which prevents learnings from being shared and built into models and tools. There is a need for retrieval studies and surveillance samples to be extended from current applications such as oil and gas to other components.



Opportunities

This section describes opportunities that, if pursued, could address the challenges to achieving the roadmap's vision. Table 3 lists detailed descriptions of the key opportunities including potential benefits, estimated timeframe of impact, and relevant Activity Area (i.e., Tools & Equipment, Standards & Techniques, and Training & Educational Resources). The highest priority opportunities also include corresponding Implementation Plans that outline key tasks, detailed requirements and considerations, and milestones; these plans are described in detail in Appendix B.

Table 3: *List of the Key Opportunities and estimated timeframes of impact for each Activity Area.*

Activity Area	Key Opportunities / Implementation Plans	Timeframe (years) NEAR 0-2	MID 3-5	LONG 6-10
Tools & Equipment	**Open data management and curation tools**—Develop data management tools that leverage open data standards to enable efficient queries and curation of datasets across product lifecycles	0-5	0-5	
	Multimodal data fusion and management governance framework—Establish a data governance framework that sets standards/practices for fusing, harmonizing, and managing multimodal data, and for evaluating data utility to support future data reuse	0-5	0-5	
	Reconfigurable testbeds and facilities—Establish a series of reconfigurable testbed facilities and/or "Centers of Excellence" to support the data capture across product lifecycles and the development and application of relevant AI/ML tools		3-5	

Activity Area	Key Opportunities / Implementation Plans	Timeframe (years) NEAR 0-2	MID 3-5	LONG 6-10
Standards & Techniques	**Applications of generative AI and LLM-based tools**—Demonstrate applications of generative AI systems (e.g., large language model [LLM]-based tools) to enable rapid development of interoperable systems and APIs for low-labor-intensity data curation and interrogation	0-2		
	Workflows for integrating computational models and experimental data—Create a standardized workflow for combining computational models and experimental data to feed data-driven methods for accurately determining the physics-based behavior of materials, processing equipment, and systems	0-5		
	Framework for qualifying processes using digital twins—Develop a framework and/or methodology for using AI-driven computational models/digital twins to qualify manufacturing processes	0-5		
	Standard methodologies for applying AI across lifecycles—Establish standardized methods for using AI and data analytics (e.g., to query unstructured data; to improve lifecycle performance)		3-5	
	Integrated verification and validation (V&V) with uncertainty quantification (UQ) techniques—Establish standards for the development of models for complete lifecycle improvement with integrated V&V and UQ techniques		3-5	
	End-of-Life Design framework for closing product lifecycle loops—Create a framework for designing products with end-of-life considerations (e.g., recycling, circularity/Re-X) to facilitate planned product obsolescence or closing of product lifecycle loops		3-10	
Training & Educational Resources	**Multidisciplinary training programs**—Support multidisciplinary educational and workforce training programs to help prepare the workforce on software and tools that support AI/ML-based analytical methods	0-2		
	Pilot programs and use cases on AI applications—Develop specific use cases and pilot programs that demonstrate real-world applications of AI-driven data analytics	0-2		
	Exemplar products and processes for complete lifecycle improvement—Identify a suite of exemplar products/processes to demonstrate the value and benefits of adopting AI-driven sensing and process control methods for improving full lifecycle performance	0-2		

TOOLS & EQUIPMENT

Delivering new manufacturing capabilities in AI-enhanced sensing and process control requires the deployment of tools, equipment, and other digital manufacturing enabling technologies that play a role in combining AI/ML with domain knowledge to integrate data streams over entire product lifecycles. This includes physical equipment like shared instrumentation, testbeds, and experimental facilities as well as software tools for processing multimodal sensor streams, acquiring and querying data, using AI and data analytics to generate insights, and applying feedback strategies to improve performance across product lifecycles. R&D opportunities can help facilitate strategies for automating data extraction and ingestion, incorporate user-friendly software/hardware interfaces, enhance interoperability across tools and platforms, and provide intuitive workflow strategies.

KEY OPPORTUNITY

Develop data management tools that leverage open data standards to enable efficient queries and curation of datasets across product lifecycles

Estimate Timeframe of Impact:
NEAR- TO MID-TERM (0-5 YRS.)

- Development of data management tools would help manufacturers improve the efficiency of data curation and query activities throughout their product lifecycles.
- In the age of Big Data, these tools are becoming increasingly important as more manufacturing environments embrace data-driven methods and digitalization of operations and product development processes.
- Ensuring these tools are open-source through a consortium-based approach would not only increase collaboration and accelerate innovation among stakeholder groups but would also provide significant flexibility and customization to accommodate different product lifecycles and manufacturers' interests.

KEY OPPORTUNITY

Establish a data governance framework that sets standards/practices for fusing, harmonizing, and managing multimodal data, and for evaluating data utility to support future data reuse

Estimate Timeframe of Impact:
NEAR- TO MID-TERM (0-5 YRS.)

- A data governance framework would manufacturers manage and fuse multimodal data across disparate information sources. Guidance on the different data fusion approaches and methods would allow manufacturing communities to survey the solution space more effectively to determine the appropriate technique given their data, assumptions, and requirements.
- Such a framework would address challenges with reconciling differences among data sources (e.g., length-scale, frequency) and varying accuracy and dependability among sensing devices, helping increase manufacturers' confidence levels in their data.
- Effective data fusion through this framework would also help ensure semantic reliability and structural consistency in manufacturing data and support data reuse to help improve performance across product lifecycles.
- The framework should provide integrated algorithms and data analytic methods extracting and fusing multiple data streams and events into single, actionable information sources. These algorithms would recommend optimum pathways for fusing data based on their provenance (e.g., short and long time-series, experimental protocols used for gathering the data).

KEY OPPORTUNITY

Establish a series of reconfigurable testbed facilities and/or "Centers of Excellence" to support the data capture across product lifecycles and the development and application of relevant AI/ML tools

Estimate Timeframe of Impact:
MID-TERM (3-5 YRS.)

- Testbed facilities allow for academia, industry, and other groups to collaborate in digital manufacturing production environments to test innovative manufacturing design concepts and pilot-scale technologies, solve grand challenge research problems, or generate datasets needed for decision-making and lifecycle improvement strategies on pre-competitive concepts.
- Testbed facilities will be a critical enabler for complete lifecycle improvement methods. Complete lifecycle improvement methods—especially those based on model-based systems engineering (MBSE)—require robust, complete datasets to support rapid development of AI/ML algorithms, which could be produced through testbed facilities and made publicly available for the broad manufacturing sector.
- Testbeds designed to be re-tooled or reconfigurable rather than "universal" could be a valuable educational tool for training the emerging workforce on AI-enhanced multimodal sensing and process control paradigms. These facilities will require a range of domain-specific instrumentation, capabilities, human capital, and computational resources.
- It would be valuable to develop a gap analysis and asset map (including national labs, government test facilities, technology consortia or manufacturing institutes, etc.) to support or leverage existing pilot programs related to testbed facilities.

STANDARDS & TECHNIQUES

Manufacturers seeking to incorporate digital manufacturing strategies to improve complete lifecycle performance into their operations require the development of standardized approaches and common practices, formal processes and procedural guidance, and frameworks for design, measurement, analysis, modeling, and decision support. R&D opportunities are needed to establish standards and techniques that reduce the labor intensity for data curation and management, increase confidence in part processing capabilities and prediction results of data-driven models, and facilitate the execution of critical steps in the qualification of materials, parts, and manufacturing processes.

KEY OPPORTUNITY

Demonstrate applications of generative AI systems (e.g., LLM-based tools) to enable rapid development of interoperable systems and APIs for low-labor-intensity data curation and interrogation

Estimate Timeframe of Impact:
NEAR-TERM (0-2 YRS.)

- Generative AI systems, such as LLMs, could support a broad variety of solutions to multimodal sensing and process controls for complete product lifecycle improvement, including automated dataset reformatting, identification or labeling of data uncertainties, multimodal data sensor fusion, and seamless interoperable communication across manufacturing systems and facilities.
- As manufacturing operations become increasingly digital and interconnected, greater interoperability will be needed to support the proper exchange of data across software and hardware systems, including the flow of information from multimodal sensors to AI/ML and data analytics to process control strategies. Generative AI tools can support these needs by enabling the rapid development of application program interfaces (APIs), metadata schema creation, programming code development, and low-labor intensity data curation across disparate sources.
- In the long-term timeframe, standards or frameworks for applying sensor imaging techniques could enhance generative AI tool robustness by providing guidance on how to optimize the installation of sensor networks to yield robust experimental datasets for training AI/ML-based models. Standardized data collection and contextualization methods can reduce the risk of improper sensor installation and ensure data are accurate and correctly measured.

KEY OPPORTUNITY

Create a standardized workflow for combining computational models and experimental data to feed data-driven methods for accurately determining the physics-based behavior of materials, processing equipment, and systems

Estimate Timeframe of Impact:
NEAR- TO MID-TERM (0-5 YRS.)

- Digital manufacturing workflows can streamline operations, enable factory floor automation, and increase industrial and operational efficiencies. Workflows break down manufacturing processes into a detailed series of steps and decision points and can inform data collection considerations such as the aspects of product development that should be monitored and the data of interest that should be captured by sensors, including its temporal and spatial resolution.
- High-throughput experimentation will become an increasingly important tool for validating the accuracy of computational methods as calculation speed and prediction reliability of computational approaches increase. In addition to validating computational models and quantifying uncertainties associated with modeling calculations, experiments provide necessary data on the properties of materials, processes, and products.
- Combining computational approaches and experiments can accelerate discovery, design, and development, and digital manufacturing workflows are increasingly needed to integrate multimodal sensing and AI/ML-driven process control capabilities to enable complete lifecycle product performance.

KEY OPPORTUNITY

Develop a framework and/or methodology for using AI-driven computational models/ digital twins to qualify and optimize manufacturing processes

Estimate Timeframe of Impact:
NEAR- TO MID-TERM (0-5 YRS.)

- Digital manufacturing approaches are expected to facilitate the acceptance—or qualification—of parts and processes to demonstrate that products will function as designed. Digital twins could significantly reduce trial and error validation testing and the duration required for qualifying end-to-end manufacturing processes.
- It is challenging to demonstrate repeatable and consistent processes that use multiple and mutually concurrent process steps—such as the combination of additive manufacturing and process heating techniques—when data-driven methods (e.g., AI and ML techniques) are used to inform complex tuning or the choice of process parameters. Digital twins can help to address this issue.
- Strategies are needed to modularize and update digital twins by developing high-throughput prediction and inspection procedures for each manufacturing operation, and subsequently chain them together to form a complete end-to-end digital twin of the process and product that combines multiple models.
- Digital twins for process qualification could also be integrated into a software suite and/or service bureau created by software developers in conjunction with manufacturers to reduce the level of expertise required for using the software for modeling, design, operations planning, and real-time control and decision-making.

KEY OPPORTUNITY

Establish standards for the development of models for complete lifecycle improvement with integrated V&V and UQ techniques

Estimate Timeframe of Impact:
MID-TERM (3-5 YRS.)

- There is a growing need for computational tools with integrated features that allow manufacturers to perform verification and validation (V&V) and uncertainty quantification (UQ) on their product simulation models—particularly for AI/ML-driven systems and products in which both trust and predictability of their behavior are currently limited.
- The absence of standards for performing V&V and UQ on AI/ML tools and models makes it difficult for practitioners to distinguish between proof-of-concept development of tools and the actual deployment of tools in real-world scenarios.
- Few standards currently exist for providing guidance on how to conduct V&V on computational models—even fewer exist for uncertainty quantification; but few-to-no tools are available for doing V&V and UQ on physics-based computational models.
- To build manufacturers' confidence in the prediction results of data-driven models, standardized methods for verifying and validating computational models under uncertainty should be directly integrated into computational modeling software packages or offered as a service by a solution provider.

KEY OPPORTUNITY

Create a framework for designing products with end-of-life considerations (e.g., recycling, circularity/Re-X) to facilitate planned product obsolescence or closing of product lifecycle loops

Estimate Timeframe of Impact:
MID-TO-LONG TERM (3-10 YRS.)

- Design for circularity (and other similarly named methods) allows for manufacturers to design high-performance products with a lower negative economic or environmental impact throughout their complete lifecycles.
- For certain applications or products that are subject to fixed expiration dates or frequent regulatory changes (e.g., child car seats), manufacturers design these products for "planned obsolescence."
- These methods for designing products with consideration toward end-of-life can help reduce any losses of value embedded within those products by keeping them in circulation (i.e., out of landfills) through reuse, recycling, or remanufacturing.
- R&D activities should leverage progress made by existing Manufacturing USA Institutes (e.g., The REMADE Institute[3]) to develop frameworks that will:
    - Support the evaluation of design trade-offs and costs associated with end-of-life decisions including pathways for manufacturability
    - Enable pathways for increasing manufacturing automation and labor associated with end-of-life disassembly
    - Increase the use of sustainable or recycled content in both new and upcycled products

3 https://remadeinstitute.org/.

TRAINING & EDUCATIONAL RESOURCES

Maintaining pace with the rapid development of multimodal sensing and AI-driven process control technologies requires curricula modernization, flexible degree pathways, collaborative training programs, experiential learning opportunities, exemplar products and use cases, and other educational resources to prepare and maintain a skilled, high-quality workforce. Training and educational resources must prepare emerging and incumbent workers on how to effectively translate domain-specific expertise to additional domains, and they must be specifically designed to facilitate a fundamental shift from traditional experimental methods to high-throughput computational-experimental methods for developing new materials and products faster and more efficiently.

KEY OPPORTUNITY

Support multidisciplinary educational and workforce training programs to help prepare the workforce on software and tools that support AI/ML-based analytical methods

Estimate Timeframe of Impact:
NEAR-TERM (0-2 YRS.)

- Multidisciplinary educational programs at universities are needed to deliver skills related to the interaction of AI/ML methods and materials science.[4] There is currently a lack of experts with deep knowledge of both manufacturing and AI/ML-based tools and analytical methods. In addition, employees often lack hands-on experience due to an emphasis on simulation instead of hardware laboratory experiences in most university curricula. Thus, entry-level engineers have a steep learning curve on the job site.
- Multidisciplinary workforce training programs will have various benefits, including:
    - Allowing for effective translation of domain-specific expertise to additional domains.
    - Preparing workers to use software and tools that use integrated AI/ML techniques, facilitating a shift from traditional/artisan experimental methods to high-throughput data-driven methods that can discover meaningful causal relationships.
    - Teaching modelers, engineers, designers, and technicians how to collaboratively develop requirements, evaluation criteria, and approaches for using computational modeling to improve complete product lifecycle performance through model-based systems engineering (MBSE) concepts.
- Training educators in sought-after skills will provide the incoming workforce with the knowledge of new technology like AI and ML and prepare them to be able to easily adapt to new technologies.
    - This training will help create avenues for educators and students to receive forward-looking technological knowledge despite strict ABET accreditation rules.
    - Workers have been deterred from certain jobs due to the notion that AI will replace them. If the future workforce receives training and education in these tools, they will have valuable, in-demand

4 E.g., Mechatronics, which combines different engineering fields around AI/ML-based software tools.

skills to support the business practices of growing companies. Rather than AI and ML eliminating jobs, education can help train the workforce for the future to use these technologies to their fullest potential, developing new, higher-value jobs.

- It will be critical to integrate with existing training resources and certification programs so that in-demand skills related to new technology and methods can be taught to incumbent educators. Community college programs as well as certifications for incumbent workers are helping to provide this training.

- Because different use cases of lifecycle enhancement will have different levels of complexities and lifecycle performance metrics, the training programs must extend beyond the undergraduate student population to include the technician-level manufacturing workforce. Requirements for a successful program will vary across the education spectrum:
  - Universities: Universities should enable and encourage interdisciplinary undergraduate and graduate degree pathways that allow for students to specialize in areas that leverage data science and AI/ML. Curricula should allow for greater flexibility to add course electives focused on the use of modern data-driven techniques.
  - Undergraduates: Approaches could include inviting guest speakers with expertise in AI-enhanced multimodal sensing for complete product lifecycle performance to academic seminars; organizing in-depth demonstration tours at manufacturing facilities; pairing senior undergraduate teams with manufacturing companies to collaborate on focused research projects; fostering cooperative education or mentorship opportunities that provide real-world experiential learning opportunities; and creating new introductory courses in university engineering programs on AI/ML methodologies—both the theory and the practice. AI/ML tools, like other engineering tools, are not one-size-fits-all, hence the importance of understanding the assumptions and limitations of their use.
  - Graduate students: Support graduate fellowship and internship opportunities in using AL/ML-based methods and software tools in manufacturing environments.
  - Technical-level workforce: Leverage existing skills development programs such as Tooling U,[5] which provides learning management systems and manufacturing certifications for the manufacturing workforce.

5 Offered by SME (Society of Manufacturing Engineers).

KEY OPPORTUNITY

Develop specific use cases and pilot programs that demonstrate real-world applications of AI-driven data analytics

Estimate Timeframe of Impact:
NEAR-TERM (0-2 YRS.)

- Many specific use cases that might otherwise serve as educational examples to prospective adopters are unavailable or unpublished due to the proprietary or sensitive nature of the data. Development of publicly available pilot programs that demonstrate different ways to implement AI/ML/analytics can provide useful educational examples and help build the manufacturing community's trust in the use of these tools.

- Use cases on the application of AI-driven data analytics could provide valuable guidance for improving complete product lifecycle performance such as enabling the predictive design of materials behavior and part characteristics through advanced part distortion control via prediction of pre-heat treatment dimensions of parts.
- To successfully foster trust in AI/ML tools, it will be essential to identify and prioritize pilot programs where specific pre-competitive cases of AI/ML implementation produce results that are semantically understandable and verifiable against materials and manufacturing domain knowledge.
- Use cases of applied AI/ML/analytics can also serve as valuable educational resources for manufacturers by showing a range of workflow types related to data organization, including specific data storage tools used, data formats and filename hierarchies, and programming tools or modules applied.

KEY OPPORTUNITY

Identify a suite of exemplar products/processes to demonstrate the value and benefits of adopting AI-driven sensing and process control methods for improving full lifecycle performance

Estimate Timeframe of Impact:
NEAR-TERM (0-2 YRS.)

- Exemplar products can educate manufacturers on how next-generation lifecycle improvement methods can be integrated into manufacturing operations, as well as their potential benefits. This makes them a valuable tool for establishing a business case for integrating digitalization technologies into an organization's manufacturing operations (e.g., for decision-making, predictive design, predictive maintenance, or sustainability manufacturing).
- Pursuing this opportunity would help drive manufacturing digitalization and Industry 4.0 adoption, as many manufacturers are not familiar with AI/ML, how it is used in manufacturing, and how it can be used to improve lifecycle product performance.
- Exemplar products would facilitate sharing lessons learned from the field, which is invaluable for new product development. Such products take hypothetical issues and ground them in reality, defining the type of problems that must be solved, establishing best practices and optimal tools for solving them, and demonstrating the potential ROI of doing so.
- There is a need for more broadly accessible exemplar products. Where exemplars do exist, they are often sensitive or proprietary. These exemplar products should include:
    - A range of application types to show that approaches for improving lifecycle performance can be scaled and applied broadly (e.g., short versus long lifespan, mission-critical versus commodity, automotive sector versus food production sector),
    - All aspects of improving lifecycle management (e.g., installing multimodal sensors and integrating AI/ML-driven approaches, tracking materials evolution over time, and correlating the impact of the manufacturing process on part/component performance), and
    - All aspects of the lifecycle data continuum from product design through in-use phase and end-of-life.

Next Steps

The integration of artificial intelligence, sensor technologies, and data from traditional materials science and manufacturing processes can strengthen U.S. manufacturing innovation and industrial productivity through significant improvements to the performance, energy efficiency, and materials efficiency across the product lifecycle.

This roadmap seeks to enable new capabilities in multimodal sensing and AI/ML-driven closed-loop control for improving manufacturing quality, efficiency, and sustainability through the pursuit of high-impact, cross-cutting research and development priorities. These roadmapping opportunities are designed to empower the broad research and manufacturing community with the necessary tools, methods, and educational resources to:

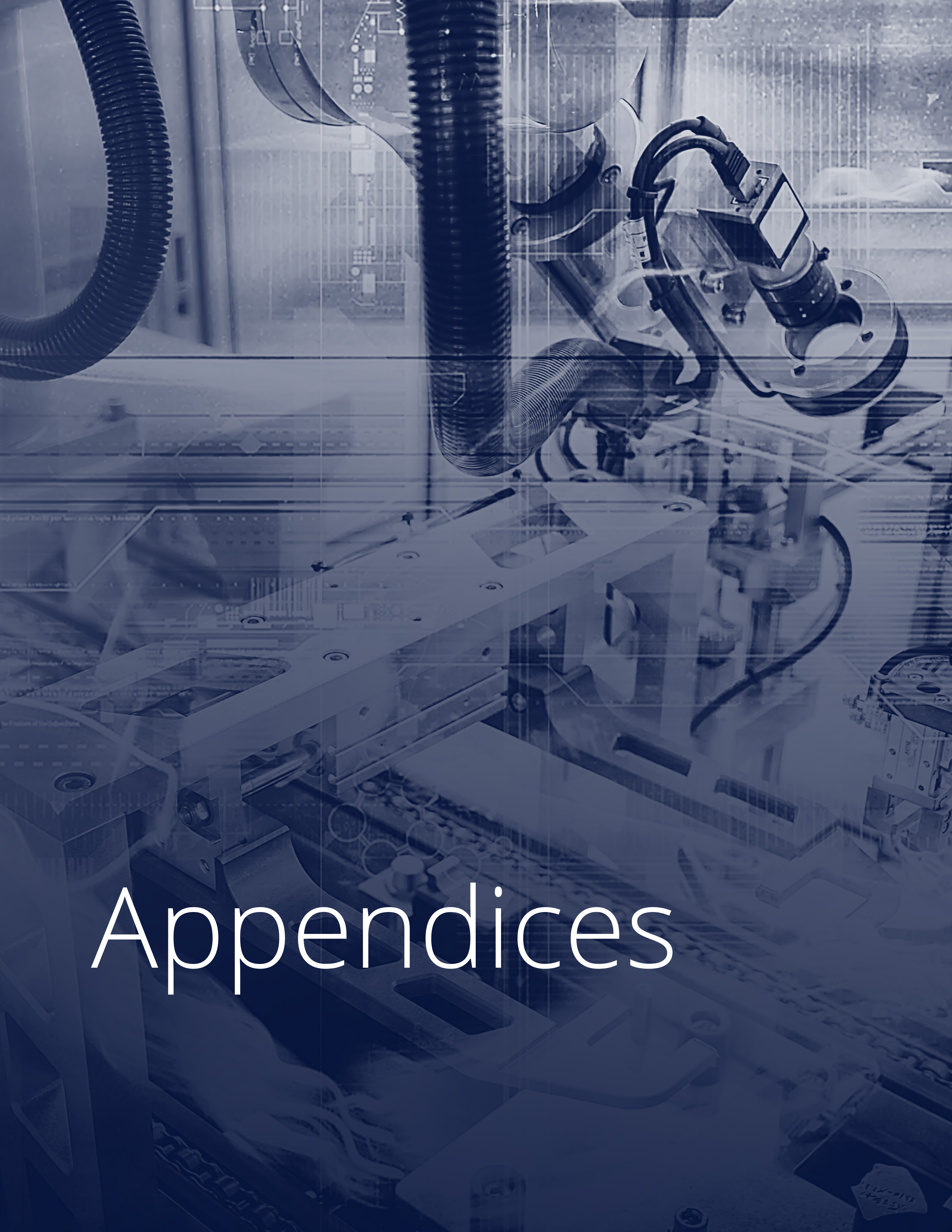
Effectively leverage digitalization technologies to capture a digital data thread across product lifecycle stages

Apply data-driven techniques to generate helpful domain- and product-specific insights

Integrate lifecycle data and insights across modes and timescales to enhance product performance and manufacturing efficiencies from cradle-to-cradle

Extended details about these high-priority opportunities are provided in Appendix B, Implementation Plans. These Implementation Plans are intended to provide a current snapshot of the recommended actionable steps and additional supplementary information required to achieve the roadmap's stated objectives successfully; they are not intended to be overly comprehensive or prescriptive.

The successful implementation of this roadmap will require shared, long-term investments in R&D and the coordination of multiple interested parties to enable U.S. manufacturers to realize the value of new digital manufacturing capabilities in product lifecycle performance improvement for a broad variety of industry sectors and applications. Inclusion of the business community is imperative to this outcome; their inputs and experiences will ensure the broad adoption of these digital manufacturing capabilities by identifying the business impact of these R&D initiatives and sound metrics to understand the potential return on investment. ISSACS, which functions as a hub for multidisciplinary project collaboration and partnership coordination across Case Western Reserve University's schools, intends to use the results of the roadmap to propose the formation of a research-based consortium to implement the roadmap's key R&D activities around pre-competitive solutions to cross-cutting challenges for its prospective members across industry, academic, and federal agencies. Pursuing these opportunities will facilitate a transformational shift how manufacturers use AI-based tools and digital data to augment traditional approaches to materials and manufacturing process development to enhance full product lifecycle performance.



Appendices

Appendix A: Glossary of Key Terms

Artificial Intelligence (AI): A branch of computer science that combines data, algorithms, and hardware to replicate the cognitive abilities of the human brain to "intelligently" identify patterns, generate insights, and inform decision-making.

Circularity/Circular Economy: Economic model and/or actions taken to retain the value and quality of resources and materials that are destined for landfills through extension of useful life, reduction of generated waste, reduction in carbon footprint, reuse, remanufacturing, and/or recycling.

Data Fusion: Combining independent or redundant data from multiple and often disparate sources to generate inferences that are more comprehensive, useful, and accurate than any individual source.

Digital Thread: A communication and/or analytical framework that enables data exchange between physical and simulated worlds to design, evaluate, and manage lifecycles.

Digital Twin: Virtual representations of one or more physical entities that use real-time and historical information to simulate the behavior of products and processes accurately.

Edge Computing/Processing: An on-site or remote computing architecture that is located in close proximity to a data source to reduce bandwidth and latency requirements.

Event-Driven Architecture: A product development software paradigm or computer program for designing and managing products in terms of "events" caused by changes in data.

Exemplar Products: A showcase of an existing product, material, or process that is used for demonstrating its actual or potential benefits concerning a specific application; may be used for training or educational purposes

Hybrid Manufacturing Approaches (e.g., Additive Manufacturing + X): The combination of additive manufacturing techniques with traditional processing or post-processing techniques including heat treatment, milling, forging, casting, etc., to enable mass production, improve accuracy, and enable net-shape fabrication.

Large Language Model (LLM): A type of artificial intelligence algorithm (i.e., deep learning algorithm or neural network) trained on large datasets to analyze statistical relationships and produce predictions based on data queries.

Lifecycle Extension: An extension of circularity/circular economy principles focused on actions intended to prolong the usable lifetime of materials and products.

Machine Learning (ML): A subfield of artificial intelligence; a computational model or algorithm that analyzes large data sets to identify patterns and infer predictions as output.

Model-Based Systems Engineering (MBSE): A formal methodology that uses graphical computational models to replace traditional document-centric approaches to define and design systems and products.

Multimodal Sensing: The use of multiple sensing modalities including visual, audio, temperature, stress, radiation, etc., with the intent of combining information from multiple devices, sensors, and data streams.

Product Certification: Formal processes used by a certification authority or organization to ensure product designs are compliant with appropriate standards and/or specification requirements.

Product Lifecycle: The stages of a product's lifecycle including product design, materials selection, manufacturing and production, quality inspection, service life, and end-of-life management (i.e., reuse, recycling, remanufacturing)

Qualification (of Materials, Machines, Products): Formal evaluation of materials, parts, machines, or techniques to verify if a product design complies with industrial or application requirements.

Reduced-Order Model (ROM): Modeling techniques that reduce the computational complexity of high-dimensional systems while preserving the product's critical properties and with sufficient reduction accuracy.

Remanufacturing: The process of restoring manufactured products to their original state to achieve conditions and/or performance levels that meet or exceed their intended design.

Sustainability: (In the context of manufacturing) design and development of products using processes that conserve energy and natural resources, reduce environmental impacts, improve human safety and welfare, and increase economic benefits.

Testbed: Platforms or testing environments for conducting experiments on materials, products, tools, or technologies.

Uncertainty Quantification (UQ): The process of quantifying uncertainties associated with model calculations with the overarching objective to account for all sources of uncertainty and quantifying the contributions of each source to the overall measure of uncertainty.

Verification & Validation (V&V): Verification processes are used to determine that computational models are accurate representations of their underlying mathematical models (e.g., the software) and its solution; validation processes are used to determine the degree to which a model accurately represents real-world behavior within the boundaries of its intended use.

Workflow Processes: A series of processes and steps designed to orchestrate a discrete sequence of activities for effectively managing the lifecycle of a product; workflows break down manufacturing processes into a detailed series of steps and decision points and can inform data collection considerations such as the aspects of product development that should be monitored and the data of interest that should be captured by sensors, including its temporal and spatial resolution.

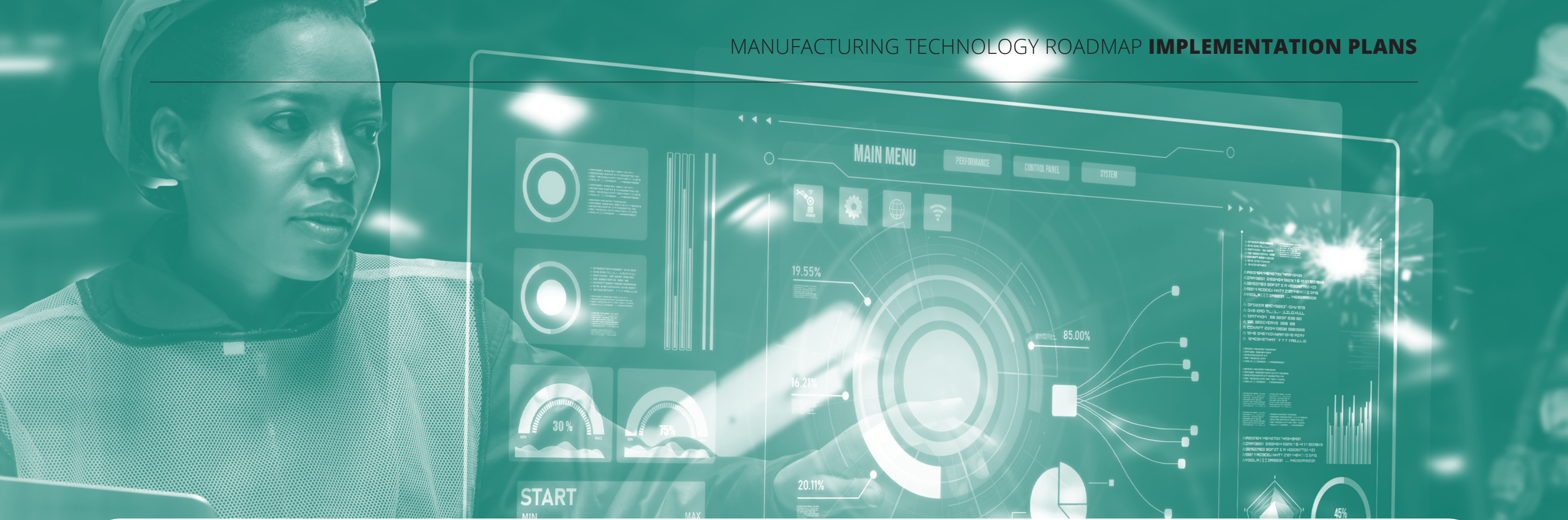
Appendix B: Implementation Plans

This roadmap proposes several high-impact, cross-cutting R&D priorities to enable new AI-driven capabilities for U.S. manufacturers by providing pre-competitively developed software **tools and equipment**, **standards and techniques**, and **training and educational resources**. These opportunities are designed to help interested parties of the U.S. manufacturing sector unify data streams across stages of product development lifecycles, use AI- and data-driven methods to uncover insights around products and manufacturing domains, and employ feedback strategies for improving specific aspects related to the design, synthesis, processing, service use, and end-of-life management of materials and products.

Table 4 summarizes of the Implementation Plans and their estimated timeframes of impact for each relevant Activity Area.

Table 4: *Description of the scope and list of relevant subtopics for each of the roadmap's core Activity Areas*

ACTIVITY AREA	KEY OPPORTUNITIES / IMPLEMENTATION PLANS	TIMEFRAME
Tools & Equipment	**Open data management and curation tools**	0-5 years
	Multimodal data fusion and management governance framework	0-5 years
	Reconfigurable testbeds and facilities	3-5 years
Standards & Techniques	**Applications of generative AI and LLM-based tools**	0-2 years
	Workflows for integrating computational models and experimental data	0-5 years
	Framework for qualifying processes using digital twins	0-5 years
	Standard methodologies for applying AI across lifecycles	3-5 years
	Integrated verification and validation (V&V) with uncertainty quantification (UQ) techniques	3-5 years
	End-of-Life Design framework for closing product lifecycle loops	3-10 years
Training & Educational Resources	**Multidisciplinary training programs**	0-2 years
	Pilot programs and use cases on AI applications	0-2 years
	Exemplar products and processes for complete lifecycle improvement	0-2 years



Tools & Equipment

Combining AI/ML with domain knowledge to integrate data streams over entire product lifecycles will require R&D activities that support the development of shared instrumentation, testbeds, and experimental facilities as well as software tools for processing multimodal sensor streams, acquiring and querying data, using AI and data analytics to generate insights, and applying feedback strategies to improve performance across product lifecycles. These R&D opportunities can help facilitate strategies for automating data extraction and ingestion, incorporate user-friendly software/hardware interfaces, enhance interoperability across tools and platforms, and provide intuitive workflow strategies.

Open data management and curation needs — 0-5 YEARS

ACTION PLAN

A **Develop data management tools that leverage open data standards to enable efficient queries and curation of datasets across product lifecycles**

- Create platforms, tools, networks, and/or interfaces to support efficient data queries
- Develop data management tools that allow for the curation of new datasets and ingestion of unused or non-digitized legacy data (e.g., PDFs, spreadsheets)
- Apply an “Event Driven Architecture”-type approach to data collection and management and create event object libraries for equipment, materials, operations workflows (master data management [MDM], scheduling, reporting, inventory, maintenance, quality, production), and process workflows

KEY REQUIREMENTS AND CONSIDERATIONS

A **Managing data often requires multiple software tools**—Some manufacturers require multiple data management tools to manage different types of datasets;

- Tools lack convenient interchange formats with respect to the reasoning and data conclusions they represent
- Different tools are often needed because they are designed to represent disjointed properties

Open data management and curation needs

0-5 YEARS

KEY REQUIREMENTS AND CONSIDERATIONS (CONT.)

B **Opportunities for digitizing legacy datasets**—Manufacturers require data management tools to curate new datasets and ingest unused or non-digitized legacy data

- Tools should be open-source to accommodate future add-ons and new functionalities within the same tool (versus using multiple tools)
- Need for the ability to search and identify available tools based on the specific use-case

C **Tools must support automation and efficient data queries**—Need for platforms, tools, networks, and/or interfaces to support efficient (cloud-based) data queries

- Upload of data via cloud-based storage may be desired to support subsequent analysis
- Tools could be integrated with standardized methods
- Required data could be integrated into software tools (e.g., for generating tool paths based on thermomechanical changes)

D **Tools must permit ad hoc definitions, associations, uses, and combinations of different data types**—Open data management and curation tools must be capable of managing different types of data (e.g., ML training data, process workflow data, metadata annotations of workflow steps)

- Both data representing process workflow and data representing properties of the system at any step in the process workflow require tools that permit ad hoc definitions, associations, uses, and combinations of different data types

KEY TASKS

A **Determine economic drivers for open data standards tool development**—Identify and support economic incentives to encourage the development of tools based on broad industry needs

B **Quantify potential ROI**—Demonstrate how data curation methods can create immediate value or returns on investments made in engineering R&D

C **Develop open data standards**—Develop open data standards that can be integrated into the data tools to enable convenient data interchange formats (i.e., to ensure insights obtained through the use of one tool are usable by other tools)

D **Develop a DMP decision matrix**—Develop a decision matrix to help users create a data management plan (DMP) for each specific use case or demonstration project

Open data management and curation needs

0-5 YEARS

MILESTONES

A	**Measure increases in the number of products supporting open data standards**
B	**Integration of DMP decision matrix into open-source data management tools**
C	**Develop an understanding of the ecosystem incentive structures for manufacturing, industry, vendors, integrators, and other contributors and service providers**

Multimodal data fusion and management governance framework

0-5 YEARS

ACTION PLAN

A **Establish a data governance framework that sets standards/practices for fusing, harmonizing, and managing multimodal data, and for evaluating data utility to support future data reuse**

- Establish standards and provide tools for ensuring data availability, semantic reliability, and structural consistency of manufacturing data
- Establish practices for multimodal data fusion and management including development or adoption of standardized data formats

KEY REQUIREMENTS AND CONSIDERATIONS

A **Event-driven architectures can help parse out desired data structures**—Algorithms and data analytics are needed to extract and fuse data from both individual and combined data sources to create a new and embellished information state that is not contained within a single data stream

B **Data fusion should be conducted early in product development**—Data fusion is challenging if not performed at earlier product development stages; early-stage data fusion otherwise enables the design of event-driven architectures that are highly effective at translating disparate data into useful information; Current practice relies on algorithmic procedures, but the context in which the fusion occurs is often missing/incomplete (e.g., in the absence of standards for describing or managing the data), thereby reducing the usefulness of the fused data

Multimodal data fusion and management governance framework 0-5 YEARS

C	**Data fusion standards can improve data repeatability and consistency**—As AI/ML are increasingly integrated into manufacturing operations, there is less demand to include a "rational" information architecture because users rely on the ML tool to help make such decisions, thus creating a repeatability challenge which is otherwise addressed by tracking statistical data outcomes and co-locating manufacturing processes; Ensuring repeatability and consistency of data within an organization necessitates the creation of standardized name spaces within manufacturing information models (versus the creation of "new" approaches that lead to inconsistency within and across organizations)
D	**Access to existing standards is fragmented**—There are some existing standards for disambiguating concepts (via standardized ontologies) but they are fragmented and dependent on the specific economic model
E	**Standards development organizations (SDO) can help offer guidance**—May be able to leverage partnerships with professional societies until data fusion methods are sufficiently mature to engage standards development organizations (SDOs

KEY TASKS

A	**Identify various manufacturing end-to-end use cases**—Propose a collection of various specific manufacturing use cases (i.e., end-to-end problem use cases) to determine which types of fusion algorithms and existing tools are useful and valuable, and to identify where gaps exist in the specific data fusion algorithms
B	**Create standardized terminology for manufacturing-based data fusion methods**—Create standard terminology/language to refer to different data fusion methods that are relevant and meaningful to materials- and manufacturing-based product lifecycles
C	**Identify AI/ML analytics needed for different lifecycle stages**—analysis Determine the specific stage of the product's lifecycle for which AI/ML analytics are applied to determine the level and form of data management and curation
D	**Define the required data format of the algorithm(s)**—Define the data format required by the algorithm(s) for sending and receiving data with considerations for data fidelity requirements, ability to assess confidence in data accuracy, and metadata and data pedigree

MILESTONES

A	Reference methodologies/language created for existing data fusion methods
B	Data management and curation decision tree developed to determine the form of the data management plan DM and analytical requirements for a given point in the lifecycle
C	Integration of initial standardized/best practices for managing/fusing data (e.g., type of data management method; pros and cons of various approaches; potential technical debt tech debt incurred for downstream commercial implementation later in the product lifecycle)

Reconfigurable testbeds and facilities

3-5 YEARS

ACTION PLAN

A **Establish a series of reconfigurable testbed facilities and/or "Platform Centers of Excellence" to support the data capture across product lifecycles and the development and application of relevant AI/ML tools**

- Create one or more testbeds or Centers of Excellence (COE) (i.e., physical "plant" plus sensing, data and computations, and human expertise) to support pilot programs, generate public datasets, and provide training opportunities for emerging workers

KEY REQUIREMENTS AND CONSIDERATIONS

A **Testbeds must have well-defined objectives**—Form and goals of the testbeds should be refined once anticipated insights are identified

B **Need for domain- or materials-specific resources**—May need additional domain-specific instrumentation equipment and capabilities, human capital, computational resources (e.g., clusters, acceleration units to support training opportunities); May be different additive manufacturing needs design needs for different industries (e.g., metals, polymers)

C **Lifecycle stage of interest may require different capabilities**—In addition to domain- and materials-specific resources, different types of capabilities will likely be needed to accommodate all product lifecycle development stages (i.e., design, in-service use, retrieval/ end-of-life management/recovery and redeployment or recycling of materials and parts)

D **Testbed activities should span the full TRL spectrum**—Testbed capabilities advance the maturity of multimodal sensing and AI-enhanced process control technologies through multiple levels of technology readiness

E **Testbeds should align with specific pilot programs**—Testbed facilities should support R&D activities aligned with specific use cases, pilot programs, and technology demonstration efforts (i.e., Tasks in the "Pilot Programs and Use Cases" Implementation Plan should inform testbeds)

F **Testbed could generate public datasets**—Open or public datasets are needed to support the rapid development of AI/ML algorithms

G **Testbeds should connect with existing assets and related initiatives**—Testbeds must have a connection to existing assets, testbeds, and Centers of Excellence; Must examine recent public testbeds and related initiatives to leverage existing resources and expertise

H **Testbeds should aim to be flexible, re-toolable**—Designing or setting up testbeds to adapt to rapidly evolving technological trends can enhance their long-term viability; testbeds should not be designed for "universal" use but could be flexible enough to accommodate a range of manufacturing domain-specific needs

Reconfigurable testbeds and facilities

3-5 YEARS

I	**Reconfigurable testbeds could provide training opportunities for emerging workers**—Testbeds could be retooled or reconfigured for academia to deliver educational experiences for future engineers in "re-solving" real-world problems; Must address proprietary concerns of industry

KEY TASKS

A	**Identify use cases**—Determine the testbed focus areas based on specific use cases or exemplar products identified in the "Pilot Programs and Use Cases" and "Exemplar Products" Implementation Plans
B	**Conduct gap analysis and create asset map**—A gap analysis and map of existing assets (including national labs, government test facilities, technology consortia or manufacturing institutes, etc.) are needed to understand how past or current pilot programs can support R&D priorities in multimodal sensing and AI-enhanced process controls
C	**Define value proposition**—Define the value proposition for operating a testbed; identify the critical need and interested parties whose progress would significantly benefit national technical goals
D	**Develop and "end-of-life" plan for testbeds**—Create a "sunsetting" strategy to ensure testbeds have an appropriate EOL/end-use plan

MILESTONES

A	Define the mission and required elements of Centers of Excellence (COEs)
B	Define stakeholders in key manufacturing sectors and customer base who would use the testbed facilities or COEs
C	Define leadership skills required for COE principals and leaders of COE divisions
D	Identify the location, awardee (university), and funding source(s) for the COE(s)/testbed(s)
E	Identify and establish testbeds including potential to re-tool testbed at an existing national lab
F	Begin construction of COE(s)/testbed(s)

Standards & Techniques

The development of standardized approaches and common practices, formal processes and procedural guidance, and frameworks for design, measurement, analysis, modeling, and decision support. These activities seek to reduce the labor intensity for data curation and management, increase confidence in part processing capabilities and prediction results of data-driven models, and facilitate the execution of critical steps in the qualification of materials, parts, and manufacturing processes.

Applications of generative AI and LLM-based tools

0-2 YEARS

ACTION PLAN

A **Demonstrate applications of generative AI systems (e.g., LLM-based tools) to enable rapid development of interoperable systems and APIs for low-labor-intensity data curation and interrogation**

- Support development of generative AI systems—such as LLMs—for creating schemas, writing code, addressing semantic issues, rapid API development (i.e., for various methodological implementations), and low-labor-intensity data curation

KEY REQUIREMENTS AND CONSIDERATIONS

A **Generative AI and LLM tools hold significant potential for a broad range of manufacturing applications**—Engineers, developers, and designers—all at various product lifecycle stages—may benefit from assistive generative AI tools (e.g., cloud-based LLM tools with integrated AI, generative pre-trained transformers [GPT])

- Example uses of generative AI uses include synthesis of scientific papers for generating schema, down-selection of target resources (i.e., of literature), and code development
- **Data visualization**—Generative AI systems (including LLMs) can be used as semantic text-based tools for generating maps of hidden representations in datasets into visual models
- **Better data interoperability**—Generative AI could be used as a tool to interconnect hundreds of manufacturing systems (within a typical facility) to boost data interoperability by contextualizing and converting data into more standardized formats; LLM-based tools could help support “data uncertainty labeling,” file naming conventions, automatic reformatting of datasets, etc.
- **Rapid API development**—Some existing open-source generative AI tools LLMs may be able to support rapid API development

Applications of generative AI and LLM-based tools 0-2 YEARS

B **Use cases can demonstrate the benefits of generative AI systems**—Must identify use cases (i.e., exemplar demonstration products) in which generative AI tools could provide a “digital thread” benefit for manufacturing operations (e.g., better data integration; data mapping; multimodal data sensor fusion; contextual summarization of sensor capability datasheets)

KEY TASKS

A **Identify generative AI use-cases**—Define use case(s) for which generative AI systems (e.g., LLM-based tools) could improve data interoperability across manufacturing systems (e.g., better data integration, data mapping, data uncertainty labeling, file naming conventions, automated data reformatting)

B **Define problem set and data curation requirements of instrumentation/equipment**—Down-select the generative AI use-cases and define the capabilities and requirements of the instrumentation and processing equipment with respect to data curation (e.g., enabling technologies such as sensor networks)

C **Identify data sources for the semantic model**—Identify the source documents and datasets required for building semantic/ontological models

D **Train the generative AI systems** on a new or synthetically generated dataset

MILESTONES

A Conduct pilot development and demonstration of generative AI tools to address a specific gap/opportunity

Workflows for integrating computational models and experimental data 0-5 YRS

ACTION PLAN

A **Create a standardized workflow for combining computational models and experimental data to feed data-driven methods for accurately determining the physics-based behavior of materials, processing equipment, and systems**

- Support the creation of a standardized workflow for combining computational models and experimental data to feed data-driven methods to support more effective determinations of physics-based behavior

Workflows for integrating computational models and experimental data 0-5 YRS

KEY REQUIREMENTS AND CONSIDERATIONS

A **Must monitor respective long-term changes to each type of manufacturing equipment**—Workflows must monitor machines/manufacturing equipment over time including their influence on the material(s)

B **Leveraging examples of knowledge engineering**—Existing examples of knowledge engineering methods may provide insights into creating standardized workflows

C **Exemplar products/processes are needed to help define standardized workflows**—Exemplar products will have different levels of criticality and types of collectible data depending on the specific component

KEY TASKS

A **Identify exemplar use cases to overlay machine/material workflows**—Identify a variety of exemplar cases to overlay the machine/material workflow that can be combined with machine/material workflow needs to combine experiments with computational approaches

- Identify one or more risk-averse applications—Identify a risk-averse application to help demonstrate the usefulness of standardized workflows for enhancing complete product lifecycle performance

B **Standardize a decision-making workflow for characterizing the retrieval, storage, and analysis of machine/material data**—Identify the specific manufacturing process(es) to develop a decision-tree workflow;

- **Identify specific material behavior and processing equipment**—Workflows must monitor the manufacturing process (i.e., materials behavior) and the specific machine/equipment
- **Define specific roles**—Workflow should set guidance on the specific roles/steps for: determining the data/sensor requirements; prioritizing the collected data; acquiring the data analytics outputs; implementing changes to the materials/equipment; inspecting/assessing the results of the change
- **Incorporate supply chain aspects into the workflow**—Workflow should involve data analysts/scientists, domain experts along the supply chain, and all types of manufacturing team members, e
    - **Machine operators**—to implement changes, monitor final product, and verify if data collection objectives are satisfied
    - **Technicians**—to calibrate and conduct predictive maintenance based on gathered data/information
    - **Process engineers**—to interpret data and decide on process-level changes (which might be indicated by the gathered data/information), and to assess the results of the implemented changes/improvements
    - **Managers**—to address monetary implications affected by changes in the project

Workflows for integrating computational models and experimental data 0-5 YRS

KEY TASKS

C **Demonstrate workflows on cross-cutting or common manufacturing processes**—Specific processes to consider in demonstration workflows include additive manufacturing (AM) and forging of high-value component(s)

- E.g., Additive manufacturing workflow could address:
  - **Feedstock reuse/recycling** (e.g., short-term reuse of AM powders; long-term recycling of the AM components/products at end-of-life)
  - **Impurity issues affecting processability/performance** (e.g., impurity accumulation during recycling)

Framework for qualifying processes using digital twins 0-5 YEARS

ACTION PLAN

A **Develop a framework and/or methodology for using AI-driven computational models/ digital twins to qualify manufacturing processes**

- Design a framework for using AI-driven digital models/twins to qualify manufacturing processes with multiple concurrent steps (e.g., combining additive manufacturing and heat treatment methods)

KEY REQUIREMENTS AND CONSIDERATIONS

A **Qualification framework must be broadly applicable**—Framework needs to be broadly useful for all manufacturing sectors (e.g., aerospace, sporting goods, food manufacturing)

B **Linking together manufacturing process models (e.g., end-to-end digital twins) supports more effective qualification of manufacturing processes**—AI/ML-driven digital twin models—predominantly end-to-end digital twins that link together multiple process models—could help facilitate the acceptance or qualification of parts and processes, and may significantly reduce trial and error validation testing as well as the duration to qualify an end-to-end manufacturing process

- Digital twins are not exclusively AI-based; however, AI would be useful for capturing highly complex physics behavior (e.g., fluid flow)

C **Digital twin/lifecycle models require frequent updates to accurately reflect changing material conditions**—The digital twin/lifecycle model represents the starting material condition and may not reflect how the material (or even the manufacturing process) may evolve with time, thereby emphasizing the need to update the digital twin/lifecycle model as new (or better) information emerges

Framework for qualifying processes using digital twins

0-5 YEARS

KEY REQUIREMENTS AND CONSIDERATIONS (CONT.)

D **Process heating technologies (e.g., heat treatment) are expected to be a useful lever in controlling manufacturing processes**—Since process heating technologies are common across sector-specific applications, the insights generated from controlling heat inputs may be transferable to other industries via digital twin modeling tools (e.g., in food manufacturing) and are expected to be useful for designing a broad range of product applications

- Digital twin modeling software tools could potentially be used to chain together multiple process models, are expected to eventually apply to a broad range of product applications

KEY TASKS

A **Establish high-throughput prediction and inspection procedures for each manufacturing operation**—Modularize digital twin modeling and updating strategies by developing high-throughput prediction and inspection procedures for each manufacturing operation and chaining them together to form a cradle-to-gate digital twin

B **Co-create a software service bureau with the manufacturing community**—Engage the software development community to create a service bureau specifically for manufacturers (i.e., software experts with the ability to distinguish different metals/alloys)

- E.g., a small software shop with qualified staff that offers modeling as a service based on the input/parameters of the manufacturing operations

C **Integrate development models into software suites**—Distill the development models into software suites for purchase and use by OEMs to enabling linking or combining of multiple manufacturing process models

- Define inputs/outputs of the digital twin, test software against real data, and ensure each output informs the next module in the pipeline

D **Build a business case for digital twin and AI implementation**—Define a clear business case for digital twin and AI implementation focused on business metrics (profit, scrap rate, lead times, etc.) instead of standard academic metrics (publication count, impact factor, h-index, etc.)

MILESTONES

A Preliminary pipeline established for a selected product that quantifies each manufacturing step, including post-printing/casting/machining steps (e.g., heat treatment)

B Future pipeline expansions to include:

- Input materials (i.e., feedstock)
- Service use of the project and its impact on the state of the part (i.e., degradation processes)
- Product dismantlement and dispersion of recovered parts into multiple recycling streams

C Successful implementation of digital twin framework and predictive modeling outside of “heavy industry” manufacturing applications, (e.g., food, consumer goods)

Standard methodologies for applying AI across lifecycles

3-5 YEARS

ACTION PLAN

A **Establish standardized methods for using AI and data analytics (e.g., to query unstructured data; to improve lifecycle performance)**

- Establish standardized methods for using AI to improve lifecycle performance as a function of manufacturer-specific operational envelopes and performance objectives (i.e., to establish confidence in part processing capabilities)
- Develop or standardize techniques to intelligently segment and quickly search unstructured data to build labeled datasets for decision-making purposes

KEY REQUIREMENTS AND CONSIDERATIONS

A **Standardized methods are needed to guide the process of applying AI/ML tools**—Existing concerns that standardization of the specific AI techniques could constrain the rapid evolution of AI methods; must focus on standardization of work processes (e.g., data structures, messaging protocols) to enable more scientific approaches to AI/ML implementation

- Well-defined modeling tasks can help determine best practices for applying AI/ML analytics, thereby setting a standard that supports effective communication and collaboration
- Must prioritize model-based systems engineering (MBSE) principles and de-emphasize the traditional “black box” mindset to facilitate trust in the modeling pipeline

B **Each application of AI/ML is unique**—Applications of AI/ML methods for improving product lifecycle performance are based on specific use/business cases including any associated enabling technologies and lessons learned

C **Need for open ontologies**—Ontologies, which describe product models, are necessary for establishing a common set of terms across the value chain

D **Must include realistic and compressive methods for querying unstructured datasets**—Methods should consist of realistic and compressive methods for unstructured data

E **AI/ML tool use must be easy, intuitive**—Improving the user-friendliness of AI/ML tools can help drive toward more standardized user experiences for both novices and more technically focused individuals (i.e., more graphical user interfaces and intuitive workflows; less code and command line interfaces)

F **Must consider broader techniques beyond AI/ML**—Broader analytical techniques (i.e., beyond AI) are needed to facilitate performance improvements across product lifecycles

G **May be challenging to implement for manufacturers with non-standard capabilities**—May be challenging for manufacturers with non-standard capabilities to select from a set of standardized methods—especially for similar roles and dissimilar offerings (e.g., additive manufacturing across modalities)

Standard methodologies for applying AI across lifecycles

3-5 YEARS

KEY TASKS

A **Conduct landscape analysis on the use of AI/ML-based techniques**—Survey existing landscape and use of AI/ML-based methods in lifecycle performance improvement (e.g., sector-based usage of tools for data queries);

- Identify common tool usage issues—Identify the most common/significant issues faced by manufacturers who have used or integrated AI/ML-based tools into their operations
- Identify methods to validate unstructured data—Identify methods for validating the unstructured data to apply an ontological framework to the query
- Identify data management methods for data harmonization—Identify new/existing techniques to harmonize multiple structured datasets into single master datasets to apply analytics

B **Develop requirements to help guide data query processes**—Define the requirements or specifications to guide data queries (i.e., purpose and expectations of data query methods)

C **Create open ontologies**—Create open ontologies that represent the interests of the ecosystem; when possible/applicable, ontologies should leverage existing standards

D **Establish definitions for processes and performance metrics**—Define concepts for describing existing data (i.e., describing dataset origin, models, services, parameters, side-effects, and performance characteristics)

E **Align tool requirements with data concepts**—Based on selected ontologies and data definitions: Define guidelines or set best practices to ensure AI/ML tools support unambiguous concepts and definitions of data, algorithms, and computational models

F **Provide educational or instructional examples of products with long-term lifecycle performance changes**—Capture key examples of end-of-life products whose properties (e.g., microstructure, chemical properties) have changed through service life to provide valuable exemplars for training or educational purposes

G **Create a decision-making framework for selecting analytical tools**—Develop a decision-making framework to help users identify appropriate analytical tools and techniques suited to different technology maturity levels (i.e., to capture the full lifecycle)

- Create a guidebook or decision matrix to help users understand what analytical tools are required as a function of the available processing equipment and materials analysis capabilities

H **Build shared or public datasets for specific industrial applications**—Support the creation of shared/public datasets for specific industrial applications

Standard methodologies for applying AI across lifecycles

3-5 YEARS

MILESTONES

A	Completion of technology landscape analysis/survey with an initial focus on unstructured data query methods
B	Quantification of ROI or evaluation of advanced data query methods
C	Prioritize/down-select analytic query methods to be investigated as candidates for standardization
D	Data queries designed and validated by cross-functional teams including laboratory experts, systems engineers, and systems modelers

Integrated V&V with UQ techniques

3-5 YEARS

ACTION PLAN

A **Establish standards for the development of models for complete lifecycle improvement with integrated V&V and UQ techniques**

- Need for modeling standards that deliver the desired lifecycle performance improvement capabilities; should include verification, validation, and uncertainty quantification

KEY REQUIREMENTS AND CONSIDERATIONS

A **Tools must integrate V&V/UQ methods**—Standards exist to conduct V&V, but few exist for UQ as they tend to be written using basic mechanical models

- Standardized methods for V&V and UQ are critical for establishing confidence (i.e., in a manufacturer's ability to process materials or fabricate parts, the accuracy of data, the validity of prediction results of data-driven models, and overall ability to use AI, sensing, and process control technologies)
- Standards development activities should include collaborative inputs from regulators and materials suppliers to enable the future integration of V&V and UQ functionalities into computational tool certification packages
- "Service bureaus" could offer V&V and UQ services as a packaged service or software suite; Tools must be available and usable

B **Must engage SDOs and government regulatory bodies**—In collaboration with SDOs: must work with government agencies to define the purpose and intended outcomes of future modeling standards with integrated VVUQ approaches

Integrated V&V with UQ techniques

3-5 YEARS

KEY TASKS

A **Identify partners willing to integrate UQ methods**—Identify 2-3 partners who are willing to engage in extending the computational model(s) of their product(s)

- Convene a multi-stakeholder team of experts including key representatives from standards development organizations (SDOs) and regulatory agencies

C **Identify key application areas and their relevant modeling requirements**—Identify high-value or high-impact product application areas to determine the specific modeling and application requirements (e.g., polymers AM, metals AM, traditional/subtractive manufacturing)

MILESTONES

A Development and incorporation of a standard for modeling a key manufacturing process including an integrated V&V step (i.e., validation to be performed by the customer of a software suite)

B Future modeling standard expansions:

- Inclusion of steps/methods for improving lifecycle performance
- Integration of UQ steps

C Measure the adoption rate by which key federal agencies use modeling standards with integrated VVUQ steps

End-of-Life Design framework for closing product lifecycle loops

3-10 YEARS

ACTION PLAN

A **Create a framework for designing products with end-of-life considerations (e.g., recycling, circularity, Re-X) to facilitate planned product obsolescence or closing of product lifecycle loops**

- Create a capability that allows manufacturers to close product lifecycle loops or continue the planned obsolescence of products (i.e., product applications intentionally designed for obsolescence due to fixed expiration dates or frequent regulatory changes such as child car seats)
- Develop tools or methods for assessing the costs and risks associated with different end-of-life product design options

End-of-Life Design **framework for closing product lifecycle loops** 3-10 YEARS

KEY REQUIREMENTS AND CONSIDERATIONS

A **Circular/end-of-life design helps reduce raw material dependence**—The ability to design products with consideration for the end-of-life stage of their respective lifecycles allows manufacturers to divert more materials from landfills and keep them in circulation through reuse, recycling, or remanufacturing, thereby capturing the inherent value of waste materials and reducing virgin materials consumption required for new product applications

B **Success stories are needed to motivate participation in the circular economy**—Proof-of-concept demos or design criteria such as recycling requirements can motivate participation in recycling strategies and improve supply chain robustness; Case studies and pilot demonstration programs (e.g., for improving product recyclability across lifecycles) could result in success stories that motivate recycling efforts for other families of materials or products

C **Must complement existing efforts to establish End-of-Life Design methods**—Existing organizations have made considerable efforts—notably the REMADE Institute—to establish “Design for Re-X” (i.e., recycling, reuse, remanufacturing); the ISSACS roadmap must be integrated with REMADE progress and maintain focus on the aspects of multimodal sensing and AI/ML-driven process control

D **Recycling or reclamation considerations must be designed into products**—End-of-life recycling and reclamation of materials currently requires significant downstream human resources, and therefore must be considered in the design phase of product development

- Must establish the business case for recycling concurrently with the push toward more energy-efficient, lower-emissions manufacturing processes
- Design for end-of-life methods would stimulate the need for data on how to refurbish end-use products, which would be helpful to downstream product recyclers/dismantlers; Methods for product disassembly could be integrated into product lifecycle design to help inform downstream dismantlers
- Labeling of products can help recyclers/dismantlers at the product’s end-of-life to direct materials into the appropriate waste/recycling streams for reuse, upcycling, or downcycling
- Incorporating legacy data on older/retired materials into end-of-life design methods and tools would provide recyclers/dismantlers with guidance on the allowable levels of recyclate materials and other trace elements that are permitted to enter waste streams

KEY TASKS

A **Coordinate with REMADE on the state of Design for Re-X/Circularity roadmapping activities**—The ISSACS roadmap should leverage related existing initiatives pursued by the REMADE Institute to identify specific opportunities focused on the lifecycle improvement aspects related to data, applications of AI/ML and data analytics, and process control

- Leverage REMADE knowledge in metallurgy and metals recycling for a pilot study on closing the lifecycle loop of a product

End-of-Life Design **framework for closing product lifecycle loops** 3-10 YEARS

KEY TASKS (CONT.)

B **Study circular product design implications on existing supply chains and recycling infrastructures**—Conduct a study to understand how existing recycling infrastructures and supply chains could be affected by Design for Re-X/Circularity methods

C **Launch pilot study on exemplar circularity product**—Identify a pre-competitive application for a pilot study to demonstrate a complete lifecycle design of a circularity-based exemplar product such as:

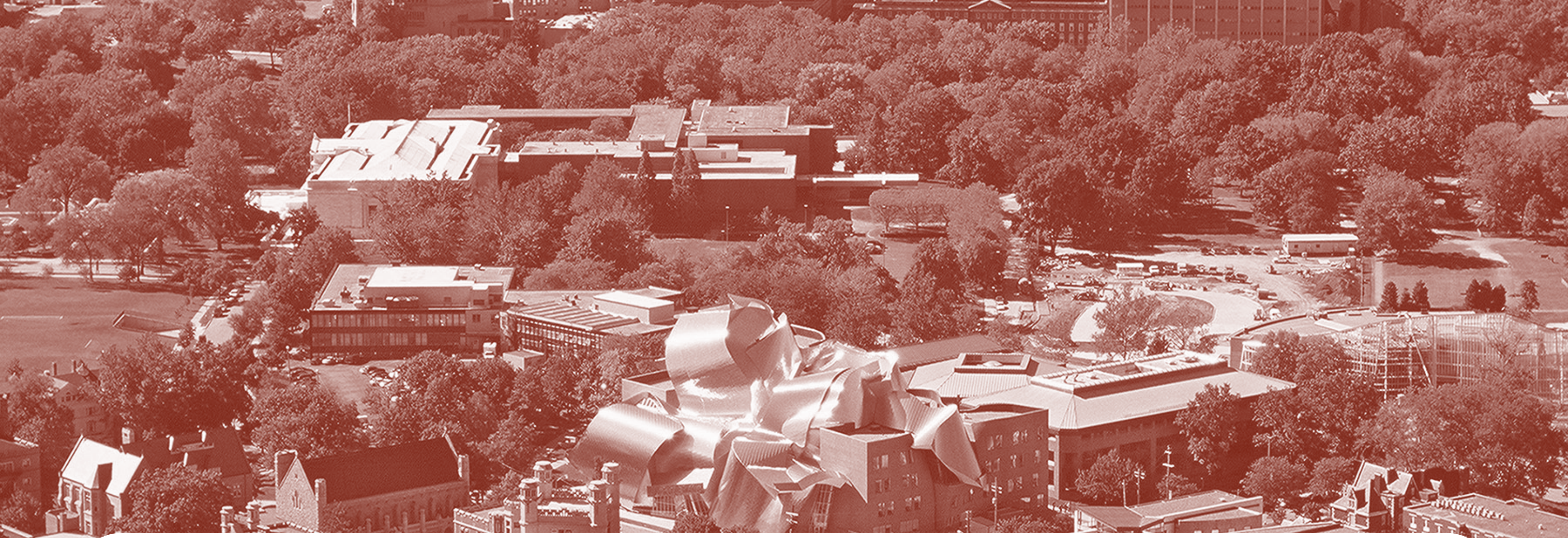
- Second-life applications of electric vehicle-based products including end-of-life disassembly (e.g., of batteries, bearings)
- End-use/fatigued windmill turbine blades
- Traceability of materials from post-factory distribution through retrieval (i.e., to reduce waste stream impurities)

MILESTONES

A Benchmarking study completed on the current state of progress of Design for Re-X methods; Engage with related initiatives and institutions (e.g., REMADE Institute) and identify unique aspects of ISSACS's capabilities and roadmapping support to address lifecycle-specific roadmap gaps related to multimodal sensing and AI/ML-driven closed-loop process control methods

B Demonstration of a closed product lifecycle loop on a material with a historically low recycling rate (e.g., generate a success story, proof of concept, or other educational resource)

C Development and/or expansion of recycling infrastructure program(s) for an exemplar product



Training & Educational Resources

Training and educational resources including modernized curricula, flexible degree pathways, collaborative training programs, experiential learning opportunities, and exemplar products and use cases are needed to prepare emerging and incumbent workers in using multimodal sensing and AI-driven process control for complete lifecycle performance.

Multidisciplinary training programs

0-2 YEARS

ACTION PLAN

A **Support multidisciplinary educational and workforce training programs to help prepare the workforce on software and tools that support AI/ML-based analytical methods**

- Develop workforce training programs to help train workers on software and tools that support AI/ML methods to facilitate a shift from traditional/artisan experimental methods to high-throughput methods
- Increase the number of trainers who can help teach the incumbent workforce the skills required for the adoption of technologies and methods for complete lifecycle improvement (e.g., sensing installation and maintenance; data interpretation; techniques for applying different AI/ML approaches)
- Provide educational program(s) that combine multiple key disciplines (e.g., educational mechanical engineering, data science) to encourage students to specialize in data science and AI/ML following completion of undergraduate or graduate degree programs
- Increase the number of transdisciplinary experts that sufficiently understand how to translate knowledge and expertise across domains
- Identify best practices for assembling multi-expert project teams that have the required skills/expertise to implement an AI/ML-based program effectively; can provide a detailed sample of the workflow and specific roles for an AI/ML digital twin-based R&D project to inform the skill requirements and elucidate the project timelines for specific tasks

Multidisciplinary training programs

0-2 YEARS

KEY REQUIREMENTS AND CONSIDERATIONS

A **Need for workers skilled on the use of AI/ML tools and methods**—Must develop workforce training programs to help train workers on software and tools that support AI/ML methods to facilitate a shift from traditional/artisan experimental methods to high-throughput methods

- Training programs must be expanded to include opportunities for the technical-level manufacturing workforce
- Must leverage existing continuing education programs including employer-led programs and non-profit-based workforce training opportunities[6]
- Need for fully pipelined and packaged AI/ML-based software tools with user-friendly interfaces and short learning curves (e.g., LLM-based tools for automatically converting speech to programming code)
- Training programs could structure cooperative education and mentorship opportunities around high-impact technology development or grand challenge problems to deliver real-world experiences and experiential learning opportunities
- Must explore ways to establish constructive dialogue or collaboration across traditionally disparate roles (e.g., technicians/operators and computational modelers) to build specification problem-solving skills, goal setting, measurement/metrics, etc.

B **Must provide training opportunities for preparing educators**—Need to increase the number of trainers who can help teach incumbent workforce the skills required for adoption of technologies and methods for complete lifecycle improvement (e.g., sensing installation and maintenance; data interpretation; techniques for applying different AI/ML approaches)

- Community colleges are developing comprehensive 2-year Industrial Internet of Things (IIoT) programs which need to be expanded in critical regions and as technologies gain market adoption
- e.g., Business schools could include courses in understanding cross-domain technologies for enhancing/improving manufacturing processes

C **Provide training opportunities on collaborative model-driven engineering and manufacturing**—Need to train modelers, engineers, designers, and technicians how to collaboratively develop modeling requirements, evaluation criteria, and approaches

D **Must identify effective team-building strategies to implement AI/ML programs**—Identify best practices for assembling multi-expert project teams that have the required skills/expertise to effectively implement an AI/ML-based program

- Create a detailed sample of the workflow and specific roles for an AI/ML digital twin-based R&D project to inform the skill requirements and elucidate the project timelines for specific tasks

6 E.g., Tooling U-SME is a workforce development organization for the manufacturing sector: https://learn.toolingu.com/.

Multidisciplinary training programs

0-2 YEARS

E **Must bridge disciplines and/or explore new fields**—Must explore the possibility of establishing a new field(s) at the intersection of AI and materials to establish connections across students/workers with different skillsets, education, and backgrounds to enable effective communication in production environments

KEY TASKS

A **Identify course curriculum needs**—Identify the curriculum needs and fund the development of new courses and labs for university-level engineering programs

- Introduction to AI—Create an academic course that gives students baseline knowledge of artificial intelligence and machine learning approaches
- Human-robot collaboration—Create an academic course that teaches students about the future and ongoing developments of human-robot collaboration and its benefits

B **Support graduate fellowship programs**—Supporting funding opportunities for new graduate fellowship opportunities that teach the use of AL/ML-based methods and software tools

C **Enable interdisciplinary undergraduate and graduate degree pathways**—Enable and encourage interdisciplinary undergraduate and graduate degree pathways that allow for students to specialize in areas that leverage data science and AI/ML and provide greater flexibility to add course electives focused on the use of AI/ML-based tools

D **Evaluate limitations of incumbent curricula accreditation system**—Evaluate the existing/incumbent system used to accredit curricula and address limitations related to the education and training of AI/ML-based approaches to product design

E **Provide career development resources**—Make career development resources available (e.g., via an online web portal) for existing/future workers

F **Create infrastructure necessary to assess curricula and worker skills**—Create infrastructure necessary to assess the quality of curricula and job candidate skill levels

MILESTONES

A Identification of target workforce groups

B Forecast future skill requirements to inform the development of a portfolio of pilot programs, curricula, etc.

C Creation/inclusion of a 1st- or 2nd-year undergraduate course in AI/ML literacy as part of a schoolwide engineering core curriculum

D Technician/associate's degree program established

E Creation/inclusion of literacy curriculum into an operator training program to teach lightweight robotics and AI/ML methods (e.g., Tooling U-SME, community college)

Multidisciplinary training programs

0-2 YEARS

MILESTONES (CONT.)

F	Interdisciplinary undergraduate engineering program that combines AI/ML and data sciences with a traditional engineering field (e.g., mechanical engineering with a focus on ML approaches) established at an R1 university
G	Certificate program developed for AI/ML and other data-driven methods

Pilot programs and use cases on AI applications

0-2 YEARS

ACTION PLAN

A **Develop specific use cases and pilot programs that demonstrate real-world applications of AI-driven data analytics**

- Develop a suite of pre-competitive use cases and pilots that support data aggregation for the envisioned AI/ML techniques

KEY REQUIREMENTS AND CONSIDERATIONS

A **Must identify successful past applications of readily demonstrable AI/ML use cases**—Define specific use cases across the manufacturing community (i.e., by small, medium, and large-sized enterprises) where the benefits of data analytics and AI/ML tools can be readily demonstrated

B **Use cases should map to the industry domain and TRL**—Map use cases to the technology readiness level (TRL) or manufacturing readiness level (MRL) and the lifecycle stage/level as well as industry to ensure use cases represent various processes, equipment, and materials

- Must identify the benefit or value proposition for each use case to help build executive buy-in for decision-makers seeking to adopt new digital technology capabilities (e.g., engineering managers)

C **Prioritize pilot program designs**—Identify and prioritize pilot program designs wherein implementation of AI/ML/analytics yields results that are semantically understandable and verifiable using domain knowledge

- For TRL 3-4: Downstream TRL requirements of pilot programs should be driven by a robust analysis of the business case, implementation risk, and expected impact/benefits

Pilot programs and use cases on AI applications

0-2 YEARS

KEY TASKS

A **Conduct a landscape analysis of existing testbeds for data-driven analytics in manufacturing**—Conduct comprehensive analysis to identify ongoing testbed efforts for data-driven analytics in manufacturing from which future pilot programs can leverage or link to existing resources;

- Focus on areas where AI/ML and data analytics are being applied to new databases, existing databases, and end-of-life/retrieval studies
- Focus on areas where the data analytics community could most likely leverage data (including evolving datasets) from existing testbeds to shorten product development timeframes
- Align topics of use cases/pilots with the "Reconfigurable Testbeds and Facilities" Implementation Plan
- Each specialized topic area requires a comprehensive staff/team (e.g., robotics use cases require a full complement of roboticist expertise)

B **Research industry-specific use cases**—Research AI/ML experts in up to 6 target industries from academia, manufacturing companies, software vendors, and equipment vendors for specific use cases in which AI/ML and data analytics are being applied to improve lifecycle performance of processes, equipment, or materials ranging from early-stage R&D to commercially manufactured products

- Research/survey academia, manufacturing companies, software vendors, equipment vendors, SDOs, and professional societies for ongoing and in-flight AI/ML or advanced analytics testbed programs and user cases currently underway
- Prioritize use cases based on analysis of working structures, deliverable forms, team/participation method, business purpose and value, funding, etc.; Apply advanced analytic maturity model to categorize use cases and interested parties

C **Document lessons learned from previous data analytics programs**—Survey prior data analytics programs to ensure future pilot program(s) avoid repeat errors or project hindrances

MILESTONES

A Conducted survey of existing/evolving national efforts where generated datasets of relevant manufacturing sectors/component(s) can be made accessible for use by AI/ML and data analytics tools in pilot programs

B Documentation of lessons learned and published results from similar use cases to inform the design of future testbed/pilot program; Engagement of project leads and participants of high-priority use-cases participants to solicit lessons learned for high-priority use-cases

C Mechanism or RFP created to initialize data analysis work

Exemplar products and processes for complete lifecycle improvement 0-2 YRS

ACTION PLAN

A **Identify a suite of exemplar products/processes to demonstrate the value and benefits of adopting AI-driven sensing and process control methods for improving full lifecycle performance**

- Develop several representative exemplar products and processes that demonstrate the roadmap value proposition, possibly covering different aspects of the lifecycle data continuum
- Need for access to, or development of, pre-competitive exemplars for component manufacture, perhaps with model of material system(s)

KEY REQUIREMENTS AND CONSIDERATIONS

A **Past successes can benefit future adopters**—Sharing lessons learned from the field are invaluable for new product development

- Retired (but saved/stored) components/structures represent valuable datasets that reflect real-world effects on the evolution of in-service materials

B **Must represent different product lifecycles of interest**—Need for a range of exemplar processes and product applications including specific lifecycle aspects to explore;

- Example lifecycle types: mission-critical (e.g., defense-related); long lifespan (e.g., jet engine); short lifespan (e.g., medical application); low-criticality/commodity (e.g., tire)
- Potential lifecycle aspects to explore with exemplar products: tracking materials evolution over time; impact of the manufacturing process on component performance

C **Examples of exemplar products**—Examples of exemplar products or aspects of complete lifecycle performance:

- Automotive applications—Recyclable automotive parts/components in existing commercial applications, such as batteries; investigate other components including drivetrains, seats, computer systems, etc.
- Embedded medical sensing—Need for the ability to detect the onset of metal ion release around arthroplastic joint implants or conditions that promote infection or that indicate infection

KEY TASKS

A **Convene industry-centric project teams**—Identify 2-3 organizations—particularly those with a history of collaboration and data sharing—to partner on a pre-competitive effort; Include multiple types of industries

Exemplar products and processes for complete lifecycle improvement 0-2 YRS

KEY TASKS (CONT.)

B **Identify pre-competitive, high-value, low-TRL parts/components**—Keep initial focus on high-value parts/components that align with program interests of key funding agencies

- Focus on pre-competitive parts to permit longitudinal analysis across exemplars

C **Address data-sharing and protection practices**—Establish industry best practices or consortium guidelines that protect the privacy, ownership, and intellectual property of all parties (individuals, manufacturers, equipment and system providers, researchers, etc.) and allow for effective data sharing and integration across supply chains

MILESTONES

A Launch partnerships with 2-3 organizations (via public-private consortium) for each exemplar product

B Attain commitments to pursue 2-3 possible exemplars

C Map the lifecycles of candidate exemplars from product design through the in-use phase and end-of-life, and define the respective value propositions (and/or problem) of each exemplar

D Successful demonstration of an exemplar product; must holistically examine the complete lifecycle of each exemplar which span different lifecycle durations (i.e., years, decades) and levels of accessibility

Appendix C: List of Roadmap Contributors

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