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AN INTEGRATED FRAMEWORK FOR RAPID PRODUCT DESIGN AND MANUFACTURING

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1 Characteristics of A Successful High-Tech Enterprise in 2040

As we look ahead to 2040, the design and manufacturing firms that prioritize innovation, operational efficiency, and sustainability will succeed. However, achieving this balance would necessitate more than just the use of new technology; it would require a profound overhaul of how businesses operate, make decisions, and create value. These businesses will operate as digitally integrated systems, with physical operations closely linked to their digital equivalents. R&D investments will continue to be critical—not only for developing new tools but also for ensuring their integration into workflows in scalable, reliable, and secure ways.

Digital twins, Artificial Intelligence (AI), Machine Learning (ML), cyber-physical systems, and Additive Manufacturing (AM) are among the technologies that are already transforming the landscape [1]. Despite their promise, many of these systems are still developing. Current research emphasizes their promise, but widespread, seamless deployment across all industrial layers—particularly for real-time decision-making and autonomous control—is still a work in progress. Such capabilities are projected to become standard by 2040, but this shift will be strongly dependent on ongoing research, validation, and cross-sector collaboration.

By 2040, the availability of various data streams will significantly impact how high-tech companies innovate and operate. Whereas product and production process data were historically limited or compartmentalized, they are now recorded at every stage—from product design to in-situ monitoring during AM to post-process inspection and real-time feedback from deployed goods. As researchers continue to develop a wide range of machine-material-process parameter combinations, they generate large volumes of data that reflect intricate process-structure-property relationships [2,3]. Over the next 15 years, this expanding data ecosystem—spanning design, production, quality control, and usage—will power advanced data-driven tools for prediction, optimization, and uncertainty quantification. These skills will enable improved material development, more reliable process control, and faster design iteration. The combination of data availability and strong analytics will be key to fulfilling the full promise of AI, ML, and digital twins, driving the shift to adaptive, self-optimizing industrial systems that are efficient, secure, and innovation-driven.

Additionally, the cybersecurity risks connected with these technologies are ever-increasing, particularly for US firms operating in globally competitive and geopolitically sensitive markets [4]. As digital infrastructures grow, so does the attack surface [5]. Long-term resilience will require safeguarding private data, preserving interconnected assets, and developing cyber-resistant systems. Sustainability will also take center stage—not as a subsidiary goal but as a driving concept. Leading organizations will incorporate environmental responsibility into all stages of production, from design for reuse and remanufacturing to closed-loop material strategy. Firms that utilize predictive analytics and extensive market data will be able to anticipate client needs and adapt swiftly, offering highly tailored products while minimizing waste and environmental impact.

In the following sections, we briefly describe the key characteristics that will define these businesses, starting with how they foster collaboration between people and machines and progressing to digital mirroring, hybrid manufacturing, and other enabling capabilities critical to competitiveness in the coming decades.

1.1 Collaboration between people and machines

Leading companies will integrate human expertise with AI, ML, and autonomous robotics. This human-machine collaborative ecosystem, equipped with cognitive capabilities, will enable real-time decision-making, predictive maintenance, and continuous process optimization [6]. Human operators will interact naturally (i.e., by issuing instructions via voice or text) with smart machines while working alongside robots that can interpret commands and make autonomous decisions. Operating within adaptive cyber-physical environments, these intelligent systems will also learn in real-time, adjusting processes to optimize quality, energy consumption, and production parameters autonomously, thereby reducing defects and improving overall efficiency [7,8]. These ecosystems will ensure the safety of human-robot collaboration through real-time sensing, adaptive control, and safety-certified design, thereby protecting workers from potential hazards.

1.2 Digital systems that mirror the real world

Enterprises will utilize digital twins — virtual models of physical systems — to simulate and monitor products, machines, and production lines in real time. These will be linked through digital threads and Industrial Internet of Things (IIoT) platforms, enabling seamless data flow and lifecycle integration. Digital twins and digital threads are foundational building blocks of future enterprises [9,10]. Real-time sensor data will be leveraged not only for performance monitoring but also for predicting machine failures before they occur, enabling predictive maintenance, reducing downtime, and ensuring higher system reliability [7,9,10].

1.3 Hybrid and flexible manufacturing

Factories will combine AM with traditional subtractive and formative processes, integrating design flexibility with precision, high product quality, and material efficiency [10]. Reconfigurable manufacturing systems (RMS) will enable rapid switching between product variants, allowing for mass customization and high-mix, low-volume production [7]. This flexibility will enable them to respond more quickly to customer needs. This hybrid approach will be enhanced by digital platforms that coordinate process planning, toolpath generation, and real-time process control across diverse machines. AI-driven decision-making and data interoperability will allow seamless reconfiguration of production lines in response to design changes, material constraints, or demand fluctuations. Moreover, modular hardware and software architecture will facilitate plug-and-play manufacturing capabilities, accelerating the transition from prototype to production. All these capabilities will allow manufacturers to respond quickly to customer needs, optimize resource use, and maintain agility in volatile market conditions.

1.4 Sustainability and circular economy models

Future high-tech enterprises will embed sustainability at the core of their operations. Products will be designed for durability, resource efficiency, and end-of-life strategies, including repair, reuse, remanufacturing, and recycling [7]. Sustainable design practices will rely on energy-efficient processes and environmentally responsible materials [6]. Circular economy principles—such as closed-loop manufacturing, design for disassembly, and waste minimization—will be standard across the product lifecycle. These efforts will reduce environmental impact while improving material efficiency and regulatory compliance. A growing concern is the use of rare earth elements, which are essential to many advanced manufacturing applications but are often sourced through environmentally and geopolitically sensitive supply chains. For U.S. manufacturers, sustainable sourcing, recycling, and material-efficient design will be critical to reducing dependence on imports and ensuring long-term resilience.

1.5 Smart and resilient supply chains

The supply chain will be intelligent, distributed, resilient, and responsive. Manufacturers can gain real-time visibility, automate logistics, and respond quickly to disruptions or market shifts by integrating blockchain, sensor networks, and advanced analytics [8,10]. Businesses will be able to forecast delays, reroute materials, and change production plans before problems worsen, thanks to predictive tools and AI-powered planning. Importantly, technologies like blockchain will aid with traceability and trust, especially when it comes to confirming the origin of parts or monitoring environmental compliance. In a world where agility and transparency are more important than ever, such supply chain skills will give manufacturers a competitive advantage.

1.6 New business models

Instead of just selling products, companies will offer Product-as-a-Service (PaaS) solutions — such as equipment leasing, performance-based contracts, and remote diagnostics [10]. For example, instead of selling an engine, they might charge for engine usage and include ongoing support. This approach creates long-term relationships with customers. These business models will be supported by sensor-enabled products, cloud computing, and digital platforms that personalize services and scale quickly [7].

1.7 Digitally skilled workforce and agile organizations

Addressing the skills gap in intelligent manufacturing, the workforce will be trained in robotics, cybersecurity, data science, and systems integration [9,10]. Human-Machine Interfaces (HMI), Augmented Reality (AR), and Collaborative Robots (cobots) will enhance productivity. Organizations will be flatter, more agile, and driven by continuous learning and cross-disciplinary teamwork.

1.8 Cybersecurity and digital trust

As manufacturing systems become increasingly connected and reliant on real-time data, cybersecurity will be a crucial foundation for maintaining operational integrity, ensuring human safety, and ensuring business continuity. Future enterprises will need to protect not only their digital assets but also the physical systems linked to them. A proactive, multi-layered security approach will be necessary to protect intellectual property, prevent downtime, and maintain stakeholder confidence [11]. Prominent firms will implement advanced cybersecurity frameworks, such as real-time threat monitoring, secure cloud infrastructure, encryption protocols, and zero-trust architectures that verify access at all levels. In an evolving cybersecurity threat landscape where cyber-physical attacks can disrupt production and compromise confidential intellectual property and business information, developing digital trust is critical—not only for internal resilience but also for supply chain reliability and regulatory compliance [12]

In summary, the high-tech enterprise of 2040 will be distinguished by intelligent automation, seamless data integration, environmental responsibility, and innovative business models—all backed by a secure digital network and communication infrastructure, as well as a workforce capable of navigating and defending complex cyber-physical systems.

2 The Most Critical Challenge

The most pressing task for high-tech enterprises in 2040 will be to reduce the product development cycle for both end-user and industrial technologies. To stay competitive in a continuously changing global market, items must be designed and manufactured quickly while avoiding quality issues, enhancing usability, and reducing prices. With an increasing demand for mass customization, smart functionality, complex designs, and sustainable solutions, manufacturers must adopt advanced digital tools, such as AI-driven design, additive manufacturing, and cyber-physical systems, to enable agile, flexible, responsive, and efficient production [7–9,13].

3 Proposed Solution: An Integrated Framework for Product Design and Development Utilizing Generative AI, Additive Manufacturing, and Data-Driven Surrogate Models

The integration of generative AI, AM, and data-driven surrogate models enables the rapid design and manufacturing of products.

3.1 Key components of the proposed solution

The proposed framework combines three essential enablers: (a) generative AI, (b) AM, and (c) surrogate modeling for rapid and enhanced product design and development. Generative AI facilitates the generation of manufacturable designs based on functional requirements, AM enables the quick production of complex geometries, and surrogate models facilitate fast, data-driven performance evaluation and optimization. Continuous data sharing throughout the design, simulation, and production stages serves as the foundation for these capabilities. Due to the integration of operational and digital technologies, as well as the increased availability of data throughout the production ecosystem, cybersecurity has emerged as a key factor. Protecting sensitive design files, process parameters, and digital manufacturing assets from cyber threats is critical to ensuring the overall system's integrity, reliability, and resilience. Therefore, defending essential manufacturing assets is the fourth component of the proposed framework.

a) ***Generative AI***: Generative AI is an effective method for quickly generating various design possibilities within specified functional and geometric limits [14]. Aside from standard design inputs, generative AI models can leverage unstructured data sources, such as social media and customer feedback, to identify recurring challenges, user preferences, and desired product requirements and enhancements. By translating these insights into parametric design constraints, generative AI can automate the generation of CAD models tailored to evolving market requirements. This data-driven, AI-assisted process substantially reduces the product development cycle by minimizing human design cycles, enhancing responsiveness to customer requirements, and accelerating the transition from concept to manufacturable product.

b) ***Additive Manufacturing*****:** AM provides a faster and more efficient approach to product design and manufacturing of bespoke components [15]. Its intrinsic advantages, including geometric complexity, product customization, and multifunctionality, have led to widespread adoption in high-value industries such as medicine and aerospace. These sectors utilize AM to fabricate lightweight, patient-specific implants, topologically optimized structural components, and multifunctional assemblies with integrated features. Although AM technologies continue to evolve, current research and industrial trends indicate a clear trajectory toward their establishment as reliable "direct production" methods [10]. Continuous developments in process control, material research, and in-situ monitoring are addressing critical concerns like as repeatability, surface quality, and mechanical performance. Lattice formation, integration of functionally graded materials, and multi-material deposition are all techniques for creating structurally efficient and performance-optimized parts. As AM matures, it is expected to become a primary manufacturing paradigm for designing and producing high-performance, application-specific components with minimal material waste and lead time.

c) ***Surrogate models***: Data-driven surrogate models are used to predict system behavior when simulations or experiments are expensive [16]. Surrogate models offer a computationally efficient means to predict key product attributes, including material requirements, build time, mechanical properties, and geometric accuracy. By replacing expensive, high-fidelity simulations with fast approximations, they enable quicker design iterations, facilitate early-stage decision-making, and promote effective optimization. This reduces development time and expense while enabling rapid exploration of complex design domains.

d) ***Multi-layer defenses against cyber-physical attacks***. By 2040, high-tech businesses operating in increasingly networked and automated environments will require multi-layer cyber-physical countermeasures against the growing cybersecurity threat [4]. Effective protection should begin with a complete vulnerability assessment that identifies flaws in network communication systems, communication protocols, digital design tools, machine firmware, quality control and assurance systems, and personnel [17]. Additionally, risk assessment models, such as those based on graph theory and cyber-physical threat and countermeasure taxonomies, can aid in quantifying how attacks compromise physical and digital assets and their associated impact on the system, allowing defenses to be prioritized [5]. Mitigation solutions should include preventive measures, such as encrypted design files, authenticated firmware, and digital watermarks, with advanced attack detection mechanisms. Physics-informed and sensor-based monitoring can provide real-time detection of malicious system deviations. Additionally, existing quality control approaches must be improved to detect cyber-physical attacks. A robust defense architecture must integrate secure design approaches, real-time monitoring, dynamic risk models, and cybersecurity-aware workforce training to ensure operational integrity, product quality, and data confidentiality in future manufacturing ecosystems.

3.2 Proposed conceptual integrated framework for rapid product development

3.2.1 Rationale for the integrated framework

Currently, generative tools often operate independently of manufacturing processes, and surrogate models do not actively guide design iterations. Generative AI's ability to generate design alternatives supports AM's intrinsic design freedom by allowing for the manufacture of complex geometries that are often impossible to produce using traditional manufacturing processes. Integrating generative AI and AM creates new opportunities for design exploration, particularly in early-stage product development. The integration of surrogate models within the framework will further enhance responsiveness in product development. Surrogate models provide feedback on process, quality, and performance predictions to guide AI-generated design decisions. This integration supports design for AM (DfAM) and manufacture-aware optimization, producing novel, functional, manufacturable, and cost-effective parts and products.

3.2.2 Proposed framework

A conceptual framework of product development utilizing generative AI, AM, and surrogate-based performance evaluators is presented in Figure 1. The generative AI model will be trained using AM manufacturable designs (e.g., 3D CAD models or parametric feature trees), design constraints for AM manufacturability (e.g., minimum feature sizes and support structures), and product requirements (e.g., functional and geometric). The model will accept as input either 3D conceptual designs for new product development or existing product designs targeted for improvement (e.g., weight reduction or dimensional modification) and generate AM-ready 3D designs. Notably, the generated designs may vary depending on specific product requirements. For instance, the incorporation of different lattice structures, material deposition patterns for multi-material components, or geometric dimensions—demonstrates the model's capacity to adapt design outputs based on varying functional requirements.

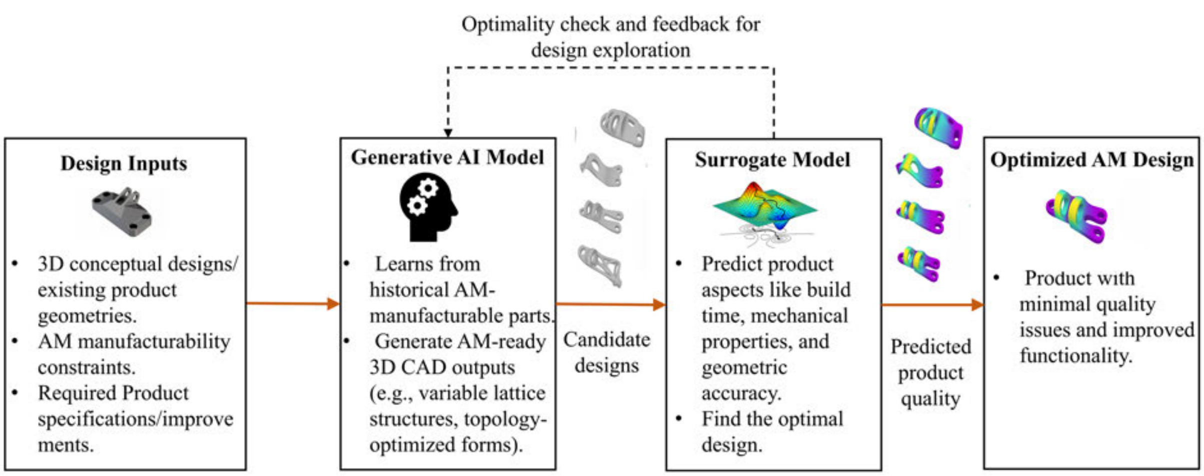

Figure 1 The proposed integrated framework for rapid product design and development

The surrogate model, on the other hand, will input the candidate 3D geometries generated by the generative AI model and predict the product characteristics (e.g., geometric accuracy, build time, mechanical properties). Based on these predictions, the surrogate model will identify optimal designs that minimize build time and quality-related issues. Furthermore, if integrated within a closed-loop framework, the surrogate model can provide feedback to the generative model, indicating regions within the design space where additional variation or exploration is required to improve design quality or performance.

While integrating generative AI, AM, and surrogate modeling facilitates rapid product development, it also introduces cyber-physical risks throughout the digital design and manufacturing workflow. As sensitive design data, predictive models, and machine instructions pass across the manufacturing ecosystem, the system becomes more vulnerable to data breaches, production disruption, malicious alterations, and sabotage. To mitigate these threats, cybersecurity must be integrated as an overarching layer of the framework, starting with vulnerability assessments to identify flaws in software, hardware, data, and network interfaces. This should be followed by a thorough risk assessment and prioritizing of essential assets, including proprietary design models and machine-specific process parameters. Based on estimated risk, targeted countermeasures—such as secure data handling protocols, access control mechanisms, and anomaly detection systems—must be established and implemented to protect the confidentiality, integrity, availability, safety, and resilience of the whole product development and manufacturing process.

4 What Needs to Be Done Today to Meet This Challenge?

The following steps should be taken to design and manufacture better quality, functionally superior products faster via integration of generative AI, AM, and surrogate models:

4.1 Development of generative AI Tools for 3D models

Generative AI has the potential to revolutionize early-stage design by converting textual or visual inputs into 3D geometry [18]. However, its current output is mainly limited to mesh or voxel-based models, which lack parametric structure, feature definitions, and tolerance annotations critical for downstream CAD/CAM applications. Existing works such as DeepCAD and ShapeAssembly offer promising starting points but do not yet support full design intent transfer or editable solid modeling for industrial use [19,20]. For proper integration into engineering workflows, generative AI tools must incorporate function-driven constraints, design standards, AM manufacturability constraints, and editable parametric entities. Domain-specific generative AI tools capable of producing constraint-compliant, parametric CAD geometries enriched with tolerance and manufacturing features need to be developed.

4.2 Advancement of AM technologies

AM offers exceptional design freedom but continues to face barriers related to repeatability, material consistency, process robustness, and scalability. Key issues such as porosity, residual stress, and dimensional inaccuracy vary with process parameters, material batches, and build orientation [21]. Post-processing steps—such as heat treatment and surface finishing—are often required to meet performance standards, increasing lead time and cost. To address these limitations, hybrid manufacturing, in-situ monitoring, and process-aware design approaches (e.g., DfAM) are being developed to improve quality and reduce reliance on trial-and-error methods. Predictive control systems are also emerging to minimize post-processing needs and enhance reliability. However, interoperability across AM platforms remains a challenge, and scaling production requires standardized material-process-property databases and integrated real-time control and certification mechanisms to ensure repeatable part quality.

4.3 Development of surrogate models for design and process simulation

Surrogate models can drastically reduce computational costs in design space exploration and accelerate optimization; however, their development is hindered by data scarcity, model generalization issues, and computational overhead associated with multi-objective and multi-output predictions [22]. Most current models rely heavily on simulation data, which can be expensive and limited in coverage. Developing surrogate models to predict the influence of varying AM part geometries on part quality requires a significant amount of data, given the flexibility of AM design, and thus, is expensive. Techniques such as multi-fidelity modeling, transfer learning, and physics-informed machine learning show promise in extrapolating beyond seen data while preserving physical validity but are not yet mainstream. Scalable pipelines must be established to generate, manage, and reuse simulation and experimental datasets for training robust, generalizable, and computationally efficient surrogate models.

4.4 Seamless integration of generative AI, AM, and surrogate models

A coherent product design framework must ensure bi-directional communication between generative AI design tools, AM manufacturability constraints (e.g., build orientation, support structure minimization, overhangs), product design and performance requirements, and surrogate-driven evaluations [23]. Generative AI tools and surrogate models are inherently data-driven; their performance and accuracy improve significantly with access to large, diverse, and high-quality datasets. Similarly, the effective utilization of AM technologies relies on comprehensive knowledge of AM materials, process parameters, potential quality issues, and design constraints related to manufacturability. To support future development, it is essential to begin compiling structured datasets that capture these aspects. Data interoperability is also critical, as translating complex AM design rules and product performance requirements into formats suitable for automated tools remains a challenge. In particular, conveying AM-specific manufacturability constraints and quality criteria to AI systems requires a deeper understanding of the relationships between design intent, manufacturing feasibility, and quality assurance. Advancing this integration will require standardized data formats and formal frameworks that bridge human expertise with machine interpretation.

4.5 Workforce training and development of human-in-the-loop frameworks

To utilize these advanced technologies, there is a growing need for engineers and designers who can develop and interact with AI-driven tools, interpret data-driven insights, and integrate them into practical product design workflow. Current training programs lack sufficient emphasis on AI literacy, data analytics, and integrated digital manufacturing. Furthermore, human-in-the-loop frameworks, which are crucial for safety, creativity, and accountability, are not yet integrated into most generative AI-driven design platforms. Interdisciplinary training programs and toolkits focused on AI-assisted design, digital manufacturing, and decision-support systems should be launched to prepare the workforce for human-machine collaborative product design.

4.6 Cybersecurity awareness and preparedness against cyber-physical attacks

Cybersecurity training programs should be integrated into workforce development to address personnel-related vulnerabilities, as recent industry reports have identified security awareness as one of the most effective countermeasures against manufacturing cyberattacks [24]. Behavioral biometric authentication and AI-driven phishing detection can further reduce insider threats and social engineering risks [25]. For inspection vulnerabilities, potential mitigation strategies include (1) implementing adaptive QC strategies, i.e., introducing randomness to the design and implementation of QC tools, (2) selecting appropriate QC tools, (3) verifying the underlying statistical assumptions before implementation, (4) monitoring security-aware alternate KQCs, and (5) introducing part and product specific tags/signature during production for improved visibility and traceability [26]. To enhance data integrity and traceability, blockchain technology provides a tamper-proof, decentralized security framework for manufacturing data [27]. Blockchain-based version control can also ensure the integrity of digital files (e.g., CAD files), process logs, and inspection records by preventing unauthorized changes. Smart contracts can automate authentication and protect digital files [28], while watermarking techniques incorporate security features into CAD models to prevent intellectual property theft and reverse engineering [29]. Additionally, Intrusion Detection Systems (IDS) can be deployed to detect unauthorized data access, misuse, and alterations by monitoring malicious user behavior, system activity, and network traffic [30].

5 Conclusion

In 2040, a high-tech enterprise will be defined by its agility, innovation, and ability to continuously enhance both workforce and technology while excelling in productivity, market intelligence, and precision product development. These capabilities will be enabled by advanced automation in production and material handling, as well as the pervasive use of data across all phases of product design, quality control, market prediction, and customer service. Cybersecurity, sustainability, and workforce training will underpin these operations. A significant challenge will be the rapid identification of product or technological needs, as well as the ability to design and manufacture high-quality products with minimal waste in shorter timeframes. To address this, an integrated framework is proposed that combines generative AI, AM, surrogate modeling, and cybersecurity to accelerate product design and manufacturing. Effective application of this framework will require focused advancements in generative design tools, AM process maturity, scalable and physics-informed surrogate models, integrated cybersecurity, and interdisciplinary workforce development.

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