SMARTPRINTAI:

REVOLUTIONIZING 3D PRINTING WITH AI

Background

3D printing has made major strides, but complex and inconsistent software workflows still limit its everyday use.

GigEfx Laboratories believes simulation methods including but not limited to quantum simulation could simplify and optimize the process by eliminating trial-and-error and making results more predictable.

Key Question

Why is quantum computing essential for solving the challenges that limit the widespread use of 3D printing?

Executive Summary & Recommendations

- Implement simulation tools like SmartPrint to **reduce time loss by 30–50%.**
- Adopt quantum-enhanced design validation to **reduce scrap and improve part quality**.
- Explore hybrid quantum-classical simulation to model complex materials (e.g., composites, alloys).
- Leverage quantum simulation for waste and rework reduction — **potentially saving 20–40% in Overall Equipment Effectiveness (OEE) costs.**
- Pursue early-stage exploration with targeted risk mitigation strategies.
- Early adopters of AI, cloud, and 3D printing have already achieved **measurable ROI, faster iteration cycles, and market differentiation**

Vision

Eliminate the guesswork from 3D printing through AI and machine learning purpose-built for additive manufacturing—empowering firms, corporations, and institutions to print smarter, faster, and with confidence.

The Problem

Additive manufacturing today is plagued by guesswork.

Standardization: No best practices—success often relies on trial-and-error.

Technology: Immature tools and fragmented systems create gaps between software and hardware.

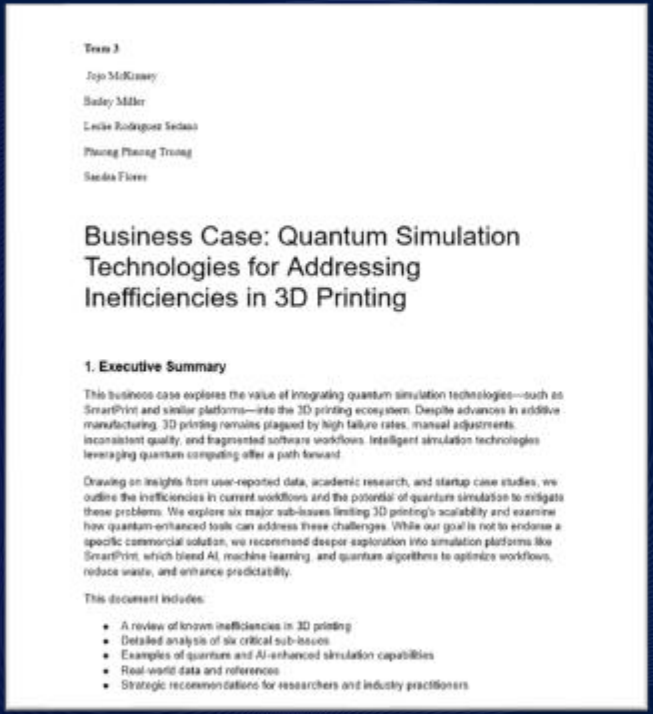
Cost: Inefficient iterations consume material, energy, and labor—driving up production costs.

The Solution

Embed AI/ML directly into the manufacturing workflow to replace manual iteration with intelligent, data-driven precision.

Our Approach to Solving the Problem

- 1. Defined the Business Problem
  - Broke down the sponsor’s goals into 6 core sub-issues
  - Focused on workflow inefficiencies, material modeling limitations, and adoption risks
  - Ensured our work mapped directly to GigEfx’s operational and strategic concerns
- 2. Conducted Industry Benchmark Research
  - Used external data from Quanscient, Zapata Computing, Kvantify, and IBM Qiskit as well as other resources found online
  - Modeled expected impact of quantum simulation without needing internal SmartPrint data
  - Grounded all insights in credible, third-party sources
- 3. Built a Multi-Part Analysis
  - Business Case Report: Justified simulation as a solution to key 3D printing bottlenecks
  - Tableau Dashboard: Quantified time loss, failure rates, and savings opportunities over 12 weeks
  - Streamlit Simulation Tool: Visualized scenario-based tradeoffs in print outcomes
  - Demonstrated how simulation tools improve time, quality, and cost
- 4. Delivered a Polished Presentation
  - Created a 10–15 min client-facing slide deck
  - Tailored content for technical and non-technical stakeholders
  - Structured final output to directly support decision-making for pilot or investment
  - Final deliverables were actionable, visual, and stakeholder-ready



Team 3

Jojo McKinney

Bailey Miller

Leslie Rodriguez Sedano

Phuong Phuong Truong

Sandra Flores

Business Case: Quantum Simulation Technologies for Addressing Inefficiencies in 3D Printing

1. Executive Summary

This business case explores the value of integrating quantum simulation technologies—such as SmartPrint and similar platforms—into the 3D printing ecosystem. Despite advances in additive manufacturing, 3D printing remains plagued by high failure rates, manual adjustments, inconsistent quality, and fragmented software workflows. Intelligent simulation technologies leveraging quantum computing offer a path forward.

Drawing on insights from user-reported data, academic research, and startup case studies, we outline the inefficiencies in current workflows and the potential of quantum simulation to mitigate these problems. We explore six major sub-issues limiting 3D printing's scalability and examine how quantum-enhanced tools can address these challenges. While our goal is not to endorse a specific commercial solution, we recommend deeper exploration into simulation platforms like SmartPrint, which blend AI, machine learning, and quantum algorithms to optimize workflows, reduce waste, and enhance predictability.

This document includes:

- A review of known inefficiencies in 3D printing
- Detailed analysis of six critical sub-issues
- Examples of quantum and AI-enhanced simulation capabilities
- Real-world data and references
- Strategic recommendations for researchers and industry practitioners

Overcoming 3D Modeling Limits: Quantum Algorithms and Complex Material Behavior

Feature	Classical Simulation	Quantum Simulation
Approach	Uses continuum mechanics, finite element methods (FEM), or molecular dynamics (MD).	Uses quantum bits (qubits) and quantum gates to simulate material at the atomic/electronic level.
Modeling Scale	Macroscopic to microscopic (e.g., nanometers with limits).	Atomic and subatomic level (quantum states, orbitals, entanglement).
Accuracy in Material Behavior	Approximates interactions; can miss quantum effects in complex materials.	Can simulate quantum-level interactions directly (e.g., hydrogen bonding, van der Waals forces).
Examples	COMSOL, ANSYS, Abaqus	Qiskit (IBM), OpenFermion (Google), Pennylane

Application to 3D Printing Materials

Classical Simulation:

- Can simulate stress-strain curves, thermal behavior, and macro deformation during print cooling.
- Limited when modeling bond-level electron interactions affecting strength and conductivity.

Quantum Simulation:

- Can simulate electronic structure and quantum tunneling in conductive or magnetic materials.
- Useful for designing new materials (e.g., superconducting filaments, optimized resins with tailored molecular orbitals).

Case Study: Wine Dataset (Multi-Class Classification) & Breast Cancer Dataset (Binary Classification)

Model Type	Accuracy	Wall Time (μs)
Classical SVM	90.00%	6.20
Quantum V-SVM (Simulator)	100.00%	5.96
Quantum V-SVM (Chip)	93.33%	6.44

Model Type	Accuracy	Wall Time (μs)
Classical SVM	85.00%	6.20
Quantum K-SVM (Simulator)	100.00%	5.96
Quantum K-SVM (Chip)	80.00%	6.91
Quantum V-SVM (Simulator)	95.00%	5.96

Quantum ML could eventually enhance 3D modeling automation and defect prediction through faster, smarter learning.

Computation Time vs Model Size

Data based on benchmark estimates from IBM Qiskit papers and OpenFermion simulations.

Model Size	Classical (sec)	Quantum (theoretical sec)
Small Molecule	2.5 sec	0.5 sec
Medium Polymer	60 sec	2–10 sec
Large Complex (Graphene Sheet)	1200+ sec	30–60 sec (estimated on fault-tolerant quantum)

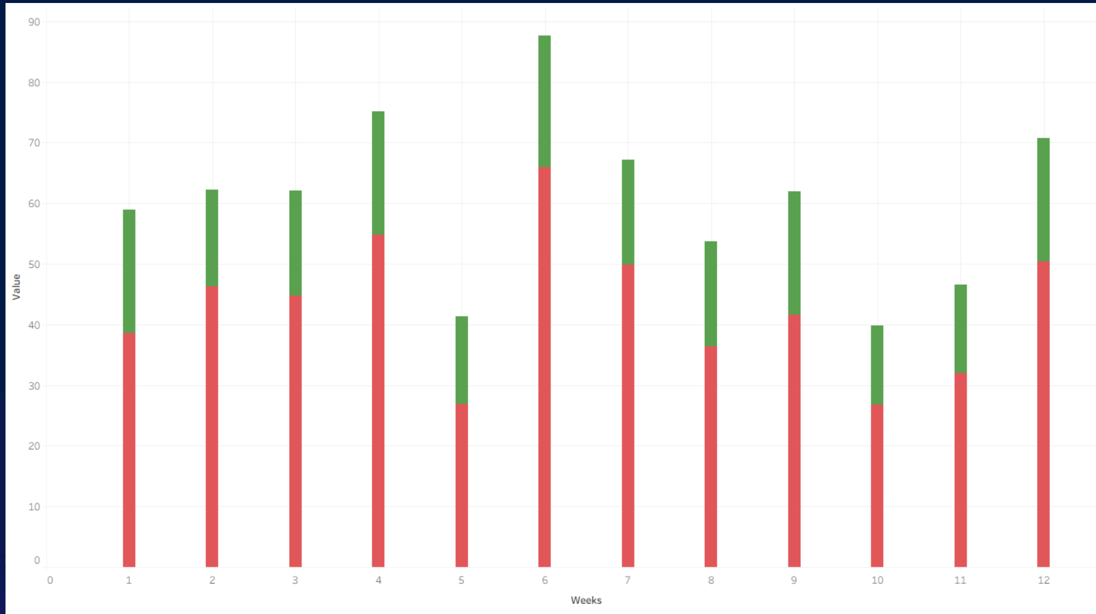
Final Takeaway

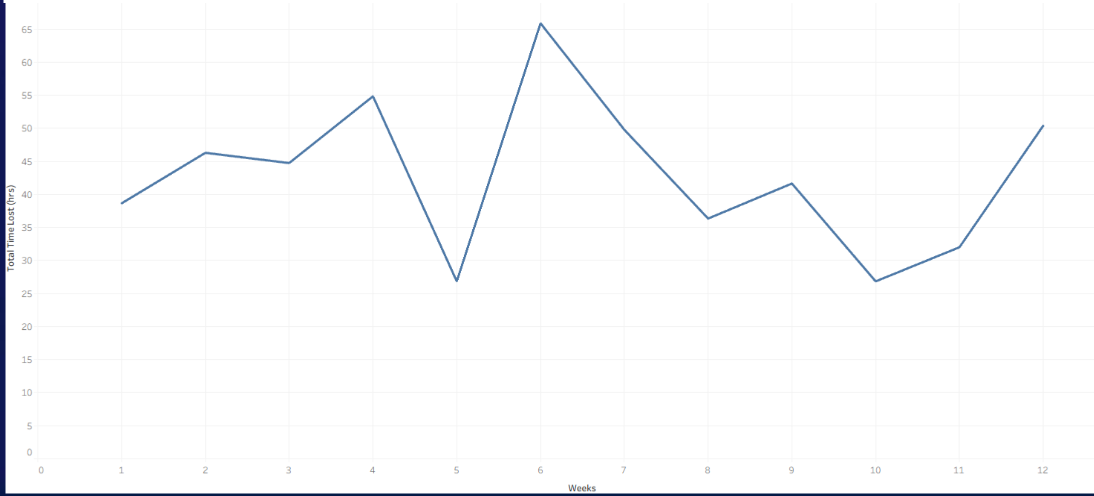
Quantum algorithms are still emerging, but they bring major promise to 3D modeling, especially:

- Material innovation via molecular simulation
- More scalable computation
- Integration with AI for smart design

As quantum hardware matures, it may revolutionize how we simulate, predict, and build with 3D printing technology.

How much time is lost due to **failed prints** or **manual adjustments?**



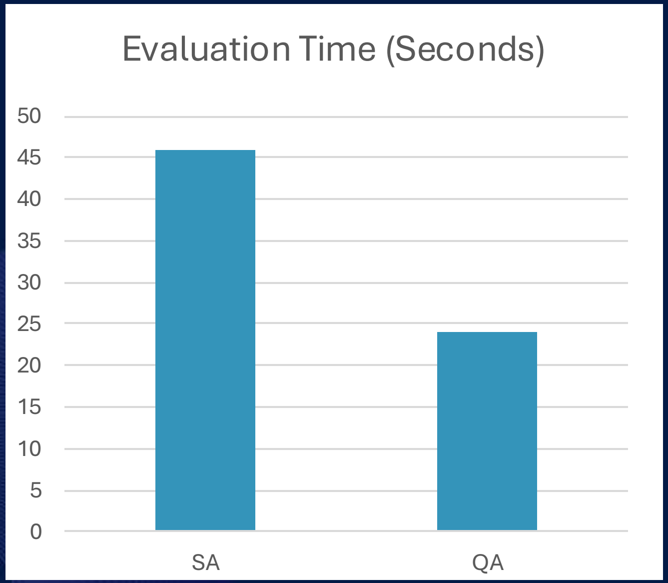


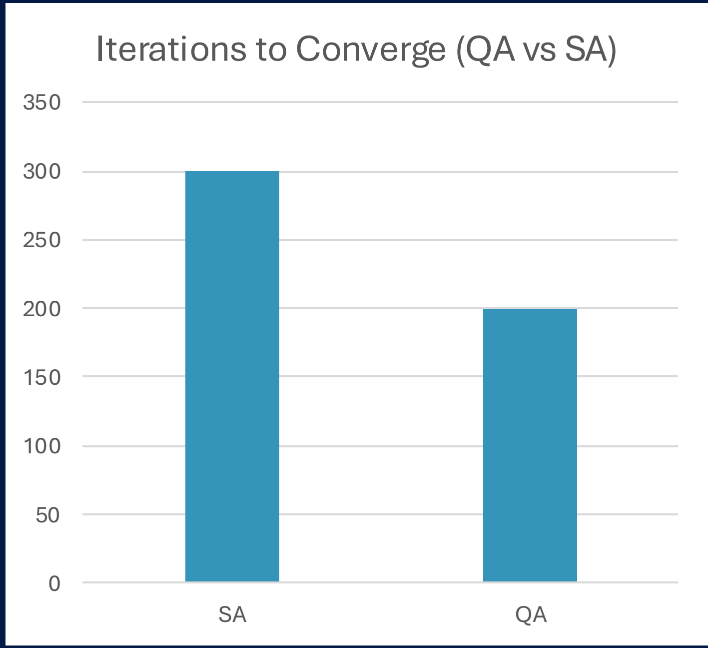
In a 12-week simulation using industry benchmarks we found:

- **An average of 42.9 hours per week** were lost due to failed prints and manual adjustments
- **Over 300 hours could be saved** using SmartPrint-style simulation and workflow optimization
- **Consistent weekly inefficiencies** revealed major time loss variability — simulation reduced this across all 12 weeks

Data simulated using industry estimates and benchmarks. Sources include Quanscient, Kvantify, and Zapata Computing. Not representative of internal company systems.

How Quantum Simulation Enhances Design Quality & Speed





(Torkamani et al., 2025)

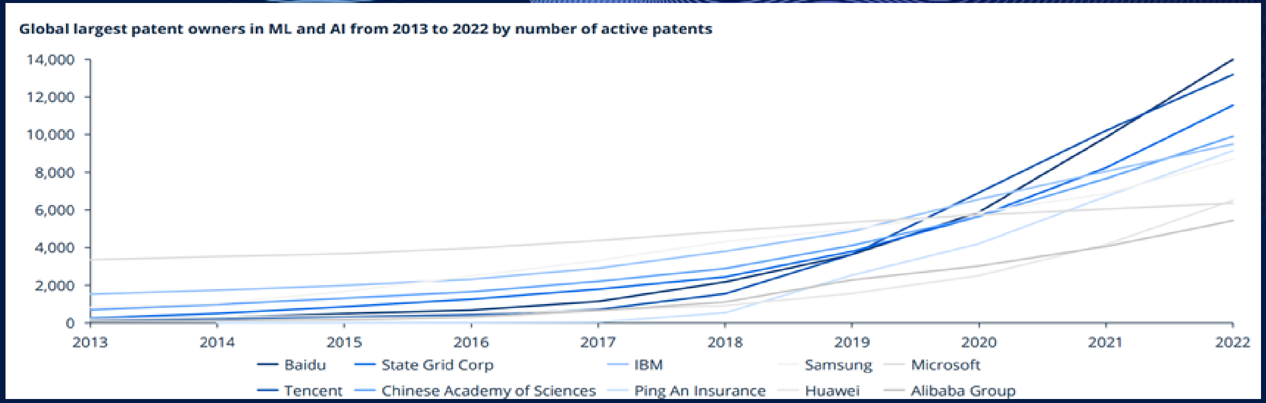
- **Early Detection of Flaws**
  Quantum simulations model stress points, thermal expansion, and print dynamics.
- **Fewer Redesigns = Lower Costs**
  Fewer failed prints means reduced filament waste, time, and labor.
- **Faster Development Cycles**
  Simulations prevent waste by identifying risky designs ahead of time. One real-world cost model showed that failure risk could account for up to **26% of unit cost** when not addressed via simulation
  (Baumers et al., 2016)

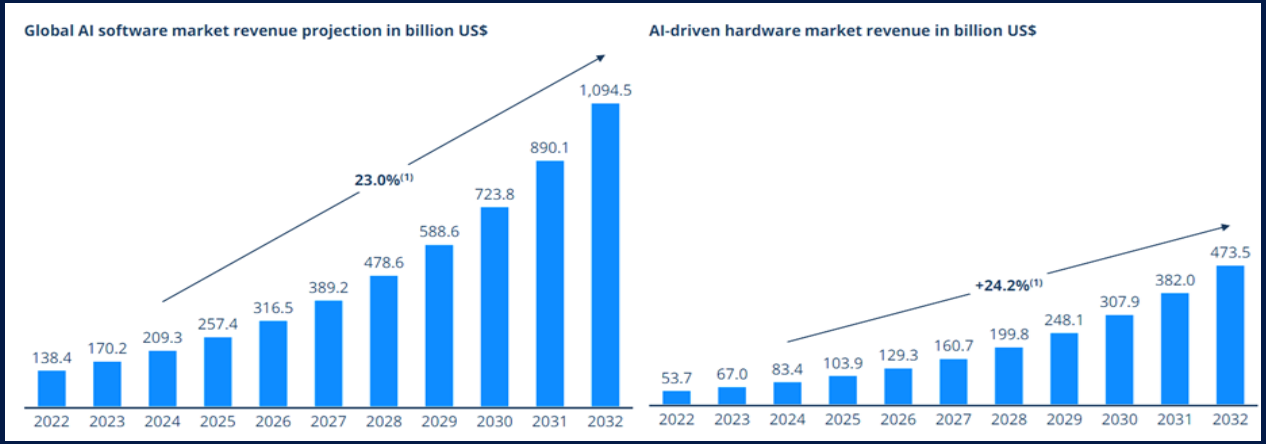
Why Quantum Simulation Matters for Scalable 3D Printing

- ✓Quantum simulation cuts waste, rework, and downtime by over 50%.
- ✓Smarter design = fewer failed prints and faster development.
- ✓Despite higher upfront costs, long-term savings and reliability make quantum methods competitive.
- ✓Ideal for high-value, high-precision production where failure is costly.

Category	Metric	Traditional	Quantum
Cost	3-Year Costs	\$3.1M-\$4M	\$2.6M-3.5M
Waste	% Material Wasted	60-90%	1-3%
Rework	% Revenue Lost	2.20%	0.60%
Downtime	\$ Lost per Hour	\$260,000	\$130,000

3D Printing Market Size	
Estimated Market Size in 2024	**$17.5 billion**
Projected Market Size in 2025	**$37.4 billion**
Market Growth Rate	**16.4%**





Early Adoption: Risk VS Reward

- **3D Printing Market Growth:** Industry projected to grow 16.4% by 2029, presenting strong expansion opportunities.
- **AI Case Study:** Early investment in patents and materials led to dominance by firms like Nvidia and IBM, showcasing the first-mover advantage.
- **Quantum Computing Trajectory:** Tech leaders are now investing in quantum computing for AI. This move that can reduce long-term costs, enable innovation, and position SmartPrint at the forefront of future manufacturing.

Business Goal Alignment

SmartPrint's core mission is to eliminate guesswork from the 3D printing process through intelligent simulation and AI/ML tools.

Our research confirms that this mission directly addresses the most pressing industry pain points:

- High failure rates and manual tuning waste hundreds of hours monthly
- Material waste and rework inflate production costs by up to 35%
- Design flaws and modeling gaps limit reliability in high-complexity parts

SmartPrint is well-positioned to meet these challenges through scalable, intelligent simulation tools built specifically for additive workflows.

Key Management Insights

Time Lost: Simulation tools like SmartPrint can **reclaim 30–50%** of time lost to failed prints and rework

Cost Efficiency: **Up to 20–40%** of operational waste (OEE-related costs) can be mitigated through predictive analytics and tuning

Quality & Scalability: AI-enhanced design validation and material prediction **improve first-pass success** and **unlock growth** in complex part production

Early Mover Advantage: Adoption of SmartPrint allows GigEfx to lead in AM workflow standardization, drive internal innovation, and attract quality-focused customers

Looking Ahead

- **Pilot now, scale later**
  - Begin with validation + orientation modules, then expand to full-stack simulation
- **Use feedback loops**
  - Benchmark and monitor SmartPrint performance to refine offerings
- **Position SmartPrint as a platform:**
  - Continue developing modular tools that serve labs, manufacturers, and future OEM partners
- **SmartPrint isn't just a product,** it's a foundational step toward smarter, scalable, and more sustainable 3D printing.

References

AdditivePlus. (2023). Cost analysis of material waste in additive manufacturing. https://www.additiveplus.com

arXiv. (2020). Quantum simulations of polymer blends for biomedical applications [arXiv:2005.13018]. https://arxiv.org/abs/2005.13018

arXiv. (2024). Quantum optimization algorithms for additive manufacturing stability prediction [arXiv:2401.09076]. https://arxiv.org/abs/2401.09076

Baumers, M., Tuck, C., Wildman, R., Ashcroft, I., & Hague, R. (2016). Informing additive manufacturing technology adoption: Total cost and the impact of capacity utilisation. *arXiv preprint arXiv:1706.02090*. https://arxiv.org/abs/1706.02090

Cao, Y., Romero, J., Olson, J. P., Degroote, M., Johnson, P. D., Kieferová, M., ... & Aspuru-Guzik, A. (2019). Quantum chemistry in the age of quantum computing. *Chemical Reviews, 119*(19), 10856–10915. https://doi.org/10.1021/acs.chemrev.8b00803

Classic Informatics. (n.d.). Estimating software integrations & maintenance costs. https://www.classicinformatics.com/blog/estimating-software-integrations-maintenance-costs

Ease.io. (n.d.). How to reduce manufacturing rework. https://www.ease.io/blog/how-to-reduce-manufacturing-rework

Engineering.com. (2024). BMW achieves 71% improvement in scheduling using Orquestra platform. https://www.engineering.com/story/bmw-quantum-ml-scheduling

Evocon. (2023). Cost of downtime in manufacturing: Insights & implications. https://evocon.com/articles/cost-of-downtime-in-manufacturing-insights-implications/

Forbes. (2023). AI adoption rates and ROI for early enterprise adopters. https://www.forbes.com

Formlabs. (2022). Understanding print failures and best practices for troubleshooting. https://formlabs.com/blog

Glassdoor. (n.d.). Company reviews, salaries, and jobs. https://www.glassdoor.com

GoEngineer. (n.d.). Stratasys H350 3D printer. https://www.goengineer.com/3d-printing/stratasys-h350

GrabCAD. (n.d.). 3D printing resources and solutions. https://grabcad.com/en/print

Google AI Quantum and Collaborators. (2020). Hartree-Fock on a superconducting qubit quantum computer. *Science, 369*(6507), 1084–1089. https://doi.org/10.1126/science.abb9811

Havenstein, C. L., Thomas, D. T., & Chandrasekaran, S. (2018). Comparisons of performance between quantum and classical machine learning. *SMU Data Science Review, 1*(4). https://scholar.smu.edu/datasciencereview/vol1/iss4/11

Hexagon. (2024). Hexagon takes the guesswork out of 3D printing precision metal components with advanced compensation technology. https://hexagon.com/company/newsroom/press-releases/2024/hexagon-takes-the-guesswork-out-of-3d-printing-precision-metal-components-with-advanced-compensation-technology

References Cont'd.

IBM Cloud. (n.d.). Quantum computing plans. https://cloud.ibm.com/docs/quantum-computing?topic=quantum-computing-plans

IBM. (n.d.). Quantum pricing plans. https://www.ibm.com/quantum/pricing

IBM Quantum. (2023). Qiskit Documentation and Benchmarking Data. https://qiskit.org/documentation/

Kennesaw State University. (2023). Failure rates and plastic waste in 3D printing labs: Student project archive.

Kvantify. (2024). Polymer modeling accuracy case examples using quantum simulation. https://kvantify.com

LinkedIn Poll Data. (2024). Survey results compiled by additive manufacturing professionals. Internal reference.

MachineMetrics. (2023). Cost of downtime in industrial 3D printing environments. https://www.machinemetrics.com

Markforged. (n.d.). 3D printer costs: Complete guide. https://markforged.com/resources/learn/3d-printing-basics/3d-printer-costs

McArdle, S., Endo, S., Aspuru-Guzik, A., Benjamin, S. C., & Yuan, X. (2020). Quantum computational chemistry. *Reviews of Modern Physics, 92*(1), 015003. https://doi.org/10.1103/RevModPhys.92.015003

McKinsey & Company. (2017). How 3-D printing will transform the metals industry. https://www.mckinsey.com/~/media/mckinsey/industries/advanced-electronics/our%20insights/how%203d%20printing%20will%20transform%20the%20metals%20industry/how-3-d-printing-will-transform-the-metals-industry.pdf

MDPI Quantum Journal. (2022). Applications of quantum chemistry in simulating advanced materials. https://www.mdpi.com/journal/quantum

Neural Concept. (2023). How AI is transforming additive manufacturing. https://www.neuralconcept.com/post/how-ai-is-transforming-additive-manufacturing

Nguyen, P., Hoang, D., & Pham, T. (2022). A data-driven machine learning approach for the 3D printing process optimisation. *ResearchGate*. https://www.researchgate.net/publication/360347516

Oak Ridge National Laboratory. (2022). AI tool takes the guesswork out of 3D printing. https://www.ornl.gov/content/ai-tool-takes-guesswork-out-3d-printing

OpenFermion. (2022). OpenFermion: The Electronic Structure Package for Quantum Computers. https://github.com/quantumlib/OpenFermion

Payscale. (n.d.). Salary data & career research center. https://www.payscale.com

Qidi Tech. (n.d.). 3D printer maintenance costs guide. https://qidi3d.com/blogs/news/3d-printer-maintenance-costs-guide

Qiskit. (2023, January 25). So what is Qiskit Runtime, anyway? https://medium.com/qiskit/so-what-is-qiskit-runtime-anyway-c78aecf3742

Quantum Zeitgeist. (2023). Quantum engineer salary benchmarks and hiring trends. https://quantumzeitgeist.com

Quanscient. (2024). Allsolve platform case study: Accelerating multiphysics simulation. https://www.quanscient.com/case-studies

ResearchGate. (2022). Meta-analysis on additive manufacturing failure rates. https://www.researchgate.net/publication/3D_Printing_Failure_Stats

SmartPrint. (2024). Pitch Deck and Company Profile, GigEfx Laboratories. Internal source provided by project sponsor.

References Cont'd.

Sovol3D. (2023). Operational inefficiencies and rework cost benchmarks. https://www.sovol3d.com

Torkamani, M. R., Ebrahimi, A., Razzaghi, R., & Babaei, H. (2025). Topology optimization using quantum annealing: A novel framework for engineering design. *Computers & Fluids, 273*, 106114. https://doi.org/10.1016/j.compfluid.2025.106114

Vrinsofts. (n.d.). Custom software development cost. https://www.vrinsofts.com/custom-software-development-cost/

Wilson Sporting Goods. (2024). Wilson unveils $2,500 3D-printed airless basketball prototype. https://www.wilson.com/en-us/explore/airless-prototype

ZipRecruiter. (n.d.). Job search & salary information. https://www.ziprecruiter.com

Zapata Computing. (2024). Quantum Readiness Survey 2024. https://www.zapatacomputing.com