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## Preview of Award 2211841 - Annual Project Report

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## Cover

Federal Agency and Organization Element to Which Report is Submitted: 4900

Federal Award or Other Identifying Number Assigned by Agency: 2211841

Project Title: FET: Medium: A Quantum Computing Based Approach to Undirected Generative Machine Learning Models

PD/PI Name: Yaroslav Koshka, Principal Investigator  
Joseph Picone, Co-Principal Investigator

Recipient Organization: Mississippi State University

Project/Grant Period: 10/01/2022 - 09/30/2027

Reporting Period: 10/01/2025 - 09/30/2026

Submitting Official (if other than PD/PI): Yaroslav Koshka  
Principal Investigator

Submission Date: 09/23/2026

Signature of Submitting Official (signature shall be submitted in accordance with agency specific instructions) Yaroslav Koshka

## Accomplishments

### \* What are the major goals of the project?

This project has two overarching goals pursued throughout its duration: first, to explore the fundamental nature of the claimed quantum annealing behavior and confirm that a wide range of configuration spaces (Markov Random Fields trained with diverse, application-relevant data) can find difficult-to-locate local valleys; and second, to apply this behavior to Deep Graphical Models to achieve superior classification and pattern reconstruction accuracy.

### \* What was accomplished under these goals and objectives (you must provide information for at least one of the 4 categories below)?

Major Activities:

- Use D-Wave to generate diverse and representative samples from RBM probability distribution.
- Train RBM using hybrid training algorithm based on D-Wave sampling.
- MSU and Temple continued identifying and preparing most promising contemporary ML datasets and using the developed hybrid quantum-classical algorithm for RBM training with contemporary ML datasets.

Additionally, the following activities, lead by the Temple group, aimed at deepening our understanding of the quantum advantage in QML:

- (1) development of a theorem that predicts when quantum machine learning will produce an improvement in performance over classical methods,
- (2) a comprehensive, controlled evaluation of quantum machine learning (QML) methods for classification of classical data, and
- (3) the development of a testbench that allows users to understand and diagnose performance issues for quantum machine learning based applications.

Specific Objectives: Objective 1: confirm the behavior of the D-Wave for graphs and datasets that are more complex than those explored in the pre-proposal work.

Task 4 (continued) – Analyze Computational Efficiency

Objective 2: develop a hybrid classical quantum (HCQ) sampling algorithm for RBM training

Task 4 (continued) – Develop the Training Algorithm for DBM

Objective 3: Apply quantum annealing computer to contemporary machine learning problems.

Task 1 (completed) – Train RBMs and DBMs on Popular Simple Benchmark Datasets Using HCQ Sampling

Task 2 (completed) – Diagnostic Experiments on Simulated 2D Datasets

Task 3 (initiated) – Adjustments to Algorithms and Optimization of Training Schedules:

Task 4 (initiated) – Experiments on Complex Real World Data.

The following objectives were pursued in support of the main objectives of the project, aiming at deepening our understanding of the potential for quantum advantage in QML. The Temple's team played the leadership role in those.

One of the most frustrating parts of QML research is the number of conflicting publications on whether there is an advantage to QML for classical non-quantum-entangled datasets. Our goal with the development of our theorem was to bring a systematic structure to these conflicting results and to definitely determine when QML can provide an advantage.

We also are at a stage in this project in which we wanted to generate comprehensive comparisons of QML to traditional ML on two realistic applications (EEG and digital pathology) for which we have an extensive inventory of experimental results. We now have a much better understanding of how these applications could benefit from QML.

In keeping with the Outreach component of this project, we also planned and executed a workshop on QML that introduced participants to the underlying theory and practice of applying QML to real world data.

#### Significant Results:

Objective 1: confirm the behavior of the D-Wave for graphs and datasets that are more complex than those explored in the pre-proposal work.

Task 4 (continued) – Analyze Computational Efficiency

The analysis of the computational efficiency primarily included comparison to the classical Montecarlo-based sampling (MCMC).

One property that makes the quantum annealing (QA) potentially attractive in the long term is the speed of obtaining samples; 1,000 or 10,000 solutions can be generated from a single D-Wave call almost instantaneously. In contrast, the standard Gibbs sampling and MCMC methods in general may require many burn-in (thermalization) steps before a reliable sample can be reached. However, quantifying the per-sample speeds (for both MCMC and QA) is not a trivial task that remains ongoing.

Given the expectation of sampling speed advantage of the D-Wave over the MCMC, even with modest improvement in the sample quality, or even with no improvements, QA could still yield significant benefits due to the sampling speed.

The scalability analysis is ongoing. While the number of qubits is significantly larger (and continues to grow) in Pegasus lattice of the hardware used in this work, compared to the previous versions, the increase in the connectivity between qubits is more modest. If, as expected, the connectivity in the hardware scales slower than the number of qubits, the increase in the number of the logical units in problems to be solved on the D-Wave must rely primarily on chaining more qubits than in the previous studies that were using earlier versions of the hardware (chaining means combining multiple qubits to represent one logical unit). This may lead to a degradation in the quality of embedding, especially for RBM. While the larger quantum processing unit allowed for embedding more practical models in this work, the quality of embedding in this work was inferior (as was also reported in the previous period). Efforts to improve the quality of embedding using weight decay, the use of the weight scaling factor, auto scaling, and other methods are ongoing. Those methods unavoidably lead to the slower convergence during the RBM training, which should be accounted for in analyzing the computational efficiency.

Objective 2: develop a hybrid classical quantum (HCQ) sampling algorithm for RBM training

Task 4 (continued) – Develop the Training Algorithm for DBM

As was expected, the newest generation hardware does not provide enough qubits to allow embedding some of the full graphs of the deep architectures – the multi-layer graph simultaneously. This year, the proposed embedding procedure was developed to embed only pairs of the neighboring layers at a time. The proposed approach to a layer-by-layer sampling using the quantum hardware has been implemented. DBM training experiments are nearing completion by the end of this year.

Objective 3: Apply quantum annealing computer to contemporary machine learning problems.

Task 1 (completed) – Train RBMs and DBMs on Popular Simple Benchmark Datasets Using HCQ Sampling

As was mentioned in the previous report, in the previous reporting period, a particular problem known as catastrophic forgetting (CF) has been identified as a promising candidate for benefiting from the identified statistical differences between the QA-based and the classical samples. A number of training protocols for classical algorithms are known to be used for mitigating CF.

This year a training protocol for a QA-based RBM training and CF mitigation following the approach known as a generative replay, to explore the abovementioned statistical differences has been developed. The OptDigits handwritten digits dataset was used as a simple benchmark dataset, within the scope of the plan for this task.

QA-generated patterns of desirable classes were successfully used for the generative replay. The use of QA in CF mitigation was implemented successfully and effectively eliminated forgetting. This result is encouraging, since this is the first known to the authors attempt to use the D-Wave QA for CF mitigation and one of the few instances of using the D-Wave as a generative model to produce samples from specific classes of interest in generative ML. Further, the performance of the D-Wave-based mitigation of the CF was at least as good as that of the mitigation utilizing classical MCMC.

We concluded that the developed CF mitigation protocol used for the QA-based and the classical mitigation was not challenging enough for the classical training, thereby not leaving enough difficulties in generating states from difficult-to-reach regions of the configuration space. The work in this direction continues.

It is important to note that the D-Wave generates patterns much faster than the classical method. This may prove to be an advantage for larger RBMs (as well as other ML architectures) for which generation using MCMC becomes computationally intensive. If the D-Wave's hardware scales sufficiently to accommodate these larger model sizes, the time advantage (even without the performance advantage) may be decisive. This is particularly promising when considered in the context of real-time training (e.g., a continuous flow of internet traffic) where the ability of the QA to generate a large sample belonging to a particular class nearly instantaneously may be both crucial and unique.

Of course, the work under this task focused on a critical, but only one, aspect of the CF mitigation: the possibility of an efficient generation of a suitable sample from the RBM model probability distribution.

A journal manuscript based on those results has been submitted to Quantum Information Processing.

Task 2 (completed) – Diagnostic Experiments on Simulated 2D Datasets

Task 3 (initiated) – Adjustments to Algorithms and Optimization of Training Schedules:

Task 4 (initiated) – Experiments on Complex Real World Data

The following results have been obtained in support of Task 2-4 of the Objective 3, as well as to deepen our understanding of the broader potential for quantum advantage in QML.

This project established a theoretical and empirical framework for identifying when quantum machine learning (QML) can provide a genuine structural advantage over optimized classical machine-learning methods. The work addresses a fundamental limitation in current QML research: quantum feature maps are frequently selected heuristically, and apparent quantum advantages can disappear when models are compared with carefully optimized classical baselines. Initial experiments demonstrated that conventional quantum support vector machines (QSVMs) generally fail to provide sustained advantages on standard classical datasets, motivating the development of a more rigorous approach to identifying task-relevant quantum structure.

A principal result of the project is the development of the Entangled Information Capacity framework, which combines centered kernel-target alignment with measures of physical quantum non-locality, including CHSH violations and Rényi-2 entanglement entropy. The resulting criterion provides a dataset-specific measure of whether a quantum feature space simultaneously contains non-classical correlations and useful class-separation information. The project established a theoretical criterion under which quantum kernel methods can possess a structural advantage over an optimized classical RBF kernel. The analysis also produced a generalization-error result showing that, under the proposed capacity condition, the quantum model has a tighter asymptotic generalization-error bound than the corresponding classical model.

#### Key outcomes or Other achievements:

To the best of our knowledge, the results achieved under Objective 3, Task 1 represent the first successful instance of using QA as a generative model for mitigating CF during continual learning of RBMs and, actually, the first instance of using QA for CF mitigation in generative ML.

The development of a tool to predict a QML advantage is a major step forward for QML research and technology development. HilbertBench is also a significant step in explainable AI (xAI) since it allows users to easily diagnose performance issues in QML systems.

The framework was empirically evaluated using 14 synthetic and benchmark datasets spanning conventional nonlinear classification problems, statistical distributions, and

quantum-generated or quantum-hardened datasets. Seven quantum feature maps were evaluated against optimized classical RBF kernels. The experiments showed three distinct regimes: datasets for which quantum feature maps provide a measurable advantage, datasets for which quantum representations are competitive but provide no necessary information beyond classical methods, and datasets for which classical methods remain superior. For example, on generated quantum data, the QSVM achieved 95.85% accuracy compared with 79.90% for the classical SVM, with the improvement reported as statistically significant at the 99% confidence level. Similar behavior was observed on the IBM Ad Hoc dataset. Conversely, on datasets such as overlapping Gaussian distributions, UCI Breast Cancer, and Set-13, the optimized classical kernel generally remained superior unless the quantum representation satisfied the proposed structural criterion.

Scaling experiments further demonstrated that the proposed capacity measure is a useful a priori diagnostic for quantum advantage. Across training-set sizes ranging from tens to 10,000 samples, the theoretical criterion generally became more reliable as the sample size increased, consistent with the expected convergence of kernel-target alignment. The experiments also showed that computing the proposed capacity metric is substantially less expensive than performing full QSVM training, whose Gram-matrix computation grows quadratically with the number of training samples. This establishes the potential for using the framework as a screening mechanism to determine whether a dataset warrants the substantially greater computational cost of quantum processing.

The project also converted the theoretical framework into a trainable algorithm, Entangled Information Capacity-driven Quantum Kernel Optimization (CQKO). Rather than relying on a fixed, heuristic quantum feature map, the algorithm directly optimizes the quantum circuit to increase both task-specific kernel alignment and non-local entanglement. Comparative experiments against both an optimized classical RBF-SVM and a conventional QSVM using a static ZZFeatureMap demonstrated statistically significant improvements on several nonlinear datasets. In particular, the optimized model achieved 67.97% accuracy on Set-10 versus 67.48% for the classical RBF model and 67.70% for the static quantum model, while on Set-13 it achieved 79.45% versus 78.64% for the classical baseline and 71.90% for the static quantum model. The statistical testing used paired McNemar tests, with significant improvements identified at the 95% confidence level.

A second algorithm, Anchor-Based Entanglement-Driven Classification (AB-EDC), addressed the computational scaling limitations of exact quantum kernels. Instead of constructing a full Gram matrix, AB-EDC represents each class using a small number of anchor states and performs classification using quantum fidelity and entanglement-weighted similarity. This reduces the computational footprint from the full quadratic kernel representation to a sub-quadratic formulation, enabling application to substantially larger datasets. Experimental results demonstrated that AB-EDC retained the benefits of the optimized quantum representation while substantially reducing computational requirements. On the challenging Set-13 dataset, AB-EDC achieved 78.18% accuracy, compared with 71.13% for the static quantum model and 78.28% for the classical RBF model. Although the absolute accuracy was essentially comparable to the classical baseline, the optimized quantum representation achieved a CKTA of 0.6357, substantially exceeding the reported classical capacity threshold of 0.308, demonstrating that the learned quantum representation contained substantially greater task-aligned structure even under the anchor approximation.

Collectively, these results establish a methodology for moving QML research away from heuristic claims of quantum advantage toward quantitative, dataset-specific evaluation of when quantum resources are actually useful. The work demonstrates that entanglement alone is not sufficient: useful quantum representations must combine non-classical correlations with task-relevant information about the target labels. The

resulting framework provides both a theoretical criterion and practical optimization algorithms for identifying and constructing such representations.

A secondary activity was the development and execution of a reproducible benchmark comparing three QML approaches: (1) quantum support vector machines (QSVM), (2) quantum neural networks (QNN), and (3) quantum restricted Boltzmann machines (QRBMs). The study evaluated eight two-dimensional benchmark datasets designed to isolate different geometric and classification challenges. More than 23,000 quantum-model configurations were evaluated while systematically varying quantum feature maps, circuit depth, ansatz layers, entanglement topology, and training-set size. Matched classical baselines were evaluated under the same data conditions to provide an apples-to-apples comparison.

We extended the benchmark to two biomedical applications: EEG-based seizure detection and high-resolution digital pathology cancer segmentation. In both applications, the quantum classifier was incorporated as a replacement for the final classification stage of an established deep-learning pipeline, allowing the project to evaluate whether QML provided additional benefit when applied to learned biomedical representations.

The team also performed systematic ablation and computational analyses to identify the factors that influence QML performance. These analyses examined the relationship between training-set size and accuracy, the effects of alternative feature maps and circuit depths, the role of entanglement topology, and the computational scaling of different QML approaches. Particular attention was given to identifying whether quantum models benefited from specific structural properties of the data rather than simply from increased model complexity.

Finally, the project synthesized the experimental results into a framework for identifying when quantum machine learning is likely to provide a practical benefit. The results motivated the development of data-dependent screening measures that could be used to determine whether a dataset contains structure that is potentially exploitable by quantum models before substantial computational resources are invested in QML training. This work provides a foundation for future research on predictive measures of quantum learning advantage.

A third major finding was that HilbertBench was shown to be a useful tool for diagnosing problems with QML system. HilbertBench is an open-source diagnostic framework for variational QML. A transparent proxy records circuit executions at the estimator/device boundary into sealed, append-only, tamper-evident traces, without altering the run. Integrations cover Qiskit and PennyLane, and the instrument was frozen at v1.0.0 and archived with a DOI.

### **\* What opportunities for training and professional development has the project provided?**

The Temple's team hosted our first training workshop in Summer 2026 at Temple university. This workshop was held in collaboration with the IEEE Philadelphia Section and Temple University's Office of the Vice President for Research. We originally planned this to be an in-person hands-on workshop in which participants would learn how to run an actual quantum machine learning experiment. However, we had overwhelming demand for remote participation, so we opened the workshop to on-line participants. We had 35 in-person participants and 251 total registrants.

The workshop was structured into three morning lectures introducing the basic theory starting with an overview of machine learning, continuing with the basics of quantum computing and ending with how to apply these concepts to a standard machine learning experiment. The afternoon session was structured into two labs driven from Python notebooks that demonstrated the basic concepts, introduced participants to how to run quantum machine learning experiments using software simulators, and concluding with participants running an actual experiment on an IBM quantum computer.

This one-day workshop is fairly unique in that it quickly brought participants up to speed by carefully condensing a vast amount of literature into the essential points needed to understand machine learning applications. Other comparable workshops often run for weeks. Feedback was very positive. Participants were very excited that within one day they were running actual experiments on a quantum computer, and that they left the workshop with a set of working scripts that could be easily modified to run additional experiments on their own data.

**\* Have the results been disseminated to communities of interest? If so, please provide details.**

Our primary means of distribution is through publication. All publications are publicly available (Dols have been provided in this report). Conference materials are available from the conference web site. Dissertation-related materials, such as the PhD proposal document and defense, are available from the web site also. Publications under development are also available in preliminary form from our web site as well.

Software is available from a GitHub site as well as from our organization’s web site. Our machine learning demo is directly runnable from the web site, though users can also download the code and run the system locally.

URLs for these resources have been provided elsewhere in the report.

**\* What do you plan to do during the next reporting period to accomplish the goals?**

We concluded that the catastrophic forgetting (CF) protocol and the CF mitigation protocol developed for the QA-based and the classical algorithms was not challenging enough for the classical training, thereby not leaving enough challenge for generating states from difficult-to-reach regions of the configuration space. Nevertheless, we developed greater confidence that CF is uniquely suited for exploring benefits from the identified statistical differences between the QA-based and the classical samples. In the next year, we plan to implement an improved training-forgetting-mitigation protocol.

The next phase of the project on Objective 3 will extend the developed methods from synthetic benchmarks to high-dimensional biomedical applications, including continuous EEG seizure detection and breast-cancer analysis in digital pathology whole-slide images.

With respect to Objective 3, we are focused on two things: (1) publication of our results in first-tier journals, and (2) refinement of our results on our two biomedical databases. Regarding (1), two conference papers have been submitted this year. Three journal papers are underdevelopment and expected to be submitted by the end of the 2026 calendar year. One PhD student will also complete her PhD students and defend her dissertation. Regarding (2), we are still exploring engineering optimization of the EEG and digital pathology systems, focusing mainly on quantum feature mapping and back-end quantum ML algorithms. We believe our current approaches, which can be best described as a hybrid approach, can be improved through joint optimizations of these processes.

**Supporting Files**

| Filename                                | Description                                                                                                                                              | Uploaded By     | Uploaded On |
|-----------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------|-------------|
| fig_01.pdf                              | Figure 1. The eight two-dimensional geometric benchmark datasets. Color is used to encode the binary class label.                                        | Joseph Picone   | 09/20/2026  |
| fig_02.pdf                              | Table 1. Best test accuracy (%) per dataset for the 8 pilot datasets                                                                                     | Joseph Picone   | 09/20/2026  |
| Fig CF_mitigation (QIP submissioni).pdf | Figure 2. The Catastrophic Forgetting (CF) mitigation experiments, showing the classification error at the end of each task of the Task-IL RBM learning. | Yaroslav Koshka | 09/22/2026  |

**Products**

**Books**

## Book Chapters

D. Hackel, M. Bagritsevich, C. Dumitrescu, Md. A. Al Mamun, S. A. Purba, D. Heathcote, I. Obeid, and J. Picone (2026). Enabling Microsegmentation: Digital Pathology Corpora for Advanced Model Development. *Signal Processing in Medicine and Biology: Applications of Artificial Intelligence in Medicine and Biology 1*. 1. A. Ahmed and J. Picone. Springer. New York, New York, USA. 1. Status = PUBLISHED; Acknowledgement of Federal Support = Yes ; Peer Reviewed = Yes ; DOI: 10.1007/978-3-032-18509-9\_6.

Dmitry Alexandrov, Claudia Dumitrescu, Sadia Purba, Anna Chau and Joseph Picone (2026). Channel Efficiency in ECG-Based Multi-Label Cardiac Diagnosis. *Signal Processing in Medicine and Biology: Applications of Artificial Intelligence in Medicine and Biology 1*. 1. A. Ahmed and J. Picone. Springer. New York, New York, USA. 1. Status = PUBLISHED; Acknowledgement of Federal Support = Yes ; Peer Reviewed = Yes ; DOI: 10.1007/978-3-032-18509-9\_4.

Thundiyl, Saneesh Picone, Joseph (2025). Time Series Analysis from Classical Methods to Transformer-Based Approaches: A Review. *Machine Learning Applications in Medicine and Biology 1*. 1. Ahmed, Ammar Picone, Joseph. Springer. New York, New York, USA. 1. Status = PUBLISHED; Acknowledgement of Federal Support = Yes ; Peer Reviewed = Yes ; DOI: 10.1007/978-3-031-88024-7.

## Inventions

### Journals or Juried Conference Papers

View all journal articles and conference papers currently available in the [NSF Public Access Repository](#) for this award.

The results in the NSF Public Access Repository will include a comprehensive listing of all journal articles and conference papers recorded to date that are associated with this award.

El-Yazizi, Abdelmoula and Koshka, Yaroslav. (2026). Comparison of D-Wave Quantum Annealing and Gibbs Monte Carlo for Sampling from a Probability Distribution of a Restricted Boltzmann Machine. *Entropy*. 28 (8) 925. Status = Added in NSF-PAR [PAR ID: 10715050](#)

Federal Government's License = Acknowledged. (Completed by Koshka, Yaroslav on 09/21/2026 ) [Full text](#) [Citation details](#)

A. El-Yazizi, Y Koshka, "Investigation of D-Wave quantum annealing for training Restricted Boltzmann Machines and mitigating catastrophic forgetting, " submitted to Quantum Information Processing, arXiv preprint arXiv:2508.15697.. Status = UNDER\_REVIEW.

Purba, S., Al Mamun, Md. A., Obeid, Iyad, & Picone, J. (2026). No Quantum Advantage Without Structure: A Controlled Benchmark of Quantum Machine Learning on Classical Data. Proceedings of the IEEE Signal Processing in Medicine and Biology Symposium (SPMB), 11.  
[http://www.isip.piconepress.com/publications/unpublished/conferences/2026/ieee\\_spmb/qml\\_benchmarks](http://www.isip.piconepress.com/publications/unpublished/conferences/2026/ieee_spmb/qml_benchmarks). Status = UNDER\_REVIEW.

Al Mamun, Md. A., Purba, S., Obeid, Iyad, & Gro, J. (2026). Parameter-Efficient Fine-Tuning of Pathology Foundation Models for Microsegmentation of Breast Whole-Slide Images in Digital Pathology. Proceedings of the IEEE Signal Processing in Medicine and Biology Symposium (SPMB), 7.  
[http://www.isip.piconepress.com/publications/unpublished/conferences/2026/ieee\\_spmb/fine\\_tuning](http://www.isip.piconepress.com/publications/unpublished/conferences/2026/ieee_spmb/fine_tuning). Status = UNDER\_REVIEW.

## Licenses

### Other Conference Presentations / Papers

Picone, J. (2025). *Is There a Quantum Advantage for Machine Learning?*. Temple University Quantum Information Science and Technology (QIST) Symposium. Temple University, Philadelphia, PA 19122. Status = PUBLISHED; Acknowledgement of Federal Support = Yes

H. Q. Nguyen, X. B. Nguyen, S. Pandey, K. Luu, I. Safro, and S. U. Khan (2025). *QMoE: A Quantum Mixture of Experts Framework for Scalable Quantum Neural Networks*. IEEE International Conference on Quantum Computing and Engineering. Albuquerque, NM. Status = PUBLISHED; Acknowledgement of Federal Support = Yes

A El Yazizi, S Khan, Y Koshka (2025). *Utilizing Differences in the Sampling Efficiency of the Quantum Annealer and the Classical Sampling for Mitigating Catastrophic Forgetting in Training Undirected Probabilistic Graphical Models*. APS March Meeting, Anaheim, CA. Status = PUBLISHED; Acknowledgement of Federal Support = Yes

Other Products

View all datasets currently available in the [NSF Public Access Repository](#) for this award.

The results in the NSF Public Access Repository will include a comprehensive listing of all datasets recorded to date that are associated with this award.

Software or Netware <https://github.com/mamuncseru/hilbertbench> *HilbertBench is a non-intrusive diagnostic framework for evaluating scientific claims in quantum machine learning.*

Software or Netware <https://isip.piconepress.com/projects/imld/> *The ISIP Machine Learning Demo is is an educational tool that allows user to learn about machine learning by visualization of data, decision surfaces, and algorithm results. Its principal features include: (1) a step-by-step visualization of the components of an algorithm including decision surfaces; uploading and downloading of user-defined data, making it ideal for use as a reference implementation; (2) a Python v3 implementation that runs on Windows, Linux and Mac. IMLD began as a Java applet developed in the late 1990's. The most recent version runs in a client/server framework. To run the application, hit "run" on the menu bar on the upper right. IMLD now contains several quantum machine learning algorithms and includes several computationally efficient modes so that realistic experiments can be performed.*

View all workshop reports currently available in the [NSF Public Access Repository](#) for this award.

The results in the NSF Public Access Repository will include a comprehensive listing of all workshop report publications recorded to date that are associated with this award.

Other Publications

Patent Applications

Technologies or Techniques

Thesis/Dissertations

Abdelmoula El Yazizi. *Using Quantum Annealing for Sampling and Pattern Generation in Generative Machine Learning and Catastrophic Forgetting Mitigation*. (2025). Mississippi State University. Acknowledgement of Federal Support = Yes

Websites or Other Internet Sites

IEEE Quantum Machine Learning Workshop (IEEE QMLW)  
[https://isip.piconepress.com/conferences/ieee\\_qmlw/2026/](https://isip.piconepress.com/conferences/ieee_qmlw/2026/)

We hosted a one-day workshop in which we trained participants on how to implement machine learning systems using quantum computing. We had 251 registered participants (in-person participation was limited to 40). All conference materials, including videos, presentation slides and lab materials (Python notebooks) are available from the conference web site.

Participants/Organizations

What individuals have worked on the project?

| Name                    | Most Senior Project Role              | Nearest Person Month Worked |
|-------------------------|---------------------------------------|-----------------------------|
| Mohammadi-Aragh, Mahnas | PD/PI                                 | 1                           |
| Picone, Joseph          | Co PD/PI                              | 2                           |
| Koshka, Yaroslav        | Co-Investigator                       | 2                           |
| Al Mamun, Md Abdullah   | Graduate Student (research assistant) | 3                           |

| Name                  | Most Senior Project Role              | Nearest Person Month Worked |
|-----------------------|---------------------------------------|-----------------------------|
| Babaei, Mahdi         | Graduate Student (research assistant) | 6                           |
| El Yazizi, Abdelmoula | Graduate Student (research assistant) | 6                           |
| Purba, Sadia          | Graduate Student (research assistant) | 12                          |
| Seifi, Somayeh        | Graduate Student (research assistant) | 12                          |
| Beligalage, Thisumi   | Undergraduate Student                 | 1                           |
| Bolshak, Dmitry       | Undergraduate Student                 | 1                           |
| Del Cura, Jara        | Undergraduate Student                 | 1                           |
| Dewidar, Mennah       | Undergraduate Student                 | 1                           |
| Frazer, Korey         | Undergraduate Student                 | 1                           |
| Heathcote, Dylan      | Undergraduate Student                 | 1                           |
| Kamana, Hemanth       | Undergraduate Student                 | 1                           |
| Meng, Phuykong        | Undergraduate Student                 | 1                           |
| Raab, Lucaa           | Undergraduate Student                 | 2                           |
| Ramos-Leiva, Brian    | Undergraduate Student                 | 2                           |
| Roxas, Erielle        | Undergraduate Student                 | 1                           |

#### Full details of individuals who have worked on the project:

**Mahnas J Mohammadi-Aragh**

**Email:** jean@ece.msstate.edu

**Most Senior Project Role:** PD/PI

**Nearest Person Month Worked:** 1

**Contribution to the Project:** Dr. Mohammadi-Aragh has served as the Substitute PI in place of the original PI Yaroslav Koshka, while he worked as an IPA PD for NSF. Currently, she assumed the role of the substitute negotiator during Dr. Koshka's "cool-down" period with NSF.

**Funding Support:** None

**Change in active other support:** Yes

**International Collaboration:** No

**International Travel:** No

**Joseph Picone**

**Email:** joseph.picone@gmail.com

**Most Senior Project Role:** Co PD/PI  
**Nearest Person Month Worked:** 2

**Contribution to the Project:** Applications of quantum computing to machine learning

**Funding Support:** None

**Change in active other support:** No

**International Collaboration:** No

**International Travel:** No

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**Yaroslav Koshka**

**Email:** ykoshka@ece.msstate.edu

**Most Senior Project Role:** Co-Investigator

**Nearest Person Month Worked:** 2

**Contribution to the Project:** Provided technical contribution and supervised GRAs under Independent Research and Development (IRD) while serving as NSF IPA. Resumed the role of the PI in Summer 2026.

**Funding Support:** None

**International Collaboration:** No

**International Travel:** No

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**Md Abdullah Al Mamun**

**Email:** abdullah18@temple.edu

**Most Senior Project Role:** Graduate Student (research assistant)

**Nearest Person Month Worked:** 3

**Contribution to the Project:** Quantum computing diagnostic tools and application development

**Funding Support:** None

**International Collaboration:** No

**International Travel:** No

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**Mahdi Babaei**

**Email:** mahdi.babaei@temple.edu

**Most Senior Project Role:** Graduate Student (research assistant)

**Nearest Person Month Worked:** 6

**Contribution to the Project:** Development of machine learning algorithms that are conducive to implementation on a quantum computer; benchmarking these algorithms on standard tasks.

**Funding Support:** None

**International Collaboration:** No

**International Travel:** No

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**Abdelmoula El Yazizi**

**Email:** ae897@msstate.edu

**Most Senior Project Role:** Graduate Student (research assistant)

**Nearest Person Month Worked:** 6

**Contribution to the Project:** quantum computing implementations of machine learning

**Funding Support:** None

**International Collaboration:** No

**International Travel:** No

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**Sadia Purba**

**Email:** tut44757@temple.edu

**Most Senior Project Role:** Graduate Student (research assistant)

**Nearest Person Month Worked:** 12

**Contribution to the Project:** research into new machine learning algorithms that support quantum computing

**Funding Support:** None

**International Collaboration:** No

**International Travel:** No

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**Somayeh Seifi**

**Email:** somayeh.seifi1361@gmail.com

**Most Senior Project Role:** Graduate Student (research assistant)

**Nearest Person Month Worked:** 12

**Contribution to the Project:** machine learning algorithms

**Funding Support:** None

**International Collaboration:** No

**International Travel:** No

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**Thisumi Beligalage**

**Email:** thisumi.beligalage@temple.edu

**Most Senior Project Role:** Undergraduate Student

**Nearest Person Month Worked:** 1

**Contribution to the Project:** Database development and error analysis.

**Funding Support:** None

**International Collaboration:** No

**International Travel:** No

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**Dmitry Bolshak**

**Email:** dmytro.bolshak@temple.edu

**Most Senior Project Role:** Undergraduate Student

**Nearest Person Month Worked:** 1

**Contribution to the Project:** Machine learning algorithm developer; quantum computing software facilitator

**Funding Support:** None

**International Collaboration:** No

**International Travel:** No

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**Jara Del Cura****Email:** jara.del.cura@temple.edu**Most Senior Project Role:** Undergraduate Student**Nearest Person Month Worked:** 1**Contribution to the Project:** Software development, quality control and release management.**Funding Support:** None**International Collaboration:** No**International Travel:** No

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**Mennah Dewidar****Email:** mennah.dewidar@temple.edu**Most Senior Project Role:** Undergraduate Student**Nearest Person Month Worked:** 1**Contribution to the Project:** Software development, quality control and release management.**Funding Support:** None**International Collaboration:** No**International Travel:** No

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**Korey Frazer****Email:** korey.m.frazer@temple.edu**Most Senior Project Role:** Undergraduate Student**Nearest Person Month Worked:** 1**Contribution to the Project:** Computer systems administration, software tools maintenance, algorithm run-time optimization**Funding Support:** None**International Collaboration:** No**International Travel:** No

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**Dylan Heathcote****Email:** dylan.heathcote@temple.edu**Most Senior Project Role:** Undergraduate Student**Nearest Person Month Worked:** 1**Contribution to the Project:** Machine learning software developer and quantum computing software facilitator**Funding Support:** None**International Collaboration:** No**International Travel:** No

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**Hemanth Kamana****Email:** tuo73589@temple.edu**Most Senior Project Role:** Undergraduate Student**Nearest Person Month Worked:** 1**Contribution to the Project:** software support for using quantum computers

**Funding Support:** None

**International Collaboration:** No

**International Travel:** No

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**Phuykong Meng**

**Email:** phuykong.meng@temple.edu

**Most Senior Project Role:** Undergraduate Student

**Nearest Person Month Worked:** 1

**Contribution to the Project:** Software developer responsible for learning how to run jobs and program the DWAVE and IBM quantum computers.

**Funding Support:** None

**International Collaboration:** No

**International Travel:** No

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**Lucaa Raab**

**Email:** lucas.raab@temple.edu

**Most Senior Project Role:** Undergraduate Student

**Nearest Person Month Worked:** 2

**Contribution to the Project:** Computer systems administration and lead developer on optimizing algorithm efficiency

**Funding Support:** None

**International Collaboration:** No

**International Travel:** No

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**Brian Ramos-Leiva**

**Email:** tup86891@temple.edu

**Most Senior Project Role:** Undergraduate Student

**Nearest Person Month Worked:** 2

**Contribution to the Project:** software support for the development of machine learning simulations; quantum computing software development on the DWAVE system

**Funding Support:** None

**International Collaboration:** No

**International Travel:** No

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**Erielle Roxas****Email:** erielle.roxas@temple.edu**Most Senior Project Role:** Undergraduate Student**Nearest Person Month Worked:** 1**Contribution to the Project:** Computer systems administration, software tools maintenance, algorithm run-time optimization**Funding Support:** None**International Collaboration:** No**International Travel:** No

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**What other organizations have been involved as partners?**

Nothing to report.

**Were other collaborators or contacts involved? If so, please provide details.**

Nothing to report

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## Impacts

**What is the impact on the development of the principal discipline(s) of the project?**

The theorem developed by the Temple's team to predict whether quantum machine learning (QML) can provide a benefit on specific data is a fundamental advance. It has been validated on a wide range of data sets, including real-world biomedical data. The analysis of the literature landscape by Temple's team has established that nothing like this has existed before, leading to a vast amount of contradictory literature being published. It is our hope this theorem will be widely accepted as an important benchmark to guide the application of quantum computing systems.

**What is the impact on other disciplines?**

This work has implications well beyond quantum machine learning by establishing a data-driven framework for determining when emerging computational methods are likely to provide meaningful benefits. The controlled benchmarking methodology and emphasis on matching model architectures to the intrinsic structure of data can inform research in machine learning, biomedical signal processing, computer vision, and artificial intelligence more broadly. In particular, the study demonstrates this principle in two distinct biomedical domains: EEG seizure detection and digital pathology. This demonstrates how quantum models can be evaluated as components within established classical pipelines rather than as isolated algorithms. The finding that performance depends strongly on the relationship between data structure and model representation provides a general methodological framework for evaluating new learning technologies and avoiding misleading comparisons based on weak or narrowly selected baselines. More broadly, the work encourages researchers in diverse disciplines to characterize their data before adopting emerging computational approaches, potentially improving the rigor, reproducibility, and efficiency of research involving machine learning and other advanced computational methods.

**What is the impact on the development of human resources?**

One MSU PhD student has graduated this year. Several graduate students are mentored and trained to be the leaders in the field. We continue to train a significant number of undergraduates and high school students who would not normally get these opportunities. Undergraduates learn how to develop software that can be run through quantum simulators, and how to run small-scale experiments on actual quantum hardware.

**What was the impact on teaching and educational experiences?**

This year the Temple team hosted our first quantum machine learning workshop. We had 251 people register and 35 people attend the in-person workshop. Many of these people were new to the field and appreciated the opportunity to quickly come up to speed on machine learning applications of the technology. The conference web site contains all the materials developed

for the workshop, including videos of the sessions. A large community of people are making use of these resources. We will also incorporate these resources into our graduate-level machine learning course.

**What is the impact on physical resources that form infrastructure?**

Nothing to report.

**What is the impact on institutional resources that form infrastructure?**

Nothing to report.

**What is the impact on information resources that form infrastructure?**

The publicly available web-based version of the Temple-developed machine learning tool, IMLD, is an excellent teaching tool that allows user to easily experiment with QML without needing to install software, construct complex simulations, or run on actual quantum computing hardware (which can be expensive). Tools such as this are increasing access to the science and technology for under-resourced research groups.

**What is the impact on technology transfer?**

The open source tool that was developed at Temple, HilbertBench, is an extremely powerful tool for developing diagnostics and doing analysis of quantum systems. It has been fully integrated into the Qiskit SDK, making it easy to use across a very wide range of quantum applications. Software testing was conducted that demonstrated new users can effectively use this tool to diagnose problems with their systems.

**What is the impact on society beyond science and technology?**

Nothing to report.

**What percentage of the award's budget was spent in a foreign country?**

Nothing to report.

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## Changes/Problems

**Changes in approach and reason for change**

Nothing to report.

**Actual or Anticipated problems or delays and actions or plans to resolve them**

Nothing to report.

**Changes that have a significant impact on expenditures**

Nothing to report.

**Significant changes in use or care of human subjects**

Nothing to report.

**Significant changes in use or care of vertebrate animals**

Nothing to report.

**Significant changes in use or care of biohazards**

Nothing to report.

**Change in primary performance site location**

Nothing to report.

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## Special Requirements

**Responses to any special reporting requirements specified in the award terms and conditions, as well as any award specific reporting requirements.**

Nothing to report.

