Quantum Algorithms and Romantic Love: Predicting Satisfaction through Personality and Partner Perceptions

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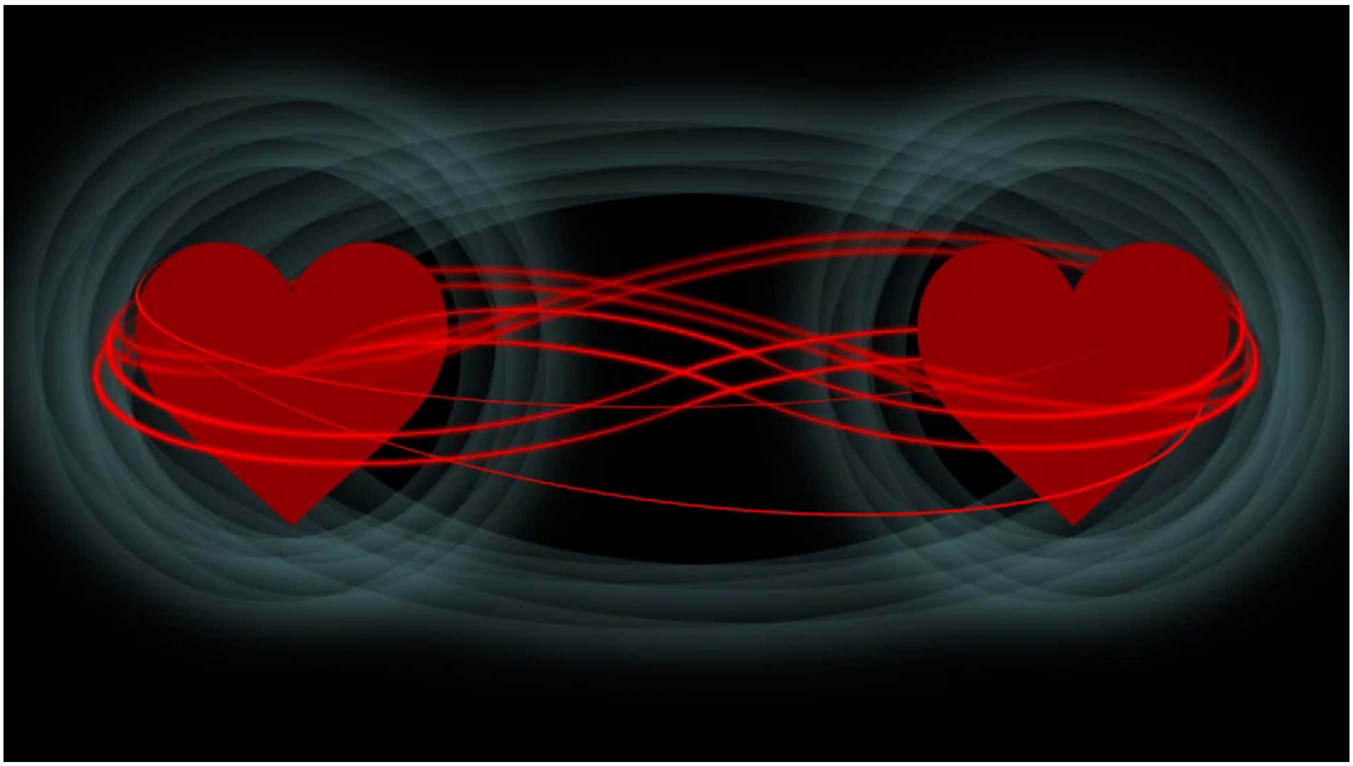

Figure 1: Relationship between Quantum Mechanics and Love [46]

Abstract

Quantum computing is a technology based on quantum mechanics, which studies the behavior of subatomic particles. In recent years, there has been a bipartisan push in the U.S. Senate for the advancement of quantum technologies. While there is still substantial progress to be made, particularly in creating fault-tolerant quantum computers, quantum computing shows promise over classical computing in certain complex problems, especially when it comes to fast computation. Quantum computing can identify patterns within data that classical computers may miss. For almost every classical computing machine learning algorithm, there is a quantum equivalent, and there are even some algorithms unique to quantum computing. IBM, a leading technology company, offers an open-source quantum software package called Qiskit, which allows users to simulate quantum computers. They also offer limited access to real quantum hardware. The goal of this research is to compare the training time and performance of a quantum classifier and a classical classifier. A Support Vector Machine and a Variational Quantum Classifier were used to predict a person's relationship satisfaction based on their responses to a survey about their relationship and personality. While the quantum algorithm did not stand up to the classical algorithm's performance, it demonstrated a time improvement that will prove to be valuable as the quantum computing field advances. These findings show how quantum machine learning models may be applied to real-world human behavior prediction tasks once quantum hardware improves.

Keywords

Quantum Computing, Quantum Mechanics, Variational Quantum Classifier, Support Vector Machine, Relationship Science, Romantic Love

1 Introduction

This project compares the performance and speed of a classical machine learning model to a quantum machine learning model, evaluating their abilities to predict romantic relationship satisfaction based on survey data. A poster presentation version of this research, under the title "Quantum Computing and Love: Two of the World's Greatest Mysteries", won the Social and Behavioral Sciences category in West Virginia University's Fall 2025 Undergraduate Research Symposium.

Quantum computers rely on the principles of quantum mechanics to represent data using quantum bits, or qubits. Some examples of quantum systems that can be used as qubits are electrons, atoms, or photons [56]. Principles of quantum mechanics, like superposition and entanglement, allow these qubits to exist in more than one state at once. These special characteristics allow quantum computing to capture some computational possibilities that classical computers cannot replicate. While quantum computers are not faster for every area of computing, they show promise in areas like encryption and decryption, the simulation of complex molecules and materials, and optimization problems. Limitations in quantum computing stem from the limited knowledge of quantum mechanics, the cost, and the error correction necessary within a quantum computer [55]. The United States government, interested in closing these gaps, invests significant resources into quantum computing. The National Quantum Initiative Act, initially signed into law by President Trump in December 2018, established five National Quantum Information Science (QIS) Research Centers. In November 2025, the U.S. Department of Energy renewed $625 million of funding for those research centers. The goal of these research centers is to advance quantum technology, keep the U.S. at the forefront of the innovation, and apply quantum technology to important scientific and national security issues [23].

Classical machine learning enables researchers to uncover insights into human personality and behavior that may not have been apparent otherwise. As the amount of available data grows, artificial intelligence (AI) can help to make sense of it all [53]. Surveys, administrative records, and social media contribute to large-scale social science datasets. This makes machine learning models extremely valuable because of their ability to manage high-dimensional data. Nonlinear models can help social scientists gain deeper insights into complex social and behavioral dynamics [45]. One study used classical machine learning methods to model people's first impressions. Thousands of people provided their judgments on a person's characteristics, such as intelligence or trustworthiness, based on a photo. Their responses were used to train a neural network, an artificial intelligence model modeled after the human brain, to judge the same characteristics. The insights from the study indicate how AI can help predict how people will be perceived based on their facial features and expressions, shedding light on humans' perceptions and views of others [53].

Love is a large part of the human experience and is critical to the study of social and behavioral sciences. While it is largely viewed to be in the realm of the humanities, as scientists uncover its physiological mechanisms, they begin to categorize and classify love according to measures like intimacy, passion, and commitment, and stages such as attraction, romantic love, and attachment. Factors such as beauty, compatibility, similarity, and reciprocity contribute towards someone's feeling of romantic love. Romantic love also has certain neurological, neurochemical, and hormonal profiles [42]. One way that algorithms influence people's romantic connections is through dating apps. In 2022, a Stanford University study found that 50.5% of all new couples met online. Dating apps' algorithms are mainly based on the user's behavior. They rely heavily on collaborative filtering, predicting which profiles a user might be interested in based on other users who seem to have similar tastes. When individuals use dating apps, they may become more "trusting" of the app's prediction of compatibility with a prospective romantic partner than their own judgment, even if the app doesn't necessarily perform better. This might cause the user to put more effort into the relationship than if they had met someone outside of the app, without a "compatibility score" given to them. Another consideration is that people are more complex than what can be conveyed in a dating profile. Often, people seek perfection based on someone's profile before they really try to get to know someone and put in the effort to build a relationship [48].

Classical machine learning techniques are often used for the analysis of romantic love. One study sought to examine the early stages of relationships. Using a random forest model, the researchers identified traits that had a significant impact on early relationship development. These traits include dyadic communication processes (interaction between both individuals, such as perceived interest, mixed signals, or self-disclosure), components of attachment theory, and attractiveness [41]. Another study assessed the effect of positive communication on satisfaction and desire in the context of romantic relationships. Preliminary statistical analyses showed that positive communication led to higher levels of satisfaction and desire. However, some nonlinear interactions were found when the researchers used machine learning techniques. When individuals received more compliments and affection from their partners, some participants had decreased levels of sexual satisfaction, while others had increased levels of sexual satisfaction. A similar phenomenon occurred within affection and sexual desire: older participants had higher levels of desire when their partners were more affectionate, while younger participants had higher levels of desire when their partners were less affectionate. These interactions highlight how romantic relationships may be different for every couple, and how classical machine learning helped to uncover these insights [39].

Current literature involving quantum mechanics and romantic love focuses on the similarities between the complicated characteristics of both quantum physics and love. The connection between partners equates to quantum entanglement, the quantum observer effect explains how attention can shape each partner's behavior, and superposition of a qubit parallels the complexity of emotions [38]. While some resources simply relate quantum and love characteristics theoretically, others argue that love involves the interaction of people's physical energy fields, connecting two people forever into an entangled state [51, 52]. One relationship therapist uses this idea to argue that someone's "energy" is mirrored by their partner. Thus, the individuals should hold a "higher frequency" to be a "magnet" for what they want [43]. At the time of this paper, no scientific papers were found that apply quantum machine learning models to romantic love data. In this project, the gap is addressed by using quantum machine learning in a new domain, romantic love.

This report begins with a brief overview of quantum computing, including the nomenclature presented in Table 1. The dataset and methodologies are then introduced. Following the training of the quantum and classical machine learning models, their performance and training time are evaluated, and conclusions are presented.

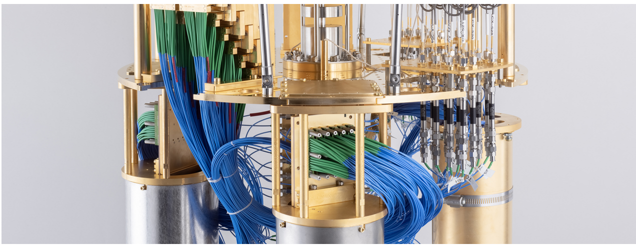

Figure 2: Quantum Computer [18]

2 Quantum Computing

Quantum computing is a rapidly developing field, combining computer science and engineering with the special characteristics of quantum mechanics. Table 2 shows some key differences between quantum and classical computing. These characteristics mean that machine learning models that utilize quantum computing have the potential to solve complex problems faster, represent large amounts of data with fewer qubits, perform large amounts of parallel processing, or find complicated patterns that classical models might miss [22, 50].

2.1 Qubits and Quantum States

Instead of classical binary bits, quantum computers use quantum bits, or qubits. The values 0 and 1 are represented in Equation 1 using *bra-ket* or *Dirac notation*, along with their linear algebra equivalents. Dirac notation is the conventional notation used in quantum physics, and will be used often in the remainder of this paper.

$$\begin{aligned} |0\rangle &= \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \\ |1\rangle &= \begin{pmatrix} 0 \\ 1 \end{pmatrix}. \end{aligned} \tag{1}$$

These two states are seen in the sphere shown in Figure 3, called a Bloch sphere [56]. As the sphere suggests, qubits can be in even more states. Some common states, $|+\rangle, |-\rangle, |i\rangle$, and $|-i\rangle$ are represented in Figure 3 and Equation 2 [56].

$$\begin{aligned} |+\rangle &= \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle), \\ |-\rangle &= \frac{1}{\sqrt{2}}(|0\rangle - |1\rangle), \\ |i\rangle &= \frac{1}{\sqrt{2}}(|0\rangle + i\,|1\rangle), \\ |-i\rangle &= \frac{1}{\sqrt{2}}(|0\rangle - i\,|1\rangle). \end{aligned} \tag{2}$$

One special feature of quantum systems is superposition, where a qubit is in more than one state at once. Superposition occurs when the state of a qubit, $|\psi\rangle$, is a linear combination of $|0\rangle$ and $|1\rangle$ (or any other computational basis), which can be written as follows:

$$|\psi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle\,.$$

The amplitudes of the qubit are the complex numbers α and β [15], and for the qubit to be normalized, it must be true that $|\alpha|^2 + |\beta|^2 = 1$.

Thus far, the discussion has been limited to single-qubit quantum systems; however, multi-qubit systems are possible and constitute a significant advantage of quantum computing.

Until now, the discussion has been limited to single-qubit quantum systems. However, multi-qubit systems are possible and constitute a significant advantage of quantum computing. A multi-qubit system occurs when a collection of multiple qubits is treated as one system, enabling more complex and robust representations. The joint state of two qubits $|\psi\rangle$ and $|\phi\rangle$ can be expressed as the tensor product of the individual vectors, $|\psi\rangle \otimes |\phi\rangle$. When two qubits

Table 1: Nomenclature Table

Notation	Description
$\|a\rangle$	Quantum state in Dirac notation, called "ket a"; a column vector
$\langle a\|$	Conjugate transpose of "ket a", called "bra a"; a row vector
$\|0\rangle, \|1\rangle$	Standard basis for one qubit. $\|0\rangle = (1,0)^T$ and $\|1\rangle = (0,1)^T$.
$\langle a\|b\rangle$	Inner product, $\sum_{i=1}^{d} a_i * b_i$. Used to find the amplitudes of quantum states.
$\|a\rangle\langle b\|$	Outer product operator (projector). Defined via matrix multiplication as $ab^\dagger$ [5]
$\|a\rangle \otimes \|b\rangle$	Tensor product of quantum states $\|a\rangle$ and $\|b\rangle$.
$\|\psi\rangle = \alpha\|0\rangle + \beta\|1\rangle$	Standard representation of a qubit, where $\alpha, \beta \in \mathbb{C}$, and $\|\alpha\|^2 + \|\beta\|^2 = 1$.
$\|\alpha\|^2, \|\beta\|^2$	Probabilities of measuring $\|0\rangle, \|1\rangle$ for $\|\psi\rangle$.
$\|+\rangle, \|-\rangle$	Plus and minus states: $\frac{1}{\sqrt{2}}(\|0\rangle \pm \|1\rangle)$
$\|i\rangle, \|-i\rangle$	i and $-i$ states: $\frac{1}{\sqrt{2}}(\|0\rangle \pm i\|1\rangle)$
X, Y, Z, H	Pauli gates and Hadamard gate
CNOT	Controlled Not gate
$\phi(\vec{x})$	Quantum encoding of a classical vector $\vec{x}$
$W(\vec{\theta})$	Variational circuit/ansatz with parameters θ

Table 2: Quantum Computing vs. Classical Computing [22]

Feature	Conventional Computing	Quantum Computing
Basic Unit	Bit	Qubit
State	Either 0 or 1	Can be in multiple states simultaneously due to superposition
Logical Operations	Boolean Logic (AND, OR, NOT)	Quantum Gates (Hadamard, CNOT, etc.)
Speed	Limited by classical physics	Can perform certain calculations much faster than classical computers
Memory	Stored in binary digits	Stored in qubits
Entanglement	Not possible	Allows two or more qubits to be correlated
Error sensitivity	Not as sensitive	Extremely sensitive to noise and errors
Applications	Software, gaming, simulations, etc.	Cryptography, chemistry, machine learning, etc.

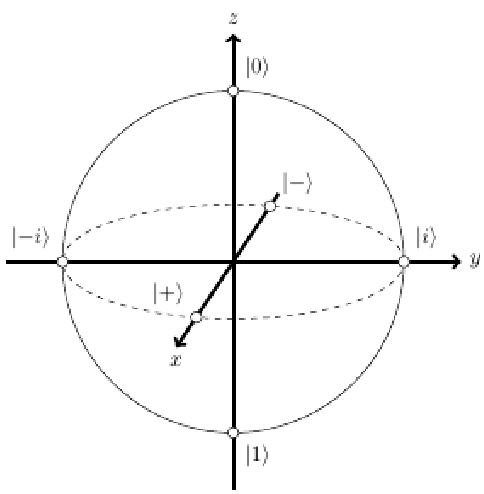

Figure 3: Bloch Sphere [19]

are both in the state $|0\rangle$, consider their combined two-qubit state, shown in Equation 3 [17].

$$|0\rangle \otimes |0\rangle = \begin{pmatrix}1\\0\end{pmatrix} \otimes |0\rangle = \begin{pmatrix}1\,|0\rangle\\0\,|0\rangle\end{pmatrix} = \begin{pmatrix}1*1\\1*0\\0*1\\0*0\end{pmatrix} = \begin{pmatrix}1\\0\\0\\0\end{pmatrix} = |00\rangle\,. \tag{3}$$

An important concept relating to multi-qubit systems is entanglement. Entanglement occurs when the quantum state of one qubit cannot be described apart from the quantum state of the other qubit(s) [30]. Some important multi-qubit entangled quantum states are the Bell states:

$$\begin{aligned}
|\phi^+\rangle &= \frac{1}{\sqrt{2}}\,|00\rangle + \frac{1}{\sqrt{2}}\,|11\rangle\,,\\
|\phi^-\rangle &= \frac{1}{\sqrt{2}}\,|00\rangle - \frac{1}{\sqrt{2}}\,|11\rangle\,,\\
|\psi^+\rangle &= \frac{1}{\sqrt{2}}\,|01\rangle + \frac{1}{\sqrt{2}}\,|10\rangle\,,\\
|\psi^-\rangle &= \frac{1}{\sqrt{2}}\,|01\rangle - \frac{1}{\sqrt{2}}\,|10\rangle\,.
\end{aligned}$$

The collection of these states makes up the Bell basis. Any quantum state vector of two qubits is a linear combination of these Bell states [12].

2.2 Quantum Computational Basis

The computational basis for a single qubit is typically defined as the Z-basis, made up of the states $|0\rangle$ and $|1\rangle$, which are orthonormal vectors. However, qubits can be measured in any basis, such as the X-basis $|+\rangle, |-\rangle$, the Y-basis $|i\rangle, |-i\rangle$, or any other basis consisting of two states on the opposite sides of the Bloch sphere [56]. Since qubits can exist in a superposition, or a linear combination of the basis states, quantum systems are able to capture a much larger amount of information than classical systems, where each bit can only be 0 or 1. As the number of qubits in a quantum system increases, the state space grows exponentially. The computational basis for a system with n qubits contains 2^n states. Since each qubit can be in a superposition, there is greater information-carrying capacity per bit than with classical computing [3].

2.3 Quantum Measurement

While qubits can be in a state of superposition, measurement of a qubit must always result in one single value. More specifically, there is some probability of getting $|0\rangle$, and some probability of getting $|1\rangle$. These probabilities are represented by the amplitudes, α and β, of $|0\rangle$ and $|1\rangle$, where we take the norm-square. So, for the $|+\rangle$ state as defined in Equation 2, we have the following probabilities:

$$\begin{aligned}
P(|0\rangle) &= \left|\frac{1}{\sqrt{2}}\right|^2 = \frac{1}{2},\\
P(|1\rangle) &= \left|\frac{1}{\sqrt{2}}\right|^2 = \frac{1}{2}.
\end{aligned}$$

Therefore, when we measure a qubit in the state $|+\rangle$, we would expect to get each $|0\rangle$ and $|1\rangle$ 50% of the time. Before a qubit is measured, it remains in this probabilistic state, the state of superposition. However, once it is measured, it is in the measured state. It is no longer in a superposition, but it has *collapsed* to the state which was measured [56].

2.4 Quantum Gates

Gates are matrices that perform operations on qubits, transforming their states. Quantum gates can act on one qubit, or even multiple qubits at once. The operation is represented in the form of a matrix. Some common single-qubit gates are shown in Equation 4.

$$\begin{aligned}\mathbb{I} &= \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \\ X &= \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}, \\ Y &= \begin{pmatrix} 0 & -i \\ i & 0 \end{pmatrix}, \\ Z &= \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}, \\ H &= \begin{pmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \end{pmatrix}.\end{aligned} \tag{4}$$

$\mathbb{I}$ is the identity matrix. The X gate is also sometimes called a *bit flip* or *NOT operation* because

$$X|0\rangle = |1\rangle \text{ and } X|1\rangle = |0\rangle .$$

Similarly, the Z gate is called a *phase flip* and does the following:

$$Z|0\rangle = |0\rangle \text{ and } Z|1\rangle = -|1\rangle .$$

The Hadamard operation performs the following transformations:

$$\begin{aligned}H|0\rangle &= |+\rangle, \\ H|1\rangle &= |-\rangle, \\ H|+\rangle &= |0\rangle, \\ H|-\rangle &= |1\rangle .\end{aligned}$$

Hadamard gates are used often in quantum computing, as this allows us to perfectly discriminate qubits in the quantum states $|+\rangle$ and $|-\rangle$ [13].

The most common multi-qubit gate, and the one that will be used the most in this paper, is the Controlled Not (CNOT) gate (Equation 5). Two qubits, a control bit and a target bit, are passed into this gate, and if the control bit is $|1\rangle$, the target bit is flipped, but if the control bit is $|0\rangle$, the target bit remains the same.

$$CNOT = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix}. \tag{5}$$

2.5 Quantum Limitations

Current limitations in quantum computing include scalability, error correction, hardware limitations, and accessibility. Complex problems require quantum computers with millions of reliable qubits, but that is still a far-off goal. Error correction in quantum computing is also extremely important: quantum systems are very susceptible to the environment, causing noise and decoherence, which leads to many errors in the computations [21]. A fully fault-tolerant quantum computer is integral to quantum computing's widespread use, but does not yet exist. Additionally, quantum processors must operate at temperatures close to absolute zero, making thm extremely delicate. Finally, access to quantum hardware is limited due to its cost and rare availability, making it difficult for researchers to fully integrate quantum computing into their normal workflow [20].

3 Data

The dataset used for this project was obtained from the Love Consortium Dataverse, available through the University of North Carolina at Chapel Hill. It contains responses to a survey with 130 questions designed by Adam Bode, a PhD student at Australian National University. Data was collected on Prolific between October 24 and December 6, 2022, from 1,744 participants between the ages of 18-25 who considered themselves to be in love with their romantic partner [32].

3.1 Description

The survey contains information on romantic love measures, demographics, personal characteristics, partners' characteristics, relationship characteristics, personality, health and functioning, elevated mood, and other variables. The survey included three attention checks. Participants who failed to answer these questions correctly were removed from the data. Other participants were removed if they took a significantly low time to complete the survey or if they claimed to be from ineligible countries. Duplicates were also removed from the data, leaving a final sample of 1,556 participants from 33 different countries.

3.2 Previous Studies

One previous study using this dataset analyzed the association of the behavioral activation system (BAS) with intensity of romantic love. Results suggested that the state of romantic love and BAS sensitivity are connected [34]. Another study investigates the variation of romantic love expression. The researchers clustered respondents into four groups, characterized by intensity, obsessive thinking, commitment, and frequency of sex. They note that because variation is necessary for evolution, it is likely that evolutionary selection affects romantic love, as shown by the clusters of romantic love expression [33]. One preprint study found no evidence of differences between students and non-students when it came to their expression and experiences of romantic love [36]. Another preprint study researched factors that are associated with the first episode of romantic love. They did not find intensity to be significantly associated, but factors such as obsessive thinking and commitment were found to be positively associated with the first episode of romantic love [35]. Previous studies tended to concentrate on a number of certain characteristics found in the survey. For this project, we take a different approach, examining a person's satisfaction based on their survey responses as a whole.

4 Methodology

The purpose of this study was to compare the performance and training time of a quantum machine learning classification model and a classical machine learning classification model. The goal was to determine if the quantum model offers an advantage over the classical model when predicting respondents' satisfaction in their romantic relationships according to their responses to the survey.

Before training the models, the data had to be prepared accordingly. The data was cleaned and split into a training set and a testing set, as shown in Figure 4. Once the data was ready for the models,

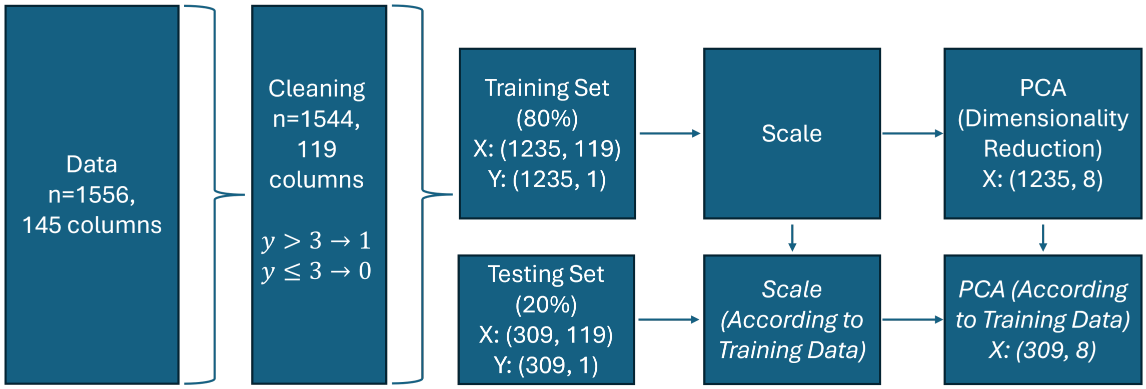

Figure 4: Data Pre-Processing

cross-validation was used to find the best combination of hyper-parameters for each model. Finally, the models were trained, and their performance was evaluated on the testing set.

4.1 Software and Hardware

4.1.1 Programming and Packages. The programming languages used were Python and shell script. The main packages used were pandas, scikit-learn, numpy, and Qiskit. All code used in this project is available in a GitHub repository [54].

4.1.2 Qiskit. A leading technological innovation company, IBM [1], offers many quantum computing tools and resources. While they do offer access to real quantum processing units (QPUs), the free tier only allows 10 minutes of quantum time on IBM's QPUs every 28 days [10]. However, through simulators, users can develop and test programs before sending them to real quantum hardware. In this project, the AerSimulator was used. This high-performance simulator can handle larger circuits than a fake backend, another alternative to using real QPUs. This simulator is best for general development [8].

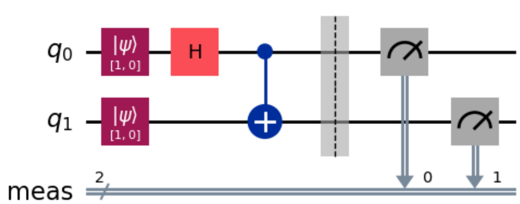

Figure 5: Quantum Circuit with Hadamard and CNOT Gate

4.1.3 Real Quantum Hardware. The circuit shown in Figure 5 was run on one of IBM's real quantum computing backends. Specifically, *ibm_torino* was used. The circuit begins with two qubits, represented by the state vector $|00\rangle$. A Hadamard gate is applied to the top qubit, then a CNOT gate to both qubits, with q_0 as the control. The Hadamard gate puts qubit q_0 into a state of superposition with equal probabilities of being in states $|0\rangle$ and $|1\rangle$. The

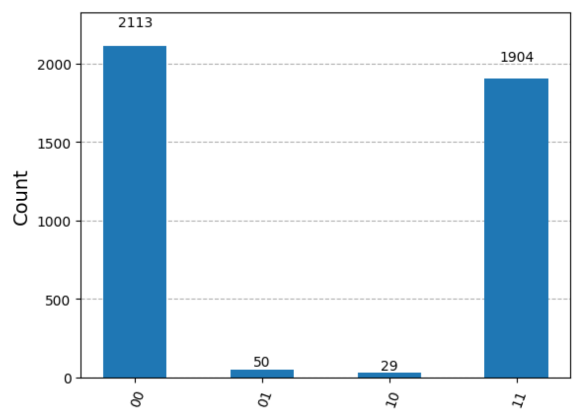

Figure 6: Measurement Counts from Circuit in Figure 5

CNOT gate, one of the most common ways to generate entanglement between two qubits [37], then places the two qubits in a state of entanglement. q_1's state depends on q_0: $q_1 = |0\rangle$ if $q_1 = |0\rangle$, and $q_1 = |1\rangle$ if $q_0 = |1\rangle$. Since q_0 is in a superposition between $|0\rangle$ and $|1\rangle$, we expect the quantum system to be in state $|00\rangle$ 50% of the time, and in state $|11\rangle$ 50% of the time. As we see in Figure 6, the results after measuring the quantum circuit are consistent with these expectations.

4.1.4 High-Performance Computing. Rather than using IBM's real QPUs, this research was conducted using their simulators. This allows for unlimited run time, which is important because the models took a significant amount of time to train. Because of this, the experiment was conducted using WVU's High-Performance Computing resources. Specifically, the models were trained on the Dolly Sods cluster. This cluster is focused on machine learning and artificial intelligence. Managing job submissions using SLURM allowed the programs to run in the background, an important factor since tuning and training the models sometimes took several hours.

4.2 Train Test Split

Before training the models, the data was split into a training set, composed of 80% of the data, and a testing set, composed of 20% of the data. Splitting the data prevents the model from overfitting to the training data, and the testing set allows for assessment of the model's performance on unseen data [47]. Figure 7 includes a representation of how the train-test split occurs.

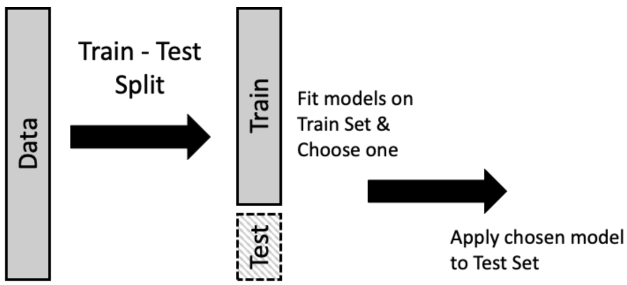

Figure 7: Train Test Split Explanation [47]

4.3 Dimensionality Reduction

Since this study is only interested in certain features, the number of columns was initially reduced from 145 to 119. Even after this reduction, there were still too many features for the quantum circuit. The dataset's dimensionality was reduced using Principal Component Analysis (PCA).

Before applying PCA, the data must be standardized. Each feature must be centered on 0 with a standard deviation of 1. This is essential since the different features in the dataset might have different scales and units. The data was scaled based on the training data.

PCA utilizes linear algebra to reduce the number of features in a dataset while retaining the most important information. The covariance matrix of the features is calculated to see how the features relate to each other. From this matrix, principal components are calculated, ranking the directions of maximum variance. The top $k = 8$ components that capture the most variance were chosen and the original dataset was projected onto these 8 components. Thus, the number of features dropped from 119 to 8 without losing important information in the data [28].

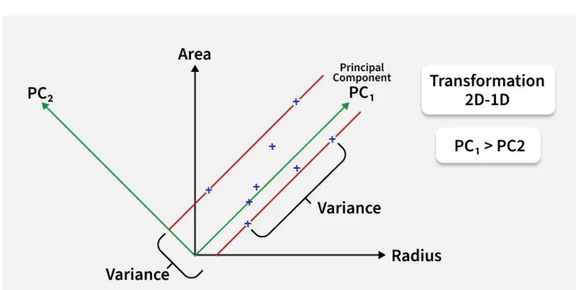

Figure 8: Principal Component Analysis for a Two-Dimensional Dataset [28]

4.4 Cross Validation

The training set was used for cross-validation to find the best model configurations. Hyperparameters, values that control the learning process, were tuned for both models using three-fold cross-validation (exemplified in Figure 9). This approach provides a robust means of assessing the performance of different hyperparameter values [26].

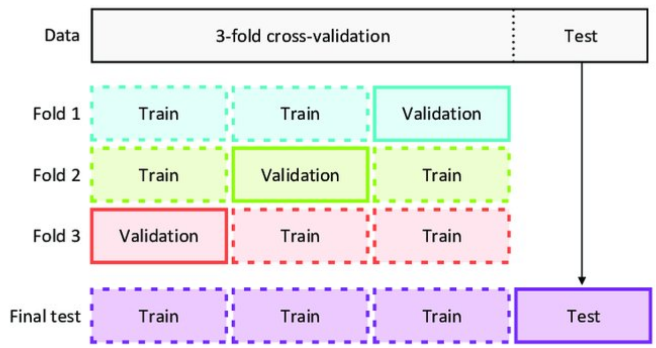

Figure 9: Cross Validation with Three Folds [40], licensed under CC BY 4.0

4.5 Variational Quantum Classifier

The quantum model chosen for this project is a variational quantum classifier (VQC). This model consists of three main parts: data encoding, a variational quantum circuit, and measurement [57].

$$f_\theta(\vec{x}) = \langle 0| U^\dagger(\vec{x}) W^\dagger(\theta) O W(\theta) U(\vec{x}) |0\rangle \tag{6}$$

In Equation 6, $U(\vec{x})$ represents the encoding circuit, $W(\theta)$ is the variational circuit, and θ is the set of parameters to be trained. O is an observable that will be estimated [14]. This flow is also seen in Figure 10.

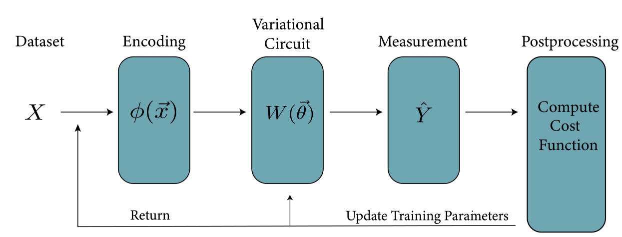

Figure 10: Schematic Diagram of VQC Model [57]

4.5.1 Data Encoding. Data encoding is the first step required for a VQC. This is what transforms the classical data into a quantum system. We use $\Phi(\vec{x})$ to refer to the feature mapping Φ of data vector $\vec{x}$. For this project, Qiskit's ZZFeatureMap, a second-order Pauli-Z evolution circuit, is used. The ZZFeatureMap is a type of phase encoding [4, 49].

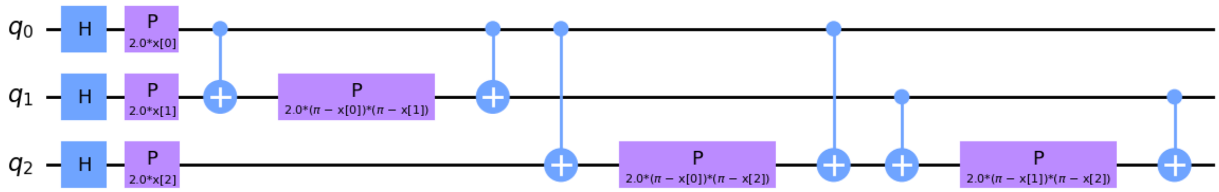

Figure 11: Example of a ZZFeatureMap for a 3 qubit system.

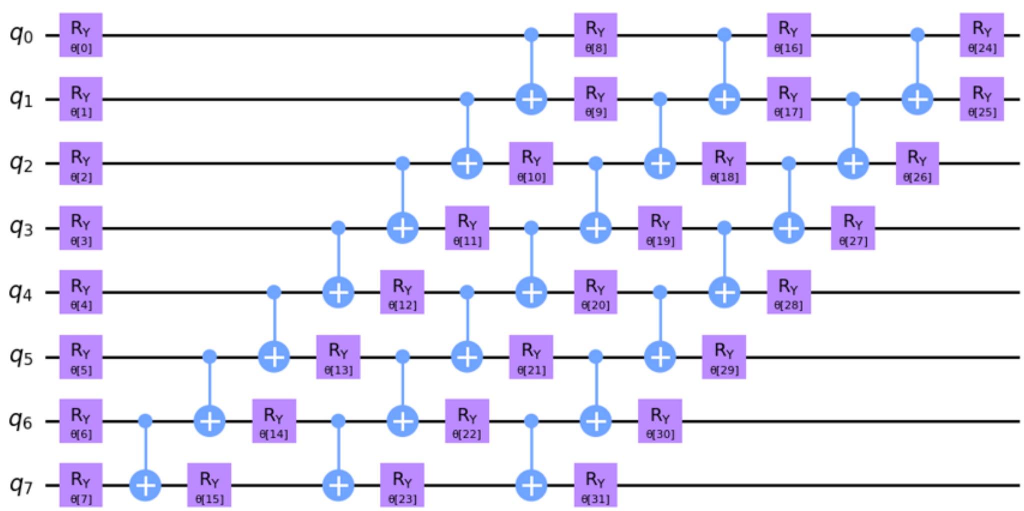

Figure 12: An example of a RealAmplitudes ansatz with 8 qubits and 3 repetitions.

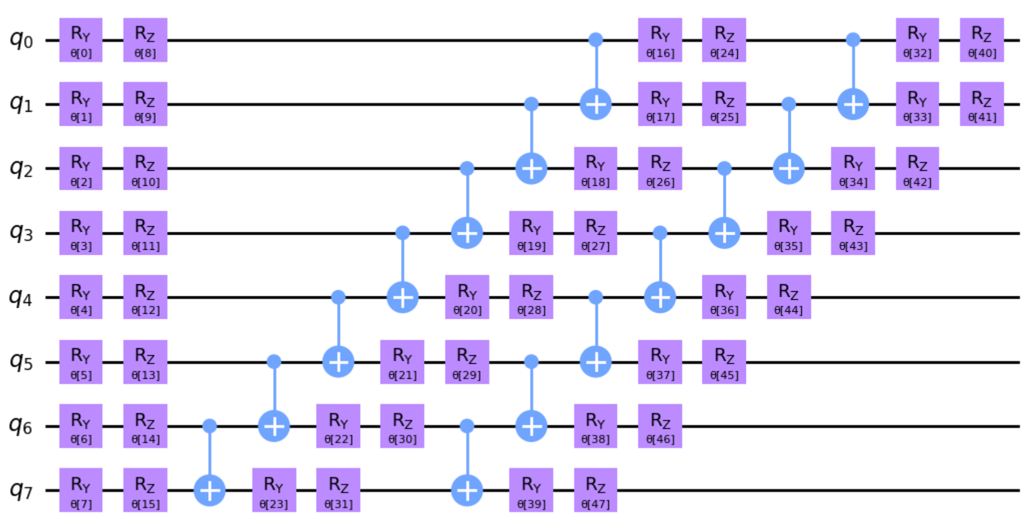

Figure 13: An example of an EfficientSU2 ansatz with 8 qubits and 2 repetitions.

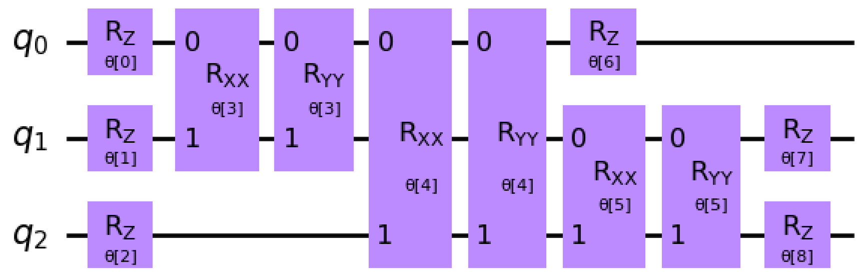

Figure 14: An example of an ExcitationPreserving ansatz with 3 qubits and 1 repetition.

4.5.2 Ansatz. Once the data is transformed into a quantum state, it passes through the variational quantum circuit, $W(\vec{\theta})$, otherwise known as the ansatz. The parameters, $\vec{\theta}$, are optimized using the classical optimizer, which minimizes the loss function. The variational circuit is defined when setting up the model. Variable elements include the depth of the circuit, the overall structure of the circuit, and the types of gates used in the circuit [14]. The three circuits tested in this research were RealAmplitudes, EfficientSU2, and ExcitationPreserving.

The RealAmplitudes circuit consists of alternating layers of single-qubit rotations about the Y-axis and CNOT (CX in the figure) entanglement gates [11]. An example of a RealAmplitudes circuit is shown in Figure 12.

EfficientSU2 circuits contain layers of single qubit operations spanned by CNOT and $SU(2)$ entanglements. $SU(2)$ means a special unitary group of degree 2: the elements of which are 2×2 unitary matrices with determinant 1, like the Pauli rotation gates [2, 6]. The default setup for an EfficientSU2 circuit is shown in Figure 13, which has alternating layers of single-qubit rotations about the Y and Z axes, as well as CX entanglement gates.

The ExcitationPreserving circuit is meant to preserve the ratio of $|00\rangle, |01\rangle, |10\rangle$, and $|11\rangle$ states. The circuit uses layers of rotations about the Z axis and 2-qubit entanglements, which use $XX + YY$ rotations [7]. An example of an ExcitationPreserving circuit is shown in Figure 14.

4.5.3 Measurement and Postprocessing. The VQC trained for this study used the gradient-free classical optimizer Constrained Optimization BY Linear Approximation (COBYLA) [9, 16]. This optimizer seeks to minimize the loss function, which is cross-entropy. Binary Cross-Entropy Loss is defined in Equation 7, where N is the number of samples, y_i is the true label for sample i, and p_i is the model's predicted probability for class 1 for sample i [29]. Cross-entropy is a commonly used loss function for classification problems.

$$BCE = -\frac{1}{N}\sum_{i=1}^{N}(y_i * \log(p_i) + (1 - y_i)\log(1 - p_i)). \qquad (7)$$

4.5.4 Hyperparameter Tuning. The best variational circuit and number of repetitions were tuned through cross-validation to find the best VQC. Three different variational circuits were tested, and the number of repetitions varied from one to six, making up a total of 18 different combinations of hyperparameters that were tested.

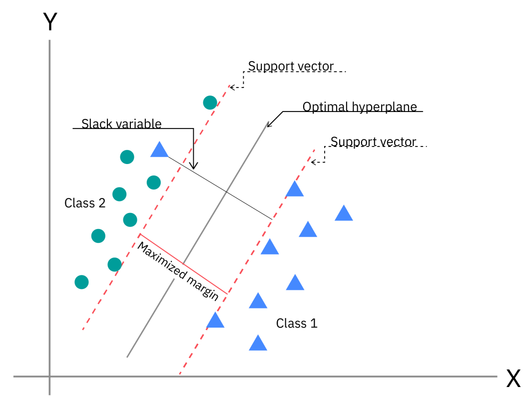

Figure 15: Support Vector Machine Representation [44]

4.6 Support Vector Machine

The classical model used in this study is a support vector machine (SVM). This machine learning classification algorithm uses an optimal hyperplane to maximize the distance between the classes, visualized in Figure 15 [44].

4.6.1 Main Concepts. Since the data used has 8 features, the hyperplane SVM solves for is in 8-dimensional space. The support vectors, shown in Figure 15, are adjacent to the optimal hyperplane and help to determine the maximized margin. Maximizing this distance means SVM will perform well on unseen data [44].

4.6.2 Hyperparameters. The hyperparameters that were tuned for the SVM model include the C-value, kernel type, and gamma value (γ).

The C-value is a regularization parameter that balances the accuracy of the model's classification with the decision boundary margin. When C-values are high, the model is more accurate but

Table 3: Results from Best Models

Model	Training Time	Accuracy	Precision	Recall	F1 Score
Support Vector Machine	0.012 seconds	91.26%	91.64%	98.87%	95.12 %
Variational Quantum Classifier	13.16 minutes	54.09%	82.47%	47.74%	60.48%

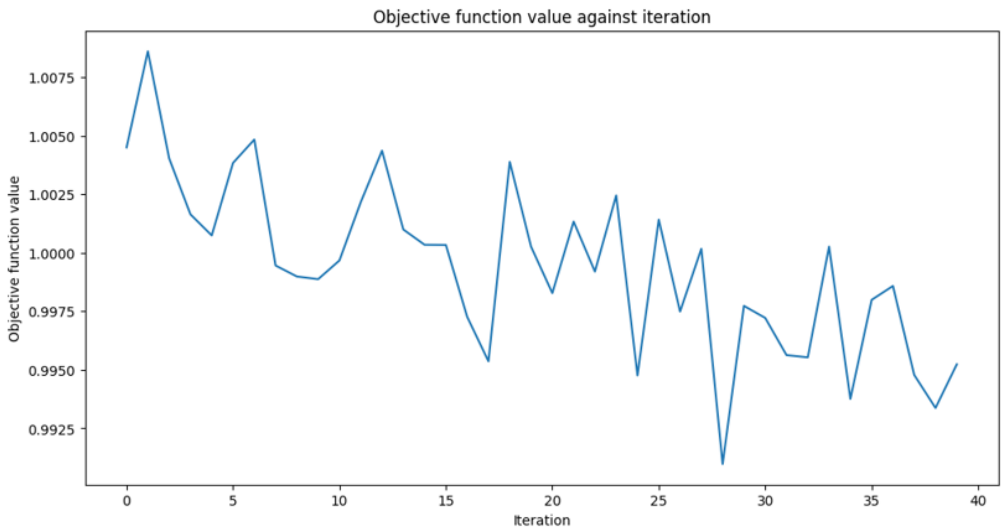

Figure 16: Optimization of Variational Quantum Classifier

may have a smaller margin, but when C-values are low, the model may be less accurate but have a larger margin [31]. Models with C-values of 0.1, 1, and 10 were compared.

Both a linear and a polynomial kernel were tested. The linear kernel is used when data is linearly separable, while the polynomial kernel is applied to data that is not linearly separable. The polynomial kernel allows for curved decision boundaries by raising feature interactions to a power [27].

Finally, the best gamma value between 0.1, 1, and 10 was found. This parameter affects the influence of a single training example. When γ is high, the model may capture noise in the training data since the influence of each observation in the training data is contained in a small region. However, when γ is low, the influence of each observation in the training data affects a larger region of the feature space, which can lead to smoother decision boundaries, possibly underfitting [25].

5 Results

For both the quantum and the classical model, the best combination of hyperparameters was used to train a model on the whole training set. We see from the results, shown in Table 3, that the quantum model had poor performance compared to the classical model. The best quantum model also took longer to train than the best classical model. For the classical model, the best hyperparameter combination was $C = 0.1$, a linear kernel, and $\gamma = 0.01$. The best hyperparameters for the VQC were the ExcitationPreserving ansatz with 3 repetitions.

5.1 Performance Comparison

We notice that the best quantum model; with about 54% accuracy, 82.47% precision, 47.74% recall, and an F1 score of 60.48%; significantly underperformed compared to the best classical model, which had about 91% accuracy, 91.64% precision, 98.87% recall, and an F1 score of 95.12%.

The following equations define accuracy, precision, recall, and F1 score. Accuracy (Equation 8) generally indicates how many observations the model classified correctly. Precision (Equation 9) measures how correct the positive predictions are. Recall (Equation 10) represents how many positive observations the model found. F1 score (Equation 11) uses the harmonic mean to combine precision and recall. This ensures that precision and recall must be balanced for the F1 score to be high [24].

$$Accuracy = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Predictions}} \tag{8}$$

$$Precision = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{9}$$

$$Recall = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{10}$$

$$F_1 Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{11}$$

While the quantum model's precision was much better than its recall, this did not help much in improving its accuracy or F1 score. Based on the optimization graph of the quantum model, seen in Figure 16, it does not look like the loss function was truly minimized.

Table 4: Variational Quantum Classifier Cross Validation Results

Time for Cross Validation (seconds)	Training Score	Validation Score	Ansatz	Number of Repetitions
930.78	51.13%	50.28%	RealAmplitudes	1
980.12	53.32%	50.12%	RealAmplitudes	2
1031.98	50.77%	50.45%	RealAmplitudes	3
1080.46	51.54%	50.12%	RealAmplitudes	4
1130.04	53.36%	49.07%	RealAmplitudes	5
1180.51	52.51%	47.36%	RealAmplitudes	6
998.49	50.40%	50.77%	EfficientSU2	1
1079.47	51.13%	50.53%	EfficientSU2	2
1168.43	54.09%	49.88%	EfficientSU2	3
1251.81	52.91%	48.99%	EfficientSU2	4
1336.84	52.14%	47.36%	EfficientSU2	5
1428.13	51.46%	48.66%	EfficientSU2	6
1130.89	51.01%	49.15%	ExcitationPreserving	1
1380.20	53.68%	52.15%	ExcitationPreserving	2
1636.84	52.22%	52.39%	ExcitationPreserving	3
1900.80	52.75%	49.07%	ExcitationPreserving	4
2168.93	51.70%	51.18%	ExcitationPreserving	5
2447.73	52.79%	48.91%	ExcitationPreserving	6

Table 5: Support Vector Machine Cross Validation Training Times

Approximate Time for Cross Validation (seconds)	C-Value	Gamma	Kernel
0	0.1	0.01	linear
0	0.1	0.01	poly
0	0.1	0.1	linear
0	0.1	0.1	poly
0	0.1	1	linear
28.5	0.1	1	poly
0	1	0.01	linear
0	1	0.01	poly
0	1	0.1	linear
0.3	1	0.1	poly
0	1	1	linear
276	1	1	poly
0.1	10	0.01	linear
0	10	0.01	poly
0.1	10	0.1	linear
2.8	10	0.1	poly
0.1	10	1	linear
5592	10	1	poly

Perhaps if the model trained for more iterations, it would perform better on the data.

5.2 Time Comparison

The best quantum model also took longer to train than the classical model. Tables 4 and 5 show the approximate training times for the hyperparameter combinations for each of the models. We see that during cross-validation, the most complex SVM configuration took over 1.5 hours, while the most complex VQC configuration took under 41 minutes. This implies greater variance in training times for the classical machine learning model compared to the quantum machine learning model, which had rather stable training times.

6 Discussion

The classical model performed well, correctly classifying relationship satisfaction over 90% of the time. The quantum model performed poorly, but its lower training time for complex configurations suggests potential efficiency advantages for more complicated problems that classical models may not perform well on. Additionally, if the model were able to run on a fault-tolerant quantum computer, we would expect a faster training time since the circuit would not have to run many times through the simulations. Exploring alternative quantum machine learning models may improve results on this dataset.

7 Conclusions and Future Work

This project showcases quantum computing's value in the human behavior domain. Due to the dimensionality reduction that was performed on the dataset, specific factors cannot be specifically associated with higher romantic relationship satisfaction. However, since satisfaction was predicted with better-than-random accuracy, it seems evident that satisfaction is associated in some way with some features measured in the survey (personality, relationship characteristics, romantic love measures, partner perceptions, and well-being).

Although the Variational Quantum Classifier failed to achieve reliable predictions of relationship satisfaction on the chosen dataset, the training-time advantage of more complicated quantum models motivates further exploration with different quantum machine learning models and datasets. Future work could apply quantum algorithms to broader areas of human behavior and relationship science, possibly using regression or clustering instead of classification. As quantum hardware improves and fault-tolerant quantum hardware is developed, quantum computers could handle higher-dimensional problems more effectively, allowing quantum computing to be applied to even more domains.

Acknowledgments

Computational resources were provided by the WVU Research Computing Dolly Sods HPC cluster, which is funded in part by NSF OAC-2117575.

I would like to extend my thanks to my professor and advisor, Dr. Ignacio Segovia-Dominguez, for helping to guide me along this capstone experience. I am thankful for a professor who challenges me to learn while truly caring. Additionally, I would like to thank Dr. Vito D'Orazio. He introduced me to WVU's HPCs through my Independent Study course and provided me access to the server, which proved to be valuable and necessary for this project. I am grateful for Dr. Srinjoy Das, my first Data Science professor at West Virginia University, who welcomed me as a transfer student, encouraging me to pursue research during my time at school.

My fellow Data Science and Mathematics classmates have helped to encourage and push me along the way. I have especially enjoyed learning alongside Grady King, Spencer Perkins, and Presley Lucas throughout multiple classes. Finally, I am grateful to my fiancé, Zackary Windsor, for inspiring me to do my project on love, and for being there throughout this capstone process, especially during this season of wedding planning and big changes for both of us.

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