Toward Quantum Social Robotics: a Hybrid Architecture for Emotion and Coping Management

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Abstract
This paper presents a novel architecture for quantum-enhanced social robotics designed to support users emotionally through the personalized suggestion of coping strategies. The system follows a classical–quantum–classical processing pipeline: user inputs (text or multimodal) are encoded into embeddings and compressed via autoencoders trained with triplet loss. An 8-qubit variational quantum classifier then detects the underlying emotional state, which is used to search a set of potential coping strategies using Grover's algorithm. Each user is associated with a personalized probability table inspired by Q-learning, allowing the system to adapt over time through feedback. The selected strategy is communicated to the user using a language model that tailors responses empathetically based on the detected emotion. Future developments include the integration of incremental learning mechanisms to support the addition of new strategies and the management of data drift in emotion classification. The proposed solution demonstrates the potential of using quantum computing to create more adaptive and emotionally responsive human-robot interactions.

Keywords
Quantum Social Robotics, VQC, Grover's algorithm,

1. Introduction

Robotics is one of the research fields undergoing continuous development. It was initially established as a framework to enable machines to become autonomous in perceiving their environment and performing actions aimed at achieving specific goals. Over time, with the objective of assisting humans in a broad range of tasks, robotics has evolved into an interdisciplinary field, driven by the introduction of new technologies and frameworks that have shaped the advancement of today's highly sophisticated machines [1]. Concurrently, Quantum Computing is undergoing rapid development, with the promise of unlocking transformative opportunities across a broad spectrum of technological domains. Among these, robotics stands out as a key area of exploration and potential innovation. As highlighted by Yan et al. [1] in their comprehensive study, quantum computing, based on the fundamental principles of quantum mechanics such as superposition and entanglement, offers significantly increased processing speed, enabling the resolution of problems that classical frameworks have struggled to address over time. While *Computational Complexity*, also known as runtime complexity, remains the most well-known advantage of quantum algorithms, it is by no means the only one. Alchieri et al. [2] have identified additional dimensions for evaluating the benefits of quantum approaches, particularly within quantum machine learning,the discipline most frequently applied in robotics:

AIQxQIA 2025: International Workshop on AI for Quantum and Quantum for AI | co-located with ECAI 2025, Bologna, Italy
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1. *Sample complexity*: Refers to the number of training examples required for algorithms to effectively generalize.
2. *Noise robustness*: Describes the ability of models to remain stable even when the dataset contains corrupted or suboptimal data.
3. *Model complexity*: Relates to the model's expressive power.

In light of this, growing attention has been devoted to the application of quantum information processing across diverse domains, including Social Robotics. This subfield of robotics focuses on developing machines capable of interacting with humans in a natural, emotionally resonant manner, offering assistance in various aspects of everyday life. Within this context, quantum computing has been explored for tasks such as emotion recognition, decision-making, cognitive modelling, and pathfinding. Nonetheless, as highlighted by De Carolis et al. [3], a major challenge in this area remains the complexity of implementing quantum circuits, largely due to current hardware limitations.

The present work is part of the broader QUADRI Project (QUAntum enhanceD human-Robot Interaction: Pioneering Intelligent Social Robotics), which aims to advance the state of the art in quantum social robotics by proposing innovative solutions that leverage quantum paradigms in human-robot interaction.

Drawing on the framework proposed by Yan et al. [1], the psychological structure of human beings can be understood as comprising three interrelated components: cognition, emotion, and behaviour. *Cognition* pertains to how individuals perceive and interpret objects or situations; *emotion* involves the subjective experience of feelings such as happiness, anger, or sadness, often triggered by the satisfaction or frustration of personal needs; and *behaviour* refers to the broad set of actions and routines that characterize daily life.

To be perceived as truly empathic while remaining functionally effective, a robot must be able to acquire contextual information, process it to identify appropriate actions, and interpret emotional cues to tailor its responses accordingly.

In this light, the study introduces a novel architecture for quantum social robots designed to provide emotional support by suggesting personalized ways to cope with distress or reinforce positive states, while also addressing computational constraints and the limitations of current quantum hardware. The proposed framework leverages quantum algorithms, such as Grover's search, performed via simulation on classic machines, ensuring compatibility with available resources. The system operates by detecting the user's emotional state through textual and visual inputs, classifying it via a quantum model, and selecting the most suitable response from a curated set of coping options using Grover's algorithm.

2. Related Work

Within the field of Quantum Social Robotics, two research areas have emerged as particularly prominent: the development of cognitive modelling frameworks and the implementation of systems for emotion recognition and decision-making. In both domains, quantum computing techniques are employed to simulate or enhance human-like cognitive processes and emotional understanding. These approaches aim to exploit the probabilistic and high-dimensional nature of quantum systems to model complex human behaviours and emotional states more effectively than classical methods. In fact, from a neuroscientific perspective, one of the most credited theories posits that human reasoning is inherently Bayesian, operating through probabilistic inference mechanisms. While our framework relies on quantum probabilistic models, these can be viewed as conceptually complementary to Bayesian approaches, potentially offering new ways to model uncertainty in human-like cognition [4].

A particularly comprehensive approach to modelling affective processes in quantum social robotics is offered by Ho et al. [5] through the development of Quantum Coppélia (Q-Coppélia). This framework adopts quantum algorithms rather than fuzzy logic to improve the simulation of brain-like emotional and decision-making processes, and builds upon a previous cognitive model known as Silicon Coppélia. The latter employs fuzzy logic to simulate affective-cognitive dynamics by interpreting environmental features, aligning them with internal goals, and selecting appropriate responses based on use intentions and engagement. By transitioning to quantum computation, Q-Coppélia enhances this architecture with mechanisms such as superposition and entanglement, enabling the representation of emotional ambiguity, probabilistic decisions, and parallel processing, key aspects in modelling complex human-like emotional behavior. Despite its conceptual richness, the authors specify that Q-Coppelia will encounter technical difficulties in executing simulations due to its high number of qubits.

A more implementation-oriented contribution is QUATRO [6], a suite of full, computationally hard classical and quantum-theoretic models, mapped to real quantum hardware. While it represents a concrete step toward practical quantum cognition, the framework is still limited by the current technologies. Another relevant effort is the model proposed by Ulyanov et al. [7] that introduces a control framework grounded in quantum computing, capable of inferring human emotional states and modulating robotic behavior in response.

Focusing a little more on the emotion recognition module, De Carolis et al. [3] offer a broad and up-to-date overview of the state of the art, highlighting numerous attempts to apply quantum computing to affective computing. The work ranges from conceptual models to more concrete implementations: from early experiments on expressive humanoid robots and quantum Bayesian networks for predicting social decisions, to the use of Quantum SVM and Quantum CNN to improve the recognition of facial, vocal or multimodal emotions. However, despite the variety and creativity of the contributions, many of these studies have some significant limitations. In fact, most models remain confined to theoretical simulations or limited experiments, without systematic validation in real-world contexts, and often lack critical reflection on the difficulties associated with scalability and hardware integration.

Consequently, in line with the emerging trend in the state of the art, this article proposes the architecture of a hybrid framework designed to offer emotional support to users through personalised suggestions for coping strategies. The definition of coping adopted is inspired by the concept introduced by Lazarus and Folkman [8], according to which coping represents the set of behaviours implemented by an individual to deal with situations perceived as relevant and potentially superior, or in any case burdensome, compared to their emotional, cognitive or behavioural resources. Furthermore, the proposed architecture aims to maintain a high degree of implementation flexibility, avoiding constraints that would limit its adoption. It has been designed to be accessible and usable through simulators, as well as to ensure good performance in terms of efficiency and adaptability in different application contexts.

3. Methods

As noted by Mennone et al. [9], the human mind remains partly irrational and difficult to fully formalize, especially in its emotional and instinctive aspects. A viable approach, they argue, is to design computational models that imitate typical human responses to external stimuli. For instance, in their work, Mennone et al. adopt the cognitive model by D'Ariano and Faggin [10] to guide the behavior of a dancing robot. Their system follows a classical–quantum–classical flow: it processes classical inputs through a quantum-inspired layer to generate classical outputs. Following their example, the proposed architecture is structured around three main components: the collection of classical inputs, quantum-based processing, and the generation of classical outputs.

In the context of Quantum Social Robotics, where the goal is to develop robots or assistive platforms that can support individuals not only efficiently but also empathetically, our objective is to design a framework capable of interpreting emotional states from user input. Specifically, the system takes either text alone or a combination of text and image as input, and classifies the underlying emotion using quantum classifiers. Based on the detected emotion, it then searches a dataset for the coping strategy the user is most likely to adopt in response. At this point, the process returns to the classical domain, where the selected strategy is communicated to the user in an empathic and supportive manner, either to help them navigate difficult moments or to reinforce positive experiences. Figure 1 provides an overview of the various modules that make up the architecture.

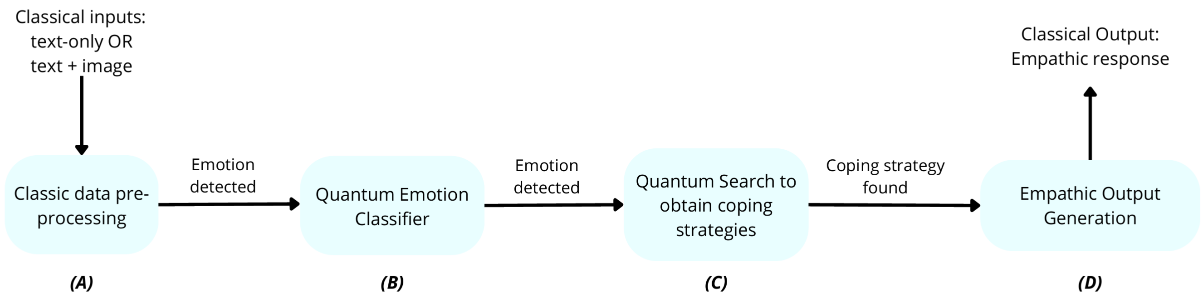

Figure 1: Architecture's overview.

3.1. Classical data pre-processing

The first module (*A* in Figure 1) of the system is dedicated to the collection and preprocessing of classical input data, which can consist of:

1. Textual data, used to capture the user's verbal expressions and infer the associated emotional state.
2. Visual data (images), used to extract emotions from facial expressions.

The framework is designed to operate in either unimodal (text only) or multimodal (text plus image) mode. Multimodal processing is activated only with the user's explicit consent to being photographed. Once the input is received, the data undergo standard preprocessing procedures. For textual data, this includes classic NLP steps such as tokenization, stop-word removal, and normalization. For images, the preprocessing step includes resizing and standardization to ensure compatibility with the embedding extraction model. Following the initial cleaning steps, both text and image data are transformed into *high-dimensional embedding vectors* using domain-specific, fine-tuned transformers trained to capture emotional features. However, quantum classifiers in our pipeline operate on input vectors of 8 dimensions, therefore, a *dimensionality reduction* phase is required.

To achieve this, we employ autoencoders trained independently for each modality. These networks learn to compress the high-dimensional embeddings into an 8-dimensional latent space while preserving the most relevant emotional features. In the multimodal case, the text and image embeddings (already reduced to 8 dimensions each) are concatenated into a 16-dimensional vector. This vector is then passed through a *fusion layer*, trained to reduce it to 8 dimensions for quantum processing.

However, emotional data often exhibit high intra-class variability and inter-class overlap, making it difficult for classifiers to distinguish between nuanced emotions. To address this, we incorporate *Triplet Loss* into the training objective of the autoencoders and of the layer.

Triplet Loss The triplet loss is a powerful objective function introduced to learn embeddings that reflect structured relationships among samples. Originally formalized in the context of large-margin nearest neighbor classification [11] and later popularized by FaceNet [12], it has proven particularly effective for tasks such as face verification and emotion classification.

In simple terms, the triplet loss forces the model to pull embeddings of similar samples (anchor and positive) closer together, while pushing embeddings of dissimilar samples (anchor and negative) farther apart by at least a margin α. The concept is illustrated in the Figure 2.

Mathematical formulation. Formally, let $f(x) \in \mathbb{R}^d$ denote the embedding of an input x into a d-dimensional Euclidean space, normalized such that $\|f(x)\|_2 = 1$. Given a triplet (x_i^a, x_i^p, x_i^n), where x^a is an anchor sample, x^p is a positive sample from the same class, and x^n is a negative sample from a different class, the objective is to ensure that the distance between the anchor and positive embeddings is smaller than the distance between the anchor and negative embeddings. In other words, we want

$$||x_i^a - x_i^p||_2^2 + \alpha < \|x_i^a - x_i^n\|_2^2, \quad \forall (x_i^a, x_i^p, x_i^n) \in \mathcal{T}. \tag{1}$$

where α is a margin enforced between positive and negative pairs, and $\mathcal{T}$ is the set of all possible triplets in the training set with cardinality N.

The loss being minimized is then defined as follows: it sums over all triplets, penalizing cases where the distance between the anchor and positive (plus the margin) exceeds the distance between the anchor and negative:

$$L = \sum_{i=1}^{N} \left[\|f(x_i^a) - f(x_i^p)\|_2^2 - \|f(x_i^a) - f(x_i^n)\|_2^2 + \alpha\right]_+ . \tag{2}$$

3.2. Quantum emotion Classifier

Once the input data has been compressed into an 8-dimensional latent vector, it is passed to the second module: the *emotion classification* module (*B* in Figure 1). Depending on the operational mode, this module may receive embeddings from textual input only (unimodal) or from both text and image sources (multimodal). In both cases, the goal is to identify the user's emotional state.

Our classification scheme follows the model of fundamental emotions devised by Paul Ekman [13], which posits the universality of a discrete set of affective states. The classifier is therefore trained to recognize the following 7 classes: Anger, Disgust, Fear, Happiness, Sadness, Surprise and Neutral, added to represent the absence of strong emotional arousal. To perform this task, we take advantage of *Variational Quantum Classifier* (VQC) operating on an 8-qubit quantum circuit, which matches the dimensionality of the input embedding.

VQC As described by Yen-Chi Chen et al. [14], a *Variational Quantum Circuit* (VQC) (called also *Parameterized Quantum Circuit* (PQC)),is often used as an implementation of *Quantum Neural Network* (QNN). VQC is generally structured into three main stages:

- **Encoding circuit**: This part, denoted by $U(\vec{x})$, maps a classical input vector $\vec{x}$ into a quantum state. It does so by applying a unitary transformation to the initial state $|0\rangle^{\otimes n}$ (where n is the number of qubits), resulting in the encoded state

$$U(\vec{x})\,|0\rangle^{\otimes n} \tag{3}$$

- **Parameterized (variational) circuit**: Represented by $W(\Theta)$, this circuit consists of multiple layers of trainable quantum gates. Each layer can be viewed as a sub-circuit $V_j(\vec{\theta}_j)$ with its own parameter vector $\vec{\theta}_j$. The entire variational circuit is then expressed as

$$W(\Theta) = \prod_{j=M}^{1} V_j(\vec{\theta}_j),$$

where Θ collects all trainable parameters across the layers.

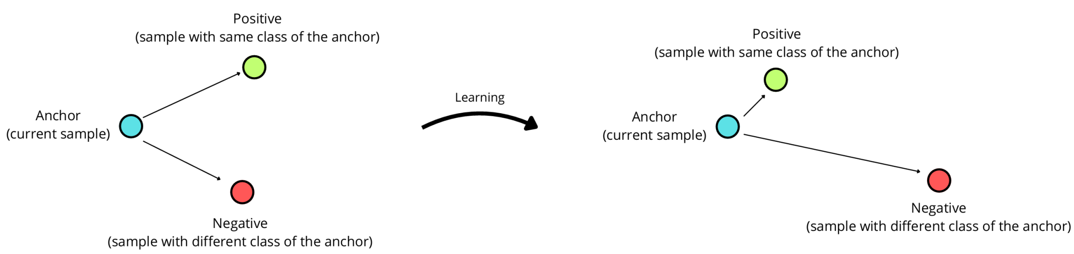

Figure 2: Triplet Loss's concept.

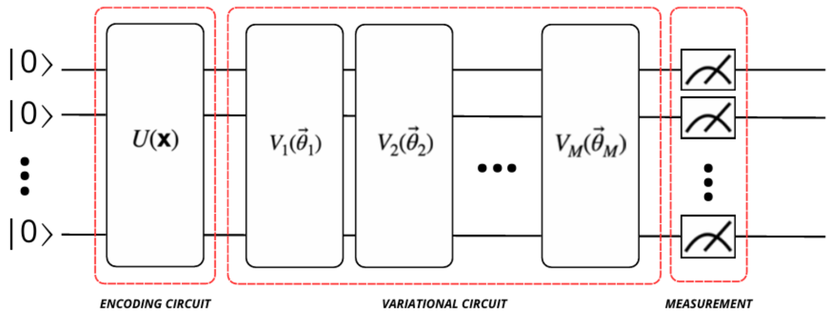

Figure 3: Generic VQC architecture.

- **Measurement**: After the encoding and variational circuits, measurements are performed on specific observables $\hat{B}_k$ to extract classical information from the quantum state.

Putting these stages together, the final quantum state prepared by the VQC becomes:

$$|\Psi\rangle = W(\Theta)U(\vec{x})\,|0\rangle^{\otimes n}. \tag{4}$$

This quantum architecture realizes a quantum function:

$$\overrightarrow{f(\vec{x};\vec{\Theta})} = \left(\langle\hat{B}_1\rangle, \ldots, \langle\hat{B}_n\rangle\right) \tag{5}$$

where each expectation value is given by:

$$\langle\hat{B}_k\rangle = \langle 0|\, U^\dagger(\vec{x})W^\dagger(\Theta)\hat{B}_k W(\Theta)U(\vec{x})\,|0\rangle \tag{6}$$

Such expectation values are typically estimated through repeated measurements (**shots**) on quantum hardware or via quantum simulators running on classical computers. In Figure 3, we can see an example of VQC architecture.

3.3. Quantum Search to Obtain Coping Strategy

Reinforcement Learning, and more recently its quantum counterpart, has been extensively applied in the context of robotics, particularly for autonomous decision-making. Among the most prominent algorithms in this area is **Q-learning**, a value-based method in which an agent learns an optimal policy through interaction with the environment [15]. As Skolik et al. discussed in their article [16], Q-learning relies on the construction and iterative update of a *Q-table*, which stores the estimated utility (Q-values) of performing a given action in a given state. This table is updated using feedback in the form of rewards, gradually improving the agent's decision-making over time.

While our architecture does not implement Q-learning in the strict sense, its conceptual foundation inspired the design of the quantum search module (*C* in the Figure 1). In particular, we adopt the notion of a *personalized Q-table* to guide the selection of coping strategies tailored to each user.

Each user maintains a custom table structured as follows:

- **Columns**: a set of general-purpose coping strategies;
- **Rows**: the seven emotional states defined by Ekman's theory (anger, disgust, fear, happiness, sadness, surprise, neutral);
- **Cells**: probabilities indicating the likelihood that a given strategy (column) will be appropriate and well-received when the user is experiencing a specific emotion (row).

Initially, all strategies are considered equally probable, with each cell initialized to $1/N$, where N is the number of available coping strategies. As the system interacts with the user and receives feedback, these probabilities are updated accordingly:

- If the user **rejects** a suggested strategy, the associated probability for that emotion is *decreased*;
- If the user **accepts** the suggestion, the probability is *increased.*

To ensure diversity and prevent convergence to a single repetitive suggestion, upper and lower bounds are imposed on these probabilities, and normalization is enforced so that the sum of all probabilities for a given emotion always equals 1.

The final selection of the coping strategy is performed using a quantum search method based on **Grover's algorithm**. Originally developed for unstructured database search, Grover's algorithm provides a quadratic speedup over classical search, allowing the identification of a marked item among N elements in approximately $\mathcal{O}(\sqrt{N})$ queries [17].

Grover's algorithm operates by amplifying the probability amplitude of the desired state through iterative applications of two operations:

1. **Oracle operator**: marks the desired item (in our case, the strategy with highest probability);
2. **Diffusion operator**: inverts all amplitudes about their average to reinforce the marked state.

In our setting, the search space corresponds to the set of candidate coping strategies for a given emotional state, and the oracle is defined to mark the strategy with the highest current acceptance probability in the user's table. By applying Grover iterations, the system amplifies the most suitable option and retrieves it with high probability after a limited number of queries, thereby reducing the search complexity while preserving adaptability to user-specific patterns.

3.4. Empathic Output Generation

Once the most appropriate coping strategy has been identified through quantum search, it must be communicated to the user in a supportive and personalized manner. The last module of the pipeline (D in the Figure 1) is handled by the classical processing of the empathic response module, which leverages a natural language model to convey the suggestion.

To ensure privacy, the language model operates using only two inputs:

- the **detected emotional state**, classified in the previous module;
- the **selected coping strategy**, retrieved via Grover's search algorithm.

No other user-specific or sensitive information is transmitted to the language model, ensuring both compliance with ethical principles and respect for the user's personal data. So, this layer transforms the abstract coping strategy into a concrete, human-understandable suggestion, thereby closing the interaction loop and supporting the user in navigating their emotional experience.

4. Preliminary Experiments

To provide initial empirical support to the proposed architecture, we conducted preliminary experiments focusing on the modules described in Sections 3.1 and 3.2, i.e., the classical pre-processing and the quantum emotion classification. A multimodal dataset was constructed by combining textual data from GoEmotions [18] and facial expressions from KDEF [19], mapped into Ekman's seven basic emotions. Textual and visual embeddings were compressed into an 8-dimensional latent space via autoencoders trained with Triplet Loss.

An 8-qubit Variational Quantum Classifier (VQC) was then trained on these embeddings. With the optimized multimodal embeddings and advanced quantum feature maps, classification performance reaches 93% test accuracy in the fused (text+image) setting and 95% in the text-only case. These results, although preliminary, indicate the feasibility of integrating quantum classifiers into an emotion recognition pipeline and validate the design choices of the proposed architecture.

5. Conclusion and Future Work

The architecture presented in this work lays the foundation for an emotionally aware quantum-enhanced assistive system capable of suggesting personalized coping strategies. While the current implementation provides a complete pipeline, from emotion recognition to empathic communication, future developments will aim to introduce an incremental learning component. On one hand, the quantum search module will be extended to support the dynamic addition of new coping strategies over time. This requires updating both the user-specific probability tables and the oracle used in Grover's algorithm, ensuring that the system remains adaptable as user needs evolve or as new strategies are introduced. On the other hand, the emotion classification module will be enhanced to handle data drift and user-specific patterns via incremental updates to the quantum classifier. By incorporating adaptive mechanisms, such as continual learning of the variational parameters, the model will maintain robustness and accuracy in dynamic environments where the user's emotional responses may shift gradually. This dual incremental design supports long-term personalization and aligns with the goals of sustainable, human-centric social robotics.

Acknowledgments

This work has been financed by the Research Program "National Quantum Science and Technology Institute" (PE0000023-NQSTI). It is supported within the framework of the National Recovery and Resilience Plan (NRRP), Mission 4 "Education and Research" – Component 2 "From Research to Business", with explicit reference to funding provided by the European Union through the NextGenerationEU initiative.

Declaration on Generative AI

During the preparation of this work, the author(s) used GPT-4o in order to: Grammar and spelling check. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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