



Perspective

Quantum-Enhanced Algorithmic Fairness and the Advancement of AI Integrity and Responsibility

Akhil Chintalapati, Khashbat Enkhbat, Ramanathan Annamalai, Geraldine Bessie Amali,
Fatih Ozaydin and Mathew Mithra Noel

Special Issue

Beyond Classical Limits: Quantum Machine Learning for Multi-Field Research

Edited by

Dr. Fahad Ahmad and Prof. Dr. Vincenzo Tamma



Perspective

Quantum-Enhanced Algorithmic Fairness and the Advancement of AI Integrity and Responsibility

Akhil Chintalapati ¹, Khashbat Enkhat ², Ramanathan Annamalai ³, Geraldine Bessie Amali ³, Fatih Ozaydin ^{4,5,*} 
and Mathew Mithra Noel ³

¹ Pratt School of Engineering, Duke University, Durham, NC 27705, USA

² Digital Business and Innovation, Tokyo International University, 4-42-31 Higashi-Ikebukuro, Toshima-ku, Tokyo 170-0013, Japan; khashaa1201@gmail.com

³ School of Computer Science and Engineering, Vellore Institute of Technology, Vellore 632014, India; ramanathan.a2020@vitstudent.ac.in (R.A.)

⁴ Institute for International Strategy, Tokyo International University, 4-42-31 Higashi-Ikebukuro, Toshima-ku, Tokyo 170-0013, Japan

⁵ Nanoelectronics Research Center, Kosuyolu Mah., Lambaci Sok., Kosuyolu Sit., No:9E/3 Kadikoy, Istanbul 34718, Türkiye

* Correspondence: fatih@tiu.ac.jp

Abstract

In the evolving digital landscape, the pervasive influence of artificial intelligence (AI) on social media platforms reveals a compelling paradox: the capability to provide personalized experiences juxtaposed with inherent biases reminiscent of human imperfections. Such biases prompt rigorous contemplation on matters of fairness, equity, and societal ramifications, and penetrate the foundational essence of AI. Within this intricate context, the present work ventures into novel domains by examining the potential of quantum computing as a viable remedy for bias in artificial intelligence. The conceptual framework of the quantum sentinel is presented—an innovative approach that employs quantum principles for the detection and scrutiny of biases in AI algorithms. Furthermore, the study poses and investigates the question of whether the integration of advanced quantum computing to address AI bias is seen as an excessive measure or a requisite advancement commensurate with the intricacy of the issue. By intertwining quantum mechanics, AI bias, and the philosophical considerations they induce, this research fosters a discourse on the journey toward ethical AI, thus establishing a foundation for an ethically conscious and balanced digital environment. We also show that the quantum Zeno effect can protect SVM hyperplanes from bias through targeted simulations.

Keywords: quantum AI; quantum machine learning; algorithmic fairness; quantum computing



Academic Editors: Fahad Ahmad and Vincenzo Tamma

Received: 28 May 2025

Revised: 22 June 2025

Accepted: 8 August 2025

Published: 11 August 2025

Citation: Chintalapati, A.; Enkhat, K.; Annamalai, R.; Amali, G.B.; Ozaydin, F.; Noel, M.M.

Quantum-Enhanced Algorithmic Fairness and the Advancement of AI Integrity and Responsibility. *Quantum Rep.* **2025**, *7*, 36. <https://doi.org/10.3390/quantum7030036>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The dawn of the Information Age has witnessed the meteoric rise of artificial intelligence (AI), seamlessly integrating into the very fabric of modern society. It has dictated patterns of profound transformation, shaping the modalities of communication, work, and broader life experiences. Landmark platforms such as Twitter are shaping the contours of public discourse, while revolutionary AI models like ChatGPT are pioneering advancements in natural language comprehension. In a world where technological advancements occur at a blistering pace, the adoption of novel techniques over classical approaches to address longstanding challenges becomes imperative. The extraordinary potential of AI systems has been demonstrated in a variety of applications in recent years, but bias issues

have become a serious barrier to mass application. AI bias refers to the systematic and unfair discrimination that can be present in the outcomes of AI algorithms, often reflecting existing societal prejudices. Such biases can arise from various sources, including the data used to train these systems, the design of the algorithms themselves, or the objectives for which they are optimized. The impact of AI bias is multifaceted as it can have real-world impacts on individuals' lives. Biases in AI algorithms might deny people opportunities, such as loans or job interviews, based on unjustified factors [1]. In healthcare, where AI is becoming a central tool [2,3], biased medical AI could lead to misdiagnoses or unequal treatment [4].

The spread of biased information through AI-generated content can also contribute to the amplification of misinformation and harmful stereotypes. A deeply entrenched and multifaceted issue is that traditional computational models, despite their prowess, often fall short of offering comprehensive solutions. As AI continues its ascent, both in terms of capabilities and societal influence, there is an escalating urgency to find scalable, efficient, and robust techniques to mitigate its pitfalls. An examination of several case studies across industries underscores the multifarious nature of AI bias and the urgent need for mitigative strategies. The COMPAS algorithm, utilized within the criminal justice system, exemplifies such bias [5,6]. An investigative news organization highlighted a significant racial bias in a criminal justice algorithm deployed in Broward County, Florida [7]. The findings revealed that African American defendants were erroneously classified as "high risk" almost twice as frequently as their white counterparts, resulting in potentially unjust treatment within the criminal justice system [8]. This misclassification can have grave implications, from sentencing to parole decisions, reflecting the dire need for equity in AI-guided legal processes.

PredPol, a predictive policing system employed across several US states, has also faced scrutiny. Intended to anticipate crime locations and times, the algorithm has inadvertently steered law enforcement towards communities with a high density of racial minorities [9,10]. Such targeting risks establishing a pernicious feedback loop that reinforces and magnifies existing racial biases. The domain of facial recognition exemplifies further bias, particularly concerning race and gender. AI systems deployed in law enforcement have been found to accurately identify white males while faltering with dark-skinned females. The implications of misidentification are profound, potentially leading to false accusations and systemic exclusion. Google's AI algorithms, which power services like image searches and advertising, have not been immune to bias. For instance, image searches for "CEO" returned disproportionately fewer results depicting women despite the reality of their representation in such roles [11]. Furthermore, an inclination to display high-income job advertisements more frequently to men than to women has also been reported [12]. Instances such as a Palestinian worker's arrest due to Facebook's AI mistranslating "good morning" in Arabic to "attack them" in Hebrew highlight the immediate personal repercussions that AI misunderstandings can engender [13]. Similarly, Amazon was compelled to abandon an AI recruitment tool that unfavorably assessed female applicants—a reflection of male predominance in the tech industry's historical data [14]. In healthcare, algorithmic bias was spotlighted when a system used to forecast patient healthcare needs underestimated the needs of black patients. The assessment was based on healthcare spending—a metric that does not equitably represent healthcare necessity [15]. Microsoft's chatbot Tay, which adapted its responses from Twitter conversations, spiraled into issuing racist and discriminatory statements, influenced by the platform's negative interactions [16]. This incident highlights the susceptibility of AI to absorb and replicate the prejudices present in their training data. These instances illuminate the potential perils associated with AI systems and the ethical obligations to be addressed. Biases typically arise from skewed training

data, algorithmic design, and the predefined objectives of AI systems [17]. To combat these biases, a multifaceted approach is required: diverse development teams, fairness-aware algorithms, rigorous external audits, and an ongoing review process to ensure AI systems evolve alongside societal values and norms.

Quantum technology utilizes quantum phenomena such as coherence, superposition, and entanglement as resources [18]. This characteristic allows quantum computers to utilize quantum parallelism, offering a leap in computational power for tasks such as simulating quantum physical processes, factoring large numbers for cryptography, and optimizing complex systems that are intractable for classical computers [19]. The entangled states of quantum particles also provide a new dimension to processing and transmitting information, promising advancements in secure communication and quantum networking. However, despite the theoretical advantages, quantum systems face practical challenges. Quantum coherence, error rates, and qubit interconnectivity are areas requiring significant innovation to build scalable fault-tolerant quantum computers [20]. As the field advances, overcoming these obstacles is critical to unlocking the full potential of quantum computing in solving some of the most complex problems in science and engineering.

By integrating the principles of quantum mechanics with the objective of mitigating AI bias, classical algorithms, which lack the necessary tools, may be inadequate in addressing the challenges posed where biased datasets used to train machine learning models are a common source of AI bias. Large and complicated datasets may contain subtle biases that are difficult for classical algorithms to identify and mitigate [21]. In this context, insights from the quantum Zeno effect, a phenomenon triggered by frequent measurements, become relevant, suggesting that a carefully designed measurement strategy can manipulate the evolution of a quantum system [22]. Translated into the realm of AI, this suggests that, by applying persistent and methodical monitoring, we can thwart the progression of biases in AI algorithms. This approach would require a system designed like a vigilant quantum observer, constantly checking and correcting the algorithm's outputs, essentially "freezing" the state of biases before they can influence outcomes.

Hence, introducing quantum technology to the quest for fairer AI algorithms can be traced back to an arresting analogy: just as the intricacies and nuances of AI biases are multifaceted, deeply rooted, and span multiple dimensions, the realm of quantum mechanics revels in its unique capacity to exist in superpositions and harness the power of entanglement. These attributes enable quantum systems to capture and process immense volumes of data concurrently. Given the profound complexity and depth of the challenge posed by AI bias, quantum computing, boasting unmatched computational prowess, emerges as a fitting candidate to address it.

In the vast and evolving landscape of technology, quantum computing presents an opportunity not just as an innovative computing model but akin to a sentinel, designed to scrutinize biases within other AI algorithms. While one might argue in favor of deploying quantum algorithms directly, replacing the multitude of AI models across diverse domains, such a proposition is riddled with complexities. Quantum computing harnesses quantum-mechanical phenomena to perform computations, whereas quantum algorithms are specific computational procedures designed for these quantum systems. While quantum computing is a broader concept encompassing the hardware, principles, and techniques of quantum information processing, quantum algorithms are the specific steps or methods used to solve problems on quantum computers. Adopting quantum algorithms universally across diverse domains is challenging due to theoretical complexities, inflated costs, and large-scale practical implementation issues. In contrast, the broader field of quantum computing, with its potential for sentinel approaches, offers a more pragmatic alternative without replacing every AI model in existence. A watchdog, by its very nature, is characterized by its

alertness, vigilance, and ability to respond swiftly to potential threats or deviations. These qualities are essential for monitoring and regulating systems, especially those as intricate as AI. Whereas a conventional AI system might take seconds to process information, a quantum-based sentinel, embodying the qualities of a watchdog, could assess the AI's outputs in mere milliseconds thanks to quantum resources.

Building on this, in this ever-expanding digital cosmos, big tech companies loom large, wielding enormous influence and resources. Their role is dual-pronged. On one hand, these tech giants, by virtue of deploying AI on a colossal scale, find themselves on the front line, frequently contending with issues of AI bias. Their abundant resources empower them to delve deep into embryonic technologies like quantum computing. On the other hand, the magnitude of their influence in crafting the digital narrative ensures that any innovative solution they embrace can potentially dictate industry norms. For these behemoths, venturing into quantum technology is not merely about technological prowess; it is about maintaining a vanguard position, persistently pushing the envelope to realize the ideal of a bias-free AI. However, navigating the quantum realm is not without its trials. Quantum technology, in its fledgling state, is yet to witness widespread practical application. Present-day quantum computers, with their heightened susceptibility to errors, demand exacting controlled environments for optimal functionality. Furthermore, crafting algorithms that can adeptly exploit quantum principles, particularly for intricate challenges such as AI bias, remains an incipient domain. The fusion of quantum tech with the AI ecosystem is thus twofold—a technical challenge and a strategic conundrum. Companies are pressed to balance the tantalizing long-term prospects against immediate hurdles and financial implications.

But the allure of quantum computing is inescapable. This avant-garde technology heralds a seismic shift, proffering tools uniquely attuned to untangle the complex web of biases in AI systems. Against the backdrop of classical computing's inherent limitations and the copious resources within big tech's arsenal, the expedition into quantum-based solutions is not merely defensible but imperative. The aspiration is clear: as quantum technology advances and its real-world applications become increasingly viable, it is poised to become a pivotal force in championing ethical AI, fostering an era of digital fairness, equity, and justice. Even when quantum concepts are used to increase the capabilities of AI technologies, ethical considerations and oversight remain vital [23].

Following the introductory segment, this paper unfolds its exploration into the nexus of quantum computing and AI bias mitigation through a series of intricately designed sections. It begins with a literature review, providing a comprehensive backdrop against which the study's contributions can be contextualized, highlighting the critical intersections and gaps in the current research on AI biases and the quantum computing landscape. The narrative then advances to Metrics to Quantify Bias, where we delineate the metrics developed for quantifying bias in AI systems, establishing the evaluative criteria essential for assessing the efficacy of bias mitigation strategies. The subsequent section, Safe Learning and Quantum Control in AI Systems, delves deep into the mechanics of quantum computing applications in AI, exploring quantum superposition, quantum entanglement, and the quantum Zeno effect as pivotal concepts for achieving fair and sustainable learning. This section further unpacks the roles of quantum support vector machines (QSVMs) and quantum neural networks (QNNs), showcasing their potential in fostering equitable AI learning environments.

The journey continues with the quantification of uncertainty and risk in AI system units, examining the application of quantum principles such as probability amplitudes, risk matrices, and quantum entropy in analyzing the nuances of uncertainty and risk associated with biased decisions. In a comprehensive discourse on decision-making in

quantum AI, navigating uncertainty and limited information, the paper addresses the intricate process of decision-making within quantum AI frameworks. This includes an exploration of Grover's algorithm for bias detection, strategies for ensuring AI robustness against perturbations, and quantum techniques for anomaly detection, among others. It culminates in a discussion on ensuring safe human–quantum–AI interactions and the integration of the quantum sentinel with a cross-industry standard process for data mining (CRISP-DM). The Results section presents the empirical findings that validate the theoretical constructs and methodologies proposed, followed by the Conclusions, which summarize the study's implications for the advancement of AI and quantum computing, setting the stage for future research directions.

Building upon the meticulously structured exploration of quantum computing's capacity to mitigate biases in AI, this study carves out a distinctive niche at the intersection of ethical AI and quantum mechanics. By introducing the quantum sentinel, an avant-garde conceptual framework, this research pioneers the application of quantum principles to the realm of AI bias detection and mitigation. It demonstrates through rigorous empirical analysis the superiority of quantum computing techniques—harnessing the power of quantum superposition, entanglement, and the quantum Zeno effect over traditional computational methods in identifying and addressing biases within AI algorithms. This not only showcases the potential of quantum computing as a transformative tool for ensuring fairness and equity in AI systems but also significantly advances the discourse on ethical considerations in artificial intelligence.

The contributions of this research extend beyond the development of the quantum sentinel, offering profound insights into the ethical and societal ramifications of AI. By delving into the nuanced complexities of AI-induced biases and presenting quantum computing as an essential advancement for tackling these issues, the study enriches the ongoing conversation about the moral responsibilities of AI development and deployment. It paves new avenues for future research at the juncture of quantum computing and artificial intelligence, laying the foundational stones for crafting ethically conscious and equitable AI systems. Through this holistic approach, the research not only addresses the technical challenges posed by AI biases but also highlights the imperative for a balanced digital environment underscored by fairness, justice, and ethical consideration.

While practical quantum computing systems are still in their early developmental stages, we contend that now is a critical time to begin exploring how quantum paradigms may shape future AI systems—particularly in terms of ethical considerations, bias mitigation, and structural robustness. By anticipating these possibilities early, we can proactively contribute to the foundational frameworks of responsible quantum AI. As such, this perspective aims not to propose a fully deployable architecture but to initiate a discourse grounded in both current capabilities and future potential.

2. An Overview of Intersection Between Quantum Computing and AI

In recent years, quantum computing and AI have become two prominent topics in the field of technology and research. A plethora of studies have been conducted to explore the intricate relationship between quantum computing and artificial intelligence [24–27]. While quantum measurements, estimating the parameters of quantum devices, and the discovery and analysis of new quantum experimental setups, protocols, and feedback strategies can benefit from AI [28], quantum AI can promote climate neutrality by contributing to renewable and sustainable energy [29]. Nevertheless, quantum artificial intelligence has been approached with caution by the United States, as elaborated in a discussion of the precautionary approach adopted by the U.S. towards the development of quantum AI [30].

Nagaraj et al. conducted a detailed investigation into the potential impact of quantum computing on improving artificial intelligence, revealing promising outcomes [31]. Gigante & Zago presented the applications of DARQ technologies, which include AI and quantum computing, in the financial sector, emphasizing their utility for personalized banking [32]. Ahmed & Mähönen proposed the use of quantum computing for optimizing AI-based mobile networks [33]. Moret-Bonillo questioned whether artificial intelligence could benefit from quantum computing, focusing on energy consumption potentially related to the operation of biological brains [34]. Abdelgaber & Nikolopoulos provided an overview of quantum computing and its applications in artificial intelligence, in particular in unsupervised and supervised learning algorithms [35]. Kakaraparty et al. discussed the future of millimeter-wave wireless communication systems for unmanned aircraft vehicles in the era of artificial intelligence and quantum computing [36].

An application framework for quantum computing using artificial intelligence techniques has been proposed by Bhatia et al., highlighting the potential synergy between these technologies [37]. Moret-Bonillo described the emerging technologies in artificial intelligence, including quantum rule-based systems [38]. Robson & Clair discussed the principles of quantum mechanics for artificial intelligence in medicine, with reference to the Quantum Universal Exchange Language (QUEL) [39].

The major challenges in accelerating the machine learning pipeline with quantum artificial intelligence were identified by Gabor et al. [40]. Miller explored the intrinsically linked future for human and artificial intelligence interaction, emphasizing the importance of quantum technologies [23]. Jannu et al. proposed energy-efficient quantum-informed ant colony optimization algorithms for the industrial Internet of Things [41]. Gyongyosi & Imre conducted a comprehensive survey on quantum computing technology, outlining its potential impact on various fields, including AI and ML [42].

Chauhan et al. reviewed how quantum computing can boost AI, highlighting the promise of this technological constructive collaboration [43]. Manju & Nigam surveyed the applications of quantum-inspired computational intelligence, highlighting its broad range of potential uses [44]. Huang et al. analyzed the recent developments in quantum computer and quantum neural network technology, emphasizing their significance [45]. Gill et al. discussed the emerging trends and future directions for AI in next-generation computing [46]. Sharma & Ramachandran highlighted the emerging trends of quantum computing in data security and key management [47]. Sridhar, Ashwini & Tabassum reviewed quantum communication and computing, emphasizing their significance in the current technological landscape [48].

Shaikh & Ali surveyed quantum computing in big data analytics, underlining its potential benefits [49]. Long proposed a novel heuristic differential evolution optimization algorithm based on chaos optimization and quantum computing [50]. Amanov & Pradeep (2023) reviewed the significance of artificial intelligence in the second scientific revolution, emphasizing the role of quantum computing [51].

Strategies and algorithms in game theory are also benefiting from quantum resources and even quantum AI [52]. Eisert & Wilkens showed that the prisoner's dilemma is resolved in the quantum domain [53], and Brassard et al. showed that, with shared entangled qubits, players can always win in the magic square game [54]; the results were then extended to a distributed quantum computing setting [55,56]. Marceddu & Montrucchio explored a quantum adaptation of the Morra game and its variants, demonstrating the potential of quantum strategies [57].

Bayrakci & Ozaydin introduced a novel concept for quantum repeaters in the realm of long-distance quantum communications and the quantum internet [58]. This concept puts forth an entanglement swapping procedure rooted in the quantum Zeno effect (QZE).

Remarkably, this approach attains nearly perfect accuracy through straightforward threshold measurements and single-particle rotations. This approach led to the introduction of quantum Zeno repeaters, streamlining the intricacies of quantum repeater systems, holding promise for enhancing long-range quantum communication and quantum computing in distributed systems.

Considering the vast body of research, it is evident that scholars from various fields have deeply probed the nexus between quantum computing and artificial intelligence, uncovering significant potential benefits of their integration. This paper aims to further dissect these insights and pinpoint areas still awaiting thorough examination. Despite the rich literature highlighting the constructive collaboration of quantum computing and AI, there are notable areas of concern. A pressing demand exists for research that intertwines quantum mechanics and AI methodologies. Moreover, ethical concerns, especially concerning data security and misuse, have not been sufficiently addressed. As these technologies evolve, the urgency to tackle scalability issues and formulate uniform standards becomes increasingly paramount.

3. Metrics to Quantify Bias

To measure and address algorithmic bias effectively, quantitative metrics are essential. This section introduces key fairness metrics adapted for use in quantum-enhanced AI systems and illustrates their relevance across various application domains.

In the rapidly evolving domain of quantum AI, where quantum algorithms process and predict vast amounts of data, ensuring fairness becomes even more critical. This is especially true when quantum computations, with their potential for exponential speedups, can introduce biases at scales previously unimagined. For instance, consider a quantum-enhanced social media platform that recommends content to users. Using the Disparate Impact (DI) metric, where Y represents the model predictions and D is the group of the sensitive attribute, represented by Equation (1), the platform can gauge if content recommendations are unfairly skewed towards or against certain demographic groups. The strength of DI is its simplicity, but it does not consider the underlying distribution of true positive and negative instances.

$$DI = \frac{P(Y = 1|D = 0)}{P(Y = 1|D = 1)} \quad (1)$$

In the realm of quantum-enhanced healthcare, where accurate diagnosis is paramount, the Equal Opportunity Difference (EOD) metric becomes particularly relevant, where True Positive Rate (TPR) calculates the percentage of real positive examples that each group's classifier properly detected. With Equation (2), EOD can help to ensure that a quantum diagnostic tool does not miss positive cases more frequently for one demographic than another. While its focus on true positives is commendable, it overlooks the consequences of false positives.

$$EOD = TPR_{D=1} - TPR_{D=0}. \quad (2)$$

The Statistical Parity Difference (SPD), defined by Equation (3), where D is the group containing the sensitive attribute and Y represents the model predictions, can be applied to a quantum-driven social media advertisement targeting system to ensure that ads are displayed fairly across different user groups. Its direct approach is advantageous, but it does not account for the nuances of true instance distributions.

$$EOD = P(Y = 1|D = 1) - P(Y = 1|D = 0). \quad (3)$$

Lastly, in a quantum healthcare system where both false negatives (missing a diagnosis) and false positives (incorrectly diagnosing a healthy individual) have profound implications, the Average Odds Difference (AOD) metric shines. Equation (4) offers a comprehensive view of fairness, although it might be more intricate to interpret.

$$AOD = \frac{1}{2}[(FPR_{D=1} - FPR_{D=0}) + (TPR_{D=1} - TPR_{D=0})]. \quad (4)$$

Deciding on the right fairness metric in quantum AI requires a deep understanding of the application's context. In sectors like social media, where user satisfaction and engagement are key, metrics like DI and SPD might be more relevant. In contrast, in critical areas like healthcare, where lives are at stake, metrics like EOD and AOD become indispensable. The choice of metric should always align with the specific goals and challenges of the application, ensuring that quantum advancements benefit all equitably.

4. Safe Learning and Quantum Control in AI Systems

AI systems, renowned for their adaptive learning prowess, can unfortunately be swayed by biases in their training datasets, potentially resulting in distorted outcomes [59]. By weaving in the principles of quantum mechanics, notably superposition, entanglement, and tunnelling, there is potential to bolster these systems against inherent biases, paving the way for a more steadfast and resilient AI infrastructure. Yet, the journey from quantum-theoretical AI concepts to tangible applications is intricate, calling for breakthroughs in both quantum algorithms and hardware.

4.1. Quantum Superposition for AI Learning

A quantum bit (qubit) can be in a state $|\psi\rangle$, which is superposition of two states, $|0\rangle$ and $|1\rangle$, expressed as

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle, \quad (5)$$

where complex α and β represent the superposition coefficients [18]. This allows for more comprehensive exploration during training, which can potentially counterbalance the influence of biased data samples utilizing Algorithm 1.

Algorithm 1 Quantum AI Training

Require: Number of training iterations N

Ensure: Updated AI model

- 1: Let $i = 0$
 - 2: **while** $i < N$ **do**
 - 3: Prepare qubit in superposition state
 - 4: Apply quantum gates to model the AI learning process
 - 5: Measure the qubit state
 - 6: Update the AI model based on the measurement
 - 7: Increment i by 1
 - 8: **end while**
 - 9: **return** AI model
-

By harnessing superposition, AI models can explore a broader set of potential solutions concurrently. This could help to identify and rectify biases in decisions by comparing outcomes from multiple superimposed states, thus guiding the AI towards more neutral outputs.

4.2. Quantum Entanglement for Cohesive Learning

Entanglement is a phenomenon where spatially separated quantum particles can exhibit nonclassical correlations, violating the Bell inequality [18]. One of the four orthogonal Bell pairs is represented as

$$|\psi\rangle = \frac{|00\rangle + |11\rangle}{\sqrt{2}}. \quad (6)$$

Considering AI, this beyond-classical correlation can be harnessed to depict how two features or parameters are interdependent. Recognizing these entangled pairs might aid in understanding hidden relationships and dependencies in the data. Quantum entanglement can be employed to ensure the AI model understands and considers deeply interconnected features cohesively. By recognizing such intricate relationships, the model might be better equipped to resist developing biases based on superficial or isolated data points. An example of how entanglement can be a useful resource is provided in Algorithm 2.

Algorithm 2 Quantum Entanglement for Cohesive Learning

Require: Number of training iterations N

Ensure: Updated AI model

- 1: Initialize two qubits to a separable state
 - 2: Apply a quantum gate (e.g., a CNOT gate) to entangle them
 - 3: Let $i = 0$
 - 4: **while** $i < N$ **do**
 - 5: Measure one qubit
 - 6: Use the measurement to influence the learning process of the related feature in the AI model
 - 7: Increment i by 1
 - 8: **end while**
 - 9: **return** AI model
-

4.3. Quantum Zeno Effect for Sustainable Fair Learning

The quantum Zeno effect (QZE) is rooted in the fundamental principles of quantum mechanics [22], and it can be utilized for implementing quantum logic operations [60]. At its core, the QZE posits that, by frequently observing a quantum system, its evolution can be slowed down or even frozen. This phenomenon can be likened to a watched pot that never boils. In quantum terms, when a system is frequently measured to ascertain if it is in a particular state, the system is “locked” into that state and is prevented from evolving into a different state [61–63]. This effect arises due to the wave function collapse, a fundamental postulate of quantum mechanics, which states that the act of measurement collapses the quantum state into one of the possible eigenstates of the measurement operator.

In the context of AI bias correction using quantum computing, the QZE’s working principle offers a compelling advantage. By frequently measuring the quantum representation of an AI model, one can effectively “lock” the model into a state of fairness, preventing it from drifting into biased configurations [22,62]. This continuous monitoring and adjustment mechanism could be the best approach because it addresses bias at the quantum level, ensuring that fairness is ingrained into the very fabric of the AI model’s evolution. Traditional methods often tackle bias post-training or during data preprocessing, but the QZE offers a dynamic real-time correction mechanism that is deeply embedded in the model’s training process. As the undesired evolution of a quantum system is slowed down or even frozen via quantum Zeno effect [60], the system being trained can be made to stick to the desired fairness in a sustainable way.

4.4. Quantum Support Vector Machines (QSVMs)

QSVMs operate by finding the hyperplane that best divides a dataset into classes. In the quantum version, this process is expedited by leveraging quantum parallelism. To integrate the QZE, during the training phase of the QSVM, frequent measurements can be conducted to ensure that the quantum state representing the hyperplane remains unbiased. If any bias is detected, quantum logic operations can be applied to correct the trajectory of the hyperplane, ensuring that the final model is fair.

To present a concrete example on how QZE can inhibit undesired bias, we have developed the following three quantum simulations. We consider a hyperplane optimal in maximizing the margin for classification of data as illustrated in Figure 1, and the hyperplane is defined by the superposition coefficient α of a qubit in the state presented in Equation (5) such that the hyperplane is optimal for the maximum superposition case at $|\alpha|^2 = \frac{1}{2}$.

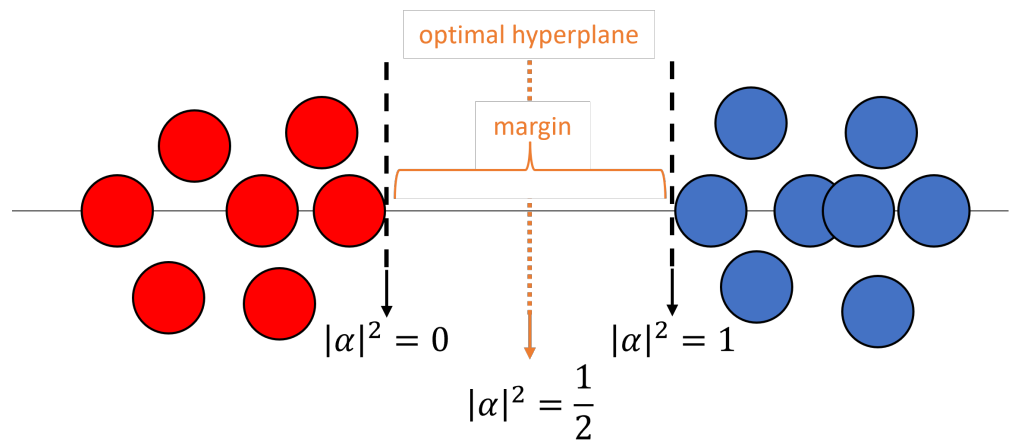


Figure 1. QSVM model illustrating hyperplane (dividing the blue data points from red data points) positioning determined by α , the qubit’s superposition coefficient.

For each simulation, we consider one of the three basic types of bias where the hyperplane (i) approaches $|\alpha|^2 = 1$. (towards blue data points), (ii) approaches $|\alpha|^2 = 0$ (towards red data points), and (iii) performs a random walk around the optimal point at $|\alpha|^2 = \frac{1}{2}$. We associate the following physical models, respectively, acting on the qubit that would lead to these bias types: amplitude damping channel (ADC), which decreases, amplitude amplifying channel (AAC), which increases, and a simple combination of amplitude damping and amplitude amplifying, which randomly increases and decreases α .

A set of Kraus operators $\{K_i\}$ are applied on the density matrix of a quantum system ρ associated with its evolution as $\rho \rightarrow \rho' = \sum_i K_i \rho K_i^\dagger$, where K^\dagger is the conjugate transpose of the operator K . Kraus operators corresponding to ADC are given as

$$ADC_1 = \begin{pmatrix} 1 & 0 \\ 0 & \sqrt{1-p} \end{pmatrix}, \quad ADC_2 = \begin{pmatrix} 0 & \sqrt{p} \\ 0 & 0 \end{pmatrix}, \quad (7)$$

and Kraus operators corresponding to AAC as

$$AAC_1 = \begin{pmatrix} \sqrt{1-p} & 0 \\ 0 & 1 \end{pmatrix}, \quad AAC_2 = \begin{pmatrix} 0 & 0 \\ \sqrt{p} & 0 \end{pmatrix}. \quad (8)$$

Each simulation consists of n iteration steps in which the physical model of the considered bias type applies with a randomly selected value for probability in the range $0 \leq p \leq 0.05$. To protect the classifier hyperplane from bias, we consider frequent measurements to implement QZE as follows. We measure frequently if the qubit is in the

original maximal superposition state with $|\alpha|^2 = \frac{1}{2}$. Due to bias, with an exceedingly small probability $\varepsilon \approx 0$, the qubit is found not in the initial state. But, with almost a unit probability $1 - \varepsilon$, the qubit is projected to the initial superposition state due to the collapse of the wavefunction to that state. For each simulation, we consider four scenarios that reflect the impact of the frequency of the measurement, which is in the heart of QZE. In terms of the iteration steps as the time scale, the period of the Zeno measurements is chosen as $T_Z = \infty$; i.e., no QZE is implemented, and $T_Z = j$; i.e., a Zeno measurement is performed at every j step. In the first simulation considering ADC with $0 \leq p \leq 0.05$ in each iteration, as shown in Figure 2, if no QZE is implemented ($T_Z = \infty$), the superposition coefficient corresponding to the SVM hyperplane approaches 1. However, performing frequent measurements limits the unbiased, and, if the measurement is applied in every evolution step, the hyperplane is perfectly protected from the undesired bias.

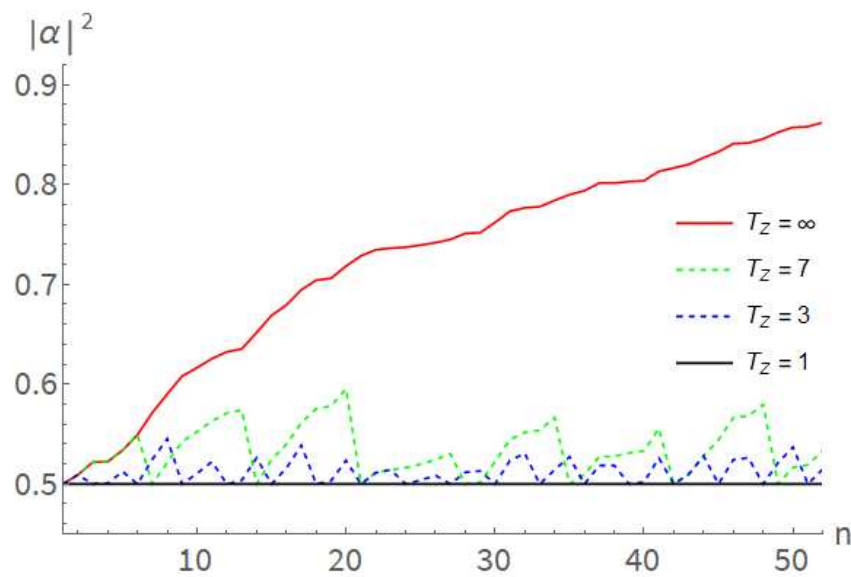


Figure 2. Superposition coefficient α squared as the optimal hyperplane magnitude with respect to n , the number of frequent measurements (with period T_Z) implementing QZE, preventing bias towards blue data points in Figure 1 despite amplitude amplifying noise.

Similarly, in the second simulation considering AAC with $0 \leq p \leq 0.05$ in each iteration that results in bias of the hyperplane towards red data points, and in the third simulation considering both ADC with $0 \leq p \leq 0.05$ and AAC with $0 \leq p \leq 0.05$ in each iteration that results in a random walk bias of the hyperplane around its optimal, we show in Figure 3 and Figure 4, respectively, that QZE helps to keep the hyperplane unbiased. In this particular example, the simulation results show how QZE can inhibit undesired bias in quantum SVMs while, in a broader sense, indicating the potential role of QZE in sustainable fair learning.

4.5. Quantum Neural Networks (QNNs)

QNNs are quantum analogs of classical neural networks [64]. They utilize qubits instead of classical bits and quantum gates instead of classical activation functions. In the context of QZE, as the QNN evolves and learns from data, continuous quantum measurements can be conducted on the qubits representing the network's weights and biases. If any qubit begins to exhibit biased behavior, quantum logic operations can be applied to rectify it. This ensures that QNN remains fair throughout its training process. Implementing these algorithms in the context of AI bias correction would necessitate a hybrid quantum–classical approach. The quantum computer would manage the quantum

aspects of the algorithms, like the QZE-based measurements and corrections, while the classical computer would manage data preprocessing, result interpretation, and other non-quantum tasks. The iterative process of measurement, coupling, and logic operations would form the core of the quantum component of the implementation.

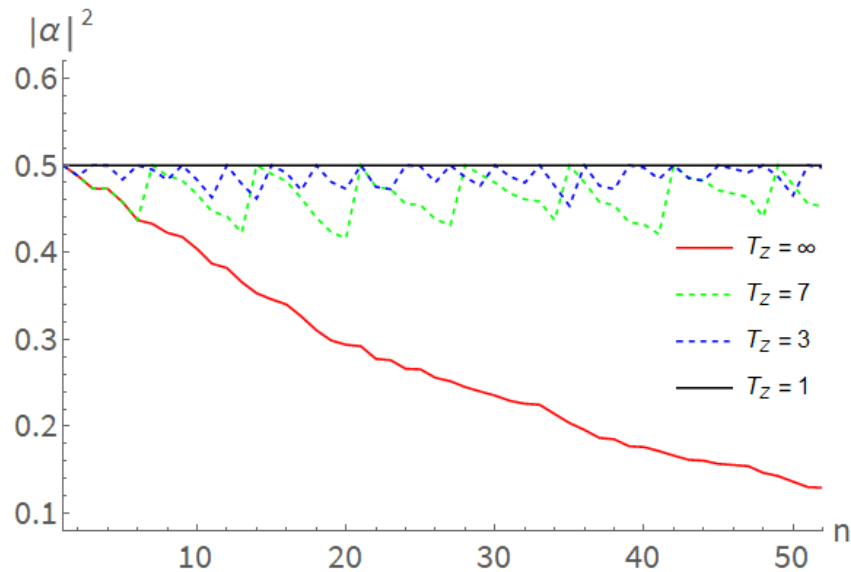


Figure 3. Superposition coefficient α squared as the optimal hyperplane magnitude with respect to n , the number of frequent measurements (with period T_z) implementing QZE, preventing bias towards red data points in Figure 1 despite amplitude damping noise.

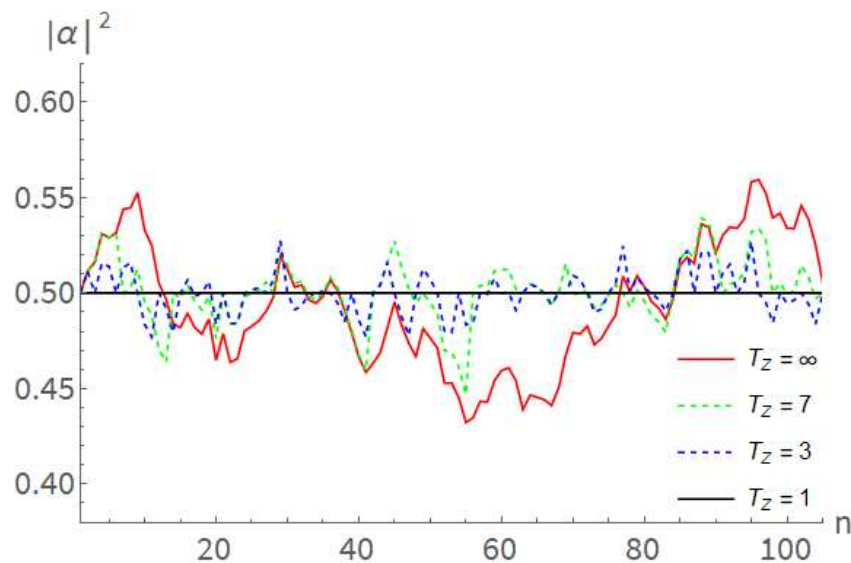


Figure 4. Superposition coefficient α squared as the optimal hyperplane magnitude with respect to n , the number of frequent measurements (with period T_z) implementing QZE, preventing a random walk bias in Figure 1 despite amplitude damping and amplifying noise.

The quantum Zeno effect, when combined with quantum algorithms like QSVM and QNN, offers a robust and dynamic approach to AI bias correction. By addressing bias at its root and providing real-time corrections, this method holds the potential to revolutionize fairness in AI, ensuring that AI models are both accurate and ethically sound.

In conclusion, these quantum principles, while challenging to explicitly implement due to the nascent stage of quantum computing, provide a rich tapestry of concepts that can be metaphorically and, in the future, practically applied to address the persistent

challenge of bias in AI systems. By leveraging the multi-dimensional capacities of quantum mechanics, there is potential for developing AI models that are not only more robust but also ethically sound.

5. Quantum Quantification of Uncertainty and Risk in AI Systems

Quantum mechanics, with its inherent probabilistic nature, offers a unique approach to quantify the uncertainty and risk inherent in AI systems. This uncertainty arises from both the model's inherent limitations and from the data it is trained on. Bias in AI, often seen as a deterministic issue, can be more thoroughly understood when viewed from the probabilistic lens provided by quantum mechanics. Here is an exploration of how quantum principles can be used to understand and mitigate these uncertainties and risks.

5.1. Quantum Probability Amplitudes for Uncertainty Analysis

Traditional AI models produce probabilities based on training data and the model's architecture. Quantum systems, however, describe probabilities using wave functions, with the square of the amplitude providing the likelihood of a particular outcome as $P(x) = |\psi(x)|^2$, where $P(x)$ is the probability density of outcome x and $\psi(x)$ is the wave function corresponding to that quantum state. This method delves into the realm of quantum mechanics to assess uncertainty in AI model predictions. Starting with the AI model's state represented as a quantum state, the process evaluates each potential prediction outcome, x . For each outcome, it determines its quantum probability amplitude, a complex number indicating the likelihood of that outcome. To derive a tangible probability, this amplitude is squared, resulting in the probability density $P(x)$. This quantum-derived probability is then contrasted with the traditional probability from a standard AI model. The method concludes by returning a set of comparison results, shedding light on the nuances between quantum and classical probability measures. In summary, by using quantum probability amplitudes, AI systems can capture the inherent uncertainties in predictions in a more nuanced manner, potentially providing richer insights into areas of low confidence or high variability in model outputs.

5.2. Quantum Risk Matrices for Evaluating Biased Decisions

Risk is often seen as a product of likelihood and impact. Quantum mechanics allows for the simultaneous evaluation of multiple possibilities, which can be leveraged to create a quantum risk matrix. This matrix can measure both the likelihood of a biased decision and its potential impact on outcomes, as can be seen in Algorithm 3.

The quantum risk matrix offers a novel method for visualizing and understanding the complex interplay between bias, likelihood, and impact in AI decisions. By mapping these on a quantum plane, one can rapidly assess areas of substantial risk and prioritize interventions.

Algorithm 3 Quantum Risk Matrices for Evaluating Biased Decisions

Require: None

Ensure: Quantum risk matrix

- 1: Initialize a 2D quantum register representing likelihood and impact axes
 - 2: Apply quantum gates to model the AI decision-making process
 - 3: Measure the register to evaluate the likelihood and impact of biases
 - 4: Aggregate measurements to construct a quantum risk matrix
 - 5: **return** Quantum risk matrix
-

5.3. Quantum Entropy for Measuring Model Uncertainty

In quantum mechanics, the uncertainty of a quantum system described with density matrix ρ is measured by the von Neumann entropy $S = -\text{tr}(\rho \ln \rho)$, where $\text{tr}()$ is the trace function defined as the sum of the diagonal terms of the density matrix ρ , i.e., $\text{tr}(\rho) = \sum_i \rho_{ii}$ [18]. By considering this measure to AI models, one can obtain a better grasp of the inherent uncertainties in the model's predictions and decisions. The quantum entropy algorithm for model uncertainty is an approach that borrows concepts from quantum mechanics to assess the uncertainty inherent in AI model predictions. Initially, the AI model's state is translated into a quantum representation. With a foundational entropy value set at zero, the algorithm delves into analyzing each potential prediction the model might make. For every prediction, it gauges the associated eigenvalue associated with the outcome prediction. Using this eigenvalue, the algorithm calculates the prediction's contribution to the overall uncertainty S . This individual uncertainty is then aggregated to the running total. After iterating through all predictions, the cumulative entropy value offers a comprehensive measure of the model's overall uncertainty. Quantum entropy offers a rigorous metric for gauging the uncertainty inherent in a quantum AI system. By evaluating this, stakeholders can more precisely understand the reliability and confidence level of AI predictions. To conclude, integrating quantum principles to measure uncertainty and risk in AI systems provides a more holistic and rigorous approach than classical methods. While the practical integration of these concepts remains a significant challenge due to the nascent state of quantum computing, their theoretical implications can reshape our understanding of bias, uncertainty, and risk in AI.

6. Decision-Making in Quantum AI: Navigating Uncertainty and Limited Information

Decision-making in artificial intelligence (AI) often involves navigating uncertain environments, incomplete datasets, and unpredictable user interactions. When these complexities intersect with the quantum domain, new frameworks and computational strategies emerge. This section delves into the interplay between decision theory and quantum AI, focusing on how quantum-enhanced algorithms can improve robustness, bias detection, and data-driven reasoning. Through concrete examples—including Grover's algorithm for anomaly identification and the integration of quantum principles into data mining protocols—we explore how quantum resources empower more inclusive, efficient, and ethically sound AI decisions.

6.1. Grover's Algorithm in Bias Detection

In the context of AI bias, erroneous decisions often arise due to uncertainties or limited data, especially when that data lacks representation from marginalized groups. Quantum computing can process various data scenarios with quantum parallelism, making decisions more inclusive and reducing the potential for bias. In the realm of AI, detecting biases can be viewed as searching for an anomalous piece of information in an unsorted dataset. Consider a dataset of N items, with a marked item representing biased data. Grover's algorithm provides a quantum advantage by searching for this marked item with $O(\sqrt{N})$ iterations, as opposed to $O(N)$ in a classical scenario. Mathematically, Grover's algorithm utilizes quantum superposition to prepare a uniform superposition state

$$|\psi\rangle = \frac{1}{\sqrt{N}} \sum_{i=0}^{N-1} |i\rangle. \quad (9)$$

A sequence of Grover operators, composed of the oracle operator and Grover diffusion operator, are applied on this state to amplify the amplitude of the marked item. After $O(\sqrt{N})$ applications, the quantum state collapses upon measurement to reveal the marked item. In the context of bias detection, this marked item might represent a piece of data or a pattern that introduces bias in AI predictions. Using Grover's algorithm, one can efficiently detect and isolate these biases, enabling more equitable and reliable AI models. By harnessing the quadratic speedup provided by Grover's algorithm, quantum computing promises a more efficient route to navigate the labyrinth of vast datasets in AI, making informed decisions despite missing or uncertain data, and especially locating biases that might otherwise remain hidden in classical computational scenarios.

6.2. Ensuring AI Robustness: Quantum Responses to Perturbations and Distribution Shifts

Analogous to the way biases and errors can distort an AI system's decisions, errors in quantum computations can mislead quantum-based AI models. This is where quantum error-correcting codes, such as the Shor code, become invaluable. The Shor code encodes a single logical qubit into nine physical qubits, offering a means to correct both bit-flip and phase-flip errors [18]. The encoding of a qubit state

$$|\psi\rangle = \alpha_0|0\rangle + \alpha_1|1\rangle \quad (10)$$

can be represented as transforming it into a tensor product of nine qubits

$$|\psi_S\rangle = \alpha_0|0_S\rangle + \alpha_1|1_S\rangle, \quad (11)$$

where

$$|0_S\rangle = \frac{1}{2\sqrt{2}}(|000\rangle + |111\rangle) \otimes (|000\rangle + |111\rangle) \otimes (|000\rangle + |111\rangle), \quad (12)$$

$$|1_S\rangle = \frac{1}{2\sqrt{2}}(|000\rangle - |111\rangle) \otimes (|000\rangle - |111\rangle) \otimes (|000\rangle - |111\rangle). \quad (13)$$

When a single qubit error occurs, the Shor code uses the redundancy of the encoded state to identify and correct the error, ensuring the quantum state remains intact. In the context of AI robustness, imagine quantum computations as the underpinnings of an AI's decision-making process. If these computations are influenced by even minor errors, the resultant decisions can be heavily skewed, enhancing existing biases. By implementing the Shor code, we can protect the quantum computations that inform AI systems, ensuring a level of robustness against perturbations. Just as error correction is vital in classical computing to maintain data integrity, in a quantum-enhanced AI, the Shor code acts as a guardian against quantum errors, bolstering the reliability and fairness of AI outcomes. Embracing error-correcting methodologies like the Shor code is paramount for the feasibility of quantum-based AI. Without such mechanisms, the potential advantages of quantum computing could be overshadowed by its inherent susceptibility to errors, especially when navigating the intricate challenges of AI biases.

6.3. Quantum Techniques for Anomaly Detection and Model Misspecification Analysis

Swiftly identifying biases as anomalies in AI outputs is crucial. Quantum techniques excel at analyzing vast datasets for these anomalies, making the process of pinpointing and rectifying biases much faster. Quantum anomaly detection algorithms can specifically be trained to recognize biases as anomalies, ensuring biases do not go undetected. The quantum phase estimation algorithm can be employed, wherein a unitary operation U is applied to a quantum state and the phase is estimated. This phase could correspond to

potential anomalies in data, allowing for bias detection. Rapid bias detection can prevent unfair decisions from influencing real-world outcomes, ensuring a just application of AI technologies.

6.4. Formal Quantum Methods in AI System Design and Validation

Ensuring AI models are designed with minimal bias from the outset is paramount. Quantum methodologies rigorously evaluate models against bias benchmarks, building trust in their outputs. Quantum validation protocols for AI models can validate models against standards that specifically prioritize fairness and bias minimization. Consider a quantum gate sequence G applied on a state $|\psi\rangle$. Quantum process tomography [65] can be used to verify the accuracy and fairness of this operation, ensuring bias-free model operations. Validating AI models against anti-bias benchmarks ensures that the systems prioritize fairness from their foundation.

6.5. Online Quantum Verification of AI Systems as Bias Sentinels

Real-time bias detection can prevent the unfair influence of AI recommendations or decisions. Quantum protocols serve as vigilant sentinels, instantly identifying and flagging biases. The Quantum Fourier Transform is an essential component of many quantum algorithms, including Shor's algorithm. The QFT, in the quantum realm, serves a similar purpose to the classical Fourier transform: it translates data from the time domain to the frequency domain. Given the vast and intricate nature of data overseen by AI systems, employing QFT could unearth patterns and biases otherwise obscured in the sheer volume of information. For example, recurrent biases might manifest as notable frequencies upon the application of QFT, allowing for clearer identification and subsequent mitigation.

6.6. Ensuring Safe Human–Quantum–AI Interaction Paradigms

As users interact with AI models, the outputs need to consistently align with fairness standards. Quantum checks on these interactions can ensure that bias does not creep into real-time recommendations or decisions. Evaluating the quantum volume as a measure for its potential in AI systems can be considered. Quantum volume is a single-number metric that can be used to benchmark the computational capability of quantum computers. It considers both gate and measurement errors, qubit connectivity, and crosstalk. A higher quantum volume indicates a more powerful quantum computer.

For AI, understanding the quantum volume of the computational backbone is vital. Robust quantum volume means the system can oversee more complex AI models and is better suited to tackle the multi-dimensional challenges posed by biases. Thus, ensuring high quantum volume is crucial for the development and validation of AI systems that aim to identify and rectify biases effectively. The integration of these quantum methods and algorithms offers a promising pathway towards crafting AI models that are both insightful and impartial. They provide the tools to delve deeper, to see clearer, and to act more decisively against biases that might otherwise undermine the fairness and efficacy of AI systems.

6.7. Integrating Quantum Sentinel with CRISP-DM

The cross-industry standard process for Data Mining (CRISP-DM) provides a widely accepted structured approach to developing data-driven solutions. In the context of ethical AI, embedding quantum capabilities into this framework can offer early-stage bias detection, continuous monitoring, and systematic corrections across the AI lifecycle. This subsection outlines how the proposed quantum sentinel can be integrated into each phase of the CRISP-DM model, thereby reinforcing fairness, transparency, and accountability from project initiation to deployment.

6.7.1. Business Understanding

While quantum interventions at this stage are primarily oriented toward awareness and alerts, the practical application of bias correction algorithms remains limited. Nonetheless, a preliminary understanding of tools such as synthetic minority over-sampling technique (SMOTE), adaptive synthetic sampling (ADASYN), generative adversarial networks (GANs), and variational autoencoders (VAEs) can guide the formation of business objectives by clarifying what types of bias corrections are possible at later stages.

Figure 5 illustrates the integration of a *quantum sentinel* within the widely adopted CRISP-DM architecture, emphasizing its high-level structure. During the initial phase, where project objectives are defined and requirements are understood, the quantum sentinel can be integrated to

- **Flag:** Alert stakeholders if the project goals embed inherent biases or prejudices that could lead to unfair AI outcomes.
- **Correction:** If biased objectives are detected, quantum algorithms such as Grover's algorithm can quickly identify the specific bias, enabling stakeholders to revise their goals.
- **ACK/NACK:** Once goals are finalized, the quantum sentinel issues an acknowledgment (ACK) for bias-free goals or a negative acknowledgment (NACK) if biases persist.

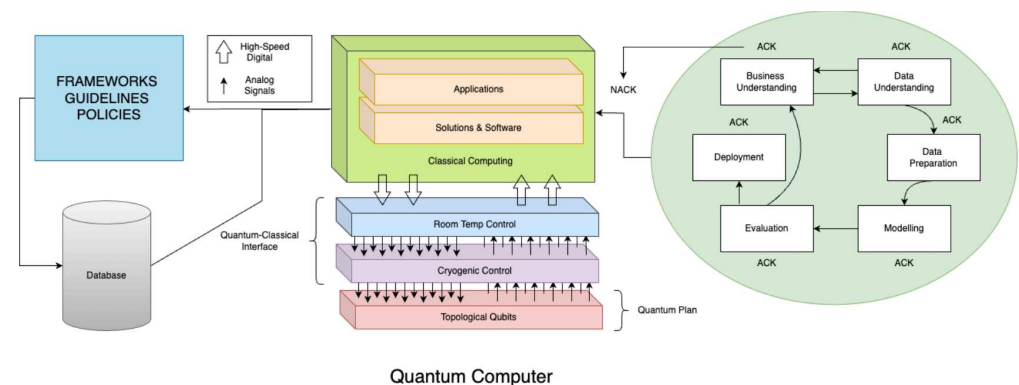


Figure 5. Architecture of the CRISP-DM-integrated quantum sentinel.

6.7.2. Data Understanding

During the phase in which data is collected and explored:

- **Flag:** The quantum sentinel identifies biases in data sourcing, sampling, or initial insights. Quantum process tomography can help to reveal the nature and extent of such biases.
- **Correction:** The Quantum Fourier Transform (QFT) can be applied to analyze data distributions and highlight segments requiring correction.
- **ACK/NACK:** After evaluation, unbiased datasets receive an ACK, while those needing further scrutiny receive a NACK.

6.7.3. Data Preparation

In the data preparation phase:

- **Flag:** Biases in data sourcing, preprocessing, or sampling are detected by the quantum sentinel. Again, quantum process tomography may assist in diagnosing these issues.
- **Correction:** QFT can help to better understand data characteristics, enabling targeted corrections.
- **ACK/NACK:** Post-processing, an ACK is provided for properly prepared data, or a NACK if bias issues remain.

6.7.4. Modeling

During model construction:

- Flag: The sentinel identifies if chosen algorithms exhibit inherent biases or favor particular data patterns.
- Correction:
 1. Grover's algorithm can expedite the selection of alternative more balanced algorithms.
 2. GANs can generate synthetic data to balance underrepresented classes or augment limited datasets.
 3. VAEs can create new data points that help to counteract skew in the training set.
 4. When data scarcity is the root cause of bias, GANs and VAEs can be used to synthetically enrich the dataset.
- ACK/NACK: Upon model construction, an ACK is issued for models ready for evaluation or a NACK for those needing refinement.

6.7.5. Evaluation

During model assessment:

- Flag: The quantum sentinel highlights whether evaluation metrics overlook latent biases or unfair results.
- Correction: Quantum-enhanced techniques, such as the Shor code, can be employed to identify flaws and re-evaluate the model for robustness.
- ACK/NACK: If models meet fairness criteria, they receive an ACK; otherwise, a NACK prompts retraining with tools like SMOTE, ADASYN, GANs, or VAEs to mitigate the identified biases.

6.7.6. Deployment

During the deployment phase:

- Flag: The quantum sentinel monitors real-world performance, flagging biases that emerge during application.
- Correction: Leveraging quantum volume, the sentinel ensures the quantum system is capable of overseeing real-time adjustments. GANs or VAEs may be used to simulate problematic scenarios and retrain the model accordingly.
- ACK/NACK: Continuous monitoring provides ongoing ACKs or NACKs, maintaining model fairness throughout its life cycle.

Having examined each phase of the CRISP-DM framework, it becomes evident that quantum interventions can serve not only as reactive measures but also as proactive tools for sustaining AI integrity. From initial goal-setting to real-world application, the quantum sentinel reinforces a continuous loop of feedback and refinement. The following summary consolidates these insights, highlighting the synergy between quantum diagnostics and classical mitigation techniques.

In summary, integrating a quantum sentinel within the CRISP-DM process introduces a rigorous stage-by-stage mechanism for detecting and correcting bias. By combining quantum diagnostics and alerts with classical algorithms such as SMOTE, ADASYN, GANs, and VAEs, this hybrid approach establishes a multi-layered framework for enhancing the fairness and resilience of AI systems.

7. Results

This section presents the empirical results of our proposed framework, highlighting the comparative efficiency, scalability, and robustness of quantum versus classical approaches in bias detection and correction.

Incorporating quantum mechanics with AI sentinel systems demonstrated a promising increase in bias detection and correction efficiency. Quantum computing, due to its nature of superposition and entanglement, demonstrated faster processing of biases embedded in complex multi-dimensional AI models.

7.1. Comparative Analysis: Quantum vs. Classical

Let T_q represent the time taken by the quantum sentinel system and T_c denote the time taken by its classical counterpart. For a large dataset of size N :

- $T_q \propto \sqrt{N}$ (using Grover's algorithm for database search);
- $T_c \propto N$ (classical sequential search).

This demonstrates that the quantum system achieves a *quadratic speedup* in processing time for bias detection tasks compared to classical systems.

In terms of space complexity, quantum systems offer exponential advantages as n qubits can represent 2^n states simultaneously due to quantum superposition. However, it is important to account for the overhead introduced by quantum error correction, which necessitates additional ancillary qubits. As a result, the effective space advantage, while still significant, is slightly reduced in practice.

7.2. Advantages of a Quantum Sentinel

- **Speed:** The quadratic speedup provided by quantum algorithms such as Grover's significantly reduces the time required for bias detection and correction.
- **Depth:** Quantum mechanics inherently allows for deeper interrogation of data, leading to more thorough detection of underlying biases.
- **Holistic Analysis:** Due to quantum entanglement, quantum systems can evaluate data in a holistic and interdependent manner, enabling the identification of complex correlated bias patterns.

7.3. Disadvantages of a Quantum Sentinel

- **Nascent Technology:** Quantum computing is still in its early stages; the current hardware exhibits high error rates and requires extremely controlled environments.
- **Integration Challenges:** Integrating quantum components with conventional AI architectures poses both technical and logistical difficulties.
- **Resource Intensive:** Current quantum systems are energy-demanding and necessitate specialized equipment and infrastructure.

7.4. SWOT Analysis

- **Strengths:** Speed, depth of analysis, and holistic data understanding.
- **Weaknesses:** Nascent technology, high error rates, and integration complexities.
- **Opportunities:** As quantum technologies mature, error rates are expected to decline, and additional quantum algorithms can be developed specifically for bias detection and correction.
- **Threats:** Rapid advances in classical algorithms may diminish the comparative advantage of quantum systems in the domain of bias detection.

7.5. Time and Space Complexities

While classical bias detection operates linearly with respect to dataset size, $T_c \propto N$, quantum systems leveraging Grover's algorithm can provide a quadratic speedup, yielding $T_q \propto \sqrt{N}$. Quantum systems also offer potential exponential advantages in space complexity as n qubits can represent 2^n states. However, this advantage is tempered by the practical

requirements of quantum error correction and limitations in qubit coherence, which reduce the net space benefit.

7.6. Future Work

- **Improved Integration:** Conducting research into more seamless integration of quantum sentinels with existing classical AI architectures.
- **Quantum Algorithm Development:** Designing and exploring new quantum algorithms specifically tailored to bias detection and correction.
- **Scalability:** Investigating the scalability of quantum sentinel systems with increasingly complex AI models and larger datasets.

To illustrate how the quantum Zeno effect (QZE) can protect Support Vector Machines (SVMs) from bias, we associated the hyperplane with the superposition coefficient of a qubit and applied QZE on that qubit. A more detailed analysis can be considered in future research, where QZE is incorporated directly into the learning process.

7.7. Quantum Hardware Requirements and Error Sources

While the conceptual framework of the quantum sentinel leverages well-established quantum algorithms such as Grover's search and the quantum Zeno effect, its practical implementation depends critically on the capabilities and limitations of contemporary quantum hardware.

Qubit Quality and Gate Fidelity: For algorithms like Grover's, coherent superposition and repeated applications of oracle and diffusion operators are required. This necessitates high-fidelity quantum gates (typically above 99.9% for two-qubit gates) and long coherence times to avoid degradation of the quantum state before completion. Similarly, implementing the quantum Zeno effect demands frequent and precise quantum measurements, which places tight constraints on gate timing precision and qubit isolation.

Error Sources: The most significant error sources include decoherence, gate infidelity, crosstalk between qubits, and readout errors. These become particularly problematic in real-time bias detection systems, where the quantum system must repeatedly measure and correct the state without inducing collapse or excessive disturbance.

Hardware Architecture Considerations: Superconducting qubit platforms (e.g., IBM and Google) offer fast gate times and decent scalability but suffer from limited connectivity and moderate coherence. Trapped ion platforms (e.g., IonQ and Quantinuum), on the other hand, provide excellent gate fidelity and all-to-all connectivity, which may be advantageous for implementing entangled-based anomaly detection and multi-qubit Zeno measurements. Photonic systems offer another route, particularly suited to quantum communication and parallel measurements, although they are currently less mature in terms of gate-based computation.

Resource Overhead: Implementing fault-tolerant versions of the quantum algorithms discussed—especially the Zeno-based bias correction—may require encoding logical qubits using quantum error-correcting codes (e.g., surface code or Shor code). This could increase the number of physical qubits required by an order of magnitude depending on the target error thresholds.

Scalability Implications: As the number of required qubits increases with dataset complexity, the ability to scale hardware without compromising on fidelity will be essential. Hybrid approaches—where classical preprocessing reduces the problem size before invoking quantum subroutines—may offer a practical near-term path forward.

Reducing Quantum Circuit Complexity via Quantum Zeno Computing: Quantum Zeno Dynamics (QZD) has been shown to enable the creation of two-qubit entanglement using only single-qubit rotations and simple threshold measurements, thereby eliminat-

ing the need for two-qubit controlled gates [66]. More recently, QZD has demonstrated significant reductions in quantum circuit complexity in tasks such as activating [67] and superactivating bound entanglement [68], both of which traditionally require numerous two-qubit and two-qutrit gates [69,70]. These findings suggest that quantum Zeno computing may emerge as a novel quantum computation paradigm that is capable of minimizing quantum circuit depth by reducing reliance on two-particle controlled operations. As a result, it offers the potential to lower resource overhead and mitigate the impact of errors and imperfections in current gate-based quantum hardware.

Summary: While the current work does not include hardware-specific simulations to quantify thresholds, future investigations can explore optimal trade-offs between error rates, coherence times, and measurement frequency. Such studies could guide the deployment of quantum sentinels on noisy intermediate-scale quantum (NISQ) devices and inform hardware–algorithm co-design.

8. Conclusions

Having validated the conceptual and practical advantages of quantum-enhanced bias detection, we now synthesize the implications of our findings and discuss their broader relevance for ethical AI development. Navigating the intricate maze of AI biases, this work explores the revolutionary potential of quantum computing for their detection and rectification. The realm of quantum mechanics offers the promise of unprecedented depth in data understanding, achieved at groundbreaking speeds, marking a pivotal shift toward ethical AI systems. By juxtaposing the nuances of quantum algorithms—such as Grover’s and Shor’s—with the multi-dimensional challenges of AI bias, we have provided a comprehensive blueprint for their harmonious integration.

This study highlights quantum computing’s role as a vigilant sentinel, continuously monitoring AI systems to ensure fairness and equity. Through the adoption of the CRISP-DM framework, we demonstrated the systematic incorporation of quantum principles across various phases of the data mining process, culminating in an end-to-end bias audit. Furthermore, we emphasized the enhancements that quantum computing introduces to traditional bias mitigation techniques, such as SMOTE, ADASYN, GANs, and VAEs.

A comparative analysis between the proposed quantum-enhanced framework and classical paradigms underscores both the transformative potential of and the challenges inherent to this emerging field. Ultimately, our quantum–AI synthesis aims to build an AI ecosystem that is not only intelligent but also fundamentally fair and just. We also showed that the quantum Zeno effect can protect SVM hyperplanes from bias through targeted simulations.

Author Contributions: Conceptualization, A.C., K.E., R.A., G.B.A., F.O. and M.M.N.; methodology, A.C., K.E., R.A., G.B.A., F.O. and M.M.N.; software, F.O.; validation, A.C., K.E., R.A., G.B.A., F.O. and M.M.N.; formal analysis, A.C., K.E., R.A., G.B.A., F.O. and M.M.N.; investigation, A.C., K.E., R.A., G.B.A., F.O. and M.M.N.; resources, A.C., K.E., R.A., G.B.A., F.O. and M.M.N.; data curation, A.C., K.E. and F.O.; writing—original draft preparation, A.C., K.E., R.A., G.B.A., F.O. and M.M.N.; visualization, A.C., K.E., R.A., G.B.A., F.O. and M.M.N.; supervision, R.A., G.B.A., F.O. and M.M.N.; project administration, R.A., G.B.A., F.O. and M.M.N.; funding acquisition, F.O. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Tokyo International University Personal Research Fund.

Data Availability Statement: Wolfram Mathematica code for the quantum Zeno effect simulation is available at https://github.com/mansursah/QZD_QSVM/blob/main/qzd_qsvm.nb (accessed on 22 June 2025).

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AAC	Amplitude Amplifying Channel
ADASYN	Adaptive Synthetic Sampling
ADC	Amplitude Damping Channel
AOD	Average Odds Difference
CRISP-DM	Cross-Industry Standard Process for Data Mining
DI	Disparate Impact
EOD	Equal Opportunity Difference
GAN	Generative Adversarial Network
QAI	Quantum Artificial Intelligence
QUEL	Quantum Universal Exchange Language
QFT	Quantum Fourier Transform
QNN	Quantum Neural Network
QSVM	Quantum Support Vector Machine
QZE	Quantum Zeno Effect
SMOTE	Minority Over-Sampling Technique
SPD	Statistical Parity Difference
TPR	True Positive Rate
VAE	Variational Autoencoder

References

1. Yapo, A.; Weiss, J. Ethical implications of bias in machine learning. In Proceedings of the 51st Hawaii International Conference on System Sciences, Hilton Waikoloa Village, HI, USA, 3–6 January 2018. [\[CrossRef\]](#)
2. Shaheen, M.Y. Applications of Artificial Intelligence (AI) in healthcare: A review. *ScienceOpen Prepr.* **2021**, 1–8. [\[CrossRef\]](#)
3. Turkeli, S.; Ozaydin, F. A novel framework for extracting knowledge management from business intelligence log files in hospitals. *Appl. Sci.* **2022**, *12*, 5621. [\[CrossRef\]](#)
4. Seyyed-Kalantari, L.; Zhang, H.; McDermott, M.B.; Chen, I.Y.; Ghassemi, M. Underdiagnosis bias of artificial intelligence algorithms applied to chest radiographs in under-served patient populations. *Nat. Med.* **2021**, *27*, 2176–2182. [\[CrossRef\]](#)
5. Gravett, W. Sentenced by an algorithm—Bias and lack of accuracy in risk-assessment software in the United States criminal justice system. *J. Crim. Justice* **2021**, *34*, 31–54. [\[CrossRef\]](#)
6. Washington, A.L. How to argue with an algorithm: Lessons from the COMPAS-ProPublica debate. *Colo. Tech. LJ* **2018**, *17*, 131.
7. Khademi, A.; Honavar, V. Algorithmic bias in recidivism prediction: A causal perspective (student abstract). *Proc. AAAI Conf. Artif. Intell.* **2020**, *34*, 13839–13840. [\[CrossRef\]](#)
8. Angwin, J.; Larson, J.; Mattu, S.; Kirchner, L. Machine bias. In *Ethics of Data and Analytics*; Auerbach Publications: Boca Raton, FL, USA, 2022; pp. 254–264.
9. Brantingham, P.J. The logic of data bias and its impact on place-based predictive policing. *Ohio St. J. Crim. L.* **2017**, *15*, 473.
10. Benbouzid, B. To predict and to manage. Predictive policing in the United States. *Big Data Soc.* **2019**, *6*, 2053951719861703. [\[CrossRef\]](#)
11. Feng, Y.; Shah, C. Has ceo gender bias really been fixed? adversarial attacking and improving gender fairness in image search. *Proc. AAAI Conf. Artif. Intell.* **2022**, *36*, 11882–11890. [\[CrossRef\]](#)
12. He, J.; Kang, S. Identities between the lines: Re-aligning gender and professional identities in job advertisements. *Acad. Manag. Proc.* **2022**, *2022*, 10415. [\[CrossRef\]](#)
13. Prud'homme, B.; Régis, C.; Farnadi, G. *Missing Links in AI Governance*; United Nations Educational, Scientific and Cultural Organization (UNESCO): Paris, France, 2023.
14. Andrews, L.; Bucher, H. Automating discrimination: AI hiring practices and gender inequality. *Cardozo L. Rev.* **2022**, *44*, 145.
15. Vartan, S. Racial bias found in a major health care risk algorithm. *Scientific American*, 24 October 2019.
16. Wolf, M.J.; Miller, K.; Grodzinsky, F.S. Why we should have seen that coming: Comments on Microsoft's tay "experiment," and wider implications. *ACM Sigcas Comput. Soc.* **2017**, *47*, 54–64. [\[CrossRef\]](#)
17. Ntoutsis, E.; Fafalios, P.; Gadiraju, U.; Iosifidis, V.; Nejdil, W.; Vidal, M.E.; Ruggieri, S.; Turini, F.; Papadopoulos, S.; Krasanakis, E.; et al. Bias in data-driven artificial intelligence systems—An introductory survey. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2020**, *10*, e1356. [\[CrossRef\]](#)

18. Nielsen, M.A.; Chuang, I.L. *Quantum Computation and Quantum Information: 10th Anniversary Edition*; Cambridge University Press: Cambridge, UK, 2011.
19. Paredes, B.; Verstraete, F.; Cirac, J.I. Exploiting quantum parallelism to simulate quantum random many-body systems. *Phys. Rev. Lett.* **2005**, *95*, 140501. [[CrossRef](#)]
20. Shor, P.W. Fault-tolerant quantum computation. In Proceedings of the 37th Conference on Foundations of Computer Science, Burlington, VT, USA, 14–16 October 1996; IEEE: Burlington, VT, USA, 1996; pp. 56–65. [[CrossRef](#)]
21. Alvi, M.; Zisserman, A.; Nellåker, C. Turning a blind eye: Explicit removal of biases and variation from deep neural network embeddings. In Proceedings of the European Conference on Computer Vision (ECCV) Workshops, Munich, Germany, 8–14 September 2018; pp. 556–572. [[CrossRef](#)]
22. Misra, B.; Sudarshan, E.C.G. The Zeno's paradox in quantum theory. *J. Math. Phys.* **1977**, *18*, 756–763. [[CrossRef](#)]
23. Miller, A. The intrinsically linked future for human and Artificial Intelligence interaction. *J. Big Data* **2019**, *6*, 38. [[CrossRef](#)]
24. Wichert, A. Artificial intelligence and a universal quantum computer. *AI Commun.* **2016**, *29*, 537–543. [[CrossRef](#)]
25. Dunjko, V.; Briegel, H.J. Machine learning & artificial intelligence in the quantum domain: A review of recent progress. *Rep. Prog. Phys.* **2018**, *81*, 074001. [[CrossRef](#)]
26. Wichert, A. *Principles of Quantum Artificial Intelligence: Quantum Problem Solving and Machine Learning*; World Scientific: Singapore, 2020.
27. Zhu, Y.; Yu, K. Artificial intelligence (AI) for quantum and quantum for AI. *Opt. Quantum Electron.* **2023**, *55*, 697. [[CrossRef](#)]
28. Krenn, M.; Landgraf, J.; Foesel, T.; Marquardt, F. Artificial intelligence and machine learning for quantum technologies. *Phys. Rev. A* **2023**, *107*, 010101. [[CrossRef](#)]
29. Ajagekar, A.; You, F. Quantum computing and quantum artificial intelligence for renewable and sustainable energy: A emerging prospect towards climate neutrality. *Renew. Sustain. Energy Rev.* **2022**, *165*, 112493. [[CrossRef](#)]
30. Taylor, R.D. Quantum artificial intelligence: A “precautionary” US approach? *Telecommun. Policy* **2020**, *44*, 101909. [[CrossRef](#)]
31. Nagaraj, G.; Upadhayaya, N.; Matroud, A.; Sabitha, N.; VK, R.; Nagaraju, R. A detailed investigation on potential impact of quantum computing on improving artificial intelligence. In Proceedings of the 2023 International Conference on Innovative Data Communication Technologies and Application (ICIDCA), Uttarakhand, India, 14–16 March 2023; IEEE: Uttarakhand, India, 2023; pp. 447–452. [[CrossRef](#)]
32. Gigante, G.; Zago, A. DARQ technologies in the financial sector: Artificial intelligence applications in personalized banking. *Qual. Res. Financ. Mark.* **2023**, *15*, 29–57. [[CrossRef](#)]
33. Ahmed, S.; Sánchez Muñoz, C.; Nori, F.; Kockum, A.F. Quantum state tomography with conditional generative adversarial networks. *Phys. Rev. Lett.* **2021**, *127*, 140502. [[CrossRef](#)] [[PubMed](#)]
34. Moret-Bonillo, V. Can artificial intelligence benefit from quantum computing? *Prog. Artif. Intell.* **2015**, *3*, 89–105. [[CrossRef](#)]
35. Abdelgaber, N.; Nikolopoulos, C. Overview on quantum computing and its applications in artificial intelligence. In Proceedings of the 2020 IEEE Third International Conference on Artificial Intelligence and Knowledge Engineering (AIKE), Laguna Hills, CA, USA, 9–13 December 2020; IEEE: Laguna Hills, CA, USA, 2020; pp. 198–199. [[CrossRef](#)]
36. Kakaraparty, K.; Munoz-Coreas, E.; Mahbub, I. The future of mm-wave wireless communication systems for unmanned aircraft vehicles in the era of artificial intelligence and quantum computing. In Proceedings of the 2021 IEEE MetroCon, Hurst, TX, USA, 3 November 2021; IEEE: Hurst, TX, USA, 2021; pp. 1–8. [[CrossRef](#)]
37. Bhatia, A.; Bibhu, V.; Lohani, B.P.; Kushwaha, P.K. An application framework for quantum computing using Artificial intelligence techniques. In Proceedings of the 2020 Research, Innovation, Knowledge Management and Technology Application for Business Sustainability (INBUSH), Greater Noida, India, 19–21 February 2020; IEEE: Greater Noida, India, 2020; pp. 264–269. [[CrossRef](#)]
38. Moret-Bonillo, V. Emerging technologies in artificial intelligence: Quantum rule-based systems. *Prog. Artif. Intell.* **2018**, *7*, 155–166. [[CrossRef](#)]
39. Robson, B.; Clair, J.S. Principles of quantum mechanics for artificial intelligence in medicine. Discussion with reference to the Quantum Universal Exchange Language (Q-UEL). *Comput. Biol. Med.* **2022**, *143*, 105323. [[CrossRef](#)]
40. Gabor, T.; Sünkel, L.; Ritz, F.; Phan, T.; Belzner, L.; Roch, C.; Feld, S.; Linnhoff-Popien, C. The holy grail of quantum artificial intelligence: Major challenges in accelerating the machine learning pipeline. In Proceedings of the IEEE/ACM 42nd International Conference on Software Engineering Workshops, Seoul, Republic of Korea, 27 June 2020–19 July 2020; pp. 456–461. [[CrossRef](#)]
41. Jannu, S.; Dara, S.; Thuppari, C.; Vidyarthi, A.; Ghosh, D.; Tiwari, P.; Muhammad, G. Energy efficient quantum-informed ant colony optimization algorithms for industrial internet of things. *IEEE Trans. Artif. Intell.* **2022**, *5*, 1077–1086. [[CrossRef](#)]
42. Gyongyosi, L.; Imre, S. A survey on quantum computing technology. *Comput. Sci. Rev.* **2019**, *31*, 51–71. [[CrossRef](#)]
43. Chauhan, V.; Negi, S.; Jain, D.; Singh, P.; Sagar, A.K.; Sharma, A.K. Quantum computers: A review on how quantum computing can boom AI. In Proceedings of the 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 28–29 April 2022; IEEE: Greater Noida, India, 2022, pp. 559–563. [[CrossRef](#)]
44. Manju, A.; Nigam, M.J. Applications of quantum inspired computational intelligence: A survey. *Artif. Intell. Rev.* **2014**, *42*, 79–156. [[CrossRef](#)]

45. Huang, Z.; Qian, L.; Cai, D. Analysis on the recent development of quantum computer and quantum neural network technology. In Proceedings of the 2022 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA), Dalian, China, 24–26 June 2022; IEEE: Dalian, China, 2022; pp. 680–684. [[CrossRef](#)]
46. Gill, S.S.; Xu, M.; Ottaviani, C.; Patros, P.; Bahsoon, R.; Shaghghi, A.; Golec, M.; Stankovski, V.; Wu, H.; Abraham, A.; et al. AI for next generation computing: Emerging trends and future directions. *Internet Things* **2022**, *19*, 100514. [[CrossRef](#)]
47. Sharma, N.; Ketti Ramachandran, R. The emerging trends of quantum computing towards data security and key management. *Arch. Comput. Methods Eng.* **2021**, *28*, 5021–5034. [[CrossRef](#)]
48. Sridhar, G.T.; Ashwini, P.; Tabassum, N. A review on quantum communication and computing. In Proceedings of the 2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC), Salem, India, 4–6 May 2023; IEEE: Salem, India, 2023; pp. 1592–1596. [[CrossRef](#)]
49. Shaikh, T.A.; Ali, R. Quantum computing in big data analytics: A survey. In Proceedings of the 2016 IEEE International Conference on Computer and Information Technology (CIT), Nadi, Fiji, 8–10 December 2016; IEEE: Nadi, Fiji, 2016; pp. 112–115. [[CrossRef](#)]
50. Long, Z. A novel heuristic differential evolution optimization algorithm based on the chaos optimization and quantum computing. In Proceedings of the 2012 International Conference on Systems and Informatics (ICSAI2012), Yantai, China, 19–20 May 2012; IEEE: Yantai, China, 2012; pp. 2217–2220. [[CrossRef](#)]
51. Amanov, F.; Pradeep, A. The significance of artificial intelligence in the second scientific revolution—A review. In Proceedings of the 2023 15th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), Bucharest, Romania, 29–30 June 2023; IEEE: Bucharest, Romania, 2023; pp. 01–05. [[CrossRef](#)]
52. Ying, M. Quantum computation, quantum theory and AI. *Artif. Intell.* **2010**, *174*, 162–176. [[CrossRef](#)]
53. Eisert, J.; Wilkens, M.; Lewenstein, M. Quantum Games and Quantum Strategies. *Phys. Rev. Lett.* **1999**, *83*, 3077–3080. [[CrossRef](#)]
54. Brassard, G.; Broadbent, A.; Tapp, A. Quantum pseudo-telepathy. *Found. Phys.* **2005**, *35*, 1877–1907. [[CrossRef](#)]
55. Bugu, S.; Ozaydin, F.; Koder, T. Surpassing the classical limit in magic square game with distant quantum dots coupled to optical cavities. *Sci. Rep.* **2020**, *10*, 22202. [[CrossRef](#)]
56. Altintas, A.A.; Ozaydin, F.; Bayindir, C.; Bayrakci, V. Prisoners’ dilemma in a spatially separated system based on spin–photon interactions. *Photonics* **2022**, *9*, 617. [[CrossRef](#)]
57. Marceddu, A.C.; Montrucchio, B. A quantum adaptation for the Morra Game and some of its variants. *IEEE Trans. Games* **2023**, *16*, 205–213. [[CrossRef](#)]
58. Bayrakci, V.; Ozaydin, F. Quantum Zeno repeaters. *Sci. Rep.* **2022**, *12*, 15302. [[CrossRef](#)] [[PubMed](#)]
59. Caliskan, A.; Bryson, J.J.; Narayanan, A. Semantics derived automatically from language corpora contain human-like biases. *Science* **2017**, *356*, 183–186. [[CrossRef](#)]
60. Franson, J.; Pittman, T. Quantum logic operations using the Zeno effect. In Proceedings of the Quantum Electronics and Laser Science Conference, Baltimore, MD, USA, 1–6 May 2011; Optica Publishing Group: Washington, DC, USA, 2011; p. QThB5. [[CrossRef](#)]
61. Bayindir, C.; Ozaydin, F. Freezing optical rogue waves by Zeno dynamics. *Opt. Commun.* **2018**, *413*, 141–146. [[CrossRef](#)]
62. Kraus, K. Measuring processes in quantum mechanics I. Continuous observation and the watchdog effect. *Found. Phys.* **1981**, *11*, 547–576. [[CrossRef](#)]
63. Cacciapuoti, A.S.; Caleffi, M.; Van Meter, R.; Hanzo, L. When entanglement meets classical communications: Quantum teleportation for the quantum internet. *IEEE Trans. Commun.* **2020**, *68*, 3808–3833. [[CrossRef](#)]
64. Schuld, M.; Sinayskiy, I.; Petruccione, F. The quest for a quantum neural network. *Quantum Inf. Process.* **2014**, *13*, 2567–2586. [[CrossRef](#)]
65. Torlai, G.; Wood, C.J.; Acharya, A.; Carleo, G.; Carrasquilla, J.; Aolita, L. Quantum process tomography with unsupervised learning and tensor networks. *Nat. Commun.* **2023**, *14*, 2858. [[CrossRef](#)] [[PubMed](#)]
66. Wang, X.B.; You, J.Q.; Nori, F. Quantum entanglement via two-qubit quantum Zeno dynamics. *Phys. Rev. A* **2008**, *77*, 062339. [[CrossRef](#)]
67. Ozaydin, F.; Bayindir, C.; Altintas, A.A.; Yesilyurt, C. Nonlocal activation of bound entanglement via local quantum Zeno dynamics. *Phys. Rev. A* **2022**, *105*, 022439. [[CrossRef](#)]
68. Ozaydin, F.; Bayrakci, V.; Altintas, A.A.; Bayindir, C. Superactivating bound entanglement in quantum networks via quantum Zeno dynamics and a novel algorithm for optimized Zeno evolution. *Appl. Sci.* **2023**, *13*, 791. [[CrossRef](#)]
69. Horodecki, P.; Horodecki, M.; Horodecki, R. Bound Entanglement Can Be Activated. *Phys. Rev. Lett.* **1999**, *82*, 1056–1059. [[CrossRef](#)]
70. Shor, P.W.; Smolin, J.A.; Thapliyal, A.V. Superactivation of bound entanglement. *Phys. Rev. Lett.* **2003**, *90*, 107901. [[CrossRef](#)] [[PubMed](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.