QUANTUM NEURAL NETWORK APPROACH TO ECONOMIC CORRUPTION DECISION-MAKING AND OPTIMAL ANTI-CORRUPTION POLICY

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Abstract

Background : Economic corruption remains a major challenge because it generates substantial fiscal losses, weakens institutional performance, and undermines public trust. Classical economic approaches, particularly Becker's rational choice framework, explain corruption decisions primarily through the expected utility derived from illegal gains, the probability of detection, and the severity of punishment.

Purpose : This study aims to develop a Quantum Becker Model (QBM) based on Quantum Neural Networks (QNNs) to provide a quantum probabilistic representation of individual and organizational corruption decisions.

Methodology : The proposed model represents individual cognitive states as qubits, with their evolution controlled by parameterized quantum rotation gates. Organizational corruption contagion is represented through quantum entanglement between individual decision states. Anti-corruption policy is formulated as an optimization problem by minimizing a Hamiltonian-based social loss function using a hybrid quantum gradient descent approach.

Findings : Numerical simulations demonstrate that the QBM can represent nonlinear relationships between corruption decisions, detection probability, and policy interventions. The model also captures organizational corruption contagion through interactions between interconnected cognitive states, providing behavioral dynamics that are not readily represented by conventional expected-utility models. The simulation results indicate that increasing the probability of corruption detection through effective auditing and institutional transparency produces a stronger deterrence effect than relying solely on increasing the severity of sanctions.

Implications : The findings suggest that anti-corruption strategies should place greater emphasis on increasing the perceived and actual probability of detection through effective auditing, transparency, and institutional monitoring. .

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Originality : The originality of this study lies in integrating Becker's economic theory of crime with quantum machine learning through a Quantum Neural Network framework. By representing cognitive uncertainty using qubits and organizational contagion using quantum entanglement, the proposed approach offers a novel computational perspective for analyzing nonlinear corruption behavior and designing economically efficient anti-corruption policies.

Keywords *: Economic Corruption; Becker Model; Quantum Decision-Making; Anti-Corruption Policy; Law and Economics*

INTRODUCTION

Economic corruption remains one of the most significant barriers to sustainable economic development, institutional effectiveness, and public welfare worldwide. Corruption distorts market competition, increases transaction costs, reduces investment efficiency, weakens public trust in public institutions, and diverts scarce public resources toward private interests. From the perspective of law and economics, corrupt behavior is commonly interpreted as a rational decision in which individuals compare the expected benefits of illegal activities with the expected costs associated with detection and punishment (Becker, 1968; Becker & Landes, 1974).

In Indonesia, corruption continues to impose substantial economic and fiscal losses despite ongoing institutional reforms. According to the Badan Pusat Statistik (BPS Indonesia, 2024), the Indonesia Anti-Corruption Behavior Index (Indeks Perilaku Anti Korupsi, IPAK) declined from 3.92 in 2023 to 3.85 in 2024 on a five-point scale, indicating a deterioration in anti-corruption behavior among Indonesian society. Since higher IPAK values indicate stronger anti-corruption attitudes, the decline suggests an increasing level of permissiveness toward corrupt practices. The reduction was consistently observed in both the Perception Dimension, which decreased from 3.82 to 3.76, and the Experience Dimension, which declined from 3.96 to 3.89. Moreover, IPAK was slightly higher among urban communities (3.86) than rural communities (3.83), while anti-corruption behavior increased with educational attainment, reaching 3.81 among respondents with education below senior high school, 3.87 among senior high school graduates, and 3.97 among respondents with tertiary education. These findings indicate that corruption is influenced not only by institutional enforcement but also by socioeconomic characteristics and behavioral factors that shape individual decision-making (BPS Indonesia, 2024).

Similar concerns are reflected in annual reports published by the Komisi Pemberantasan Korupsi (KPK), which consistently identify public procurement, licensing, budgeting, and public financial management as sectors with high corruption risks (Komisi Pemberantasan Korupsi [KPK], 2024). Likewise, audit findings and empirical studies concerning public-sector financial management continue to demonstrate the relationship between weaknesses in internal control, non-compliance with financial regulations, state financial losses, and corruption in Indonesian government institutions (Budiman & Amyar, 2021). Collectively, these findings demonstrate that corruption remains not only a legal issue but also a persistent economic challenge that undermines fiscal sustainability, public investment, and national competitiveness (Ehrlich, 1996; Polinsky & Shavell, 1999; Shavell, 2014).

Gary Becker's seminal economic theory of crime introduced a rational-choice framework in which offenders maximize expected utility by comparing illegal gains with the expected costs generated by the probability of apprehension and punishment severity (Becker, 1968). This framework fundamentally transformed the economic analysis of unlawful behavior and continues to underpin many contemporary deterrence policies (Becker & Landes, 1974). Nevertheless, the classical Becker model assumes a relatively simplified representation of individual decision-making based on expected utility. Such assumptions may be insufficient to fully represent cognitive uncertainty, bounded rationality, and social interactions that characterize corruption in real institutions, where corrupt decisions may emerge

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through interactions among multiple institutional actors rather than through isolated individual choices (Ehrlich, 1996; Polinsky & Shavell, 1999; Shavell, 2014).

Recent developments in quantum computing and quantum machine learning have created new opportunities for modeling complex decision systems. Quantum Neural Networks (QNNs) exploit quantum superposition, parameterized quantum rotations, and quantum entanglement to represent nonlinear relationships within compact computational architectures (Cuéllar, 2024; Kwak et al., 2021). Unlike conventional neural network architectures, quantum machine-learning approaches provide a framework for representing probabilistic states and correlated interactions among multiple components of a system. These characteristics create potential opportunities for representing uncertainty and dependencies in complex decision-making environments. Nevertheless, the application of QNN-based approaches to economic corruption and anti-corruption policy analysis remains largely unexplored.

This study addresses this research gap by proposing a Quantum Becker Model (QBM) that reformulates Becker's rational-choice framework within a Quantum Neural Network architecture. Individual corruption decisions are represented as qubit states whose evolution is governed by parameterized quantum rotation gates based on expected illegal gains, detection probability, and punishment severity. Organizational corruption is further modeled through quantum entanglement to capture behavioral dependence among institutional actors. Finally, anti-corruption policy is formulated as a Hamiltonian optimization problem in which enforcement parameters are optimized using hybrid quantum gradient descent to minimize the overall social loss associated with corruption.

METHODOLOGY

This study developed a Quantum Becker Model (QBM) by integrating Becker's rational-choice theory with the computational framework of Quantum Neural Networks (QNNs). The proposed methodology reformulated the classical economic decision-making process into a quantum probabilistic representation, enabling corruption decisions to be modeled under cognitive uncertainty and nonlinear behavioral dynamics. The framework consisted of four sequential stages: 1) representing an individual's corruption decision as a quantum state, 2) encoding economic variables into parameterized quantum rotation gates, 3) modeling organizational corruption through quantum entanglement, and 4) optimizing anti-corruption policy using a Hamiltonian-based social loss function. The overall methodology preserved the economic interpretation of Becker's model while extending its mathematical formulation through quantum information theory.

2.1. Qubit Representation of the Cognitive State

In the classical Becker framework, an individual faces a binary decision: either comply with the law or engage in corruption. The classical formulation assumes that this decision is deterministic after comparing the expected benefits and costs of corruption. However, behavioral economics suggests that real decision-making is frequently characterized by uncertainty, incomplete information, and cognitive ambiguity before a final action is taken. To capture this behavioral uncertainty, the present study represented the cognitive state of a decision-maker as a quantum bit (qubit) defined within a two-dimensional Hilbert space. The two orthonormal basis states corresponded to legal behavior and corrupt behavior, respectively. Consequently, the individual's mental state existed as a superposition of both alternatives until the decision was observed. This quantum representation naturally modeled probabilistic decision-making without requiring additional behavioral assumptions.

$$|\varphi\rangle = \alpha|0\rangle + \beta|1\rangle \quad (1)$$

The probability amplitudes satisfied the quantum normalization constraint.

$$|\alpha|^2 + |\beta|^2 = 1 \quad (2)$$

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The probability associated with the corruption state directly represented the likelihood that an individual would engage in corrupt behavior after cognitive evaluation. Unlike deterministic utility models, this probabilistic interpretation enabled the model to represent uncertainty inherent in economic decision-making.

2.2. Feature Mapping via Parameterizable Quantum Rotation Gates

After establishing the quantum representation of the cognitive state, the economic determinants of corruption were encoded into the quantum circuit through parameterized rotation gates. Following Becker's economic framework, three explanatory variables were considered: the expected illegal economic gain, the probability of detection, and the severity of legal sanctions. These variables collectively determined the direction and magnitude of the cognitive state rotation. The internal cognitive rotation angle was expressed as

$$\theta_j = w_1 Y_j - w_2 p_j - w_3 f_j + \phi_j \tag{3}$$

The weighting coefficients represented the relative importance assigned by an individual to each economic variable, whereas the bias term represented the baseline ethical disposition or intrinsic preference toward lawful behavior. During model development, these coefficients were treated as trainable parameters that could be estimated from empirical observations using hybrid quantum-classical optimization. The cognitive state subsequently evolved through the quantum rotation operator.

$$|\varphi_j(\theta_j)\rangle = R_y(\theta_j)|0\rangle = \begin{pmatrix} \cos(\theta_j/2) & -\sin(\theta_j/2) \\ \sin(\theta_j/2) & \cos(\theta_j/2) \end{pmatrix} \begin{pmatrix} 1 \\ 0 \end{pmatrix} \tag{4}$$

$$|\varphi_j(\theta_j)\rangle = \begin{pmatrix} \cos\left(\frac{\theta_j}{2}\right) \\ \sin\left(\frac{\theta_j}{2}\right) \end{pmatrix} = \cos\left(\frac{\theta_j}{2}\right)\begin{pmatrix} 1 \\ 0 \end{pmatrix} + \sin\left(\frac{\theta_j}{2}\right)\begin{pmatrix} 0 \\ 1 \end{pmatrix} = \alpha|0\rangle + \beta|1\rangle \tag{5}$$

The probability of getting a qubit $|1\rangle$ (illegal/criminal choice) from the output is as follows:

$$\langle 1|\varphi_j(\theta_j)\rangle^2 = (\langle 1|\beta|1\rangle)^2 = |\beta|^2 \tag{6}$$

The probability of corruption was then obtained directly from Born's rule, producing a nonlinear relationship between economic incentives and corruption behavior. This nonlinear mapping constituted one of the principal advantages of the proposed QBM compared with conventional linear expected utility models. Finally, the aggregate corruption probability for the population was obtained as

$$O_j(w, \phi_j) = |\beta|^2 = \sin^2\left(\frac{\theta_j}{2}\right) = \sin^2\left(\frac{w_1 Y_j - w_2 p_j - w_3 f_j + \phi_j}{2}\right) \tag{7}$$

This formulation provided a direct quantitative interpretation of how improvements in detection probability or punishment severity shifted the quantum cognitive state toward legal compliance.

2.3. Modeling Social Contagion via Quantum Entanglement

Corruption rarely occurs as an isolated individual decision. Instead, corruption frequently emerges through interactions among public officials, organizational hierarchies, or institutional networks in which one individual's behavior influences others. Conventional economic models generally assume that individual decisions are statistically independent and therefore cannot explicitly represent corruption contagion. To overcome this limitation, the present study modeled organizational dependence using quantum entanglement. Two interacting agents were represented within a four-dimensional Hilbert space. A Hadamard gate first transformed the primary decision-maker into a cognitive superposition state, while the second individual remained unchanged through the identity

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operator. Subsequently, a Controlled-NOT (CNOT) gate generated quantum entanglement between both agents. The complete entanglement procedure is described mathematically in Equations (8)–(12).

$$|\varphi_0\rangle = |00\rangle = |0\rangle|0\rangle = \begin{pmatrix} 1\begin{pmatrix}1\\0\end{pmatrix} \\ 0\begin{pmatrix}1\\0\end{pmatrix} \end{pmatrix} = \begin{pmatrix}1\\0\\0\\0\end{pmatrix} \tag{8}$$

$$H\otimes I = \frac{1}{\sqrt{2}}\begin{pmatrix}1 & 1\\ 1 & -1\end{pmatrix}\otimes\begin{pmatrix}1 & 0\\ 0 & 1\end{pmatrix} = \frac{1}{\sqrt{2}}\begin{pmatrix} 1\begin{pmatrix}1 & 0\\ 0 & 1\end{pmatrix} & 1\begin{pmatrix}1 & 0\\ 0 & 1\end{pmatrix} \\ 1\begin{pmatrix}1 & 0\\ 0 & 1\end{pmatrix} & -1\begin{pmatrix}1 & 0\\ 0 & 1\end{pmatrix} \end{pmatrix} \tag{9}$$

$$= \frac{1}{\sqrt{2}}\begin{pmatrix}1 & 0 & 1 & 0\\ 0 & 1 & 0 & 1\\ 1 & 0 & -1 & 0\\ 0 & 1 & 0 & -1\end{pmatrix}$$

$$|\varphi_1\rangle = \frac{1}{\sqrt{2}}\begin{pmatrix}1 & 1\\ 1 & -1\end{pmatrix}\otimes\begin{pmatrix}1 & 0\\ 0 & 1\end{pmatrix}|00\rangle = \frac{1}{\sqrt{2}}\begin{pmatrix}1\\0\\1\\0\end{pmatrix} = \frac{1}{\sqrt{2}}(|00\rangle + |10\rangle) \tag{10}$$

$$CNOT = \begin{pmatrix}1 & 0 & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 0 & 1\\ 0 & 0 & 1 & 0\end{pmatrix} \tag{11}$$

$$|\varphi_{AB}\rangle = CNOT(H\otimes I)|00\rangle = \begin{pmatrix}1 & 0 & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 0 & 1\\ 0 & 0 & 1 & 0\end{pmatrix}\frac{1}{\sqrt{2}}\begin{pmatrix}1 & 1\\ 1 & -1\end{pmatrix}\otimes\begin{pmatrix}1 & 0\\ 0 & 1\end{pmatrix}|00\rangle$$

$$= \begin{pmatrix}1 & 0 & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 0 & 1\\ 0 & 0 & 1 & 0\end{pmatrix}\frac{1}{\sqrt{2}}\begin{pmatrix} 1\begin{pmatrix}1 & 0\\ 0 & 1\end{pmatrix} & 1\begin{pmatrix}1 & 0\\ 0 & 1\end{pmatrix} \\ 1\begin{pmatrix}1 & 0\\ 0 & 1\end{pmatrix} & -1\begin{pmatrix}1 & 0\\ 0 & 1\end{pmatrix} \end{pmatrix}|00\rangle$$

$$= \begin{pmatrix}1 & 0 & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 0 & 1\\ 0 & 0 & 1 & 0\end{pmatrix}\frac{1}{\sqrt{2}}\begin{pmatrix}1 & 0 & 1 & 0\\ 0 & 1 & 0 & 1\\ 1 & 0 & -1 & 0\\ 0 & 1 & 0 & -1\end{pmatrix}|00\rangle$$

$$= \frac{1}{\sqrt{2}}\begin{pmatrix}1 & 0 & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 0 & 1\\ 0 & 0 & 1 & 0\end{pmatrix}\begin{pmatrix}1 & 0 & 1 & 0\\ 0 & 1 & 0 & 1\\ 1 & 0 & -1 & 0\\ 0 & 1 & 0 & -1\end{pmatrix}\begin{pmatrix}1\\0\\0\\0\end{pmatrix}$$

$$= \frac{1}{\sqrt{2}}\begin{pmatrix}1 & 0 & 1 & 0\\ 0 & 1 & 0 & 1\\ 0 & 1 & 0 & -1\\ 1 & 0 & -1 & 0\end{pmatrix}\begin{pmatrix}1\\0\\0\\0\end{pmatrix} = \frac{1}{\sqrt{2}}\begin{pmatrix}1\\0\\0\\1\end{pmatrix} = \frac{1}{\sqrt{2}}\left(\begin{pmatrix}1\\0\\0\\0\end{pmatrix} + \begin{pmatrix}0\\0\\0\\1\end{pmatrix}\right)$$

$$= \frac{1}{\sqrt{2}}(|00\rangle + |11\rangle) \tag{12}$$

2.4. Formulation of the Quantum Social Loss Function

The objective of public anti-corruption policy is to minimize the total social costs generated by corruption while accounting for the financial resources required for enforcement. Therefore, the proposed framework formulated government intervention as an optimization problem based on the expectation value of a Hamiltonian operator. The total Hamiltonian incorporated three principal components: expected economic losses caused by corruption, enforcement expenditures, and punishment costs. The complete Hamiltonian formulation is presented in Equation (13).

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$$\hat{H}_{Loss} = \sum_{j}^{N} \left(\hat{H}_j + C(p, O_j)\hat{I}\right) \tag{13}$$

The social objective function was evaluated by calculating the expectation value of the Hamiltonian over the quantum state.

$$\hat{H}_j = \sum_{j}^{N} (D + b.p.f)|1\rangle\langle 1|_j \tag{14}$$

$$L(p, f) = \langle\varphi|\hat{H}_{Loss}|\varphi\rangle = \sum_{j}^{n} \langle\varphi|\hat{H}_j + C(p, O_j)\hat{I}|\varphi\rangle \tag{15}$$

$$L(p, f) = \sum_{j}^{n} \left\langle \varphi_j \middle| (D + b.p.f)|1\rangle\langle 1|_j + C(p, O_j)\hat{I} \middle| \varphi_j \right\rangle$$

$$= \sum_{j}^{n} (D + b.p.f)\langle\varphi_j||1\rangle\langle 1||\varphi_j\rangle + C(p, O_j) \tag{16}$$

$$\langle 1|\varphi_j(\theta_j)\rangle = \begin{pmatrix} \cos\left(\frac{\theta_j}{2}\right) \\ \sin\left(\frac{\theta_j}{2}\right) \end{pmatrix} = \langle 1| \left(\cos\left(\frac{\theta_j}{2}\right)\begin{pmatrix}1\\0\end{pmatrix} + \sin\left(\frac{\theta_j}{2}\right)\begin{pmatrix}0\\1\end{pmatrix}\right) = \alpha\langle 1|0\rangle + \beta\langle 1|1\rangle = \beta$$

$$= \sin\left(\frac{\theta_j}{2}\right) \tag{17}$$

$$\langle\varphi_j|1\rangle\langle 1|\varphi_j\rangle = \left|\langle 1|\varphi_j(\theta_j)\right|^2 = \sin^2\left(\frac{\theta_j}{2}\right) \tag{18}$$

$$L(p, f) = \sum_{j}^{n} (D + b.p.f)\sin^2\left(\frac{\theta_j}{2}\right) + C(p, O_j)$$

$$= \sum_{j}^{n} D\sin^2\left(\frac{\theta_j}{2}\right) + \sum_{j}^{n} b.p.f\sin^2\left(\frac{\theta_j}{2}\right) + C(p, O_j) \tag{19}$$

$$= \sum_{j}^{n} 20\sin^2\left(\frac{\theta_j}{2}\right) + \sum_{j}^{n} b.p.f\sin^2\left(\frac{\theta_j}{2}\right) + 10p^2$$

Because quantum states satisfy orthogonality and normalization conditions, the multidimensional expectation value simplified into a tractable expression involving individual corruption probabilities. The final objective function therefore quantified the overall economic losses attributable to corruption while simultaneously accounting for enforcement and punishment expenditures. This Hamiltonian formulation enabled the identification of economically efficient anti-corruption policies through quantum optimization**.**

RESULT AND DISCUSSION

3.1 Numerical Analysis of Individual Cases and Non-Linear Deterrence

In this case, it represented a high-surveillance public procurement corruption scenario. The expected illegal gain was set to $Y = 15.0$, while the probability of detection ($p = 0.75$) reflected intensive auditing and anti-corruption monitoring. The punishment severity was assigned $f = 20.0$ to represent strict legal sanctions. The cognitive state was parameterized using the weight vector $w = [w_1; w_2; w_3] = [0.25; 0.65; 0.15]$ with a positive moral bias of $\phi = 0.15$. The Socio-economic Net Damage

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($D = 20.0$) acts as a static macroeconomic factor. Under a financial fine paradigm characterized by zero deadweight wealth transfer friction ($b = 0$), the total social loss is calculated via Eq. (19), $L_{fines} = D \sin^2\left(\frac{\theta}{2}\right) + 0 + 10p^2$, resulting in a baseline of 6.621. Conversely, when the enforcement framework shifts to judicial imprisonment, institutional friction parameters are introduced ($b = 0.5$). This forces the incorporation of systemic custodial infrastructure overhead back onto the public ledger via the complete Hamiltonian expectation function $L_{prison} = D \sin^2\left(\frac{\theta}{2}\right) + b.p.f \sin^2\left(\frac{\theta}{2}\right) + 10p^2$ escalating the final simulated total public loss value to 6.994. These parameters were used to evaluate the influence of strong enforcement on corruption probability within the proposed Quantum Becker Model. The numerical experiments demonstrate that the proposed Quantum Becker Model (QBM) effectively captures the cognitive complexity underlying corruption decisions in the economic sector. Unlike conventional expected utility models, the QBM represents the decision-maker's mental state as a quantum superposition whose evolution depends on the interaction between expected illegal economic gains, the probability of detection, and the severity of legal sanctions. Consider a government procurement official who has the opportunity to manipulate a large infrastructure procurement project in exchange for substantial illegal financial benefits. In this scenario, the expected illicit gain (Y) is economically attractive, while the probability of apprehension (p) depends on the effectiveness of anti-corruption audits, digital procurement transparency, and investigative agencies.

The punishment severity (f) represents imprisonment, financial asset recovery, and professional disqualification. Using some numerical parameters, the quantum rotation angle is calculated as θ = 0.4500 rad. The wave vector centers heavily on legal compliance: $|\varphi\rangle = 0.9748\ |0\rangle + 0.2231\ |1\rangle$, yielding a corruption probability of only 4.98 %. This result indicates that effective anti-corruption enforcement rotates the cognitive state toward the legal basis state $|0\rangle$, significantly reducing the probability that public officials engage in corrupt procurement practices. Economically, the result suggests that increasing transparency mechanisms, strengthening procurement supervision, and improving the probability of detection may be more cost-effective than relying exclusively on harsher criminal penalties. Once the perceived likelihood of detection exceeds a critical threshold, the quantum cognitive state naturally collapses toward lawful behavior. The Quantum Rotation Angle (θ) therefore represents the net psychological balance between economic incentives for corruption and institutional deterrence. Positive values of θ indicate that illegal economic rewards dominate the decision process, rotating the cognitive state toward the corruption basis state $|1\rangle$. Conversely, negative values indicate that anti-corruption enforcement dominates the decision process, shifting the mental state toward legal compliance. Since criminal behavior is modeled using Born's Rule, $O = \sin^2\left(\frac{\theta}{2}\right) = 4.98\%$. the corruption probability changes nonlinearly rather than linearly. Small improvements in audit quality or enforcement may therefore produce disproportionately large reductions in corruption probability, a phenomenon that cannot be represented adequately using classical linear deterrence models.

The proposed Quantum Becker Model evaluates anti-corruption policies by minimizing the quantum expectation value of the social loss Hamiltonian as in Eq. (15). This equation simultaneously accounts for the expected economic losses caused by corruption and the government's enforcement costs. The Hamiltonian term $\widehat{H}_j$ represents the economic damage generated by each potential corrupt actor, while the enforcement cost function $C(p, O_j)$ incorporates the fiscal expenditure required to achieve a given probability of detection. Because the expectation value is evaluated over the quantum cognitive state, each individual's contribution is weighted by the probability of engaging in corruption according to Born's rule. Consequently, the optimization minimizes the total expected social loss rather than corruption probability alone. Numerical simulations indicate that the optimal policy is achieved by

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balancing the probability of detection and punishment severity instead of maximizing sanctions indiscriminately. These findings suggest that strengthening auditing systems, institutional transparency, and monitoring mechanisms provides a more economically efficient anti-corruption strategy than relying solely on harsher penalties, thereby minimizing both corruption losses and enforcement expenditures. These calculations demonstrate how stronger enforcement reduces the quantum corruption probability to only 4.98%, resulting in relatively low expected social losses. Although imprisonment further discourages corruption, it introduces additional fiscal costs associated with incarceration, producing a slightly higher total social loss than the fine-based policy. This illustrates the economic trade-off captured by the Quantum Becker Model between deterrence effectiveness and enforcement expenditure.

3.2. Public Policy Simulations and Social Entanglement Dynamics

The entanglement mechanism provides an intuitive interpretation of corruption networks commonly observed in public institutions and large corporations. Suppose Agent A represents a senior procurement director responsible for approving strategic government contracts, while Agent B represents a subordinate procurement officer. Through the entanglement circuit $CNOT\cdot(H\otimes I)$, their cognitive decisions become correlated. Once the senior official adopts corrupt behavior, subordinate officials become significantly more likely to participate in procurement manipulation, document falsification, collusive bidding, or kickback schemes. The QBM mathematically models this organizational contagion using a maximally entangled Bell state, where corruption propagates through institutional relationships rather than independent individual decisions. This result provides a quantitative justification for integrity-centered anti-corruption strategies. Instead of allocating enforcement resources uniformly across all employees, the model indicates that greater social benefits are obtained by concentrating investigations on influential decision-makers occupying strategic positions within procurement networks. Removing corruption from key organizational actors simultaneously rotates multiple entangled agents back toward the legal state, thereby reducing corruption throughout the institutional network with substantially lower enforcement costs. The Hamiltonian-based optimization further illustrates that excessively severe punishment alone does not necessarily minimize total social loss. Beyond a certain threshold, imprisonment generates considerable fiscal costs through judicial processes, prison expenditures, and administrative burdens. Consequently, the optimal anti-corruption policy is obtained by balancing: 1) probability of detection, 2) punishment severity, 3) enforcement expenditure, and 4) expected economic losses caused by corruption. The QBM automatically converges toward this equilibrium through quantum gradient descent without requiring arbitrary policy assumptions.

3.3. Analysis of the Quantum Gradient Descent Optimization Code

The optimization algorithm presented in the Appendix evaluates the policy parameters using analytical quantum gradients while maintaining the mathematical formulation of the proposed Hamiltonian. The derivative can be shown in Eq. (20). It quantifies how sensitive corruption probability is to changes in the internal cognitive state.

$$\frac{\partial O_j(w,\phi_j)}{\partial\theta}=\frac{\partial}{\partial\theta}\left(\sin^2\left(\frac{\theta_j}{2}\right)\right)=2\ \sin\left(\frac{\theta_j}{2}\right)\cos\left(\frac{\theta_j}{2}\right)=0.5\ \sin(\theta_j) \tag{20}$$

Through the chain rule, these gradients are propagated to the government-controlled policy variables, the probability of detection (p) and punishment severity (f). The optimization process iteratively updates these enforcement variables until the total social loss reaches its minimum value. From an anti-corruption perspective, the gradient descent algorithm represents an adaptive policy-

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learning mechanism. Rather than selecting enforcement intensity using fixed administrative rules, the government continuously adjusts investigative resources and sanction levels according to the observed behavioral response of potential offenders. The resulting optimization identifies the combination of audit intensity, investigation probability, and legal sanctions that minimizes the overall economic damage generated by corruption while avoiding unnecessary public expenditure. These findings demonstrate that the Quantum Becker Model functions not only as a behavioral prediction framework but also as a computational decision-support system capable of assisting policymakers in designing economically efficient anti-corruption strategies under highly nonlinear behavioral environments

CONCLUSION

This study proposes a Quantum Becker Model (QBM) that extends Becker's rational choice theory by integrating Quantum Neural Networks (QNNs) into corruption decision-making analysis. By representing cognitive states as qubits and encoding expected illegal gains, detection probability, and punishment severity through quantum rotation gates, the model captures nonlinear behavioral responses and cognitive uncertainty beyond classical economic frameworks. Quantum entanglement further enables the representation of organizational corruption, illustrating how corrupt behavior propagates through interconnected institutional actors. The Hamiltonian-based optimization formulates anti-corruption policy as a social loss minimization problem, balancing enforcement costs, punishment severity, and expected economic damage. Numerical results indicate that increasing the probability of detection through effective auditing and institutional transparency is generally more efficient than relying solely on harsher sanctions. The proposed framework provides a novel computational approach that combines quantum machine learning and behavioral economics to support evidence-based anti-corruption policy design. Future work should validate the model using empirical corruption data and extend it to dynamic multi-agent corruption networks and hybrid quantum-classical learning architectures, improving its applicability to real-world economic governance and public policy optimization.

AUTHOR'S CONTRIBUTION

Risita Dwi Astuti: Data curation, formal analysis, investigation, and writing—original draft. Wiwiek Eka Mulyani: Conceptualization, methodology, investigation, and writing—review and editing. Valentinus Galih Vidia Putra: Conceptualization, methodology, formal analysis, software, and writing—review and editing. Surya Mega Wijaya: Legal analysis, investigation, and writing—review and editing. Juliany Ningsih Mohamad: Methodology, validation, formal analysis, and writing—review and editing. Arief Dewanto: Investigation, validation, and writing—review and editing. Fadil Abdullah: Conceptualization, methodology, supervision, project administration, and writing—review and editing. All authors have read and agreed to the published version of the manuscript.

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DECLARATION OF COMPETING INTEREST

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