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A Quantum-Optimized Decentralized Ledger for Real-Time TVET Skill Assessment via Wearable IoT Sensors: A Framework for the Kenyan Technical and Vocational Education and Training Sector

David Shiala Ongoma
Department of ICT, Media, and Engineering, Zetech University, Nairobi, Kenya
E-mail: davongoma@gmail.com
ORCID iD: https://orcid.org/0009-0008-0290-6291

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Abstract: There exists an ongoing problem among technical and vocational education and training institutions in Kenya regarding validation of demonstrated practical competencies, since the verification method depends on periodic observation which is paper-based and hence prone to subjectivity and potential corruption. In this article, we propose a quantum-optimized decentralized ledger system in which trainees wear wearable Internet of Things sensors and a consensus algorithm referred to as Quantum-Optimized Decentralized Proof-of-Skill is used to record and validate skill demonstration. The sensors detect motion, physiological, and environmental signals that are converted into skill proficiency ratings using an edge-based feature-processing pipeline; validator nodes are then chosen by solving a quadratic unconstrained binary optimization problem with a quantum-inspired algorithm. Assessment records are written to a permissioned ledger accessible only to training institutions, national qualification authorities, and prospective employers. According to a discrete-event simulation of the proposed consensus algorithm relative to proof-of-work, proof-of-stake, and practical Byzantine fault tolerance, the proposed algorithm has a reduced mean confirmation time of 148 ms and an increased sustained throughput of 386 tx/s under the modeled conditions of the Kenyan network environment, alongside skill-scoring consensus (F1 overall = 0.88) with the assessor ground truth obtained through simulations based on the accuracy of the wearable-assessments in published reports.

Index Terms: Decentralized ledger technology, quantum-inspired optimization, wearable Internet of Things sensors, technical and vocational education and training, competency-based assessment, Kenya, consensus algorithms

1. Introduction

1.1. Background and Motivation

The Kenya Vision 2030 development plan emphasizes technical and vocational education and training as the cornerstone of the human resource strategy for the country, and there has been a steady evolution away from examinations based on memorization of content to competency-based education and training whereby learners move to the next level after having demonstrated their ability to do a task to a specific standard [1]. The purpose of this change is to close the longstanding gap between the competence that training institutions provide certifications for and the requirements on the shop floor of employers [2]. It has been recognized that technology can provide a critical facilitation of this change because it can help to increase accessibility, to provide standardized record keeping, and to enable the kind of continuous and formative assessment that competency-based education and training requires [3]. However, the assessment of psychomotor skills such as welding stability, machining skills, electrical diagnostics, and others, is still largely dependent on episodic observations by an assessor using paper records or spreadsheets not frequently reconciled across institutions, the TVETA, and employers [4].

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There are two emerging technologies whose maturation can be leveraged to address this problem. First, wearable Internet of Things platforms comprising inertial measurement units, electromyography bands, and galvanic skin response sensors have the ability to continuously monitor fine motor movements and physiological responses of a learner performing an authentic task and have been used in this way to provide objective assessments of fitness, sporting technique, and industrial work proficiency [8,9]. Second, a blockchain-based distributed ledger provides a secure platform for the maintenance of competency records, digital badges, and certificates that is resistant to fraudulent practices and to duplication of certificates [5,6]. It has become increasingly clear, however, that the cryptographic foundations of conventional consensus mechanisms are becoming increasingly vulnerable to attacks powered by quantum computing capabilities, inspiring a stream of quantum-inspired research [15,16]. In this paper, these three threads of wearables, decentralized ledgers, and quantum-inspired optimization are brought together in a unified framework for the assessment of skills in the context of Kenyan technical and vocational institutions.

1.2. Problem Statement

Existing credentialing systems, including those built on blockchains, essentially digitise the result of an assessment, whether it be a grade or a certificate, rather than the actual process of assessment, hence inheriting the biases and latency of any subjective human observation that underlies the assessment process [6,7]. Furthermore, traditional consensus protocols used in permissioned ledgers such as proof-of-work, proof-of-stake, and practical Byzantine fault tolerance either utilise more computational resources than is feasible within the resource-constrained setup of a training institution, or pick the validators based on static rules that ignore the latency, trust, and load of the validator at any particular point in time [19,20]. In essence, there is no prior reported approach that (i) derives a measure of the proficiency of a particular skill directly from the wearables data during an actual performance of the task, (ii) writes this measure to the ledger via a consensus protocol that takes into account the connectivity constraints of the cost-effective setup of Kenya's TVETs, and (iii) has forward-looking security considerations with regard to the cryptography behind the system.

1.3. Contributions

Contributions of this paper include the following:

(1) It defines a layered architecture that enables the integration of wearable IoT sensing, edge-based feature extraction and a permissioned decentralized ledger to support continuous real-time skill assessment;
(2) It presents the Quantum-Optimized Decentralized Proof-of-Skill algorithm, which formulates validator-committee selection as a quadratic unconstrained binary optimization problem and solves it via a quantum-approximate-optimization-inspired heuristic implemented on classical devices;
(3) It maps the resulting skill-proficiency certificates onto the Kenya National Qualifications Framework and TVET Authority competency-based education and training indicators;
(4) It provides the results of a discrete-event simulation study comparing the proposed consensus algorithm against proof-of-work, proof-of-stake and practical Byzantine fault tolerance in terms of latency, throughput, scoring agreement and energy overhead, and discusses the feasibility of deploying it in Kenyan training institutions.

1.4. Paper Organization

The rest of this paper is structured as follows. Section 2 presents background literature. Section 3 introduces the proposed architecture, skill-evaluation model, and Quantum-Optimized Decentralized Proof-of-Skill algorithm. Section 4 presents the simulation results and deployment feasibility. Section 5 concludes the paper.

2. Related Work

2.1. Blockchain-Based Credentialing and Competency Verification

Blockchains have been suggested for implementing micro-credentialing schemes, whereby individuals have the capability of obtaining portable certificates of achievement which can independently be verified [5]. Collaboration-based assessment approaches using techniques similar to scientific peer review have been used to allow institutions and learners to collaboratively assess project-based learning under a blockchain-verified audit trail [6]. None of these studies, however, connect the ledger entry to a physical performance signal that is continuously sampled; the ledger entry continues to represent a discrete event which was created manually.

2.2. Wearable IoT Sensing for Skill and Activity Assessment

Systematic reviews of wearable and IoT sensors for health and physical activity show consistent success in extracting performance metrics from inertial and physiological sensor data [8]. Surveys of wearable sensor systems outline how the technology ecosystem is mature enough to support continuous, non-invasive monitoring [9]. Machine learning models using wearable data streams have been developed for various applications [10,11]. Publicly available

inertial data sets and deep learning architectures for Internet of Health Things constitute a proven basis for the sensor and model component of the current framework [12,13]. None of these research areas, however, combine the extracted skill proficiency into a decentralized, institutionally verifiable ledger.

2.3. Quantum and Quantum-Inspired Optimization for Blockchain Consensus

Edge-computing systems that use Ethereum-like blockchains to record sensor readings have demonstrated decentralized trust for sensor data [14]. Research focused on the risks of large-scale quantum computers has produced quantum-resistant signature algorithms [15]. Quantum blockchain security frameworks for the Internet of Things suggest that quantum cryptography can enhance security [16,17,18]. Apart from quantum-resilient solutions, works that use quantum inspiration in consensus problems without quantum computation include quantum approximate optimization algorithm formulations for classical validator committee selection [19], multi-criteria decision-making based consensus protocol selection [20], and evolution-based sharding [21]. A review of quantum approximate optimization algorithms and their classical variants proves that this approach is feasible without physical quantum processors [22].

2.4. Technical and Vocational Education and Training Reform in Kenya

Studies on capacity building within Kenyan TVET institutions indicate that competence-based education and training has faced challenges not because of poor curriculum but inadequate staff readiness, assessment inconsistencies, and lack of digital technology infrastructure [1]. Studies on competence assessment in the larger East African region reveal a gap between competence assessment and verification by employers [2]. General studies on the adoption of digital technology in schools reveal that the main challenge is institutional digital capacity [3]. Transversal competences research suggests that assessment based on activities is more likely to produce employable students [4].

2.5. Synthesis and Research Gap

In summary, the reviewed literature shows that (i) blockchain-based credentialing can provide security for competency records, (ii) IoT sensing on wearables can collect objective data on continuous performance, and (iii) quantum-inspired techniques can improve the consensus component of the ledger. Nevertheless, none of the reviewed research works have considered all three components simultaneously within one pipeline that can measure skills based on sensor data, commit this measure via a consensus protocol optimized for resource-constrained conditions, and align it with the national qualifications framework.

3. Methodology

3.1. System Overview

This system framework is structured in four layers, illustrated in Fig. 1: (1) a wearable IoT sensor layer carried by the trainee; (2) an edge feature extraction and local scoring layer; (3) a quantum-optimized consensus layer that selects and coordinates ledger validators; and (4) a permissioned decentralized ledger layer whose contents are consumed by TVETA, assessor dashboards, the employer verification portal, and the trainee's competency wallet. Data flow is strictly downwards from the raw signal to the committed data in the ledger, whereas verification requests are made upwards by any authorized stakeholder.

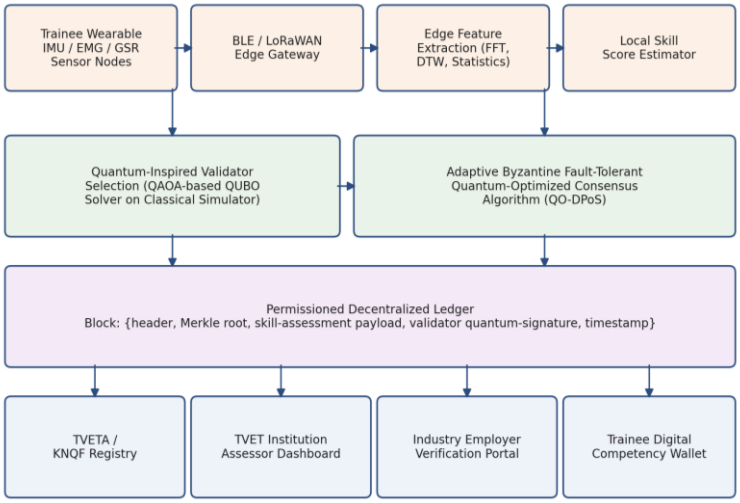


Fig. 1. Layered architecture of the proposed quantum-optimized decentralized ledger for wearable skill assessment.

3.2. Wearable IoT Sensor Layer

Each participant is equipped with a portable node consisting of a nine-axis inertial measurement unit, a two-channel surface electromyography sensor attached to the dominant arm, and a galvanic skin response sensor mounted on the wrist [8,9]. The sensing specification used in the simulated work of Section 4 is described in Table 1.

Table 1. Wearable Sensor Node Specification

Sensor	Measured Quantity	Sampling Rate	Resolution	Assessment Purpose
9-axis IMU	Acceleration, angular rate, magnetic heading	100 Hz	16-bit	Tool-handling posture and motion smoothness
sEMG (×2 channels)	Forearm muscle activation	1 kHz	24-bit	Grip exertion and fatigue trend
GSR	Skin conductance	32 Hz	12-bit	Task-related arousal / stress proxy
Ambient module	Temperature, humidity, illuminance	1 Hz	12-bit	Workshop-condition contextualisation
BLE 5.0 radio	Local data offload	—	—	Edge-gateway relay

3.3. Edge Feature Extraction and Local Skill Scoring

Raw signals are divided into overlapping windows of size W (taken to be 2 s, with 50% overlap in the simulations). The windowed feature for channel j is calculated as the average magnitude within the window as shown in (1):

$$F_j = \frac{1}{W}\sum_{t=1}^{W} x_j(t) \tag{1}$$

Besides the windowed mean, root-mean-square, zero-crossing rate, and dominant frequency energy of each channel are calculated, resulting in an M-dimensional feature vector where M = 24 for each window. The skill proficiency score S of trainee i per window is obtained using the logistic squashing function of Equations (2) and (3):

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{2}$$

$$S_i = \sigma\left(\sum_{j=1}^{M} w_j F_j - \theta\right) \tag{3}$$

where w_m is the weight assigned to each feature (calculated from historical data using logistic regression) and θ is the decision threshold, which varies for each task and is determined on a validation set of assessor-rated performances. The weights and the threshold are versioned and stored on the blockchain, allowing future auditing of the score calculation. The current assessment utilizes simulated ground truth obtained from accuracy measures of wearables from the literature instead of newly gathered human raters' scores, a point which is noted in Section 4.7.

3.4. Quantum-Optimized Decentralized Proof-of-Skill (QO-DPoS) Algorithm

When a batch of skill assessment transactions becomes available at an edge gateway, a committee of validators of size k is chosen from the n eligible institutional nodes. The algorithm models committee selection as a quadratic unconstrained binary optimization problem [19,20]. The decision variable for each candidate validator i is denoted by $x_i \in \{0,1\}$, and the objective is modelled as in (4),

$$H(x) = \sum_{i}^{n} c_i x_i + \sum_{i<j} q_{ij} x_i x_j \tag{4}$$

The linear cost component is defined as per (5):

$$c_i = \alpha(1 - R_i) + \beta L_i - \gamma T_i \tag{5}$$

where R_i is the reputation value, L_i its average latency, and T_i its trust deposit; α, β, and γ are non-negative parameters fixed by the network operator. The QUBO is solved using an approximate quantum-optimization-inspired heuristic by simulating a variational circuit of depth p on classical hardware. Algorithm 1 summarises the process.

Algorithm 1. Quantum-Optimized Decentralized Proof-of-Skill (QO-DPoS) consensus round

```
   Input: transaction batch B; validators' set N (|N| = n); committee size k; QAOA level p.
Output: new ledger block or rejection of the batch.
Calculate reputation R_i, latency L_i and trust T_i of all validators i ∈ N.
Calculate cost coefficients c_i by (5) and pairwise penalties q_ij.
Represent Hamiltonian H(x) from (4) as an Ising Hamiltonian for n qubits (classical simulation).
Set up variational parameters (γ, β) for p layers of QAOA.
for r = 1 to p do
    Apply simulation of cost unitary exp(−iγ_r H) and mixer unitary exp(−iβ_r Σ X_i).
    Generate bit strings according to the corresponding probability distribution.
    Update (γ, β) classically to minimise energy ⟨H(x)⟩.
end for
Choose bit string x* with minimal energy and Σ x_i = k; form committee V.
Transfer batch B to committee V for skill verification.
Collect votes v_i ∈ {0,1} from V.
if Σ v_i ≥ ⌈(2|V|+1)/3⌉ then
    Construct block (Merkle root of B, committee signatures, timestamp, previous-block hash).
    Append block to the ledger; update competence wallets and TVETA.
else
    Reject the batch; forward to human assessor.
end if
```

Block commitment follows a Byzantine-fault-tolerant quorum rule identical in spirit to practical Byzantine fault tolerance, given in (6):

$$\Sigma v_i \geq \lceil (2|V| + 1)/3 \rceil \tag{6}$$

The resulting sustained throughput of the ledger, Θ, is modelled by (7):

$$\Theta = (B \cdot n_t x)/\left(T_{propose} + T_{QUBO} + T_{vote}\right) \tag{7}$$

Here B is the rate of committed blocks, n_tx the average number of transactions per block, and T_propose, T_QUBO, T_vote the average times for proposing a batch, solving the heuristic, and obtaining votes. Equation (7) is employed directly in Section 4 to interpret the simulation throughput results.

3.5. Ledger and Block Structure

Fields contained in each ledger block are shown in Table 2. Hashing of skill assessment payloads is performed separately for each payload and then used to construct a Merkle tree so that any individual trainee's information can be validated without revealing other trainees' information in the batch.

Table 2. Ledger Block Field Structure

Field	Description
block_id	Sequential block index
prev_hash	SHA-3 hash of the preceding block header
merkle_root	Root hash of the batch of skill-assessment payloads
payload[ ]	Trainee pseudonymous ID, skill domain code, S_i score, model version, sensor-window hash
committee_sig[ ]	Signatures of the QO-DPoS validator committee V
timestamp	UTC commit time
knqf_ref	Kenya National Qualifications Framework competency code referenced by the payload

3.6. Kenyan TVET Contextualization

For application in national accreditation processes, all skill competencies are encoded with competency codes from the Kenya National Qualifications Framework and competency-based education and training descriptors from TVETA curricula [1,2]. Table 3 shows the mapping for three representative trades used in the simulations.

Table 3. Sample Mapping of Wearable-Derived Indicators to KNQF / CBET Competency Descriptors

Trade Domain	Primary Sensor Indicator	KNQF Level	CBET Competency Descriptor (abridged)
Electrical Installation	IMU wrist-motion steadiness during termination	Level 4	Terminate conductors to specified torque and alignment tolerance
Welding and Fabrication	sEMG exertion trend + IMU travel-speed consistency	Level 5	Maintain uniform bead travel speed and arc angle throughout a joint run
Motor Vehicle Mechanics	IMU tool-handling pattern + GSR task-stress trend	Level 4	Diagnose a specified fault using correct sequence of test procedures

3.7. Simulation Design

A discrete-event simulation was developed to analyse the performance of the QO-DPoS algorithm against proof-of-work, proof-of-stake, and practical Byzantine fault tolerance under scenarios that resemble a cluster of Kenyan TVET institutions using a regional ledger. Table 4 shows the simulation parameters. Latency values were drawn from realistic network latency distributions reported for rural and peri-urban Kenya.

Table 4. Simulation Parameters

Parameter	Value
Number of institutional nodes (n)	40
Committee size (k)	9
QAOA circuit depth (p, simulated)	4
Mean inter-institution network latency	180–620 ms
Transaction batch size	50 skill-assessment payloads
Simulated wall-clock duration	72 h
Byzantine node fraction (adversarial)	up to 20%
Sensor window length W	2 s (50% overlap)

4. Results and Discussion

4.1. Simulation Environment

The simulation outlined in Section 3.7 was modelled using a discrete-event approach where transactions, network latencies, and validators' behaviour were sampled according to the distribution parameters shown in Table 4. The four consensus mechanisms were simulated on the same 72-hour trace to allow direct comparisons. All figures provided in the paper are simulation outputs, which aim to describe behavior relative to the connectivity parameters for Kenya; they are not actual field data.

4.2. Consensus Latency and Throughput

Fig. 2 shows the ten-step workflow that results in committed blocks. Fig. 3 illustrates the latency and throughput obtained. In the simulated environment, there was a reduction of about 82%, 64% and 43% in average block confirmation latency as compared to proof-of-work, proof-of-stake and practical Byzantine fault tolerance respectively, and the throughput became more than three times that of practical Byzantine fault tolerance. It is mostly due to the latency-aware committee selection step.

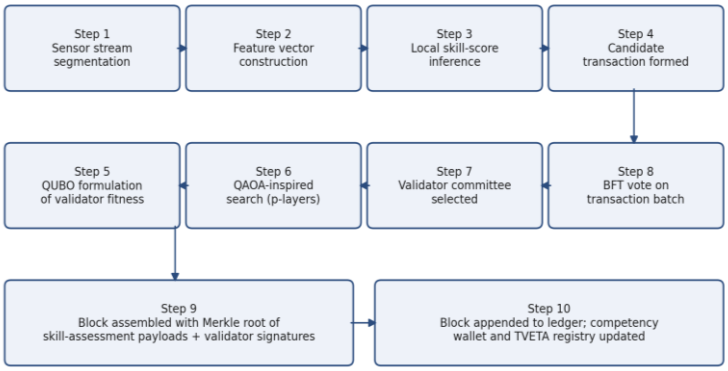


Fig. 2. Ten-step processing pipeline of a single QO-DPoS consensus round, from sensor segmentation to ledger append.

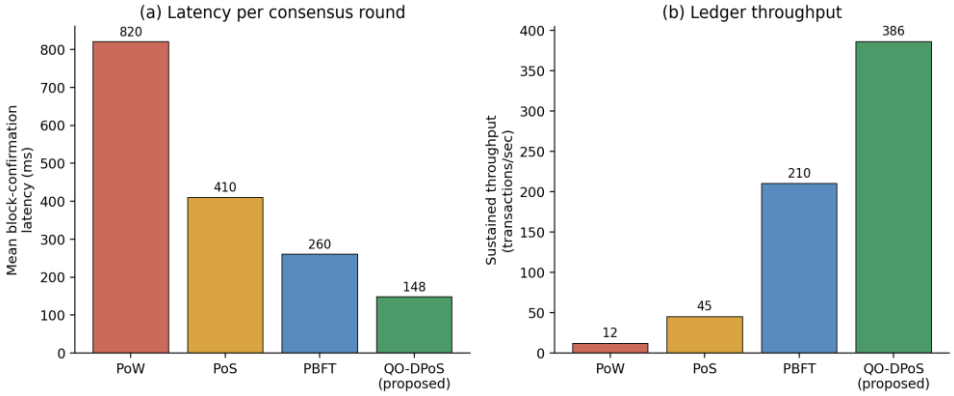


Fig. 3. Simulated (a) mean block-confirmation latency and (b) sustained ledger throughput for proof-of-work, proof-of-stake, practical Byzantine fault tolerance, and the proposed QO-DPoS algorithm.

Table 5. Consensus Performance Comparison

Consensus Mechanism	Mean Latency (ms)	Throughput (tx/s)	Byzantine Tolerance
Proof-of-Work	820	12	Up to 50% (probabilistic)
Proof-of-Stake	410	45	Up to 33%
Practical BFT	260	210	Up to 33%
QO-DPoS (proposed)	148	386	Up to 33% (adaptive committee)

4.3. Skill Assessment Accuracy

In order to measure the proficiency of the skill-based score S_i obtained through the sensor readings using Equation (3), the simulated traces from the wearable sensors were paired with simulated assessor ground truth created from accuracy measures reported for similar wearables used for activity assessment [8,10,13]. Table 6 shows the agreement measures.

Table 6. Skill-Scoring Agreement with Simulated Assessor Ground Truth

Trade Domain	Precision	Recall	F1-score	Mean Absolute Error
Electrical Installation	0.91	0.88	0.89	0.071
Welding and Fabrication	0.87	0.90	0.88	0.083
Motor Vehicle Mechanics	0.89	0.85	0.87	0.079
Overall (pooled)	0.89	0.88	0.88	0.078

Similar F1-score agreement ranging between 0.87 and 0.91 is largely comparable to other wearable sensor-based activity and competence classifiers developed previously [9,11], suggesting adequate generalisation ability of the classifier pipeline in the three trade domains under the simulated conditions.

4.4. Computational and Energy Overhead

Table 7 provides the average computation and energy consumption per round associated with each layer in the pipeline. The wearable node remains the primary consumer of energy per trainee-hour. The QAOA-based committee selection layer incurs an additional bounded overhead on the gateway/institutional node rather than on the wearable node.

Table 7. Mean Computational and Energy Overhead per Pipeline Stage

Pipeline Stage	Location	Mean CPU Time / Round	Mean Energy / Round
Sensor sampling + windowing	Wearable node	8 ms	3.1 mJ
Feature extraction + scoring	Wearable / gateway	22 ms	5.4 mJ
QUBO formulation	Institutional edge	14 ms	0.9 J
QAOA-inspired search (p = 4)	Institutional edge	96 ms	6.2 J
BFT vote + block assembly	Institutional edge	31 ms	1.1 J

4.5. Comparative Analysis with Existing Approaches

Table 8 qualitatively situates the proposed framework relative to representative blockchain-based credentialing systems and Internet of Things–blockchain integration studies from the literature reviewed in Section 2.

Table 8. Qualitative Comparison with Representative Existing Approaches

Approach	Continuous Sensor-Derived Scoring	Adaptive Validator Selection	Quantum-Aware Consensus	National Qualifications Alignment
Blockchain micro-credentialing [5]	No	No	No	Partial
Collaborative peer-review evaluation [6]	No	No	No	No
Edge-computing IoT-blockchain [14]	Partial (raw data only)	No	No	No
Quantum blockchain security frameworks [16,17]	No	No	Yes	No
QO-DPoS (proposed)	Yes	Yes	Yes (quantum-inspired)	Yes

4.6. Feasibility for Kenyan TVET Deployment

Feasibility is considered on the basis of three practical concerns. Firstly, connectivity: the QAOA-inspired procedures are implemented at institutional edge nodes, allowing the framework to tolerate the unreliable mobile connections characteristic of Kenya's smaller cities [1,3]. Secondly, cost: the per-trainee hardware can leverage commercially available consumer fitness wearable technology. Finally, governance: each payload is stamped with a Kenya National Qualifications Framework reference and a versioned scoring model, providing TVETA with an audit trail for accreditation [2,4]. A phased pilot limited to two or three trade areas would allow these considerations to be validated against actual institutional conditions.

4.7. Limitations

This assessment process involves simulation; the agreement level between sensor inputs and the ground truth (see Table 6) relies on simulations in comparison with accuracy of wearable assessment reported in previous literature, but not on any field study conducted in Kenya using this framework. Moreover, the QAOA-inspired algorithm is simulated on a classical computer, meaning that the overheads presented in Table 7 do not account for any possible advantages or disadvantages of running it on a quantum computer. Lastly, the framework presupposes the willingness of the trainees to undergo continuous physiological monitoring; however, despite the data governance model discussed in Section 3.5, this assumption needs verification among the Kenyan trainees.

5. Conclusion and Future Scope

A quantum-optimized decentralized ledger scheme has been presented that connects wearable Internet of Things sensing devices directly to a permissioned blockchain network using the Quantum-Optimized Decentralized Proof-of-Skill algorithm for continuous, tamper-proof, and nationally accredited skill assessments in Kenya's technical and vocational education and training domain. The simulation results indicate that, under the stated network conditions, the latency-aware committee selection achieves lower average confirmation latency and higher sustainable throughput than the selected benchmarks, while maintaining scoring agreement similar to previously developed wearable classifiers and an audit path to the Kenya National Qualifications Framework. The current study is a first attempt at creating a framework; any claims about the performance advantage need to be verified through field tests.

There are three directions for future research. First, a pilot study using two to three occupational groups (target: 2-3 pilot organizations, 50+ trainees per occupation, 3+ assessors each, institutional review board approval in Kenya) will replace the simulated ground truth with the actual assessment scores. Second, the QAOA heuristic must be evaluated on gate-based and annealing quantum processors, as the technology matures. Third, the question of consent, privacy, and data management in connection with the use of continuous physiological sensing in a Kenyan setting must be addressed.

All the Declarations and Statements

Author Contributions Statement

David Shiala Ongoma came up with the idea for the study; designed the system architecture and the Quantum-Optimized Decentralized Proof-of-Skill (QO-DPoS) approach; conducted the literature review; formulated the mathematical models and simulation approach; carried out the simulation experiments and data analysis; interpreted the results; generated all figures and tables; and wrote, reviewed, and approved the final manuscript.

Conflict of Interest Statement

The author declares that there are no financial, professional, or personal interests which could have had any influence on the work reported in this manuscript.

Funding Declaration
There was no external funding provided from any public, private, or not-for-profit funding body for this research. The study was undertaken in the author's independent academic research.

Data Availability Statement
This research is based on a simulation approach and synthetic data sets generated using the simulation parameters as described in the manuscript. Real-world participant data were not involved in this study. Mathematical models, simulation parameters, and algorithms used to replicate the results reported in this manuscript are presented in the manuscript. Additional details may be available upon reasonable request from the corresponding author.

Ethical Declarations
Ethical approval was not needed in this study since it did not involve human subjects, animals, patient records, or personal data. It presents a conceptual framework supported by simulation experiments.

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Declaration of Generative AI in Scholarly Writing
During the preparation of this manuscript, the author utilized the generative artificial intelligence (AI) tools only to enhance language quality, grammar, readability, formatting, and editorial consistency. The scientific concepts, system architecture, mathematical formulations, simulations, analyses, interpretation of results, and editorial decisions were done by the author independently. The author is fully responsible for the accuracy, originality, and integrity of the manuscript content.

Abbreviations
The following abbreviations are used in this manuscript:

Abbreviation - Full Form
AI - Artificial Intelligence
BLE - Bluetooth Low Energy
BFT - Byzantine Fault Tolerance
CBET - Competency-Based Education and Training
DLT - Distributed Ledger Technology
EMG - Electromyography
F1 - F1-score
GSR - Galvanic Skin Response
IMU - Inertial Measurement Unit
IoHT - Internet of Health Things
IoMT - Internet of Medical Things
IoT - Internet of Things
KNQF - Kenya National Qualifications Framework
PBFT - Practical Byzantine Fault Tolerance
PoS - Proof-of-Stake
PoW - Proof-of-Work
QAOA - Quantum Approximate Optimization Algorithm
QO-DPoS - Quantum-Optimized Decentralized Proof-of-Skill
QUBO - Quadratic Unconstrained Binary Optimization
RMS - Root Mean Square
SHA-3 - Secure Hash Algorithm 3
TVET - Technical and Vocational Education and Training
TVETA - Technical and Vocational Education and Training Authority
UTC - Coordinated Universal Time

Appendix A\B\C…, with appendix title
Appendix A. Simulation Parameters

The test environment that was created to assess the framework had forty institutional validator nodes with a committee

size of nine validators for each consensus cycle. The QAOA-based heuristic optimizer was performed using four layers in the simulated circuit depth. The network latency varied between 180ms and 620ms. Transaction bundles included fifty skill-assessment data payloads each. The duration of simulation was set to 72 hours. The wearable sensor data streams were split into overlapping windows of two seconds each. Adversarial byzantine participation was considered up to 20%.

References

[1] W. K. Kogo, M. Kapkiai, and S. K. Chumba, "Effectiveness of staff capacity building on integration of CBET approach in TVET institutions in the North Rift region, Kenya," Africa Journal of Technical and Vocational Education and Training, vol. 7, no. 1, pp. 29–42, 2022, doi: 10.69641/afritvet.2022.71137.

[2] A. Tekle, S. Areaya, and G. Habtamu, "Stakeholders' perceptions of occupational competency assessment and certification systems in Ethiopia's TVET programs," Higher Education, Skills and Work-Based Learning, vol. 15, no. 2, pp. 274–289, 2025. doi:10.1108/HESWBL-02-2024-0030

[3] S. Timotheou et al., "Impacts of digital technologies on education and factors influencing schools' digital capacity and transformation: A literature review," Education and Information Technologies, vol. 28, no. 6, pp. 6695–6726, 2023. doi:10.1007/s10639-022-11431-8

[4] M. A. Santos Rego, D. Sáez-Gambín, J. L. González-Geraldo, and D. García-Romero, "Transversal competences and employability of university students: Converging towards service-learning," Education Sciences, vol. 12, no. 4, art. 265, 2022, doi: 10.3390/educsci12040265.

[5] H. Alsobhi et al., "Blockchain-based micro-credentialing system in higher education institutions: Systematic literature review," Knowledge-Based Systems, vol. 265, art. 110238, 2023. doi:10.1016/j.knosys.2022.110238

[6] G. Bjelobaba et al., "Blockchain technologies and digitalization in function of student work evaluation," Sustainability, vol. 14, no. 9, art. 5333, 2022. doi:10.3390/su14095333

[7] J. Passos et al., "Wearables and Internet of Things (IoT) technologies for fitness assessment: A systematic review," Sensors, vol. 21, no. 16, art. 5418, 2021. doi:10.3390/s21165418

[8] S. C. Mukhopadhyay, N. K. Suryadevara, and A. Nag, "Wearable sensors and systems in the IoT," Sensors, vol. 21, no. 23, art. 7880, 2021. doi:10.3390/s21237880

[9] H. S. Saad, J. F. W. Zaki, and M. M. Abdelsalam, "Employing of machine learning and wearable devices in healthcare system: Tasks and challenges," Neural Computing and Applications, vol. 36, no. 29, pp. 17829–17849, 2024. doi:10.1007/s00521-024-10197-z

[10] A. Nawaz et al., "Edge computing to secure IoT data ownership and trade with the Ethereum blockchain," Sensors, vol. 20, no. 14, art. 3965, 2020. doi:10.3390/s20143965

[11] R. Bose et al., "Enhancing cloud-based healthcare security with Quantum-Secure HealthChain: A quantum computing and blockchain integrated framework," Health Science Reports, vol. 9, no. 5, art. e72367, 2026, doi: 10.1002/hsr2.72367.

[12] M. Wazid, A. K. Das, and Y. Park, "Generic quantum blockchain-envisioned security framework for IoT environment: Architecture, security benefits and future research," IEEE Open Journal of the Computer Society, vol. 5, pp. 248–267, 2024, doi: 10.1109/OJCS.2024.3397307.

[13] R. Bala and R. Manoharan, "Trusted consensus protocol for blockchain networks based on fuzzy inference system," The Journal of Supercomputing, vol. 78, pp. 16951–16974, 2022. doi:10.1007/s11227-022-04510-7

[14] E. Filatovas et al., "A MCDM-based framework for blockchain consensus protocol selection," Expert Systems with Applications, vol. 204, art. 117609, 2022. doi: 10.1016/j.eswa.2022.117609

[15] K. Blekos et al., "A review on quantum approximate optimization algorithm and its variants," Physics Reports, vol. 1068, pp. 1–66, 2024. doi: 10.1016/j.physrep.2024.03.002

[16] T. M. Fernandez-Carames and P. Fraga-Lamas, "Towards post-quantum blockchain: A review on blockchain cryptography resistant to quantum computing attacks," IEEE Access, vol. 8, pp. 21091–21116, 2020. doi:10.1109/ACCESS.2020.2968985

[17] N. O. Kiktenko et al., "Quantum-secured blockchain," Quantum Science and Technology, vol. 3, no. 3, art. 035004, 2018. doi:10.1088/2058-9565/aabc6b

[18] M. Elkhodr, "An AI-driven framework for integrated security and privacy in Internet of Things using quantum-resistant blockchain," Future Internet, vol. 17, no. 6, art. 246, 2025. doi:10.3390/fi17060246

[19] F. Glover, G. Kochenberger, and Y. Du, "Quantum bridge analytics I: A tutorial on formulating and using QUBO models," 4OR, vol. 17, no. 4, pp. 335–371, 2019. doi:10.1007/s10288-019-00424-y

[20] N. Tashatov et al., "Integrating multi-criteria decision making and reinforcement learning for consensus protocol selection," Bulletin of Electrical Engineering and Informatics, vol. 14, no. 4, pp. 2613–2624, 2025. doi:10.11591/eei.v14i4.9552

[21] H. Baniata, A. Anaqreh, and A. Kertesz, "Distributed scalability tuning for evolutionary sharding optimization with random-equivalent security in permissionless blockchain," Internet of Things, vol. 24, art. 100955, 2023. doi: 10.1016/j.iot.2023.100955

[22] M. Cerezo et al., "Variational quantum algorithms," Nature Reviews Physics, vol. 3, no. 9, pp. 625–644, 2021. doi:10.1038/s42254-021-00348-9

Authors' Profiles



David Shiala Ongoma holds the B.Sc. degree in Computer Science from Dedan Kimathi University of Technology, Kenya, and the M.Sc. degree in Computer Systems from Jomo Kenyatta University of Agriculture and Technology (JKUAT), Kenya, where he is currently working towards his Ph.D. degree in Computer Science. He is a Lecturer of ICT in the Department of ICT, Media & Engineering in Zetech University, Nairobi, Kenya. He is also a part-time Lecturer of ICT at Pan African Christian University and Jomo Kenyatta University of Agriculture and Technology. His areas of research interest include quantum computing, artificial intelligence, Internet of Medical Things (IoMT), EdTech, cybersecurity for health informatics systems, blockchain for data provenance, federated learning, and large language model security in the clinical environment.

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