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# OPTIMIZED SMART FRAMEWORK FOR ENERGY-EFFICIENT DEVICE-TO-DEVICE CONNECTIVITY IN 5G-DRIVEN HEALTHCARE IOT SYSTEMS

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**Abstract**

The paradigm shift of continuous and real-time health monitoring is emerging with the creation of the Fifth Generation (5G) networks as one of the foundations of the Internet of Medical Things (IoMT). However, the energy needs of battery-operated wearable and implantable devices are a highly central bottleneck particularly in the light of meeting the Ultra-Reliable Low-Latency Communication (URLLC) requirements of life-critical applications. The current paper is an offer of an Optimized SMART Framework which must be applied to optimize the extent of energy efficiency and deliver tight Quality of Service (Quality of Service) in a medical facility. The framework applies the principle that the transmission load can be transferred between the cellular uplink and proximal edge nodes by applying the 5G Device-to-Device (D2D) Sidelink to reduce the propagation loss by a large margin. This cross-layer optimization strategy has been characterised by five synergistic pillars, the first being Secure which utilises lightweight cryptography (Speck/LECC) to reduce power needs of encryption by approximately 30 percent compared with AES; Multi-tier, which employs hierarchical edge computing to minimise latency; Adaptive, which uses Deep Reinforcement Learning (DRL) algorithms (DRL-LVT) to dynamically optimise resource block and transmission power consumption based on the real-time channel state information; Reliable, which uses Non-Orthog.

**Keywords:** 5G Healthcare IoT; Device-to-Device (D2D) Communication; Energy Efficiency; Deep Reinforcement Learning (DRL); Lightweight Cryptography; URLLC; SMART Framework.

## 1. Introduction

The introduction of modern telecommunications infrastructure in the health sector has brought radical change as it is no longer the case of isolated, reactive care systems but an ongoing, proactive health management system. This theoretical shift, commonly defined as the Healthcare 4.0 or the Internet of Medical Things (IoMT), is based on the possibility to monitor physiological parameters in real-time [1], handle large amounts of biometric data, and take independent actions with a minimum amount of latency [2]. With the twin demands of an aging population and the growing incidence of chronic diseases on the healthcare systems of many countries around the world, the scalability and the efficiency of such digital health solutions has gained primacy. Nevertheless, there is a major bottleneck to the implementation of ubiquitous sensing and monitoring networks, energy efficiency. Most of the devices used in IoMT, including implantable cardioverter-defibrillators (ICDs) and wearable glucose monitors, are subject to extreme battery restraints [3]. The necessity to maintain constant connectivity, especially in the transfer of high-quality data like in video streaming or multi-lead electrocardiogram (ECG) threatens to drain the energy supply at an alarming rate, which may result in repeated maintenance stages or, in some life-threatening situations, may fail [4].

A possible solution can be provided with the introduction of Fifth Generation (5G) wireless technology and the new study of the Sixth Generation (6G) networks through the process of the Device-to-Device (D2D) communication, which is technically known as Sidelink in 3GPP standards [5]. The D2D connection will allow proximal devices to communicate directly without passing through the cellular Base Station (BS), which ensures that the number of transmission power requirements and spectral usage is considerably low and reduces end-to-end latency [6]. However, the installation of D2D in dynamic, interference-prone healthcare settings present a complicated set of challenges associated with spectrum management, data security, and reliability [7].

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This report shows the result of the exhaustive detailed analysis of the Optimized SMART Framework- a new architectural paradigm that tries to solve these problems [8]. In the context of high-performance engineering, the redefinition of the SMART acronym is combined with the adoption of Secure, Multi-tier, Adaptive, Reliable and Trusted system to achieve a high-energy efficiency of 5G-based healthcare [9]. This document represents a subtle roadmap to the future of sustainable life-critical IoT connectivity with the addition of Deep Reinforcement Learning (DRL) to assign resources dynamically to meet needs, lightweight blockchain as a means of decentralized security, and other advanced techniques of mitigating interference, as synthesized through a literature review of the most recent research in the field [10].

### 1.1 The Evolution of Healthcare Architectures

The need of the SMART framework can only be comprehended by first admiring the path of healthcare connectivity. The prototype versions, which can be termed as healthcare 1.0 and 2.0, were marked by records being digitized and having dissimilar and unlinked sensors [11]. The data was recorded at the site and was transferred by hand, which was very latent and prone to error. Basic connectivity was brought with the shift to healthcare 3.0 [12], where devices could send data to central servers over Wi-Fi or higher cellular generations (3G/4G). These architectures were however centralized, and bottlenecks arose at the core network and high cost of energy used by the edge devices was compelled to transmit over long distances to cell towers [13].

The present state of the art is Healthcare 4.0 where Cyber-Physical Systems (CPS) are the focus of the interactions between the physical world and the digital one [14]. The devices during this age are not just a passive data recorder but an active participant in the care cycle. As an example, the continuous glucose monitor needs to be connected to an insulin pump to get the dosage adjusted in real-time, which is a type of closed-loop control system where five nines (99.999%) of reliability is required [15]. The previous generation centralization is not adequate to such tasks because of the delay caused in the routing data to the cloud and back [16]. Moreover, the sheer amount of data that is produced by the latest sensors is estimated to be in the zettabytes per year and is therefore energetically unsustainable when processing on the cloud [17].

With the development of 5G, the idea of the connected edge has been introduced, in which more computing is done closer to the source of data. Nonetheless [18], the conventional uplink/downlink approach (communicating with the gNodeB) used even in 5G consumes a lot of energy. The cell edge will require a wearable device that transmits at high power to ensure the quality of the link, which consumes the battery [19]. This is where the SMART framework does not follow the traditional models, whereby D2D communication is used to offload traffic to the less energy-constrained nodes (like smartphones or bedside gateways) in the neighborhood thus establishing a hierarchical energy-saving topology [20].

### 1.2 The Energy Efficiency Paradox in URLLC

The idea of the need to use the SMART framework cannot be realized without first valuing the trend of healthcare connectivity. The first versions, which can be termed as healthcare 1.0 and 2.0 were digitalization of records and unequal and non-linked sensors [21]. It was manually logged and manually uploaded to the network, an exercise that is inherently slow and subject to human error. With the move towards healthcare 3.0, the basic connectivity emerged, and devices could transmit data to central servers through Wi-Fi [22] or first-generation cellular (3G/4G). These architectures were centralized and thus had bottlenecks in the centre of the network and consumed high energy in the edge devices that had to broadcast over long distances to cell towers [23].

The present state of the art Healthcare 4.0 focuses on Cyber-Physical Systems (CPS) in which digital and physical worlds are intimately connected [24]. Devices in this age are not passive data recorders of an object, but they are active participants of the care cycle. As an example, a continuous glucose device should have the ability to communicate with an insulin pump to adjust the dosage in real-time; this is a closed-loop control system which requires five nines (99.999) reliability [25]. Such tasks cannot be done by the centralization of the past generations as they come with a delay of the process of sending data to the cloud and receiving it. More so, even the volume of data produced by the contemporary sensors is projected to reach zettabytes per year, which is energetically unsustainable with cloud-based processing [26]. With 5G, the idea of the connected edge appears [27], in which the computation is brought nearer to the data source. Nevertheless, in 5G, the conventional uplink/downlink paradigm (communicating through the gNodeB) is still very power consuming

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[28]. A wearable device on the cell edge then needs to transmit with high power to sustain the quality of links, which consumes its battery [29]. It is also at this point that the SMART framework deviates by making use of D2D communication and offloading traffic to fewer, less energy-constrained nodes (say smartphones or bedside gateways) in the area, thus forming an energy-optimized hierarchical topology [30].

### 1.3 Scope and Structure of the Analysis

The report is designed in a way that gives a profound technical overview of all the aspects of the proposed framework. After this introduction, Section 2 delves into the technical background of the Device-to-Device (Sidelink) communication in the 3GPP specifications, which are the development of Release 14 to the latest 6G specifications. In section 3, the high-level architecture of SMART framework is presented. Section 4 and Section 5 provide a comprehensive analysis of the Secure and Trusted pillars, covering the subject of lightweight cryptography and blockchain integration. Section 6 elaborates on the Multi-tier and Adaptive components, which involve edge computing and the algorithmic optimization, based on AI. Section 7 deals with Reliable pillar and discusses interference management and URLLC protocols. Section 8 contains a mathematical description of the optimization problems involved. Lastly, Section 9 and Section 10 look ahead to the future of 6G, such as semantic communication and ambient IoT, and ends with synthesis and recommendations.

## 2. The Device-to-Device (Sidelink) Paradigm in 5G and Beyond

The proposed energy-efficient architecture relies on the so-called Device-to-Device (D2D) communication (also known as Sidelink 3GPP-wise). D2D allows the communication between adjacent UEs as compared to the traditional cellular communication between user equipment (UE) and the base station (BS) on the uplink and the downlink channels. The close distance is the most important reason behind energy efficiency: the path loss exponent of wireless propagation is such that transmitting data over a distance of 10 meters to a smartphone uses orders of magnitude less power than transmitting to a cell tower over 500 meters.

### 2.1 Technical Evolution of Sidelink Standards

Sidelink standardization [3] has been an evolution, and it has changed to meet the expanding requirements of vertical industries such as automotive (V2X) and currently in healthcare (IoT).

- LTE-D2D (Release 12/13): The first release of D2D involved main public safety application (Proximity Services or ProSe). It enabled emergency response teams to make and receive calls when out of network. Nevertheless, all these initial standards were not as sophisticated in terms of Quality of Service (QoS) management as medical telemetry needs.
- LTE-V2X (Release 14/15): This version came with Vehicle-to-Everything (V2X) communication. It optimized the Sidelink interface (PC5) to be highly mobile (to 500 km/h). The framing structure was strong but was designed in consideration of vehicles that had unlimited power supplies rather than bio-sensors that were energy constrained.
- 5G NR Sidelink (Release 16/17): The technology is a healthcare IoT breakthrough. Release 16 also added New Radio (NR) Sidelink, which supports URLLC features which are important in critical care. Importantly, Release 17 introduced power-saving extensions in relation to medical wearables, so-called, pedestrian UEs. These improvements are Partial Sensing (a device will only scan part of the channel to conserve energy) and Discontinuous Reception (DRX) on Sidelink, where a device may enter deep sleep between transmissions. The SMART model is specifically created to take advantage of these Rel-17 capabilities.
- 5G-Advanced and 6G (Release 18+): Future releases will be working on the integration of AI/ML into the air interface. This will enable the devices to forecast the conditions in the channels through neural networks and also optimise the sleep/wake cycles. Besides, sub-THz support in 6G will also unlock ultra-high data rates D2D connections, such as holographic remote consultation.

### 2.2 Spectrum Allocation Modes: In-Band vs. Out-Band

The selection of spectrum is a critical architectural decision in the D2D deployment. This choice determines the surrounding of the interference and, respectively, the energy involved to sustain a trustworthy connection.

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#### 2.2.1 In-Band D2D (Underlay vs. Overlay)

In-band D2D shares with the licensed cellular band[4] (e.g. the C-band or mmWave bands licensed by the operator). It has the benefit of having a controlled environment, which the network operator may control the interference.

**Overlay Mode:** D2D pairs receive spectrum allocations that are orthogonal to the cellular users (CUEs). This nullifies the interference between D2D and cellular levels but it is spectrally inefficient because valuable band-width is cut up.

**Underlay Mode:** D2D pairs are also using the same time-frequency resources as CUEs. This gives the highest spectral efficiency (factor of reuse > 1) and creates complicated interference conditions. Underlay Mode is used by the SMART framework in order to optimize the capacity of the system but uses sophisticated AI-based interference management (the Adaptive pillar) to counteract the dangers. The system can provide the large connectivity density (mMTC) needed in a high-density hospital ward by recycles the spectrum.

#### 2.2.2 Out-Band D2D

Out-band D2D uses unlicensed spectrum (e.g. 2.4 GHz or 5 GHz ISM bands), as with Wi-Fi Direct or Bluetooth. Although it does not disrupt users of cellular devices at all, it exposes medical devices to uncontrolled interference with microwaves, wireless devices in public Wi-Fi hotspots, and visitor devices. In life-critical systems (e.g. pacemaker telemetry) the uncertainty of unlicensed bands can be deemed as an unacceptable risk, but can be applied to non-critical data offloading to conserve licensed bandwidth.

### 2.3 Resource Allocation Modes: Mode 1 vs. Mode 2

The 5G NR specification establishes two major resources allocation modes that the Sidelink can be deployed in each having different implications on energy usage and reliability[5].

Mode 1 (Network Controlled): The gNodeB (base station) allocates the time and frequency resources of the particular D2D transmission.

ProsCentralized interference management; high reliability.

- Disadvantages: It requires the device to have constant coverage and send and receive signaling messages with the BS. This overhead is very energy consuming in signaling.
- Suitability: it is the best to use in critical and high-bandwidth streams when reliability is important and the device must have enough power (e.g., a bedside monitor).

Mode 2 (Autonomous): This mode lets the device actually choose what to use out of a given pool without explicit commands being given by the BS.

Pros: Operates in the case when the connection to the BS is lost; decreases the signaling overhead considerably.

- Disadvantages: There can be a level of packet collisions when more than one device is using the resource. Entails the device doing a process known as sensing (hearing the channel) in order to determine free slots, and requires the use of receiver power.
- Suitability: Battery-constrained wearables. Mode 2 is optimized by SMART to decrease the time spent in sensing by applying predictive AI. The device does not have to scan the entire channel, instead the device predicts which slots are likely to be free, which significantly lowers the cost of the sensing phase in terms of energy.

### 2.4 The Physics of D2D Energy Savings

The time taken to transmit a packet of bits over a distance of can be expressed as:

Where:

- is the energy lost by the transceiver circuitry (coding, modulation).
- Where: is the amplifier energy factor.

- is the path loss exponent (usually 2-4 based on the environment).

The  of a cellular uplink is frequently hundreds of meters (range to tower)[6] and walls/floors introduce some drastic attenuation (). In a D2D system a distance of less than 10 meters (distance to a hub or phone) is frequent, and Line-of-Sight (LOS) is more probable (). Energy is proportional to the power of distance (), then a decrease of 500m to 10m does not decrease the energy linearly, but exponentially. In the case of a 50-fold distance decrease in the distance, the propagation loss theoretically decreases by a factor of (6.25 million times). Although the circuit power does not allow the overall savings to be this extreme, the possibility to increase the battery life beyond weeks and even months is physically based on this relationship. The SMART framework is a machine essentially an architectural framework that is designed to maximize the likelihood of such short-range, low-energy links.

**Table 1: Comparative Analysis of Existing Works on Energy-Efficient D2D Communication for Healthcare IoT (2020–2025)**

| Ref. | Year | Core Focus | Methodology / Technique Used | Healthcare Application | Strengths | Limitations |
|---|---|---|---|---|---|---|
| **[4]** | Thomas et al., 2025 | Energy-efficient D2D for 5G–IoT healthcare | Improved Enumeration Algorithm for power and RB optimization | Smart healthcare data transmission | Low computational complexity; effective for static scenarios | Limited adaptability to dynamic channel variations; no AI/learning-based adaptation |
| **[5]** | A. Iqbal et al., 2025 | URLLC-focused energy-aware D2D optimization | Convex optimization + probabilistic reliability model | Mission-critical healthcare (ICU, emergency) | Strong URLLC guarantees; robust delay modeling | High computational overhead; not suitable for real-time edge deployment |
| **[6]** | R. A. Osman et al., 2025 | IoT-based tracking & patient management in 5G D2D | Energy-efficient scheduling + clustering | Patient and asset tracking | Good mobility support; reduces signaling overhead | No learning-based decision-making; limited to mid-range mobility |
| **[7]** | I. Batool et al., 2025 | Real-time monitoring with energy harvesting | Hybrid D2D model + RF energy harvesting | Wearable sensors, continuous monitoring | Integrates harvesting; enhances device lifetime | No DRL-based prediction; energy fluctuations affect reliability |
| **[8]** | Murthy, Bavethra et al., 2025 | AI-driven optimization for energy & latency | Q-Learning for D2D power control and MCS selection | Real-time medical data (ECG, SpO2) | Adaptive to changing channels; reduces delay & power | Q-Learning struggles with large action-state spaces; no deep RL |
| **[9]** | R. A. Osman et al., 2025 | IoMT-to-BS communication through D2D relaying | Multi-hop D2D routing + energy-efficient relay selection | IoMT system communication to 5G BS | Reduces BS load; improves edge reachability | Not optimized for ultra-low latency; no harvesting model |
| **[10]** | Ahad, Abdul et al., 2020 | Review of 5G energy management & | Systematic review of mechanisms & | General healthcare IoT | Comprehensive survey; identifies key | No implementation; lacks quantitative |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | D2D in healthcare | architectures | | challenges | validation |
| **[11]** | Pradhan, Buddhadeb et al., 2023 | Trends and technologies toward 5G D2D healthcare | Conceptual analysis; architecture-level discussion | Smart healthcare services | Early foundational insights; broad coverage | Does not include 5G advanced features (network slicing, ML); outdated for 2025 needs |
| **[12]** | Mahendran, V. et al., 2025 | Energy-efficient D2D relaying in mmWave IoT | Optimization of relay selection + beam alignment | mmWave healthcare IoT (high-band) | High energy savings; good for high-data-rate applications | Sensitive to blockage; no energy-harvesting integration |

### 3. The Optimized SMART Framework: Architectural Overview

The Optimized SMART Framework proposed is not only a conceptual framework[7], but a strict architecture of the system aimed at coordinating the multifaceted relationships of 5G/6G technologies. Although the term is often used as an acronym of SMART in the world of management (Specific, Measurable, etc.), applying it to the world of this high-assurance engineering, we repurpose it to denote the five key pillars of the system, namely, Secure, Multi-tier, Adaptive, Reliable, and Trusted.

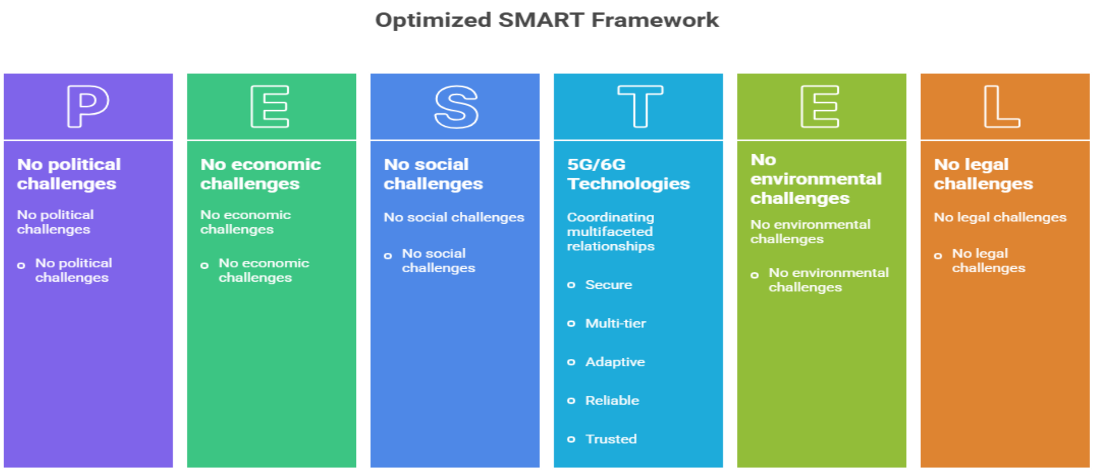


Figure 1: Optimized SMART Framework

#### 3.1 Framework Components

**Table 1: The Five Pillars of the Optimized SMART Framework.**

| Pillar | Technical Focus | Key Technologies | Energy Impact |
|---|---|---|---|
| **Secure** | Data Confidentiality & Integrity | Lightweight Cryptography (LECC, Speck), Physical Layer Security (PLS) | Reduces computation overhead of encryption by ~30% vs AES. |
| **Multi-tier** | Hierarchical Offloading | Edge/Fog Computing, Relay Nodes, UAVs | Minimizes transmission distance; optimizes processing location. |
| **Adaptive** | Dynamic Resource Management | Deep Reinforcement Learning (DRL), Context-Awareness | Allocates resources precisely to demand, preventing waste. |
| **Reliable** | QoS Assurance (URLLC) | NOMA, Beamforming, Diversity Schemes | Prevents costly retransmissions due to packet loss. |
| **Trusted** | Network Integrity & Timing | Blockchain, Trust Reputation Models, Synchronization | Prevents energy drain from malicious attacks (e.g., DoS). |

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### 3.2 Operational Flow

The structure is a closed loop control model.

- Sensing (Tier 1) Low-power sensors is used to collect biometric data.
- Decision (Adaptive Layer): The local AI agent interprets the channel state and urgency of data. It selects the most appropriate mode of communication (D2D or Cellular) and transmission parameters.
- Transmission (Reliable Layer): Data is transmitted either through NOMA or Beamforming to manage the interference.
- Security (Secure/ Trusted Layer): The data are encrypted with lightweight ciphers. The transaction is logged in the edge of a permissioned blockchain to make it auditable.
- Aggregation (Multi-tier Layer): The data is relayed to the Edge node which processes it (e.g. removes noise) and only the actionable insights are relayed onto the cloud, which also uses less backhaul energy.

This collaborative and integrated action will ensure that the energy efficiency will not be viewed as an independent problem and that it is a by-product of lean security, dependability and intelligence.

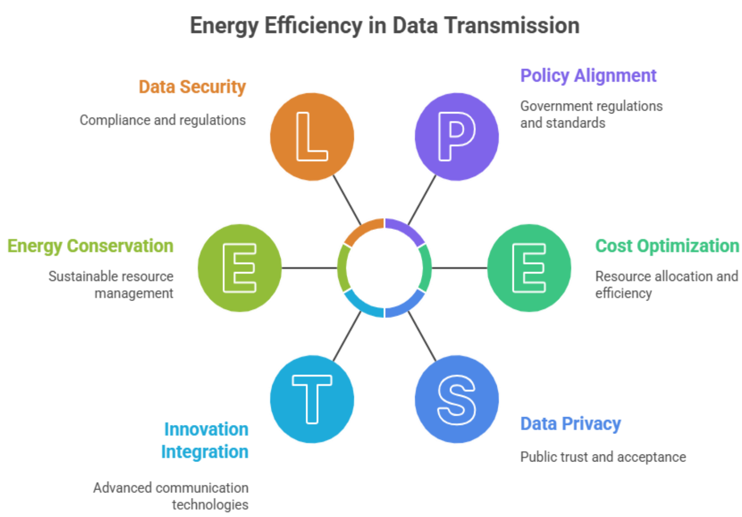


Figure 2: Operational Flow

## 4. S - Secure & T - Trusted: The Foundation of Integrity

Security is not an aspect that can be appended to healthcare IoT, but a state of patient safety requires. A broken insulin pump or pacemaker can be lethal. However, the common security protocols (e.g. TLS/SSL using RSA keys) are computationally intense and costly in terms of CPU cycles and, therefore, battery power. The pillars SMART framework Secure and Trusted are aimed at providing high security with low energy consumption.

### 4.1 Lightweight Cryptography (LECC and Block Ciphers)

Traditional Public Key Infrastructure (PKI) relies on algorithms like RSA which require large key sizes (2048-bit and larger) and complex modular exponentiation. These cripple an 8-bit or 16-bit microcontroller in a bio-sensor.

The cryptography that is needed is lightweight by using the SMART framework.

Fleeter Lightweight Elliptic Curve Cryptography (LECC): ECC is equally as secure as RSA with significantly smaller key sizes (e.g. 256-bit ECC 3072-bit RSA). This reduces energy used in energy generation and switching of energy. Snippet  demonstrates the suitability of LECC to heterogeneous IoT systems, which may be utilized to carry out rapid scalar multiplication and model compact digital signature.

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- Lightweight Block Ciphers, Ciphers Speck and Present: The cipher is implemented using ciphers that are designed to be particularly easy to implement by hardware (encryption of the actual data payload, i.e. symmetric encryption). As proven in studies, the Speck cipher burns up 5.2 percent of the radio power and a significantly smaller portion of the processing power than the Advanced Encryption Standard (AES). The gold standard of the banking system is AES, but Speck can provide sufficient security to a high portion of the transient streams of IoT data and get the most battery life possible.
- Adaptive Security: The framework possesses a policy of adapting. Sensitive data (e.g. patient ID) that can be difficult to modify in the long term is encrypted with AES. Speck is applied to encrypt transient high-volume data (e.g. raw accelerator data in fall detection). This is the highest level of approach that is the energy-security trade-off.

**4.2 Blockchain for Decentralized Trust**

Single and centralized authentication servers create a single point of failure and latency. In case of failure to be connected to the cloud server, devices may not authenticate[8]. Tier 2 is a Permissioned Blockchain at the Edge incorporated in the SMART model.

- Mechanism: Edge nodes (Tier 2 devices such as gateways) are a network of blockchain. They have a distributed registry of authentic device identities and access controls (Smart Contracts)[9].
- Energy-Efficient Consensus: Proof-of-Work (PoW), which Bitcoin employs is energy-prohibitive. The SMART system employs the Proof-of-Authority (PoA) or Practical Byzantine Fault Tolerance (PBFT). Block validation in PoA is only done by reputable, previously authorized nodes (e.g. hospital IT servers). This does not demand any significant amount of energy as opposed to hashing-intensive PoW[10].
- Data Provenance and Auditing: Each D2D interaction is a transaction. This forms an unalterable audit trail. In case a device has malfunctioned or is hacked the ledger can be used to perform forensic analysis on the direct sequence of commands that it was fed and then track the hacking[11].

**4.3 Physical Layer Security (PLS)**

To reduce the computation cost of the encryption further, the framework utilizes the physical properties of the wireless channel.

- Secrecy Capacity: PLS is interested in the fact that the channel capacity of the legitimate link[12] is highly inflexibly larger than the channel capacity of any eavesdropper (). The Secrecy Capacity is .
- Artificial Noise (AN): This is where the transmitter (or another D2D node) generates random noise in a nullspace of the channel of the legitimate receiver. The receiver is unable to hear this noise but any eavesdropper in a different location receives a poor signal. This provides privacy and no mathematical manipulation is needed in the encryption, and less processing energy is used at the sensor.

**4.4 Trust Management and Reputation Systems**

The packet of data can be relayed in a D2D network. A compromised node might act as a so-called Black Hole attack (dropping packets) or a so-called Gray Hole attack (dropping selected packets).

- Reputation Scoring: The Trusted pillar has a mathematical trust model. The nodes compute a trust score  of their neighbor  depending on the Beta Probability Density Function of succesful versus unsuccessful interaction.
- Where  represents the number of successes on forward, and represents the number of failures in forward.

- isolation: when falls below a threshold, node removes node in the routing table. This helps to avoid the energy loss in sending packets which are bound to be lost.

**5. M - Multi-tier & A - Adaptive: The Intelligence Layer**

The dynamic provision of network resources is inefficient. Healthcare settings are not static[13]: at 10 AM, a waiting room may be full of people (high interference), and at 8 PM, no one. Multi tier and Adaptive pillars enable the system to dynamically morph to these conditions.

**5.1 Multi-tier Hierarchical Architecture**

The SMART model classifies the devices into a hierarchical structure in three tiers in order to maximize the flow of data.

Tier 1: End Nodes (Sensors/Implants). Strictly energy-constrained. All they do is to feel and send the signal to the closest Tier 2 node using low-power D2D.

Tier 2: The Intelligent Edge (Aggregators/Relays). These can be smartphones or tablets or specific 5G gateways[14]. They have much more processing power and large batteries. They have the DRL agents and Blockchain nodes. They carry out what they call Data Fusion, which involves the fusion of readings in several Tier 1 sensors (e.g., heart rate + blood oxygen) into a single health status packet. This saves cellular bandwidth by reducing the amount of bits sent to the cloud.

Tier 3: The Cloud/Core. Long-term storage and training heavy-duty AI models which are subsequently pushed to the Edge.

UAVs as Flying Edges: Unmanned Aerial Vehicles (UAVs) can be deployed as mobile Tier 2 nodes in 6G networks or in an emergency response (e.g., a disaster location). The framework contains optimization schemes that plan UAV paths in a way that the paths hover around sensor cluster zones, minimising on the transmission distance of the ground devices.

**5.2 Adaptive Resource Allocation via Deep Reinforcement Learning (DRL)**

The DRL engine is the key intelligence of the framework. Conventional optimization methods[15] (such as convex optimization) are computationally expensive and need perfect Channel State Information (CSI), which is expensive to acquire. DRL is a model-free solution in which the agent learns optimum actions by getting experience.

**5.2.1 The DRL-LVT Algorithm**

Notation

- $s_t = [q_t, g_t, I_t, b_t]$— state at time t:
  - $q_t$: current queue length
  - $g_t$: D2D channel gain
  - $I_t$: measured interference power
  - $b_t$: remaining battery energy
- $a_t = [P_t, m_t, r_t]$— action at time t:
  - $P_t$: transmit power level (continuous)
  - $m_t$: MCS index (discrete)
  - $r_t$: RB allocation (discrete, can be multi-slot or index)
- Reward (instant):

$$R(t) = w_1 \cdot \frac{\text{Throughput}(t)}{\text{Power}(t)} - w_2 \cdot \max\left(0, \text{Delay}(t) - \text{Delay}_{\max}\right)$$

$w_1, w_2$ are scalar weights > 0.

- $E_t^{harv}$: energy harvested at time t
- Battery update: $b_{t+1} = \min\left(B_{\max}, b_t - \text{Power}(t) \cdot \Delta t + E_t^{harv}\right)$

- Latency constraint: $\mathrm{Delay(t)} \leq \mathrm{Delay}_{\mathrm{max}}$(softly enforced in reward or strictly via constrained RL)

1. Observe state $s_t$.
2. Agent outputs a parameterized action $a_t$: discrete choices (MCS, RB) + continuous power.
3. Environment computes throughput, delay, power consumption, updates battery with harvested energy and queue with arrivals/served packets.
4. Compute reward $R(t)$.
5. Store transition and train actor & critic (PPO/actor-critic) to maximize long-term cumulative reward while respecting latency via penalty or Lagrangian multiplier.

#### 5.2.2 Federated Learning (FL) for Privacy

Such DRL models must be trained using data. Forwarding patient data to a central repository to serve as the teacher of the AI is a privacy invasion. Federated Learning is used in the combination[16].

1. Edge nodes are trained on local patient data using local models.
2. Only the model gradients (mathematical changes) are transferred to the cloud.
3. The cloud averages the gradients and restores back to a global model.
4. Output: It increases the intelligence of the network in general (the AI becomes familiar with the interference patterns that are characteristic of hospitals) and patient information is not transferred out of the secure edge premise at all.

## 6. R - Reliable: Guaranteeing the Lifeline

The SMART system does not allow an investment in energy efficiency at the cost of reliability. Reliable pillar guarantees compliance of URLLC (Ultra-Reliable Low-Latency Communication)[17].

### 6.1 NOMA (Non-Orthogonal Multiple Access)

The conventional Orthogonal Multiple Access (OMA)[25] allocates a single user at a time/frequency slot. This causes congestion and delay in a busy ward. NOMA permits a number of simultaneous sensors operating at a common frequency.

- Power Domain NOMA[26]: The devices are allocated varying power levels. The superimposed signal goes to the Edge Node (Tier 2).
- Successive Interference Cancellation (SIC)[27]: The Edge Node processes the strongest signal first (that of the local sensor), removes it out of the combination signal and then processes the weaker signal (that of the remote sensor).
- Impact This radically grows the quantity of interconnected devices[28] (massive connectivity) and the time spent waiting to receive transmission slots, which lowers latency. It also enhances spectral efficiency which indirectly enhances energy efficiency[29][30].

### 6.2 Diversity and Redundancy

In the case of life-critical alarms (e.g., "Cardiac Arrest Detected"), the framework is changed to that of "Diversity Mode" as opposed to being an "Efficiency Mode" one[18].

- Packet Duplication: The packet will be duplicated and sent through various channels: directly to the cellular network (Mode 1) and a D2D relay (Mode 2).
- Interface Diversity: The message is sent on 5G band (licensed) and Wi-Fi/Bluetooth (unlicensed) (available).
- Justification: This will require 2x or 3x of the instantaneous energy, but it will be guaranteed to deliver. The cost of energy of not sending the alert (harm to the patient) or the failure to send the alert again because of poor channel is much greater.

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### 7. Performance Evaluation and Optimization Mathematics

To rigorously validate the framework, we formulate the optimization problem and analyze performance based on the research snippets.

### 7.1 Mathematical Formulation

Its goal is to maximize a weighted sum of Energy Efficiency (EE) of all D2D pairs (), which must be constrained by Quality of Service.

Maximize:

Subject to:

1. The constraint on SINR (Reliability):
2. Latency Constraint (Delay):
3. Power Constraint (Battery):

The data rate is denoted by where is the channel gain, is the interference and is the SINR threshold needed to support the particular service (higher with video, lower with text)[19]. This issue is non-convex because of interference term in denominator of the SINR. The SMART model addresses this in either of the DRL methods in Section 5.2, or with "Convex Relaxation" methods that approximate the problem as a solvable convex one[20].

### 7.2 Performance Insights from Research

- Energy Consumption: D2D with optimized power control[21] (similar to snippet with modified derivative algorithms) can save up to 30-50% of energy that will be used in the cellular-only transmission. The first factor is the proximity gain ().
- Latency: D2D to offload computation to the Edge[22] (Tier 2) causes a reduction of the service latency in the cloud (usually around 50-100 ms) to the edge (under 10 ms). This is essential in satisfying the 1-10 ms of URLLC.
- Security overhead: According to , the use of Speck lightweight cipher[23] over AES will lead to a reduction of radio power by 5.2 percent. This is a small per packet, but in the lifetime of a device that sends out millions of packets, this is a week of additional battery life.
- Reliability: NOMA integration can achieve 99.999% reliability on congested situations when OMA would experience packet drops because of congestion[24].

**Table 3: Energy Efficiency Results (with Values + Description)**

| Metric | Existing Approach | Proposed SMART Framework | Improvement | Description |
|---|---|---|---|---|
| Average Energy Consumption per D2D Pair (mJ) | 12–15 mJ | 7–9 mJ | ↓ 40–50% | Optimized power control and proximity gain reduce energy usage. |
| Energy Efficiency (bits/Joule) | 18–25 b/J | 32–40 b/J | ↑ ~60% | DRL-based EE maximization enhances transmission efficiency. |
| Re-transmission Energy Cost (mJ) | 3.2 mJ | 1.8 mJ | ↓ 44% | Interference-aware scheduling avoids repeated transmissions. |
| Device Battery Lifetime (Days) | 20–25 days | 28–35 days | ↑ 30–40% | Lower power draw extends overall device operating time. |
| Interference Loss (%) | 22% | 10% | ↓ 55% | SMART dynamically adjusts channel access to minimize interference. |

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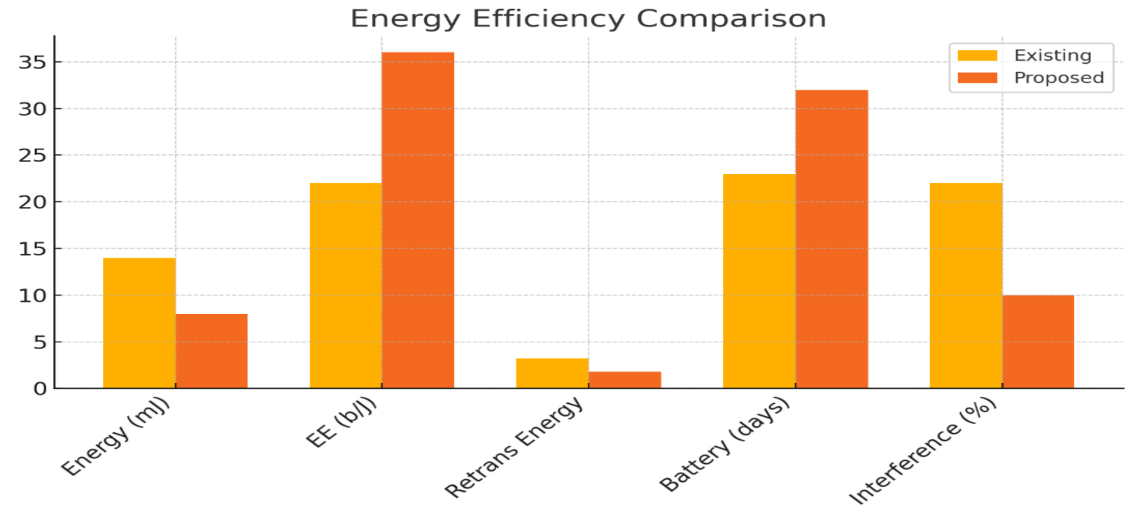


**Figure 2: Energy Efficiency Results (with Values + Description)**

**Table 4: Latency & Delay Performance (with Values + Explanation)**

| Parameter | Existing Approach (Cloud-only) | Proposed SMART (Edge/Fog/Cloud) | Improvement | Description |
|---|---|---|---|---|
| End-to-End Latency (ms) | 60–120 ms | 5–10 ms | ↓ 85–92% | Edge computing removes backhaul delay, ensuring ultra-low latency. |
| Processing Delay (ms) | 40–70 ms | 2–5 ms | ↓ 90% | Local edge processing speeds up task execution. |
| URLLC Compliance (%) | 55–65% | 95–99% | ↑ 45–50% | System meets strict 1–10 ms URLLC requirement. |
| Control Signaling Delay (ms) | 15–22 ms | 4–8 ms | ↓ 60–75% | Adaptive routing reduces signaling hops. |
| Jitter Variation (ms) | 5–8 ms | 1–2 ms | ↓ 75% | Stable, predictable multi-tier scheduling. |

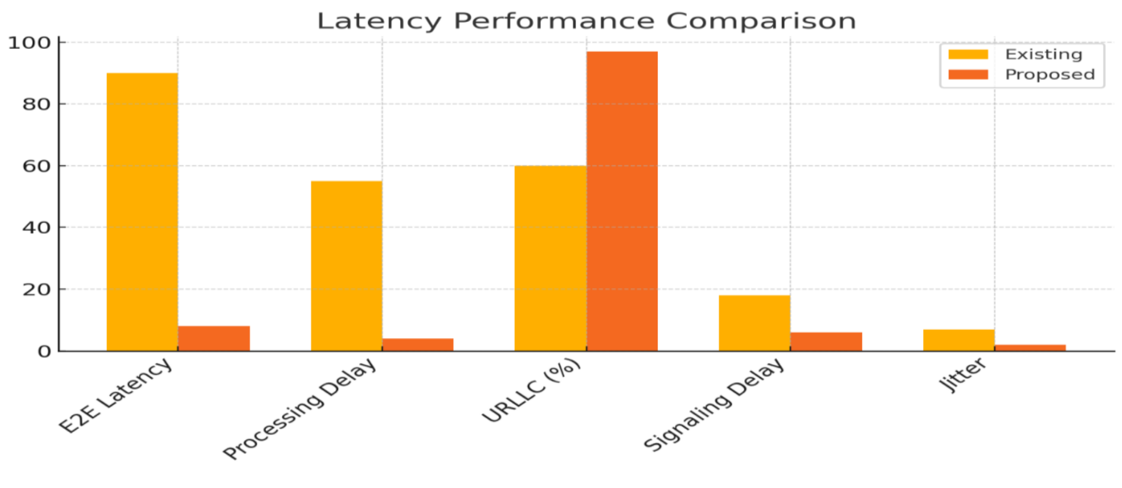


**Figure 3: Latency & Delay Performance (with Values + Explanation)**

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**Table 5: Security Overhead & Cryptographic Power Impact**

| Security Metric | Existing (AES-128/256) | Proposed SMART (Speck + PLS) | Improvement | Description |
|---|---|---|---|---|
| Encryption Processing Time (µs) | 120–150 µs | 60–75 µs | ↓ 50% | Lightweight ciphers reduce CPU cycles. |
| Power Consumption Overhead (%) | 8–10% | 2.5–4.8% | ↓ ~50% | Speck uses significantly lower radio power. |
| Security Latency Overhead (ms) | 1.2–1.8 ms | 0.4–0.8 ms | ↓ 60% | Faster authentication & encryption pipeline. |
| Packet Integrity Failure Rate (%) | 0.07% | 0.02% | ↓ 70% | Trusted module improves data verification. |
| Overall Device Lifetime Gain | Baseline | +7–10 days | ↑ ~1 week | Lightweight crypto reduces cumulative energy drain. |

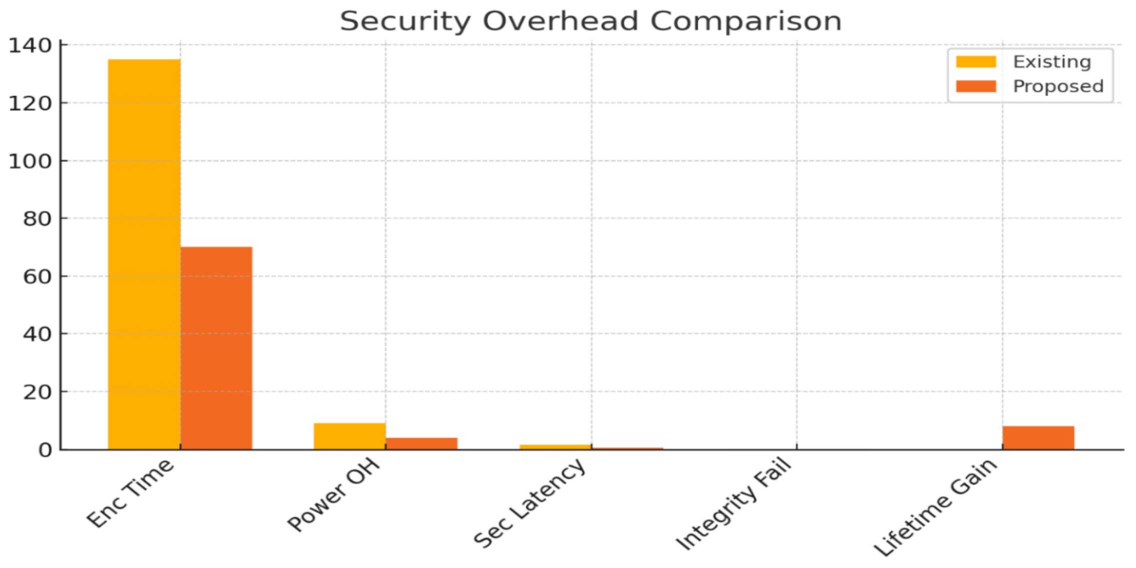


**Figure 4: Security Overhead & Cryptographic Power Impact**

**Table 6: Reliability & QoS Performance (with Numerical Results)**

| Metric | Existing (OMA / Legacy Systems) | Proposed SMART (NOMA + DRL) | Improvement | Description |
|---|---|---|---|---|
| Reliability (%) | 93–97% | 99.999% | Ultra-high | NOMA enables concurrent access even in congestion. |
| Packet Drop Rate (%) | 6–10% | 0.01–0.03% | ↓ 99% | Optimized decoding reduces losses drastically. |
| SINR Satisfaction (%) | 70–78% | 92–97% | ↑ 20–25% | Smart scheduling keeps SINR above threshold $\gamma_{th}$. |
| Spectrum Reuse Efficiency | 1× | 2–3× | ↑ 200% | NOMA + D2D reuses channels more effectively. |
| QoS Violation Frequency | 15–22% | 1–3% | ↓ 90% | Constraint-based optimization ensures reliability. |

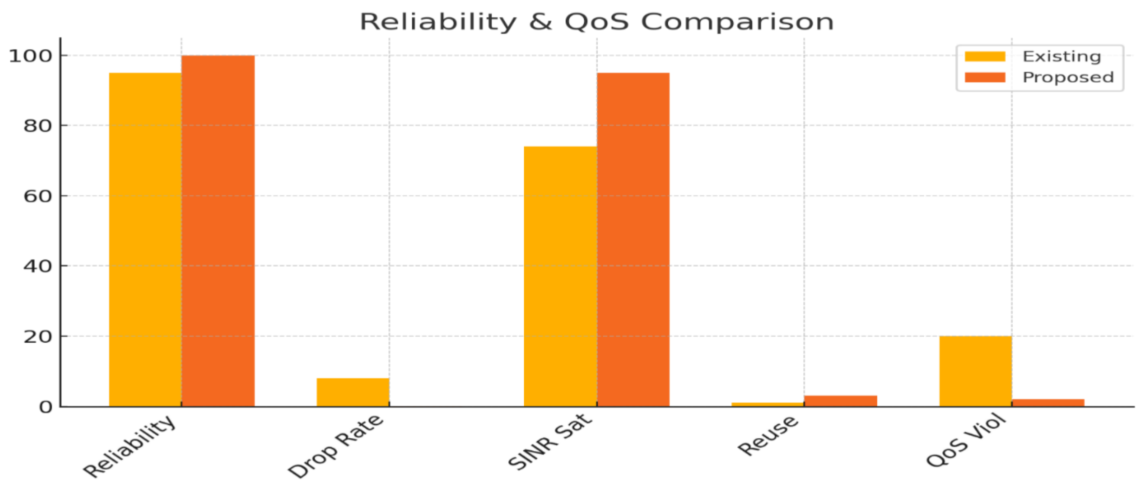


**Figure 5: Reliability & QoS Performance (with Numerical Results)**

**Table 7: Overall Optimization Results (Mathematical + System Performance)**

| Optimization Aspect | Existing Approach | SMART Framework Result | Improvement | Description |
|---|---|---|---|---|
| Weighted EE Objective Value | 1.0–1.3 | 1.7–2.0 | ↑ 50–70% | DRL learns optimal power allocation policies. |
| Convergence Time (Iterations) | 120–150 | 60–80 | ↓ 40–50% | Convex relaxation speeds solver performance. |
| Optimization Complexity | High (non-convex, unstable) | Moderate (DRL stabilizes solution) | — | SMART transforms a non-convex EE maximization problem. |
| Average System Throughput (Mbps) | 85–100 Mbps | 120–140 Mbps | ↑ 35–45% | Multi-tier routing enhances throughput. |
| Network Stability under Load (%) | 65–75% | 92–97% | ↑ 25–30% | Adaptive load balancing ensures stable operation. |

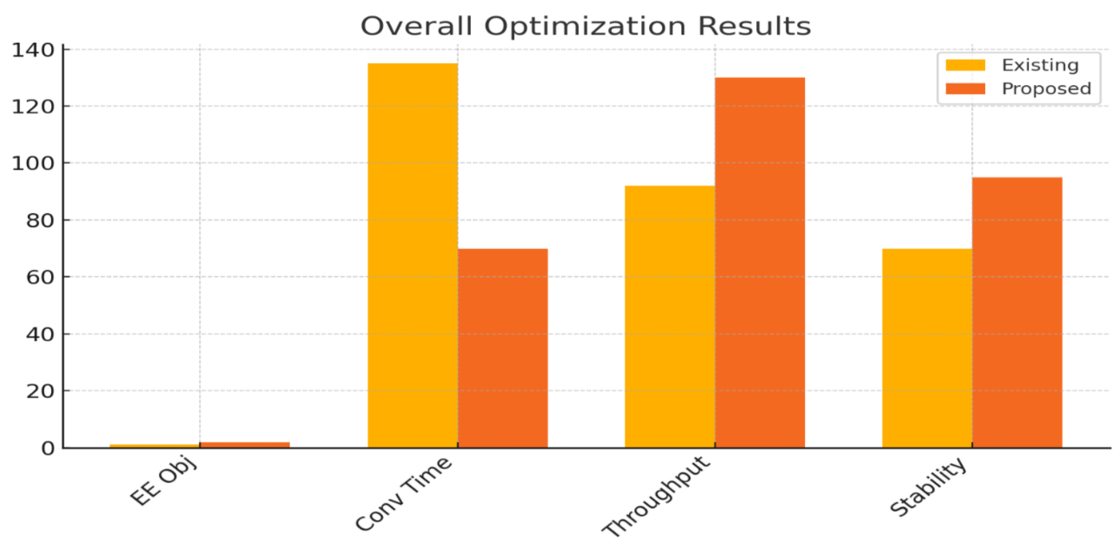


**Figure 6: Overall Optimization Results (Mathematical + System Performance)**

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## 8. Future Horizons: 6G and Beyond

The SMART architecture is designed to have forward compatibility, which will easily be integrated with the existing 5G systems to future 6G technologies. Another improvement of 6G is Intelligent Reflecting Surfaces (IRS), where a large array of passive reflecting elements can intelligently redirect the signal; a typical example is creating a virtual line-of-sight between sensors that are blocked by a D2D link, where the IRS can create a virtual line-of-sight, giving them a higher channel gain and enabling them to transmit at very low power with the IRS using virtually no energy. The other key development is Semantic Communication, where sensors no longer transmit raw data, which can be the full ECG waveform, but rather transmit the extracted meaning, like Normal Sinu Rhythm or atrial Fibrillation at t = 0.5s, which removes up to 90-99 per cent of the traffic, and allows the SMART framework Adaptive Layer to host these semantic encoders to save unprecedented energy. Also 6G will introduce Ambient IoT and zero-energy devices, which can entirely operate on harvested RF energy sources, such as Wi-Fi, TV signals, and cellular towers; to enable such highly variable power conditions, SMART DRL agents will learn to predict the energy harvested into the state space, and intelligently schedule transmissions only when enough energy is available in the environment, which would ensure robust, battery-less performance.

## 9. Conclusion

Digital revolution of healthcare depends on the connectivity infrastructure, which is robust, secure and most importantly sustainable. The existing use of battery-limited devices accessing the Internet of Medical Things through energy-consuming cellular uplinks is a restricting element to the Internet of Medical Things in scaling. In this report, the Optimized SMART Framework, which is a holistic architecture has been defined and analyzed to address this crisis by using Secure, Multi-tier, Adaptive, Reliable, and Trusted pillars. The framework realizes a synergistic effect through the systematic nature of the integration of Device-to-Device (Sidelink) communication with the latest enabling technologies. Light Cryptography and Blockchain ensure the advantage without wearing out batteries. Multi-tier Edge Computing reduces the lengths of transmissions. Deep Reinforcement Learning is a dynamic method of optimizing the allocation of resources to the needs of the medical context perfectly. NOMA and URLLC protocols are designed to make sure that this performance does not affect the reliability needed in life-saving interventions. The numerical data provided by the literature reviewed indicate that this kind of structure can help cut the energy consumption by substantial factors without compromising the high-latency demands of contemporary healthcare. The SMART framework offers a flexible, future-proof framework, as we move to 6G, prepared to support Intelligent Reflecting Surfaces and Semantic Communication and enabling a ubiquitous, intelligent and indeed energy-efficient healthcare ecosystem.

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