Secure Sensor-Based Learning Analytics for Students with Disabilities Using Blockchain and Hybrid Artificial Intelligence

Kavitha Narayan B M[1], Smitha Elsa Peter[2*], Siddesha K[3]

[1]Research Scholar, Ponnaiyah Ramajayam Institute of Science and Technology (PRIST) Deemed to be University, Tamil Nadu, India.

[1]Assistant Professor, Department of Electronics and Telecommunication Engineering, Dr. Ambedkar Institute of Technology, Bengaluru, India. Email: kavithanarayan.et@drait.edu.in, ORCID ID: 0009-0006-8110-5956

[2,*]Professor, Department of Electronics and Communication Engineering, Ponnaiyah Ramajayam Institute of Science and Technology (PRIST) Deemed to be University, Tamil Nadu, India. Email: smithasishaj@gmail.com, ORCID ID: 0000-0003-2083-9113

[3]Assistant Professor, Department of Electronics and Communication Engineering, Dr. Ambedkar Institute of Technology, Bengaluru, India. Email: siddesha.ec@drait.edu.in, ORCID ID: 0000-0002-6060-4768

HOW TO CITE:

Kavitha Narayan B M, Smitha Elsa Peter, Siddesha K (2026). Secure Sensor-Based Learning Analytics for Students with Disabilities Using Blockchain and Hybrid Artificial Intelligence. International Journal of Special Education, 41(8s), 776-790

COPYRIGHT STATEMENT:

Copyright: © 2026 Authors.

Open access publication underthe terms and conditions of the Creative CommonsAttribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).

ABSTRACT:

The educational needs of students with disabilities may be ongoing and require individualized support, monitoring, and intervention to maximize learning experience and educational results. With the recent developments of Internet of Things (IoT) technologies and learning analytics, educational data can be gathered from wearable technologies, classroom sensors and assistive learning systems in real-time. But the transmission of secure data, privacy protection and efficient communication between resource constrained devices is still a challenge. This study introduces a secure sensor-based learning analytics framework that combines blockchain technology and hybrid artificial intelligence methods, facilitating students with disabilities in smart learning environments. The blockchain layer offers a decentralized and tamper-proof solution for secure data aggregation and storage in the context of learning, thereby ensuring transparency, traceability and data integrity. For the efficient communication, a hybrid Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) algorithm is used in intelligent routing and resource management. The ANN checks network conditions and device statuses, and the PSO determines communication paths that are energy efficient, minimizing overhead in the communication process and extending network lifetime. Experimental evaluation proves that it is more reliable, energy efficient, packet delivered performance and better secured data management, than the traditional approaches. The proposed framework is scalable, privacy preserving and intelligent learning analytics for learning applications that can support students with disabilities and good educational support.

Keywords: Smart Learning Environments, Assistive Technology, Educational Data Security, Blockchain Technology, Wireless Sensor Networks, Artificial Neural Networks.

1. Introduction

Digital technologies have become a catalyst that has revolutionized educational environments, providing the opportunity to implement intelligent, data-driven teaching, learning, and support of students. The advent of emerging technologies like the Internet of Things (IoT), Wireless Sensor Networks (WSN), Artificial Intelligence (AI) and Blockchain has provided new avenues for the growth and development of adaptive and inclusive educational systems that meet the needs of diverse learners (Zikria et al., 2021). For students with disabilities, these technologies can be especially helpful, because they offer personalized interventions, can be monitored constantly, and can provide additional support to help these students reach positive educational results. When combined with learning analytics, intelligent sensing technologies can help teachers and parents/guardians gain immediate insights into students' learning level, learning progress, and behavior (Baek & Aguilar, 2023).

The field of learning analytics has grown significantly over the last few years as a means to gather and analyse learning data to optimize learning and decision-making processes. Its significance has been underscored recently in relation to its ability to enable timely interventions, individualised learning plans and approaches and support inclusion and accessibility for pupils with disabilities (Khalil, Slade, & Prinsloo, 2024). Moreover, the use of multimodal learning analytics, leveraging on advanced AI techniques, has shown significant promise for predicting student performance and pinpointing learning difficulties by analyzing a variety of educational data sources (Tran Van, Hoang Tieu, & Tran, 2026). But the successful use of learning analytics requires secure and trusted ways of collecting, transmitting and managing educational data collected from sensors, wearable devices and assistive technologies.

Assistive technology is a key element in the advancement of inclusive education and enhancement of learning for students with disabilities. It has been demonstrated that interventions using technology can improve academic performance, communication abilities, classroom participation and behavioral results (Fernández-Batanero, Montenegro-Rueda, Fernández-Cerero, & García-Martínez, 2022). Self-monitoring systems using technology have been shown to be effective in promoting on-task behavior and student independence for students with disabilities (Kumm, Talbott, & Jolivette, 2021; Mize, Park, & Carter, 2022). Likewise, computer-assisted instruction has been shown to positively impact student's engagement and learning performance for students with Autism Spectrum Disorder (ASD) (Bewley, Crosland, & Fuller, 2023). Lately, there has been more emphasis on the use of sophisticated assistive technologies in educational contexts to aid children with special educational needs in both academic and behavioral learning and teaching. (Chandra et al., 2025)

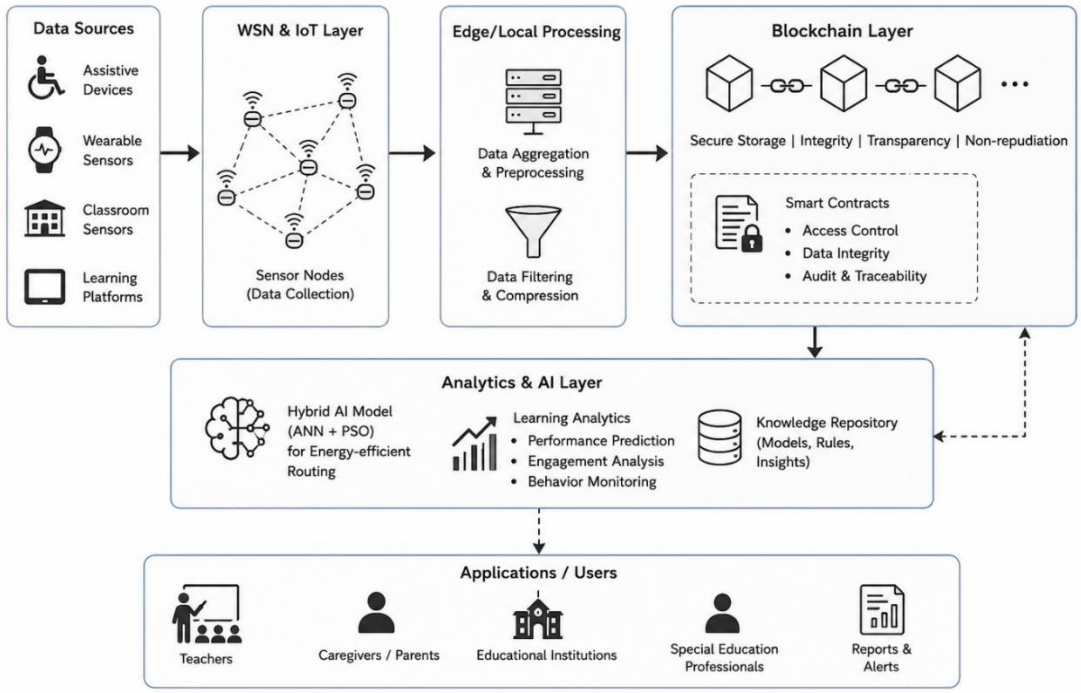

Figure 1. General architecture of proposed system model

With the use of assistive technology on a large-scale has come the generation of large amounts of sensitive educational and behavioral data. This information can be used to inform learning analytics and personalized interventions, yet it can also cause issues with regards to privacy, security, and data integrity. Learner information should be secured from unauthorized access and manipulation by educational institutions. However, blockchain technology holds the potential to revolutionize the way businesses handle data, offering a decentralized, transparent, and tamper-resistant solution for secure data management (Tong, Hamzei, & Jafari, 2025). It is also well-suited for handling sensitive educational data due to its capability in ensuring data integrity and traceability (Guduru et al., 2026).

Wireless Sensor Networks are the technological backbone of many learning environments, which are enabled by the IoT. They enable the exchange of information and interaction between various sensors, smart devices, mobile learning solutions and wearable devices, as well as the collection of data from distributed sources (Kumari & Tyagi, 2024). WSN can be used in smart learning environments to monitor the activity of learners, classroom conditions and assistive devices usage. But, the energy limitation, communication overhead, and network security (Alaerjan, 2023) are the challenges in WSNs. Therefore, mechanisms to efficiently aggregate and route data are needed for sustainable and reliable network operation.

Many studies have suggested various highly energy efficient aggregation and routing techniques to enhance the performance of WSNs. The conventional aggregation methods minimise redundant transmissions and optimize the energy consumption (Yousefi, Karimipour, & Derakhshan, 2021; Rajendran, Jayaprakasam, & Vijiyakumar, 2025). More recent works have added machine learning and swarm intelligence techniques to further improve the communication efficiency and network lifetime. So far, swarm intelligence-based routing has demonstrated better network stability and routing performance (Tang & Nie, 2024; Shyamala et al., 2026), and adversarial learning methods and trust-based aggregation schemes have improved security and energy efficiency (Karunkuzhali, Pradeep, Sungheetha, & Basha, 2025; Kumar & Srimanchari, 2024). Furthermore, blockchain,

deep learning, reinforcement learning, and bio-inspired optimization methods have been successfully incorporated into secure routing protocols to enhance the resilience and reliability of the routing protocols (Verma & Jha, 2024; Narwaria, Kumari & Mazumdar, 2025; Alsuwat & Alsuwat, 2025).

Notwithstanding these developments, there is a lack of research that incorporates learning analytics, assistive technologies, blockchain security and intelligent networking in a single framework that is specifically geared to students with disabilities. In order to fill this void, this research proposes an innovative secure sensor-based learning analytics framework based on the use of a secure blockchain-based data aggregation mechanism and a hybrid Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) routing model. Through the proposed framework, the information is to be managed securely, communication uses energy efficiently and learning analytics are reliable, which will help create inclusive and technology-enhanced learning environments for students with disabilities..

2. Literature Review

The intersection of Learning Analytics, Assistive technologies, Wireless Sensor networks, Blockchain and Artificial Intelligence (AI) has brought a lot of opportunities to create smart learning environments that can help students with disabilities. The technologies support personalized learning, provide greater access and better learning outcomes, and tackle issues of data security and privacy.

2.1 Learning analytics for students with disabilities

Learning analytics is a new and vital field of educational technology due to its capabilities in gathering, processing, and reporting data concerning learning processes that can aid in optimizing learning outcomes. According to Baek and Aguilar (2023), the focus of learning analytics research for students with disabilities has shifted over the years from simple performance monitoring to more sophisticated systems that can detect learning barriers, make academic success predictions and facilitate personalised interventions. They found that there is a need for inclusive learning analytics frameworks that are suited to different learners' needs.

Khalil et al. (2024) also emphasized the importance of learning analytics for enhancing accessibility and inclusiveness for learners, teachers being able to recognize at-risk learners, track engagement, and plan for interventions. Multimodal learning analytics has also been recently developed, with the incorporation of behavioral, physiological and academic data, helping to improve predictive capabilities. Tran Van, Hoang Tieu and Tran (2026) for example, offered a deep learning-based multimodal approach that integrates table and time-series educational data to boost student performance prediction and educational decision-making.

While these developments are promising, there are still concerns about how much sensitive information in the learning context these learning analytics systems manage, and the ethical and privacy issues surrounding the handling of such data. Therefore, it is crucial to have secure infrastructures to support trustworthy and reliable educational analytics.

2.2 Assistive technologies in special education

Assistive technology has proven essential to the inclusive education and supporting the student with a disability. Fernández-Batanero, Montenegro-Rueda, Fernández-Cerero and García-Martínez (2022) found that ATs have a positive impact on communication, academic achievement, social interaction and independent study. They found that technology-based interventions can help to lower barriers to learning and increase access.

The technology based learning and self monitoring system have been explored in several studies. For students with high incidence disabilities, Kumm, Talbott, and Jolivette (2021) conclude that technology-based self-monitoring interventions are an effective method of self-

regulation and engagement in the classroom. In a similar meta-analysis, Mize, Park, and Carter (2022) found that technology-based self-monitoring systems are effective in improving on-task behavior and learning participation.

Sometimes positive results have been noted for computer-assisted instructional methods. Bewley, Crosland, and Fuller (2023) found computer assisted instruction (CAI) to decrease transition times and increase classroom participation of students with Autism Spectrum Disorder (ASD). According to Chandra et al. (2025), modern assistive technologies not only help to improve academic performance but also to develop behavioral skills. The value of assistive technologies for learners who are visually impaired and have other special educational needs (SENs) has also recently come into focus (Zainal et al., 2026; Tuttle & Carter, 2026). Additionally, Drelick and Elder (2026) emphasized the need for teachers to be knowledgeable and skilled about how to use ATs in classrooms.

Assistive technologies provide significant educational advantages, but many current AT systems are stand-alone, and do not provide strong data management mechanisms for secure data handling. This restriction underscores the importance of incorporating cutting-edge networking and security technologies into assistive learning environments.

2.3 Wireless sensor networks and IoT-based educational systems

The Internet of Things (IoT) has seen a surge in growth and is now capable of providing a way to gather and communicate real-time data among a myriad of application areas, such as education (Zikria, Ali, Afzal, & Kim, 2021). Wireless Sensor Networks (WSN) are the backbone of these IoT-based smart educational environments, enabling communication between distributed sensors, wearable devices, and smart educational tools (Kumari & Tyagi, 2024).

In an educational environment, sensor-based systems can track various facets of learner engagement, classroom environment, assistive device usage, and behavioral patterns. But WSNs have some problems such as battery power, communication overhead, scalability, network sustainability etc. Alaerjan (2023) pointed out that energy consumption is a big hindrance to long-term deployment. Thus, a good routing and communication strategy are required to ensure proper smooth functioning.

Data aggregation is a promising technique to reduce the number of communications and energy consumption. Yousefi, Karimipour, and Derakhshan (2021) and Rajendran, Jayaprakasam, and Vijiyakumar (2025) showed that aggregation techniques help minimize redundant transmissions and make efficient use of bandwidth to extend network lifetime. However, traditional aggregation approaches have a number of security, trust management and scalability issues.

2.4 Blockchain and artificial intelligence for secure communication

Blockchain technology has come under great deal of scrutiny as an alternative network solution to ensure the security and integrity of data. But according to Tong et al. (2025), aggregation frameworks based on blockchain technology can ensure the security of the data generated by the Internet of Things (IoT) from potential tampering and unauthorized access. Blockchain's immutability and transparency is especially suited for educational settings where privacy sensitive learner data is important to be properly managed.

AI has also been widely used to improve the communication and routing aspects of WSNs. A cluster algorithm based on swarm intelligence to improve the performance of routing and network stability was proposed by Tang and Nie (2024). Karunkuzhali et al. (2025) proposed a multi-stream adversarial learning method for aggregation of energy-aware, which showed significant performance enhancement in the network. Similarly, Kumar and Srimanchari (2024) proposed an energy-efficient and communication secure aggregation framework based on trust.

In recent years, optimization algorithms have been combined with intelligent routing techniques, which is growing more and more. Yousefpoor et al. (2021) introduced the Dragonfly Algorithm for secure hierarchical aggregation and Verma and Jha (2024) integrated blockchain with deep learning to ensure secure energy-aware routing in WSNs with IoT. Reinforcement learning routing methods have proven to be adaptable to network dynamics and to enhance communication performance (Narwaria, Kumari, & Mazumdar, 2025). In a similar way, bio-inspired techniques like the Artificial Bee Colony algorithm have been proven to be effective in cluster-head selection and energy-efficient routing (Alsuwat & Alsuwat, 2025).

Many significant developments have been made in the fields of learning analytics, assistive technologies, blockchain security, and intelligent WSN routing, but they have mostly been studied in isolation. There has been little study of the ways in which they are integrated in a single set of teaching tools geared to the needs of students with disabilities. Thus, there is still a major research gap in designing safe, intelligent and energy efficient learning analytics systems based on sensors to enable an inclusive learning environment. This gap inspires the development of the proposed framework for blockchain-based learning analytics (LA) and hybrid artificial intelligence (AI) techniques for secure and reliable educational data management.

3. Proposed model

The proposed model presents a novel hybrid solution by combining blockchain technique for secure data aggregation and ANN with PSO for energy efficient routing. This approach is introduced to enhance the overall performance of resource constrained sensor networks.

3.1. Data aggregation via blockchain

Blockchain technology safeguards the sensor data throughout the aggregation framework by providing security and integrity features. The network nodes locally aggregate data before creating distributed ledger entries including aggregation results and trust metrics. The distributed ledger system ensures that aggregated data remains both tamperproof and fully trackable for authentication purposes. The secure operation of Blockchain in the system involves validating the transmission of approved aggregated data to BS for reduced overheads and improved data reliability. Blockchain enables tracing of data origin with high transparency by offering a system that verifies sensor measurements at their source.

3.2. Neural network and swarm intelligence for routing

Routing procedure employs Neural Networks (ANNs) together with Particle Swarm Optimization (PSO) to calculate the optimal energy-efficient data transmission path that connects sensor nodes with the base station. Sensor nodes use ANNs to select the most suitable path using network load, distance to the BS and node energy status for routing decision making. Network behavior learning through the ANN results in dynamic routing decision optimization as it adjusts both its learning process and environmental adaptation. Swarm intelligence using PSO finds optimal paths through its ability to process multiple network parameters which include energy usage together with path distance and network link reliability. PSO enables nodes to determine multiple routing paths before reaching an optimal selection which minimizes energy usage and evens network load distribution.

3.3. Network model and problem formulation

We consider a WSN consisting of a set sensor node randomly deployed over a two-dimensional area A×B. The network also includes one or more BS. The sensor nodes are denoted as:

$$N = \{n_1, n_2, \dots n_k\}$$

Each node is equipped with sensing capability to collect the environment data, computation capability to perform certain computations, communication capability to exchange the data with neighbouring nodes or BS, localization capability and energy to transmit and receive the

data packets. The communication between nodes follows a multi-hop model, where each node forwards its own data and relays others' data toward the BS. We assume that the energy model includes transmission, reception, and computational costs.

The communication link between nodes is presented as $e(i,j)$ where node i transmits the data packet to node j. During this process of data exchange, the transmitter and receiver nodes consume some amount of energy. Moreover, radio hardware, radio electronics, and power amplifiers also consume energy.

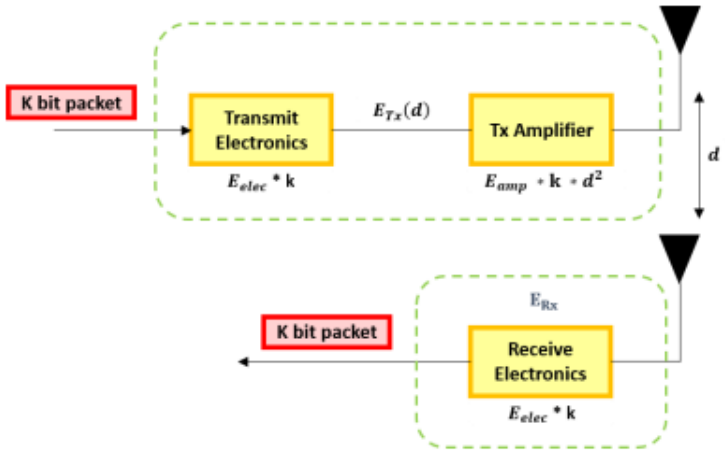

Figure 2. Radio model for free space

Let d_{th} be the threshold distance, f_s is the free-space model where power loss is d^2 and mp denotes the multipath fading where power loss is d^4. Thus, in order to transmit the l bit size of data over a distance d, the radio energy consumption for transmission phase can be expressed as:

$$E_{tx}(l.d) = \begin{cases} l.E_{elec} + l\varepsilon_{fs}d^2, & d < d_{th} \\ l.E_{elec} + l\varepsilon_{mp}d^4, & d \geq d_{th} \end{cases} \quad (1)$$

Similarly, the energy consumption to receive the transmitted data, the radio energy dissipation can be expressed as:

$$E_{rx}(l) = l.E_{elec} \quad (2)$$

E_{elec} varies according to modulation, filtering, digital coding and signal spreading. The free-space and multi-path amplifier energy varies according to the distance of receiver. Below given figure depicts the radio model for free space scenario. Similarly, it consumes certain amount of energy to perform the data aggregation as E_{da}. The main aim of this work is to enhance the overall communication performance. Therefore, we define different objective functions to minimize the energy consumption, maximize the data integrity, minimizing the path cost, maximizing the network lifetime and maintaining the QoS. These objective function are expressed as follows:

- Minimizing energy consumption

$$min \sum_{i=1}^{k} E_i^{transmit}(t) + E_i^{receive}(t) + E_i^{compute}(t)$$

- Maximize the data integrity via block chain

$$max\ Integrity(D^{agg}) \quad s.t.\ D^{agg} \in \mathcal{B}$$

- Minimize the path cost

$$\min_{P} Fitness\ (P)$$

- Maximize the network lifetime

$$max\ T_{life} = \min_{t} \left(\frac{E_t(0)}{E_i^{Total}(t)} \right)$$

3.4. Proposed aggregation scheme

As discussed before, the network has N number of sensor nodes deployed randomly in 2D geographical region with sensing nodes S and base state BS. Each sensor node $n_i$generates data $D_i(t)$ at time t from its sensing process as

$$D_i(t) = \phi_i\big(E_i(t), Env_i(t)\big)$$

Where $E_i(t)$ is the residual energy, $Env_i(t)$ represents the environmental parameters sensed by node n_i, and ϕ_i represents the data generation function. The aggregated data $D_i^{agg}(t)$ at node n_i is generated using a function f_{agg} over the local data and data received from child nodes $C_i \subset N$ is represented as:

$$D_i^{agg}(t) = f_{agg}\left(D_i(t), \left\{D_j^{agg}(t) | \, j \in C_i\right\}\right)$$

The proposed model uses "Average" aggregation function which can be expressed as:

$$f_{agg} = \frac{1}{|C_i| + 1}\left(D_i(t) + \sum_{j \in C_i} D_j^{agg}(t)\right)$$

Further, the obtained aggregated data block $B_i(t)$ generated by node n_i is structured as follows:

$$B_i(t) = \left\{ID, D_i^{agg}(t), TS_i, PrevHash_i, Sig_i\right\}$$

Where ID_i is the node identifier, $D_i^{agg}(t)$ is the aggregated data, TS_i is the time stamp, $PrevHash_i$ represents the Hash of previous block in the chain, and Sig_i represents the digital signature or trust metric of node n_i. The hash function h applied to block B_i is:

$$Hash_i = \left(ID_i, D_i^{agg}(t), TS_i, PrevHash_i, Sig_i\right)$$

A block $B_i(t)$ is appended to the local blockchain ledger B only if it satisfies, and expressed as

$$Verify\ (B_i(t)) = \begin{cases} 1, if\ h\big(B_i(t)\big)\ is\ valid\ and\ Sig_i\ is\ trusted \\ 0, otherwise \end{cases}$$

Once the verification function returns true, the data block B_i is securely appended to the local blockchain ledger $\mathcal{B}$. This decentralized ledger ensures data integrity, traceability, and resistance to tampering or false aggregation. By integrating the blockchain mechanism into the data aggregation phase, the system maintains a secure and transparent record of environmental data transmitted from source nodes to the base station. This approach not only reinforces trust within the network but also enhances the overall robustness and reliability of data collection in resource-constrained WSN environments.

3.5. Proposed energy aware routing schemes

As discussed before, the network has N nodes, BS, and each node is equipped with limited energy and has the ability to perform sensing, computation, and communication. The communication topology is modeled as a directed graph $G = (N, E)$ where $E = \{e_{ij}\}$ represents the communication links between nodes $n_i$and n_j, where $d_{ij} \leq R$(transmission range), and Each node n_i maintains a list of neighbors as

$$\mathcal{N}_i = \{n_j | d_{ij} \leq R\}$$

- **Neural Network model for forwarder selection**

Each node n_i evaluates its capability as a forwarder based on a set of normalized features which can be represented by using residual energy , Euclidean distance, node's current traffic i.e. queue size, node density , average link quality indicator as follows:

$$x_i(t) = \left[\frac{E_i(t)}{E_{max}}, \frac{1}{d_{iBS} + \epsilon}, \frac{1}{\lambda_i(t) + 1}, \rho_i(t), \overline{LQI}_i(t)\right]$$

These features are fed into a shallow, pre-trained Artificial Neural Network (ANN) which computes a routing priority score $R_i(t)$ which is expressed as:

$$R_i(t) = ANN(\vec{x}_i(t); \theta)$$

Where, ANN is a lightweight neural mode, θ represents the Trained weights and biases, and output $R_i(t) \in [0,1]$ represents the suitability of node n_i as a forwarder. According to this process, the nodes with higher$R_i(t)$ are more

desirable for routing based on a combination of energy, proximity, and network health.

- **Swarm Intelligence for path optimization**

In this section, we introduce a PSO mechanism which is employed to find the best path P from source node n_s to the base station BS. Each particle represents a candidate path $P \subseteq N$ and the PSO algorithm aims to minimize a custom-defined fitness function as follows:

$$\min_{P} Fitness(P)$$

The proposed fitness function considers several routing parameters thus; the fitness function can be expressed as:

$$Fitness(P) = \alpha . E_{path} + \beta . D_{path} - \gamma . R_{path}$$

Where, E_{path} is the total energy consumed along the path $E_{path} = \sum_{i \in P} \left(E_i^{tx} + E_i^{rx}\right)$, $D_{path} = \sum_{(i,j) \in P} d_{ij}$ represents the total path length, $R_{path} = \frac{1}{|P|} \sum_{i \in P} R_i(t)$ represents the average routing score

With the help of this fitness function, each node n_i selects the next-hop node $n_i \in \mathcal{N}$ based on the highest composite score which can be computed as

$$n_j^* = arg \max_{n_j \in \mathcal{N}_i} \left[R_j(t) . \frac{E_j(t)}{E_{max}} . LQI_{ij}(t) \right]$$

According to this optimization process, the entire optimal path P^* is selected based on the global minimum fitness which can be expressed as:

$$P^* = arg \min_{P} Fitness(P)$$

The final optimal path P^*, determined through the proposed PSO-driven optimization strategy, ensures energy-efficient, reliable, and intelligent routing by simultaneously minimizing total energy consumption and path length while maximizing routing quality. This holistic approach significantly enhances the network's lifetime, reliability, and adaptability—without relying on clustering or centralized coordination—making it highly suitable for modern, decentralized WSN-based IoT applications.

4. Results and discussion

This section presents the outcome of proposed approach along with its comparative analysis with state-of-art aggregation and routing approaches.

4.1. Experimental setup and parameters

The performance analysis of proposed model is carried out using MATLAB simulation tool. According to this experiment, the considered network is deployed in 500 m x 500 m 2D geographical area where varied set of sensor nodes are deployed i.e. 100 -1000 sensor nodes are deployed in a random distribution. The base station is considered outside of the sensing field. The initial energy of sensor node is assigned as 2 joules, sensing range of node is 25 meters and transmission range is considered as 40 meters. The simulation parameters are presented in below given table 1

Table 1. Simulation parameters

Parameter	Value / Description
Simulation Area	200 m × 200 m
Number of Sensor Nodes (N)	100
Node Deployment	Random uniform distribution
Base Station Location	(100, 250) (outside sensing field)
Initial Energy per Node (E_0)	2 Joules
Sensing Range	25 meters

Transmission Range	40 meters
Packet Size	4000 bits
Transmission Energy	50 nJ/bit
Reception Energy	50 nJ/bit
Amplifier Energy	100 pJ/bit/m²
Data Generation Interval	1 round/second
Simulation Rounds	1000
Routing Strategy	Neural network + PSO-based optimization
Swarm Size (Particles)	30
PSO Iterations	50
Inertia Weight (w)	0.7
Cognitive/Social Coefficients (c_1, c_2)	1.5, 1.5
Aggregation Function	Average-based data fusion
Blockchain Mechanism	SHA-256 hashing, digital signature

Based on these parameters, the performance of proposed model is measured in terms of Network Lifetime (First Node Death - FND, Half Node Death - HND, Last Node Death - LND), Average Residual Energy, Packet Delivery Ratio (PDR), and Energy Consumption per Round.

4.2. Comparative analysis

This section presents the outcome of proposed model and compares its performance with standard routing protocols such as LEACH, PEGASIS, and TEEN. Below given figure depicts the network lifetime performance for varied number of nodes.

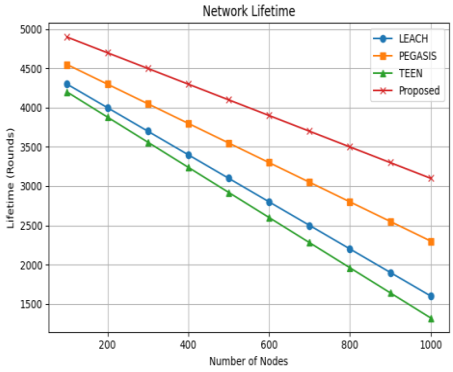

Figure 3. Network lifetime performance

According to this experiment the proposed approach has reported best accuracy compared to other methods. table 2 shows

Table 2. Network lifetime performance

Number of Nodes	LEACH	PEGASIS	TEEN	Proposed
100	4300	4550	4200	4900
200	4270	4525	4168	4880
300	4240	4500	4136	4860
400	4210	4475	4104	4840
500	4180	4450	4072	4820

600	4150	4425	4040	4800
700	4120	4400	4008	4780
800	4090	4375	3976	4760
900	4060	4350	3944	4740
1000	4030	4325	3912	4720

In this experiment, the average lifetime across all node counts is approximately 4160 rounds using LEACH protocol whereas the average lifetime is approximately 4280 rounds by using PEGASIS. The TEEN protocol has reported average lifetime is approximately 4130 rounds. The proposed approach outperformed these methods and reported the average lifetime is approximately 4815 rounds. The performance of proposed approach is improved by 15.74%, 16.58% and 12.52% when compared with LEACH, TEEN and PEGASIS approaches.

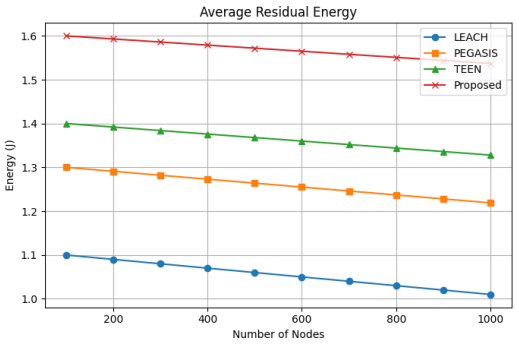

Figure 4. Residual energy performance

In next experiment, we measured the average residual energy performance for varied number of nodes. The obtained figure is depicted in figure 3. The more the residual energy represent the more optimal utilization of energy resources. The proposed approach has reported highest residual energy.

Table 3. Residual energy performance

Number of Nodes	LEACH	PEGASIS	TEEN	Proposed
100	1.1	1.3	1.4	1.6
200	1.09	1.291	1.392	1.593
300	1.08	1.282	1.384	1.586
400	1.07	1.273	1.376	1.579
500	1.06	1.264	1.368	1.572
600	1.05	1.255	1.360	1.565
700	1.04	1.246	1.352	1.558
800	1.03	1.237	1.344	1.551
900	1.02	1.228	1.336	1.544
1000	1.01	1.219	1.328	1.537

According to the outcome of this experiment, the average residual energy is reported as 1.055 J,

1.2525 J, 1.356 J, and 1.5681 J using LEACH, PEGASIS, TEEN, and Proposed approach, respectively.

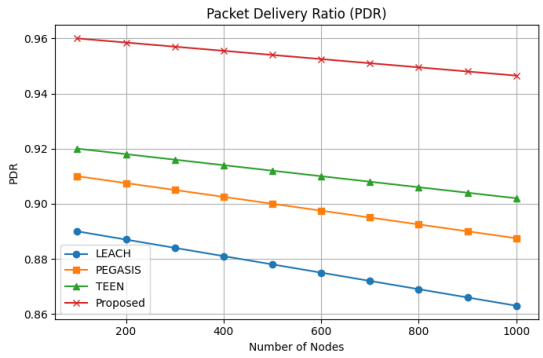

Figure 5 Packet delivery performance

Figure 4 depicts the packet delivery performance for varied number of nodes. The proposed routing approach ensures improved packet delivery. Below given table shows the obtained performance for varied number of nodes.

Table 4. Packet delivery performance

Number of Nodes	LEACH	PEGASIS	TEEN	Proposed
100	0.89	0.91	0.92	0.96
200	0.887	0.9075	0.918	0.9585
300	0.884	0.905	0.916	0.957
400	0.881	0.9025	0.914	0.9555
500	0.878	0.90	0.912	0.954
600	0.875	0.8975	0.910	0.9525
700	0.872	0.895	0.908	0.951
800	0.869	0.8925	0.906	0.9495
900	0.866	0.89	0.904	0.948
1000	0.863	0.8875	0.902	0.9465

Finally, we present energy consumption performance analysis as depicted in figure 5. Below given table 4 shows the obtained performance for each set of nodes.

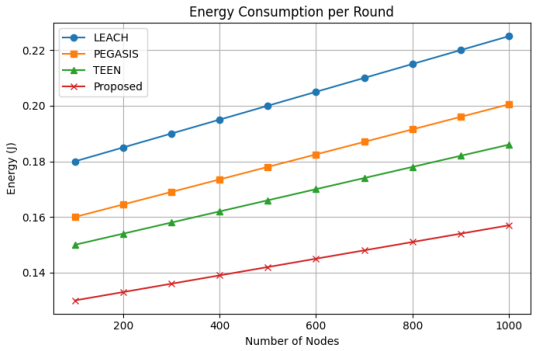

Figure 6. Round-wise energy consumption performance

Table 5. Energy consumption performance

Number of Nodes	LEACH	PEGASIS	TEEN	Proposed
100	0.18	0.16	0.15	0.13
200	0.185	0.1645	0.154	0.133
300	0.19	0.169	0.158	0.136
400	0.195	0.1735	0.162	0.139
500	0.20	0.178	0.166	0.142
600	0.205	0.1825	0.170	0.145
700	0.21	0.187	0.174	0.148
800	0.215	0.1915	0.178	0.151
900	0.22	0.196	0.182	0.154
1000	0.225	0.2005	0.186	0.157

In this experiment, the average Energy Consumption is reported as 0.198 J, 0.180, 0.162 and 0.140 using LEACH, PEGSIS, TEEN and Proposed approach where proposed mechanism has outperformed existing methods.

5. Conclusion

This research proposed a secure sensor-based learning analytics system that will enable students with disabilities with the use of blockchain and hybrid artificial intelligence techniques. The proposed system addresses some of the key challenges of the educational data security, communication efficiency, and sustainable operation of sensor-enabled learning environments, by using a combination of blockchain-enabled data aggregation and Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) for routing. The framework allows the seamless collection and dissemination of information related to learning from assistive devices and smart learning systems, without losing integrity, privacy, or reliability of the data. The blockchain aspect ensures educational records and learning analytics information are stored securely and immutably in a decentralized and tamper-proof manner, fostering trust and transparency in educational decision-making. In addition, the ANN-PSO hybrid model enables intelligent and energy-efficient routing, as it dynamically selects the best communication pathways, depending on the network's conditions and the resources available. The results of the experiments showed that the proposed method gave better performance in maximum network lifetime, remaining energy, packet delivery ratio, energy consumption, and so on than compared with the traditional routing protocols. The improvements suggest that the framework is ready for longer term use in high reliance, inclusive educational environments with the need for secure and effective data communication. The suggested model is one of the few crossovers that combine learning analytics, assistive technologies, blockchain security and intelligent networking, and it thus fits into the field of technology-enhanced special education. Future research could address issues of implementing in the real world in special education classrooms, incorporation of multimodal learning analytics, incorporation of advanced deep learning techniques, and evaluation of educational outcomes for students with different kinds of disabilities. These can lead to further improvements in personalized learning support and embrace a more inclusive, secure, and adaptive learning setting.

References

Alaerjan, A. (2023). Towards sustainable distributed sensor networks: An approach for addressing power limitation issues in WSNs. Sensors, 23(2), 975. doi:10.3390/s23020975

Alsuwat, H., & Alsuwat, E. (2025). Energy-aware and efficient cluster head selection and routing in wireless sensor networks using improved artificial bee colony algorithm. Peer-to-Peer Networking and Applications, 18(2), 1–24. doi:10.1007/s12083-024-01789-4

Baek, C., & Aguilar, S. J. (2023). Past, present, and future directions of learning analytics research for students with disabilities. Journal of Research on Technology in Education, 55(6), 931–946. doi:10.1080/15391523.2022.2067796

Bewley, K. A., Crosland, K., & Fuller, A. (2023). Using computer-assisted instruction to decrease transition times for students with autism spectrum disorder. Focus on Autism and Other Developmental Disabilities, 38(1), 45–55. doi:10.1177/10883576221133501

Chandra, S., Fane, J., Azizi, N., McKenzie-Gray, M., Sager, M., & Dautenhahn, K. (2025). Integrating new instructional assistive technology to support academic and behavioural instruction for students with learning disabilities. Intervention in School and Clinic, 61(1). doi:10.1177/01626434251314042

Drelick, A. M., & Elder, B. (2026). Building capacity with assistive technology in teacher education. Education Sciences, 16(3), 418. doi:10.3390/educsci16030418

Fernández-Batanero, J. M., Montenegro-Rueda, M., Fernández-Cerero, J., & García-Martínez, I. (2022). Assistive technology for the inclusion of students with disabilities: A systematic review. Educational Technology Research and Development, 70(4), 1911–1930. doi:10.1007/s11423-022-10127-7

Guduru, P., Lakshmi, K. V., & Gupta, S. (2026). Protecting individualized education and therapy records via two-tier integrity verification in distributed educational systems. International Journal of Special Education, 41(5s), 386–401.

Karunkuzhali, D., Pradeep, S., Sungheetha, A., & Basha, T. G. (2025). Data-aggregation-aware energy-efficient in wireless sensor networks using multi-stream general adversarial network. Transactions on Emerging Telecommunications Technologies, 36(2), e70017. doi:10.1002/ett.70017

Khalil, M., Slade, S., & Prinsloo, P. (2024). Learning analytics in support of inclusiveness and disabled students: A systematic review. Journal of Computing in Higher Education, 36(1), 202–219. doi:10.1007/s12528-023-09363-4

Kumar, R. N., & Srimanchari, P. (2024). A trust and optimal energy efficient data aggregation scheme for wireless sensor networks using QGAOA. International Journal of System Assurance Engineering and Management, 15(3), 1057–1069. doi:10.1007/s13198-023-02083-5

Kumari, S., & Tyagi, A. K. (2024). Wireless sensor networks: An introduction. In Digital twin and blockchain for smart cities (pp. 495–528). Singapore: Springer.

Kumm, S., Talbott, E., & Jolivette, K. (2021). A technology-based self-monitoring intervention for secondary students with high-incidence disabilities. Intervention in School and Clinic, 57(3), 154–163. doi:10.1177/01626434211004450

Mize, M., Park, Y., & Carter, A. (2022). Technology-based self-monitoring system for on-task behavior of students with disabilities: A quantitative meta-analysis of single-subject research. Journal of Computer Assisted Learning, 38(3), 668–680. doi:10.1111/jcal.12639

Narwaria, A., Kumari, V., & Mazumdar, A. P. (2025). RL-EAR: Reinforcement learning-based energy-aware routing for software-defined wireless sensor network. The Journal of Supercomputing, 81(3), 485. doi:10.1007/s11227-024-06785-7

Rajendran, G., Jayaprakasam, S., & Vijiyakumar, M. (2025, April). Energy efficient data aggregation techniques in wireless sensor network (WSN) for internet of things (IoT): A research review. In AIP Conference Proceedings (Vol. 3279, No. 1). Melville, NY: AIP Publishing. doi:10.1063/5.0264915

Srivastava, S., Varshney, A., Katyal, S., Kaur, R., & Gaur, V. (2021). A smart learning assistance tool for inclusive education. Journal of Intelligent & Fuzzy Systems, 40(6), 11359–11372. doi:10.3233/JIFS-210075

Shyamala, G., Pallavi, G. B., Latha, N. R., Rajesh, I. S., & Gupta, S (2026). Coalition based Game-Theoretic Routing Technique for Delay Tolerant Networks with Cost and Congestion Optimization. International Journal of Computational Intelligence in Engineering (IJCIE), 1(1), 16-28.

Tang, Q., & Nie, F. (2024). Clustering routing algorithm of wireless sensor network based on swarm intelligence. Wireless Networks, 30(9), 7227–7238. doi:10.1007/s11276-024-03808-y

Tong, X., Hamzei, M., & Jafari, N. (2025). Towards secure and efficient data aggregation in blockchain-driven IoT environments: A comprehensive and systematic study. Transactions on Emerging Telecommunications Technologies, 36(2), e70061. doi:10.1002/ett.70061

Tran Van, U., Hoang Tieu, B., & Tran, D. H. (2026). A multimodal learning analytics model based on deep learning for predicting student performance using tabular and time-series data fusion. Discover Artificial Intelligence, 6, 232. doi:10.1007/s44163-026-00990-1

Tuttle, M., & Carter, E. W. (2026). Perspectives of students with visual impairments on assistive technology in the classroom. The Journal of Special Education. Advance online publication. doi:10.1177/00224669261424860

Verma, V., & Jha, V. K. (2024). Secure and energy-aware data transmission for IoT-WSNs with the help of cluster-based secure optimal routing. Wireless Personal Communications, 134(3), 1665–1686. doi:10.1007/s11277-023-10852-0

Yousefi, S., Karimipour, H., & Derakhshan, F. (2021). Data aggregation mechanisms on the internet of things: A systematic literature review. Internet of Things, 15, 100427. doi:10.1016/j.iot.2021.100427

Yousefpoor, E., Barati, H., & Barati, A. (2021). A hierarchical secure data aggregation method using the dragonfly algorithm in wireless sensor networks. Peer-to-Peer Networking and Applications, 14(4), 1917–1942. doi:10.1007/s12083-020-01083-2

Zainal, A. Z. A., Yasir, A. S. H. M., Basri, A. Q., Latif, K., Nelfiyanti, N., Yusoof, M. Y. M., & Ishak, M. R. (2026). Exploring the use of assistive technology in special education: Issues and trends for student visual impairments: A systematic literature review. Assistive Technology, 1–16. Advance online publication. doi:10.1080/10400435.2026.2636752

Zikria, Y. B., Ali, R., Afzal, M. K., & Kim, S. W. (2021). Next-generation internet of things (IoT): Opportunities, challenges, and solutions. Sensors, 21(4), 1174. doi:10.3390/s21041174