MULTILAYERED QUALITY EDUCATION ECOSYSTEM (MQEE): A COGNITIVE-IOT BASED NOVEL SOLUTION FOR EDUCATION 4.0

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2026

DECLARATION

I, hereby declare that the presented work in the thesis entitled "MULTILAYERED QUALITY EDUCATION ECOSYSTEM (MQEE): A COGNITIVE-IoT BASED NOVEL SOLUTION FOR EDUCATION 4.0" in fulfilment of the degree of **Doctor of Philosophy (Ph.D.)** is the outcome of the research work carried out by me under the supervision of Dr. Parampreet Kaur, working as Associate Professor, in the School of Computer Science and Engineering of Lovely Professional University, Punjab, India. In keeping with general practice of reporting scientific observations, due acknowledgements have been made whenever work described here has been based on findings of other investigators. This work has not been submitted in part or full to any other University or Institute for the award of any degree.



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CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled "MULTILAYERED QUALITY EDUCATION ECOSYSTEM (MQEE): A COGNITIVE-IoT BASED NOVEL SOLUTION FOR EDUCATION 4.0" submitted in fulfillment of the requirement for the award of the degree of **Doctor of Philosophy (Ph.D.)** in the Computer Applications, is a research work carried out by Anil Verma, 41801014, is a bona fide record of his/her original work carried out under my supervision and that no part of the thesis has been submitted for any other degree, diploma or equivalent course.



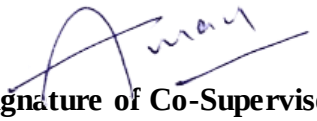
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ABSTRACT

Education has long been recognized as a fundamental driver of individual empowerment and socio-economic development. In the contemporary knowledge-driven world, ensuring **sustainable quality education** has become a central objective for nations across the globe. Despite significant advancements in educational infrastructure, pedagogy, and policy frameworks, maintaining consistent quality in education remains a complex and evolving challenge. Traditional education systems, which originated from teacher-centric models, have progressively transitioned toward student-centric and technology-supported paradigms. This evolution has culminated in the emergence of **Education 4.0**, a transformative approach that integrates advanced digital technologies to create intelligent, adaptive, and learner-centric educational ecosystems.

Education 4.0 aligns closely with the principles of Industry 4.0, emphasizing the use of technologies such as Artificial Intelligence (AI), Internet of Things (IoT), Machine Learning (ML), Fog Computing, and Cloud Computing to enable real-time interaction, continuous learning, and personalized educational experiences. However, while teaching and learning processes have undergone substantial transformation, the **assessment and accreditation mechanisms**—which are critical for ensuring quality—remain largely traditional, periodic, and manual in nature. These conventional systems primarily focus on three core parameters: infrastructure, faculty, and learning environment. Although these parameters are essential, they are insufficient to fully capture the complexity and dynamism of modern educational ecosystems.

One of the major limitations of existing quality assurance frameworks is their inability to identify, quantify, and monitor **hidden parameters** that significantly influence educational outcomes. These parameters include awareness, participation, accessibility, satisfaction, and academic engagement (or academic loafing). Such factors play a critical role in shaping the effectiveness of the teaching-learning process but are often overlooked due to the absence of appropriate monitoring mechanisms. Furthermore, the reliance on periodic evaluation leads to delayed feedback, reduced transparency, and inefficiencies in decision-making. As a result, there exists a pressing need for a **real-time, intelligent, and technology-driven framework** that can provide continuous monitoring, assessment, and accreditation in alignment with the requirements of Education 4.0.

The present research addresses this gap by proposing a novel framework termed the **Multilayered Quality Education Ecosystem (MQEE)**, based on the concept of **Cognitive Internet of Things (C-IoT)**. The primary purpose of this study is to design and develop a comprehensive system capable of real-time monitoring, intelligent analysis, and automated decision-making for assessment and accreditation in the Education 4.0 environments. The research is guided by the following key objectives: (i) to design a C-IoT-based framework for real-time assessment and accreditation; (ii) to develop a trust-based algorithm for monitoring and ensuring reliability in the system; and (iii) to evaluate the performance of the proposed framework across multiple quality parameters.

The central hypothesis of this research is that **the integration of C-IoT with multilayered data processing and intelligent algorithms can significantly enhance the accuracy, transparency, and efficiency of assessment and accreditation processes in Education 4.0**, thereby leading to improved quality of education. To validate this hypothesis, the study adopts a systematic research methodology comprising three major phases: problem analysis, conceptual design, and detailed solution implementation.

In the problem analysis phase, an extensive review of national and international education systems and quality assurance frameworks is conducted to identify existing limitations and research gaps. The study reveals that current systems are largely reactive rather than proactive, lack real-time capabilities, and fail to incorporate hidden quality-affecting parameters. In the conceptual design phase, the traditional Quality Education Ecosystem (QEE) is restructured into a **Multilayered Quality Education Ecosystem (MQEE)** by incorporating both primitive parameters (infrastructure, faculty, learning environment) and hidden parameters (awareness, participation, accessibility, satisfaction, and academic engagement). This multilayered approach provides a more comprehensive and holistic representation of educational quality.

The detailed solution design phase introduces the proposed **C-IoT-based MQEE framework**, which operates within an integrated **IoT–Fog–Cloud (IFC)** computing paradigm. The architecture of the framework is organized into four primary layers: the **Data Perception Layer (DPL)**, **Data Classification Layer (DCL)**, **Information Mining and Abstraction Layer (IMAL)**, and the **Predictive Decision-Making Layer (PDML)**.

The Data Perception Layer serves as the foundation of the system, utilizing IoT devices, sensors, and actuators to collect real-time data from various stakeholders and environmental

conditions within the educational ecosystem. This data encompasses multiple dimensions, including physiological metrics, environmental parameters, academic activities, and stakeholder interactions. Due to its heterogeneous and high-dimensional nature, the collected data requires efficient preprocessing and classification mechanisms.

The Data Classification Layer, primarily implemented at the fog computing level, employs machine learning techniques to process and filter incoming data streams. This layer ensures low-latency processing and enables near real-time responses for critical operations such as irregularity detection and alert generation. By distributing computational tasks across fog nodes, the system reduces reliance on centralized cloud infrastructure while improving efficiency and scalability.

A key innovation of this research is the introduction of the **Incremental Abstraction Model (IAM)** within the Information Mining and Abstraction Layer. The IAM transforms raw data into meaningful insights through successive levels of abstraction, generating multi-level reports ranging from device-level observations to institution-level analytics. This approach facilitates comprehensive analysis and supports decision-making at different hierarchical levels of the education system.

The Predictive Decision-Making Layer incorporates advanced deep learning techniques to enable intelligent analysis and forecasting. In particular, the study employs a **Multilayered Bidirectional Long Short-Term Memory (M-BiLSTM)** model, integrated with Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Gated Recurrent Units (GRUs), and Rectified Linear Units (ReLU). This hybrid architecture effectively captures temporal dependencies and complex patterns in educational data, enabling accurate prediction of anomalies, performance trends, and potential risks. Additionally, an **Adaptive Optimization Unit (AOU)** is incorporated to dynamically adjust model parameters, ensuring robustness and adaptability in diverse scenarios.

To support the analytical processes, the study utilizes multiple datasets, including the Stakeholder Fitness Dataset (SFD), Campus Environment Dataset (CED), Location Dataset (LDS), and Course Authenticity Dataset (CAD). These datasets collectively represent various dimensions of the educational ecosystem and enable comprehensive evaluation of the proposed framework.

Another significant contribution of this research is the development of a **Trust Algorithm** designed to enhance transparency, reliability, and objectivity in assessment and accreditation

processes. By minimizing human intervention and leveraging real-time data validation, the algorithm reduces biases and ensures consistency in decision-making. This trust-based approach strengthens stakeholder confidence and improves the credibility of the overall system.

The implementation and evaluation of the proposed framework are carried out using the **iFogSim simulation environment**, which enables modeling and performance analysis of IoT–Fog–Cloud infrastructures. The results demonstrate that the MQEE framework achieves superior performance in terms of latency, scalability, resource utilization, and accuracy compared to traditional systems. The framework successfully enables **real-time and intervallic assessment and accreditation**, thereby addressing the limitations of periodic evaluation models.

The scope of this research extends beyond the education sector, as the proposed framework can be adapted for use in other domains such as Smart Cities, Healthcare Systems, and Industrial IoT environments. Its ability to provide real-time monitoring, intelligent decision-making, and trust-based evaluation highlights its versatility and scalability.

In terms of contribution to knowledge, this research offers several key advancements. It introduces a novel multilayered framework for quality education, identifies and validates hidden parameters affecting educational outcomes, proposes an incremental abstraction model for multi-level data analysis, and develops a C-IoT-based trust algorithm for transparent and reliable assessment. Furthermore, it demonstrates the practical feasibility of integrating IoT, fog, and cloud computing with advanced deep learning techniques to enhance quality assurance in Education 4.0.

The findings of this study are aligned with global and national educational objectives, including the **Sustainable Development Goal 4 (SDG 4)** and the **National Education Policy (NEP) 2020**, which emphasize inclusive, technology-driven, and outcome-based education systems. By providing a comprehensive and scalable solution for real-time assessment and accreditation, the proposed MQEE framework contributes to the advancement of intelligent, data-driven education systems.

In conclusion, this research presents a robust, innovative, and future-oriented approach to addressing the challenges of quality assurance in Education 4.0. The integration of C-IoT technologies, multilayered architecture, incremental abstraction, and advanced predictive models results in a comprehensive framework capable of transforming traditional educational

evaluation systems into intelligent, real-time, and transparent ecosystems. Future research may focus on integrating blockchain for decentralized trust management, incorporating explainable AI for enhanced interpretability, and conducting real-world implementations for large-scale validation.

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ABBREVIATIONS

Sr. No.	Abbreviation	Meaning
1.	AAS	Average Absolute Shift
2.	AD	Activity Dataset
3.	AGI	Artificial General Intelligence
4.	AI	Artificial Intelligence
5.	AICTE	All India Council for Technical Education
6.	AISHE	Auditing Instrument for Sustainability in Higher Education
7.	ANN	Artificial Neural Network
8.	AR	Augmented Reality
9.	ARM	Advanced RISC Machine (RISC-Reduced Instruction Set Computer)
10.	asTTle	Assessment Tools for Teaching and Learning
11.	BBN	Bayesian Belief Network
12.	BC	Blockchain
13.	BIAD	Boundary Intellect Acoustic Detection
14.	BIVD	Boundary Intellect Vibration Detection
15.	BSDL	Boundary Sense Deep Learning
16.	CAD	Course Authenticity Dataset
17.	CAD/CW	Course Authenticity Dataset/Courseware
18.	CAF	Checkable answer feedback
19.	CCH	Central Council of Homoeopathy
20.	CCIM	Central Council of Indian Medicine
21.	C-IoT	Cognitive-Internet of Things
22.	CRASN	CRASN (Cognitive Radio Ad-hoc Sensor Network)
23.	CWSN	Cognitive Wireless Sensor Networks
24.	D2D	Device to Device
25.	DARE	Distributed Application Run-Time Environment
26.	DCI	Dental Council of India
27.	DDDAS	Dynamic Data-Driven Application System
28.	DE	Delay Efficiency
29.	DPWC	distributional profile of multiple word categories
30.	DSOC	Decentralized Self-Organized Cooperative
31.	DT	Decision Tree
32.	EC2	Elastic Compute Cloud
33.	ECSF	Environmental Change in Study Factor
34.	ED	Environment Dataset
35.	EFQM	European Foundation for Quality Management
36.	EM	Expectation-Maximization
37.	EMIS	National education management information system
38.	EQ	Emotional Quotient
39.	F&CF	Fast and Continuous Feedback Activity
40.	FD	Fitness Dataset
41.	GPS	Global Positioning System
42.	GPU	Graphics Processing Unit
43.	GRU	Gated Recurrent Unit
44.	HEF	Human Error Flag

45.	HEIs	Higher Educational Institutions
46.	HIBJS	Hybridized Interference Bounded Intuitive Splitting
47.	ICAR	Indian Council of Agricultural Research
48.	ICT	Information and Communication Technology
49.	IFC	IoT, Fog Computing and Cloud Computing
50.	IioT	Industrial Internet of Things
51.	IoT	Internet of Things
52.	IPR	Research and Professional Practice
53.	IQ	Intelligence Quotient
54.	IQAC	Internal Quality Assurance Cell
55.	KNN	K-Nearest Neighbors
56.	LBN	Learning Bayesian Network
57.	LDVSL	linear fitting algorithm, Diameter-varying spiral line
58.	LMSs	Learning Management Systems
59.	LowPAN	Low power Wireless Personal Area Networks
60.	LSTM	Long Short Term Memory
61.	M.Phil.	Master of Philosophy
62.	MaC	Monitoring as Code
63.	MAP	Maximum A Posterior
64.	MAPE	Mean Absolute Percent of Error
65.	MAQAS	Multimedia and Agent-based Question Answering System
66.	M-Bi-LSTM	Multilayered-Bidirectional Long Short Term Memory
67.	MCI	Medical Council of India
68.	ML	Machine Learning
69.	ML	Maximum likelihood
70.	MQEE	Multi-layered Quality Education Ecosystem
71.	NAAC	National Assessment and Accreditation Council
72.	NBA	National Board of Accreditation
73.	NIRF	National Institutional Ranking Framework
74.	OGC	Open Geospatial Consortium
75.	OTA	Over-the-air
76.	PCI	Pharmacy Council of India
77.	PG	Postgraduate
78.	Ph.D.	Doctor of Philosophy
79.	Postdoc	Postdoctoral
80.	QAA	Quality Assurance Agency
81.	QEE	Quality Education Ecosystem
82.	QoE	Quality of Education
83.	RAM	Random Access Memory
84.	ReLU	Rectified Linear Unit
85.	RTC	Reporting Temporal Chunk
86.	SEMIoTICS	Semantically enhanced IoT-enabled Intelligent Control Systems
87.	SEPT	School of Engineering Practice and Technology
88.	SPEM	Systems Process Engineering Metamodel
89.	SQAC	State Quality Assurance Cell
90.	SSD	Solid State Drives
91.	SSN	Semantic Sensor Network

92.	SSS	Student Satisfaction Survey
93.	SVM	Support Vector Machine
94.	TCBCSS	trustful cluster-based cooperative compressed spectrum sensing
95.	TCR	Teaching Learning and Resources
96.	TDM	Temporal Data Mining
97.	THE	Times Higher Education
98.	TM	Teaching Methodology
99.	TMs	Trust Metrics
100.	TVWS	White Space TV
101.	UG	Undergraduate
102.	UGC	University Grants Commission
103.	UNESCO	United Nations Educational, Scientific and Cultural Organization
104.	UNICEF	United Nations International Children's Emergency Fund
105.	UTs	Union Territories
106.	VAK	Visual, auditory and kinaesthetic
107.	VAR	Virtual and Augmented Reality
108.	VR	Virtual Reality
109.	WNCS	Wireless Networked Control System
110.	ZKP	Zero-Knowledge Proof

CHAPTER 1

Introduction

***Chapter Briefing*— This chapter provides a comprehensive overview of the foundational elements of the education system, including its hierarchical structure, assessment mechanisms, and accreditation processes. It discusses the vital role these components play in ensuring quality education across primary and higher education institutions. The chapter also examines the diverse implementation approaches of educational systems globally, highlighting the roles of national and international agencies such as UGC, AICTE, NAAC, NBA, and private organizations like Times Higher Education and QS Rankings. A focal point of this chapter is the dynamic evolution of education, with a detailed exploration of the transition from Education 1.0 to Education 4.0. This progression underlines the shift from teacher-centric models to technologically driven, real-time assessment environments. The concept of Education 4.0, its alignment with Industry 4.0, and the utilization of advanced technologies such as AI, IoT, Machine Learning, Fog and Cloud Computing, and Blockchain are extensively analysed. Furthermore, the chapter delves into the challenges of implementing Education 4.0, particularly the need for real-time assessment and accreditation. It underscores the significance of data accuracy during acquisition, classification, and integration as essential components for maintaining the integrity of assessments. This research investigates the integration of emerging technologies into Education 4.0, aiming to propose a robust framework for real-time assessment, irregularity detection, and decision-making. The contributions of this study include the identification of technological solutions, the evaluation of their accuracy, and the exploration of effective methods for data handling. The chapter concludes by outlining the objectives of the research, its methodologies, and the organization of the thesis, setting the stage for subsequent chapters.**

1.1 Introduction

Education is a primary requirement of an individual for learning life skills and employable skills. Every nation is spending huge amounts of money on providing Primary and Higher Education to its citizens. Maintaining the quality of education in every primary and higher education institution is one of the principal tasks of every nation. Every nation has its own educational system hierarchy; for example, India follows a Pre-Primary, Primary, Secondary, and Higher Education hierarchy for the implementation of its educational curriculum. Numerous public and private sector agencies are deployed to maintain the quality

of education, for instance in India more than 20 public-sector apex bodies are deployed including the University Grants Commission (UGC), All India Council for Technical Education (AICTE), National Assessment and Accreditation Council (NAAC), National Board of Accreditation (NBA), and many more. Most of these agencies are deployed for assessment and accreditation of a specific type of educational institution; for example, AICTE deals only with technical education courses whereas the Pharmacy Council of India (PCI) is associated with various Pharmacy courses. This type of segregation is implemented because the nature of courses differs; as a result, the respective assessment and accreditation mechanisms must also be different in respect of their nature. In simple terms, assessment is the mechanism followed by a particular apex body for evaluation of quality education imparted by an institution and accreditation is a set mechanism to award a rank or score based on the assessment of the institution. These public sector agencies are evaluating the quality of education only on the national level. Similar private sector agencies are also working for the assessment of institutions, mostly higher education institutions, at the international level. The global leaders include Times Higher Education (THE), QS-Webometric University Ranking, and Scimago World Ranking; these agencies are employed for the evaluation of quality education at the global level. All the public and private sector agencies are working on an intervallic or periodic model; real-time assessment and accreditation are not possible without the intervention of technology.

Technology is used for maintaining accuracy and reliability in most applications. Continuous evaluation of each stakeholder and institution is a primary requirement of the Education 4.0 environment, therefore involvement of technology in the education environment for real-time assessment and accreditation is mandatory. Further, with the help of Artificial Intelligence (AI)-based intelligent algorithms real-time monitoring, irregularity detection, alert generation, assessment, and accreditation are also possible in the Education 4.0 environment.

1.2 Assessment, Accreditation and Ranking of Educational Institutions

Assessment, accreditation, and ranking constitute three interrelated components of the institutional quality assurance and performance evaluation ecosystem in higher education. Within the Indian and global higher education contexts, these mechanisms provide systematic approaches for measuring institutional performance, assuring compliance with established quality standards, and comparatively positioning institutions within the broader educational landscape. Although closely interconnected, assessment, accreditation, and ranking differ in their objectives, methodological approaches, evaluation criteria, and expected outcomes.

Assessment is a systematic and evidence-based process for measuring, analysing, and evaluating specific dimensions of institutional performance. These dimensions may include student learning outcomes, teaching and learning processes, infrastructure, research productivity, governance, administrative efficiency, and other academic and institutional parameters. Assessment primarily generates quantitative and qualitative evidence that supports institutional decision-making, continuous quality improvement, and subsequent external evaluation processes [1].

Accreditation is a structured external quality assurance process conducted by an authorized or recognized accrediting body to evaluate whether an educational institution or academic programme conforms to predetermined quality standards and performance criteria. Based on the evaluation outcomes, the institution or programme may receive formal recognition, certification, or a graded accreditation status. Therefore, accreditation primarily addresses the fundamental question: "Does the institution or programme satisfy the prescribed quality standards and benchmarks?"

Ranking represents a comparative and relative evaluation mechanism in which institutions are positioned according to their performance across a defined set of quantitative and qualitative indicators. These indicators are generally assigned specific weights and aggregated through an established ranking methodology [2]. Rankings may be developed and published by government agencies, independent organizations, or other recognized bodies and primarily address the question: "How does the performance of an institution compare with that of other institutions within a defined peer group or educational system?"

Collectively, these three mechanisms form complementary components of the higher education quality ecosystem. Assessment generates the underlying performance evidence, accreditation evaluates institutional conformity with established quality standards, and ranking provides a comparative representation of institutional performance. The comprehensive comparison among assessment, accreditation, and ranking is presented in Table 1.1, while their conceptual relationship within the institutional quality assurance ecosystem is illustrated in Figure 1.1.

Table 1.1. Comparative differentiation of Assessment, Accreditation and Ranking

Dimension	**Assessment**	**Accreditation**	**Ranking**
Purpose	Diagnose strengths/weaknesses; support improvement and decision-making	Certify minimum quality standards are met	Compare and order institutions competitively
Nature of outcome	Descriptive/diagnostic (reports, scores, feedback)	Binary or graded (accredited/not accredited; grades like A++, A+, A)	Ordinal (numeric rank or tier, e.g., 1st, 25th, Top 100)
Conducted by	Internal teams, self-study committees, or external evaluators	Recognized statutory/autonomous bodies (e.g., NAAC, NBA, AACSB, ABET, regional accreditors)	Ranking agencies, media, or governments (e.g., NIRF, QS, THE, US News)
Basis of evaluation	Absolute standards or institutional goals	Predefined minimum benchmarks/criteria	Relative performance against peer institutions
Frequency	Continuous/periodic (annual, per-cycle)	Periodic, usually every 3–5 years	Usually annual

Voluntary/Mandatory	Often mandatory internally; may feed into accreditation	Often mandatory for recognition, funding, or degree validity	Voluntary participation (institutions submit data or are ranked using public data)
Scope	Can be narrow (a course, department, or specific process)	Institution-wide or program-specific	Usually institution-wide, sometimes discipline-wise
Consequences	Internal quality improvement plans	Legal/regulatory recognition, funding eligibility, degree validity	Reputation, student choice, market competitiveness, brand value
Methodology	Mixed methods: surveys, audits, learning outcome measures	Standardized rubrics, site visits, document verification	Weighted composite indices (research output, faculty ratio, perception, employability, etc.)
Public disclosure	Often internal or shared selectively	Publicly disclosed accreditation status	Publicly published, often widely publicized
Comparability across institutions	Limited (context-specific)	Limited (pass/fail or grade, not comparative ordering)	High (designed explicitly for comparison)
Example bodies	Internal Quality	NAAC, NBA, UGC,	NIRF, QS World

(India/Global)	Assurance Cells (IQAC), Academic Audits	AICTE, ABET, AACSB	University Rankings, THE, ARWU (Shanghai Ranking)

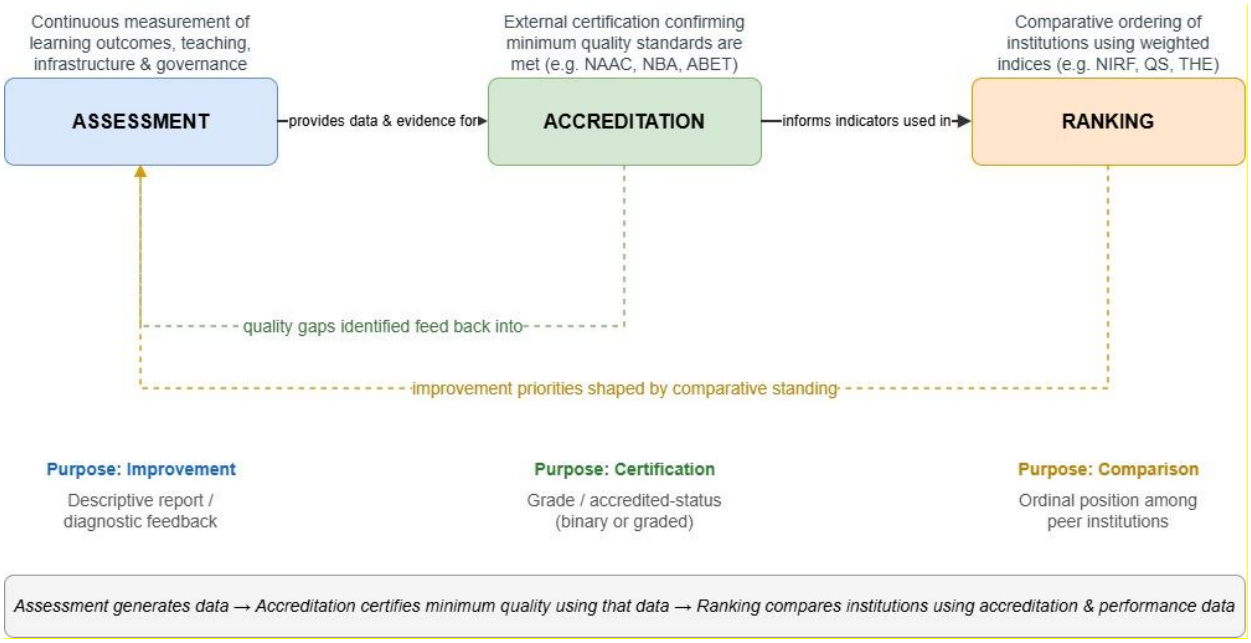


Figure 1.1. Relationship between Assessment, Accreditation and Ranking of Educational Institutions

1.3 Education 4.0

Education is a dynamic environment, and the changes with time in the education sector are obvious. Initially, the authoritarian system of education was adopted by most countries which supports the Teacher-Centric approach under Education 1.0. The exam-based student-centred approach evolved with time to extend communication and collaboration learning under Education 2.0. After this sequence, the evolution of flipped classrooms took place for collaborative learning under Education 3.0 [3]. Education 4.0 is all about continuous evaluation, innovation, and creative learning [4]. Education 4.0 is the spine of the Fourth Industrial Revolution i.e. Industry 4.0. Education 4.0 uses cutting-edge technology for its implementation and execution. Robust technologies including IoT, Fog Computing, Cloud Computing, Edge Computing, Artificial Intelligence (AI), Machine Learning (ML), and Blockchain Technology are used in the Education 4.0 environment [5]. Education 4.0 provides

a real-time ubiquitous environment for all the stakeholders including students, teachers, parents, administrators, and Policy Makers. Under Education 4.0 major educational assignments including monitoring, irregularity detection, assessment and accreditation, and decision-making for policy upgradation are supposed to be executed by numerous intelligent algorithms. So, in brief Education 4.0 is the technologically empowered environment for sustainable quality education.

The evolution of the education system is a gradual process. Each revolution in education took decades to implement. Each education revolution has its own importance based on advancement in technology, availability of resources, geographical challenges, and other implementation and execution challenges [6]. Some of the developed countries are moving towards Education 4.0. On the other hand, some developing nations are still stuck on Education 1.0 [3]. The hybridization of the educational revolution is very common in most of the nations, as in some rural areas of a country Education 1.0 is executed whereas some urban areas are moving towards Education 3.0 or Education 4.0. Table 1.2 illustrates the different aspects of the educational revolution.

Education 4.0 is a new dimension of education. Emerging technologies including C-IoT (Cognitive-Internet of Things), ML (Machine Learning), AI (Artificial Intelligence), Fog and Cloud Computing, Augmented Reality (AR) and Virtual Reality (VR) are providing multidimensional support for the implementation of Education 4.0 [7]. Real-time assessment is one of the key challenges in the implementation of Education 4.0. Real-time assessment of every stakeholder including students, teachers, and administrative staff is of paramount importance for Education 4.0 [8]. Accuracy in the assessment process of an educational institution directly depends upon the accuracy during data acquisition, data classification, and integration. The main motivation behind this study is to explore the most suitable technological integration for the implementation of Education 4.0 and to propose a suitable framework for assessment and irregularity detection for Education 4.0. The proposed study contributes in many dimensions to Education 4.0. Some of the main contributions are listed below:

- The proposed study explores all existing emerging technologies used in Education 4.0 and explores the most suitable technological integration for assessment and irregularity detection.
- The proposed study evaluates the accuracy of the proposed technological integration for assessment and irregularity detection.

- The proposed study explores the suitable methods for data acquisition, data classification, and integration for Education 4.0.
- The proposed study suggests a suitable framework for assessment and irregularity detection under the Education 4.0 environment.
- The proposed study also evaluates the accuracy of the suggested framework for assessment and irregularity detection.

The proposed study recommends the involvement of sensor-based data acquisition methods (IoT), AI-based data classification and integration methods over fog nodes, AI-based assessment, and irregularity detection methods over the cloud nodes for the implementation of the Education 4.0 environment.

Table 1.2. Revolution in education from Education 1.0 to Education 4.0

Educational Revolution	Prospective	Teacher	Student	Learning Approach	Technology Used
Education 1.0	Authoritarian	Absolute Leader	Passive Recipient	Teacher-Centric	Technology is forbidden
Education 2.0	Communication and collaboration	Orchestrator	Active Recipient	Exam-based approach, Student-centered approach,	Collaborative, Interactive Web Tools: Wikis, Blogs, Google Docs, Edmodo, etc.
Education 3.0	Collaborative learning	Coordinator, Advisor, Facilitator	Researcher	Student-Centric, Flip Classrooms,	E-Learning, M-Learning, L-Cloud, etc.
Education 4.0	Creative Learning	Skill Developer	Researcher and Creator	Continuous evaluation, learning, and Innovation.	AR/VR Courseware, IoT, AI, ML, Fog & Cloud Computing, Blockchain Technology, etc.

1.4 Aims and Objectives

The contribution and awareness of every stakeholder for the improvement of quality education at the institutional level and implementation of the "Principle of total participation for total quality control" are some of the main purposes of this research. The other aims behind this research are listed below:

- Study the existing education ecosystem presently deployed at national and international levels
- Find out the various variables that are affecting the presently deployed education ecosystem in India.

- Reconstruct the education ecosystem by exploring its hidden layers, and adding appropriate and unexplored parameters that are affecting the present education ecosystem. Complete the education ecosystem and make a multilayered quality education ecosystem.
- Make a pilot study on any one of the apex bodies like NAAC, AISHE, or AICTE, etc., and implement the proposed multilayered quality education ecosystem on the selected apex body.
- Improve the present assessment and accreditation process by improving the variables that are affecting the present education ecosystem.
- Develop a framework and implement it with suitable technology.
- After implementation of the proposed framework, prepare a detailed report on the proposed framework.

All the above-mentioned aims are realized during this research under the following main objectives:

1. To design a C-IoT based novel solution for assessment and accreditation for Education 4.0.
2. To develop a C-IoT based trust algorithm for monitoring and trust building in Education 4.0.
3. To evaluate the performance of the proposed framework on various quality parameters.

1.5 Research Methodology

The methodology behind the proposed research framework is categorized into three different phases i.e. Problem analysis and problem definition, Conceptual design of the ecosystem, and Detailed solution design. The subsequent section will explain all the phases one by one:

Phase-I (Problem analysis and problem definition): For initial problem analysis, an exhaustive literature review of the national and international education systems presented by some of the authentic agencies already working in the field of quality education was carried out. The detailed description of Phase-I is illustrated in Figure 1.2.

After completion of all the steps mentioned under phase-I, the following limitations and requirements have been explored for further research.

- There is an urgent need for the exploration of other factors that are affecting quality education.

- The Quality Education Ecosystem (QEE) needs to be updated as a Multi-layered Quality Education Ecosystem (MQEE).
- Early involvement of state-of-the-art technology in the education sector will improve the quality of education faster.
- Instead of infrastructure, technologically enhanced infrastructure is required for sustainable quality education.
- Involvement of IoT, Fog, Cloud, and AI for the initial level of Education 4.0; and distributed AI or advanced Blockchain technology are required for the latter stages of Education 4.0.

Figure 1.3 presents the limitations of the present assessment and accreditation system used in the education industry.

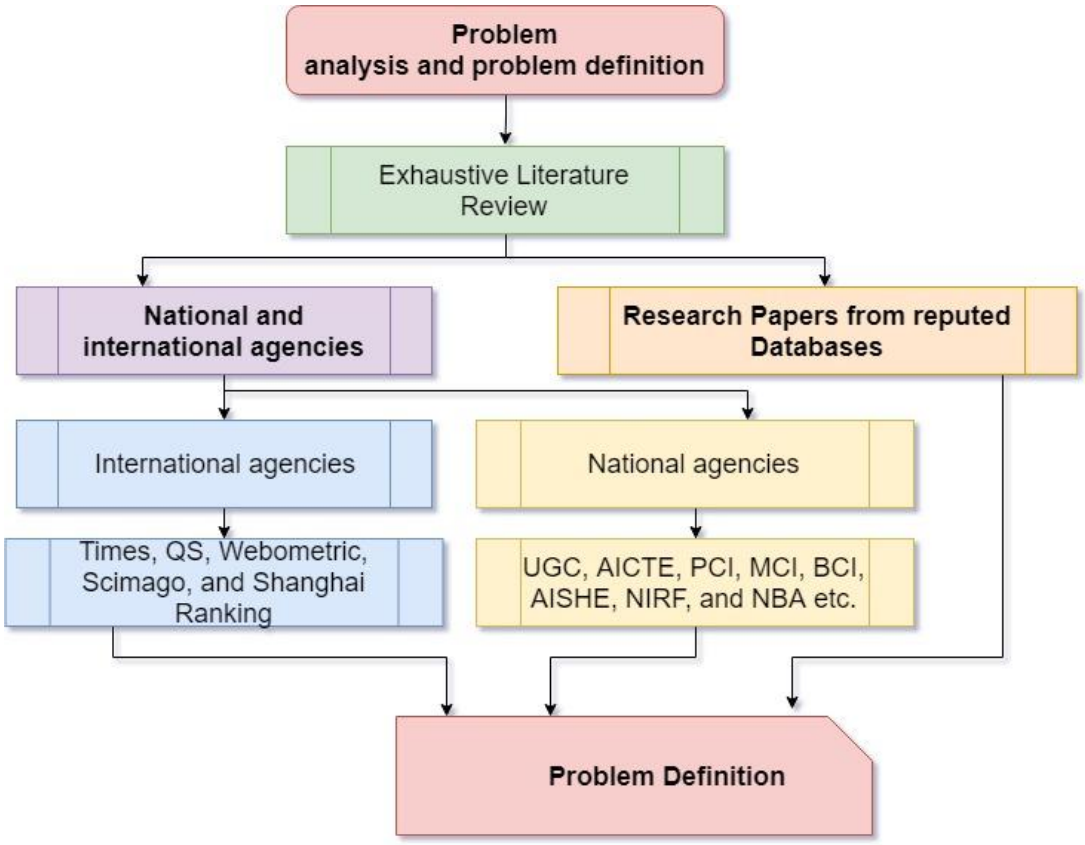


Figure 1.2. Phase-I (Problem analysis and problem definition)

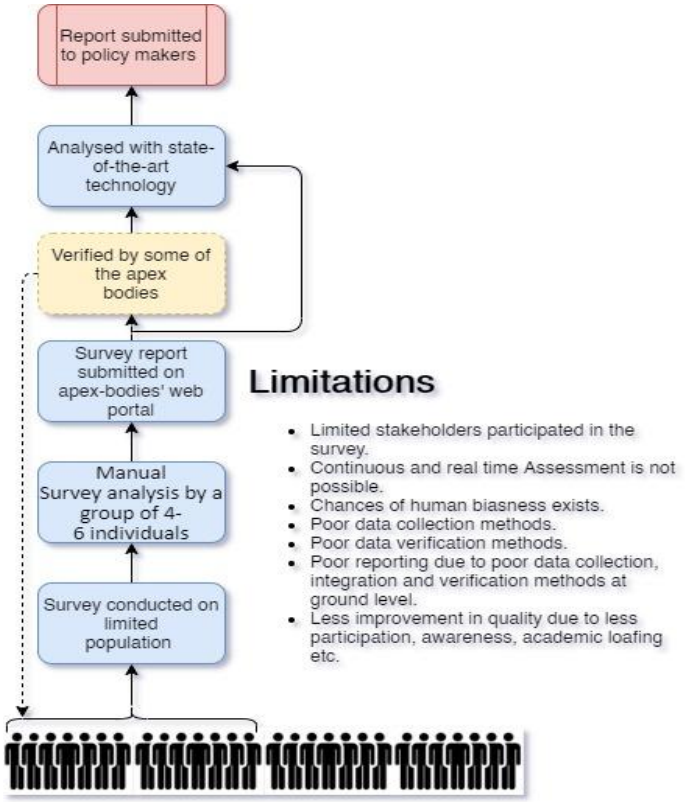


Figure 1.3. Present assessment and accreditation scenario and its limitations

Phase-II (Conceptual design of education ecosystem): After initial inspection and problem definition the following eight parameters are selected for the study that have a significant role in the quality education ecosystem:

i. Infrastructure
ii. Intellectual Faculty
iii. Learning Environment
iv. Awareness (About quality education and responsibilities of every stakeholder for quality education)
v. Participation (Total Participation)
vi. Accessibility (Direct accessibility connection between every stakeholder and respective apex bodies)
vii. Academic loafing (Individual's efforts toward quality education)
viii. Satisfaction

Presently only the first three i.e. Infrastructure, Intellectual Faculty, and Learning Environment are focused on quality education. But the other five parameters are also found momentous for quality education during initial inspection. The present

education ecosystem and the required multi-layered education ecosystem are illustrated in the following Figure 1.4:

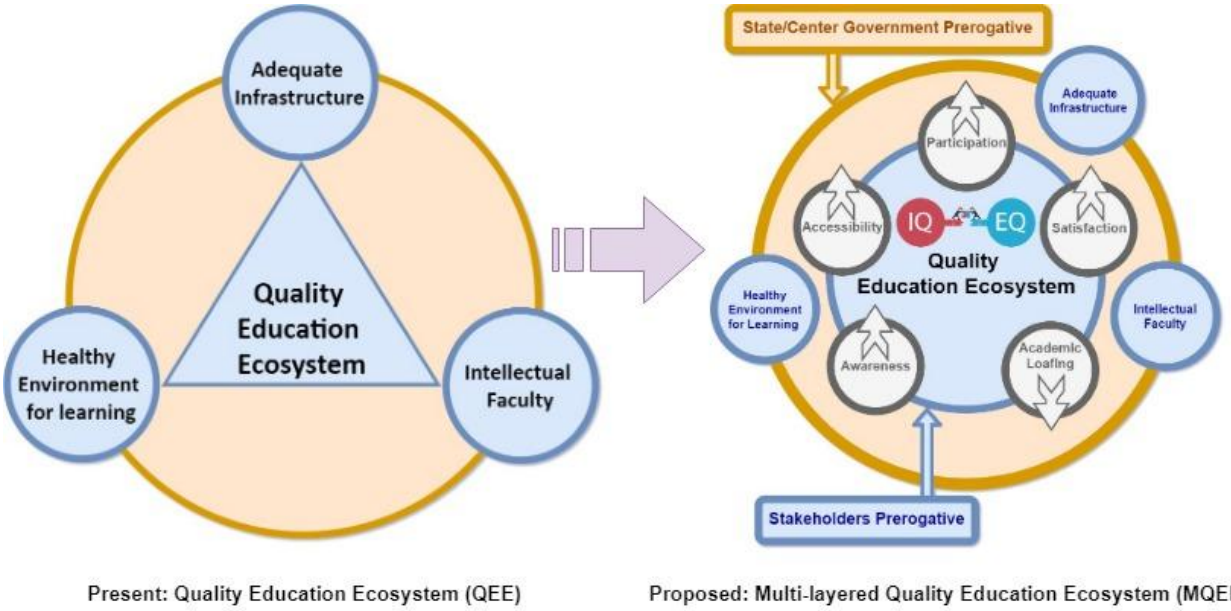


Figure 1.4. Phase-II (Conceptual design of education ecosystem)

Phase-III (Detailed solution design and Data Set): C-IoT based solution is proposed for the construction of the proposed Multi-layered Quality Education Ecosystem (MQEE). The C-IoT based proposed solution is illustrated in Figure 1.5. The very first layer i.e. Layer-I is termed a physical layer or IoT Layer as various IoT devices, sensors, and actuators are deployed over this layer at the physical level. Layer-II dedicatedly handles the data analysis and various trust-building algorithms, Layer-III handles the assessment part, and finally all types of accreditations and decision-making are handled over Layer IV i.e. Accreditation/Decision Making-Layer.

Trust Algorithm/Trust Layer: The algorithm mentioned under the second objective and layer II of the detailed design of this research work is termed "Trust Algorithm". No trust matrix is used to maintain trust in this research work, nor is any physiological analysis performed. Rather by the deployment of IoT devices and various other algorithms, the involvement of humans (and Human mistakes) in the assessment and accreditation process under the Education 4.0 environment is minimized, which makes the overall system more transparent and reliable. Transparency and reliability are the two major factors that make the proposed framework trustworthy.

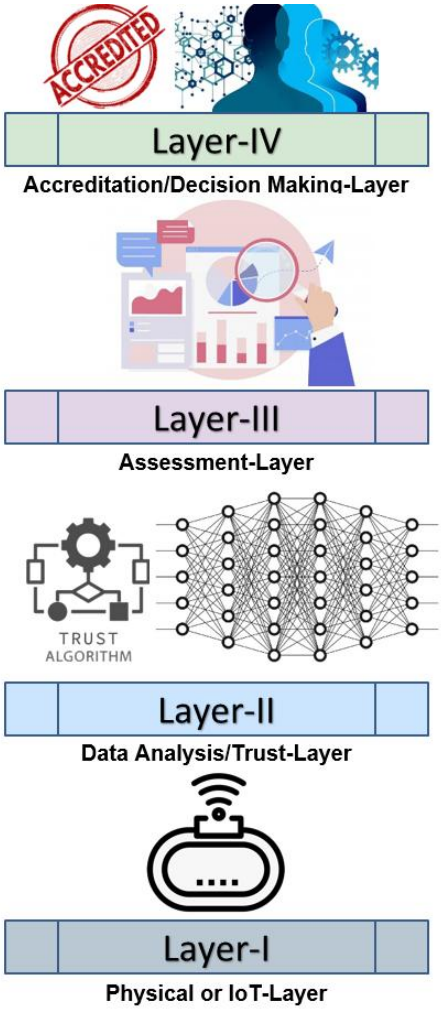


Figure 1.5. Phase-III (C-IoT based Multi-layered proposed framework)

Data Set: Stakeholder Fitness Dataset (FD), Campus Environment Dataset (ED), Stakeholder Activity Dataset (AD), and Course Authenticity Dataset (CAD). All the datasets except the Course authenticity Dataset are acquired with the help of various IoT devices, Sensors, and Actuators for an ambient educational environment. The Course authenticity dataset is defined by the institution as per the specifications of various courses offered by that institution at the time of implementation of this framework. Various courses related data including Course Name, Course Code, Programme Name, Programme Course, Number of Theory hours required, Number of required practical hours, Grades Offered, etc., are included in this dataset.

1.6 Significance of the Study

This research makes a significant and timely contribution to the domain of **educational quality assurance** by introducing a **Multilayered Quality Education Ecosystem (MQEE)** underpinned by **Cognitive Internet of Things (C-IoT)** technologies. The proposed

framework addresses the limitations of conventional assessment and accreditation mechanisms by embedding **intelligence, real-time responsiveness, and automation** into the educational evaluation process. The significance of the study can be understood in the following dimensions:

1. **Enabling Real-Time Assessment and Accreditation through C-IoT Technologies**
   The proposed framework harnesses the capabilities of Cognitive IoT to support the real-time monitoring of educational processes and environments. By integrating sensors, edge devices, and cloud analytics, it enables continuous data acquisition and intelligent processing, thereby facilitating timely, automated, and evidence-based assessment and accreditation. This real-time capability ensures that institutional performance is monitored dynamically rather than periodically, allowing for proactive quality improvements.
2. **Optimization of Manpower and Time for Institutions and Accreditation Agencies**
   The proposed framework offers a transformative solution for significantly reducing the manpower and time investment required for assessment and accreditation processes. Traditionally, universities and higher education institutions maintain dedicated teams or entire divisions responsible for preparing and managing quality assurance documentation and compliance for various accrediting bodies. Similarly, accreditation agencies deploy substantial human resources to conduct periodic evaluations, verifications, and audits. By introducing automation, real-time data acquisition, and intelligent processing, the proposed framework minimizes the dependency on manual operations at both ends. This not only enhances operational efficiency but also allows institutions and agencies to reallocate human resources toward more strategic and developmental activities. Consequently, the framework ensures streamlined, timely, and cost-effective quality assurance with reduced administrative burden.
3. **Fostering Transparency and Accountability through Trust-Based Algorithms**
   A core innovation of this study is the development of a trust algorithm that enhances the transparency, reliability, and objectivity of the accreditation process. By minimizing manual intervention and human biases (Recently observed in NAAC assessment and Accreditation), the trust algorithm supports data-driven decision-making and builds confidence among stakeholders, including students, faculty, and

regulatory bodies. This contributes to establishing an ecosystem where accountability is systemic and verifiable.

4. **Supporting the Vision of Education 4.0 and National Education Policy (NEP) 2020**

   The research aligns closely with the strategic objectives of **Education 4.0**, which advocates for a technology-enabled, learner-centric, and skill-oriented education system. Moreover, it complements the vision outlined in India's **National Education Policy (NEP) 2020**, which calls for robust digital infrastructure, outcome-based assessment, and continuous institutional evaluation. The proposed MQEE serves as a practical enabler for realizing these national policy goals.

5. **Contributing to the Achievement of Sustainable Development Goal (SDG) 4**

   The study also contributes to global educational priorities, particularly **Sustainable Development Goal 4 (SDG 4)**, which emphasizes inclusive, equitable, and quality education for all. By promoting a data-informed, inclusive, and scalable quality assurance framework, the research supports the advancement of equitable education practices and continuous institutional improvement on a global scale.

6. **Serving as a Guiding Framework for Modernizing Quality Assurance**

   The MQEE framework provides a replicable and adaptable model for educational institutions, accreditation agencies, and policymakers seeking to modernize their quality assurance systems. It lays the groundwork for transforming traditional evaluation mechanisms into smart systems capable of self-regulation, intelligent assessment, and adaptive learning support. This paves the way for large-scale adoption of intelligent accreditation systems in higher education and beyond.

Through the strategic integration of **smart devices and real-time analytics**, the proposed MQEE offers a **sustainable, transparent, and scalable approach** to educational quality enhancement. It not only addresses existing systemic gaps but also sets the foundation for **future research, innovation, and practical implementation** in the evolving landscape of Education 4.0.

1.7 Thesis Organization

This thesis is organized into 8 main chapters. Chapter 1 focused on the existing system and the need for Education 4.0, it further explored the research methodologies used and a brief layout of the research progress. Chapter 2 presented the taxonomy-based literature review on

Education 4.0, C-IoT, and various other technologies including Machine Learning and Artificial Intelligence. Chapter 3 elaborates an analysis of the various hidden parameters and their impact on various components of Education 4.0. This chapter also includes the significance and relevance in Education 4.0. The mathematical models presented in the chapter prove the relevance of these hidden parameters in Education 4.0. Chapter 4 validates these hidden parameters with the help of a systematic study. Chapter 5 focused on the proposed novel solution for assessment and accreditation for Education 4.0. This chapter also explains the various layers of the proposed Multilayered-Quality Education Ecosystem (MQEE). Chapter 6 elaborates various algorithms defined and used for monitoring and trust building in Education 4.0 for monitoring, irregularity detection, assessment, and accreditation under Education 4.0 scenario. Chapter 7 elaborates the implementation scenario and analyses the performance of the proposed model; it also elaborates various recommendations w.r.t., real-time and intervallic framework for Education 4.0, and finally chapter 8 concludes this thesis with its future scope. The objectives of this study, respective chapters of this thesis and various publications are elaborated in Figure 1.6.

- **Chapter 1:** This chapter provides a comprehensive introduction to the study, beginning with a clear statement of its objectives and the underlying background that establishes the context for the research. It further outlines the significance of the study in the domain of Education 4.0 and explains the rationale for undertaking this work. In addition, the chapter details the research methodology adopted, describing the overall approach, design, and techniques employed to achieve the stated objectives and ensure the validity and reliability of the findings.

  -Verma, Anil, Aman Singh, Edwin Lughofer, Xiaochun Cheng, and Khalid Abualsaud. "Multilayered-quality education ecosystem (MQEE): an intelligent education modal for sustainable quality education." Journal of Computing in Higher Education 33, no. 3 (2021): 551-579.
- **Chapter 2:** The taxonomy-based literature review is presented in this chapter. Numerous research articles on Education 4.0, C-IoT, Education System, etc., have been explored. The focused area, Techniques, methods used, and application and results of all the articles are summarized under a literature review table. Various National and International reports on quality education are also elaborated. Further, the research gap obtained during the literature review is also presented in this chapter.

-Verma, Anil, and Aman Singh. "New Era Of Technology Empowered Education: Education 4.0 A Systematic Review." In 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO), pp. 1-7. IEEE, 2021.

- **Chapter 3:** Chapter 3 presents an in-depth analysis of various hidden parameters and examines their influence on multiple components of Education 4.0. The discussion encompasses the identification, categorization, and interpretation of these parameters, highlighting their significance and relevance within the evolving educational landscape. Special emphasis is placed on how these parameters contribute to enhancing the quality, adaptability, and efficiency of Education 4.0 frameworks. Furthermore, the chapter introduces and explains mathematical models developed to substantiate the importance of these hidden parameters, providing empirical evidence and theoretical justification for their integration into the proposed framework.

  -Verma, Anil, Parampreet Kaur, and Aman Singh. 2024. "Assessment in the Age of Education 4.0: Unveiling Primitive and Hidden Parameters for Evaluation" *Information* 15, no. 8: 486. https://doi.org/10.3390/info15080486

- **Chapter 4:** This chapter focuses on the validation of the identified hidden parameters through a systematic study. In order to develop the conceptual framework of the proposed system, the chapter examines various hidden elements that warrant exploration and prioritization for enhancing the Quality of Education (QoE). A Bidirectional Weighted Sum (BWS) approach is employed to analyse different components of the education ecosystem. Specifically, five key hidden elements—awareness, accessibility, participation, satisfaction, and academic loafing—are investigated in detail, and their significance in achieving quality education is critically discussed. Based on these findings, a multilayered quality education ecosystem model encompassing all these elements is proposed, aimed at reinforcing and strengthening the education ecosystem at the foundational level.

-Verma, Anil, Parampreet Kaur, and Aman Singh. 2024. "Assessment in the Age of Education 4.0: Unveiling Primitive and Hidden Parameters for Evaluation" *Information* 15, no. 8: 486. https://doi.org/10.3390/info15080486

- **Chapter 5:** This chapter introduces the proposed novel solution for assessment and accreditation tailored to the requirements of Education 4.0. The chapter offers a detailed exposition of the Multilayered-Quality Education Ecosystem (MQEE), explaining its structural composition, functional layers, and the interrelationships among them. Each layer is analysed in terms of its specific role in fostering quality, innovation, and continuous improvement within the education system. The discussion also emphasizes how the MQEE framework aligns with the core principles of Education 4.0, ensuring a holistic, data-driven, and sustainable approach to assessment and accreditation.

  -Verma, Anil, Aman Singh, Edwin Lughofer, Xiaochun Cheng, and Khalid Abualsaud. "Multilayered-quality education ecosystem (MQEE): an intelligent education modal for sustainable quality education." Journal of Computing in Higher Education 33, no. 3 (2021): 551-579.

  -Verma, Anil, Divya Anand, Aman Singh, Rishika Vij, Abdullah Alharbi, Majid Alshammari, and Arturo Ortega Mansilla. "IoT-Inspired Reliable Irregularity-Detection Framework for Education 4.0 and Industry 4.0." Electronics 11, no. 9 (2022): 1436.

  -Verma, Anil, Aman Singh, Divya Anand, Hani Moaiteq Aljahdali, Khalid Alsubhi, and Baseem Khan. "IoT Inspired Intelligent Monitoring and Reporting Framework for Education 4.0." IEEE Access 9 (2021): 131286-131305.
- **Chapter 6:** This chapter presents a detailed discussion of the algorithms developed and employed for monitoring and trust-building within the framework of Education 4.0. These algorithms are designed to address critical functions such as continuous monitoring, irregularity detection, performance assessment, and accreditation in an Education 4.0 environment. The chapter explains the underlying logic, operational flow, and implementation strategies of each algorithm, highlighting their role in

ensuring transparency, reliability, and quality assurance across the educational ecosystem.

-Verma, Anil, Divya Anand, Aman Singh, Rishika Vij, Abdullah Alharbi, Majid Alshammari, and Arturo Ortega Mansilla. "IoT-Inspired Reliable Irregularity-Detection Framework for Education 4.0 and Industry 4.0." Electronics 11, no. 9 (2022): 1436.

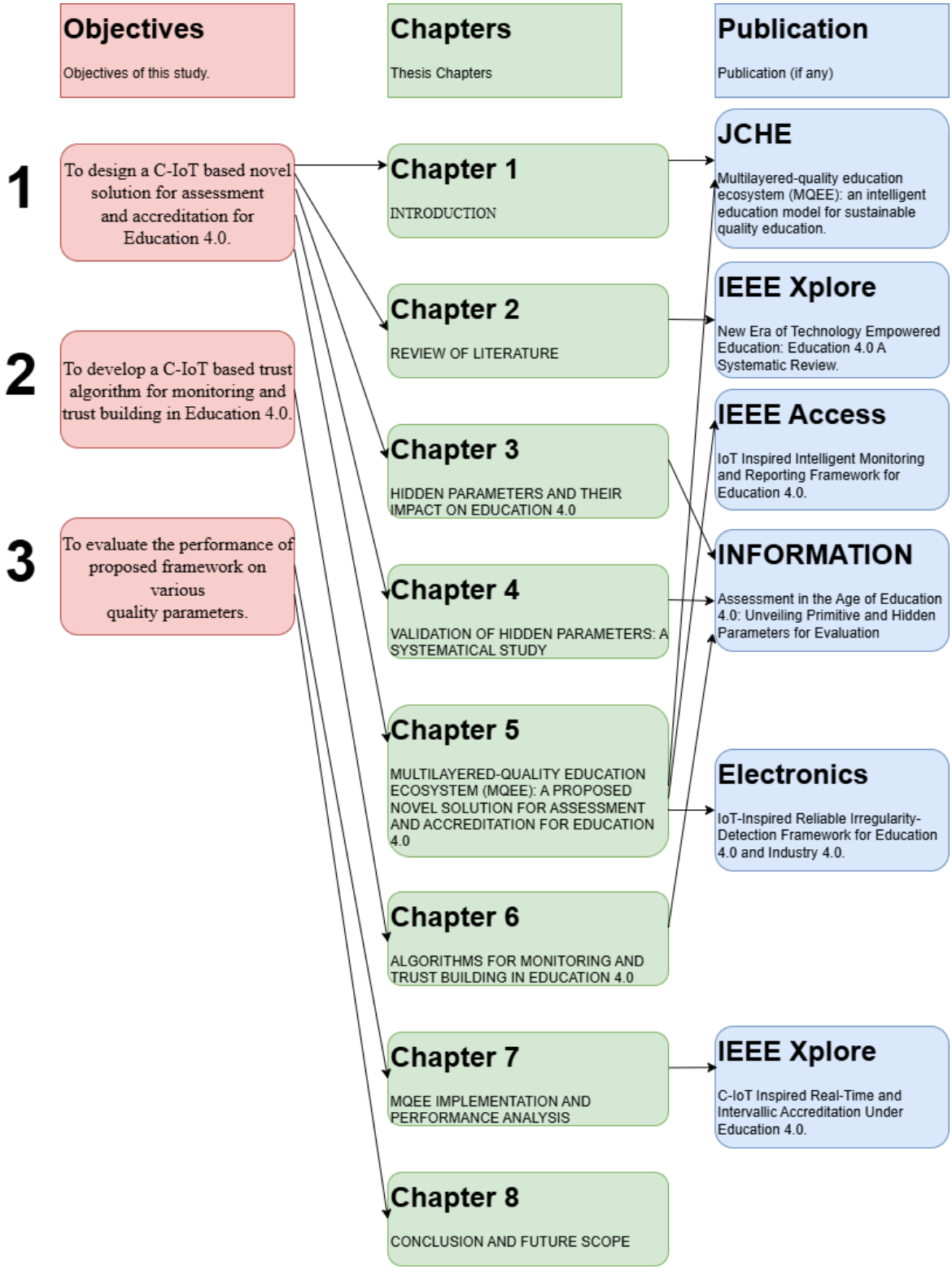


Figure 1.6. Objectives, Chapters and Publications' Organization

- **Chapter 7:** This chapter elaborates on the implementation scenario of the proposed model and presents a comprehensive analysis of its performance. The chapter evaluates the model's effectiveness through practical case studies and performance metrics, demonstrating its applicability in real-world educational settings. Furthermore,

it outlines a series of recommendations pertaining to both real-time and intervallic frameworks for Education 4.0, aimed at enhancing operational efficiency, ensuring continuous quality improvement, and facilitating scalable adoption of the proposed approach.

-Verma, Anil, Divya Anand, Aman Singh, and Rishika Vij. "C-IoT Inspired Real-Time and Intervallic Accreditation Under Education 4.0." In 2022 8th International Conference on Advanced Computing and Communication Systems (ICACCS), vol. 1, pp. 1793-1798. IEEE, 2022.

- **Chapter 8:** The complete conclusion and future scope of the presented framework are elaborated.

1.8 Summary

Education is a part and parcel of the life of every individual across the globe. Every nation has its own educational scenario. Assessment and accreditation for the quality of education is a mandatory process followed by most nations globally. From the current educational scenario, it has been observed that the assessment and accreditation process of the current educational scenario is not suitable for the Education 4.0 environment. To fulfil the technological requirements of the Education 4.0 environment, IoT, Fog Computing, Grid Computing, Cloud Computing, Edge Computing, ML, AI, and Blockchain technology can be used. Ubiquitous monitoring under Education 4.0 can be achieved by the deployment of various IoT devices and sensors at the institutional level. The acquired data from IoT devices can be easily processed by various intelligent algorithms over the fog and cloud nodes. Deployment of the proposed framework for Education 4.0 can be used for real-time monitoring, irregularity detection, alert generation, assessment, and accreditation.

CHAPTER 2

Review of Literature

Chapter Briefing— **This chapter delves into the critical foundations and advancements of a sustainable quality education ecosystem, with particular emphasis on the transformative potential of Education 4.0. It begins by addressing the global challenges faced by nations, including leaders such as the US, UK, Germany, Canada, and China, in establishing robust educational frameworks. Despite India's unparalleled infrastructure, housing over 51,649 higher educational institutions, and its recognition for high-quality research output, there remains a significant gap in meeting global standards, with 98.8% of educational systems falling short. The chapter explores the evolution of Education 4.0, a concept that emerged in response to the technological revolutions underpinning Industry 4.0. It underscores the pivotal role of innovative technologies—IoT, AI, ML, Blockchain, Fog Computing, and Edge Computing—in reshaping educational assessment and accreditation processes to cater to this new paradigm. By leveraging cutting-edge tools for real-time monitoring, irregularity detection, and intelligent assessment, Education 4.0 proposes solutions to improve institutional frameworks, ensuring inclusivity, adaptability, and scalability.**

A systematic review of literature provides further insight into the global discourse surrounding Education 4.0, tracing its origin to AM Harkins' 2008 article and highlighting its growing academic significance with 498 research articles explicitly titled on the subject and over 5,460 citations worldwide. The analysis reveals the dominance of non-technical studies, comprising 77% of the research, which focus on pedagogical frameworks, policy implications, and theoretical constructs.

This chapter offers a comprehensive examination of past efforts, current gaps, and prospects within the Education 4.0 landscape. It paves the way for researchers and policymakers to reimagine quality assurance systems, ensuring the alignment of educational practices with the needs of the digital era and addressing the societal necessity of accessible and equitable education.

2.1 Introduction

A sustainable quality education ecosystem is the fundamental requirement of every nation. The global leaders in quality education US, UK, Germany, Canada, and China are also facing challenges in providing a sustainable quality education ecosystem. More than 80% of institutions of all the nations including the global leaders are struggling to provide the average quality of education to young aspirants on the global platform [9]. Only 0.2% of Indian institutions that participated in Webometric University Ranking-2019 touched the scale of average quality education [10]. More than 51649 educational institutions are presently

imparting higher education in India. The present infrastructure of Indian Higher Education is the largest in the world [11]. India has even more infrastructure than the other 4 most populated nations of the world together i.e. China, the US, Indonesia, and Brazil. The QS-World University Ranking-2020 recognized the quality of research executed by Indian faculty during the year 2019 [9]. India is listed among the top three nations of the world in citations per faculty with the US and China. UGC, AICTE, NAAC, BCE, ICAR, NCTE, DCI, MCI, PCI, CCH, CCIM, and many other apex bodies are working sincerely for the assessment and improvement of quality education in India in their respective domains. AISHE is the largest survey conducted on a national level across the globe [11]. These apex bodies including AISHE [11], NIRF [12], NBA [13], and others are sincerely and persistently working for the improvement of the quality education ecosystem for higher education in India.

For a sustainable quality education ecosystem adequate infrastructure, intellectual faculty, and a healthy environment for learning are mandates. 51649 higher educational institutions [11], the world's best research-oriented and intellectual faculty [9], and more than two dozen domain-specific national-level apex bodies for assessment and monitoring accomplished the quality education ecosystem in India. Although the Government of India is strengthening all three walls of this quality education ecosystem still 98.8% of the education system fails to touch the global parameters of quality education [10], [14]. So there is an urgent need for extension and improvement of the quality education ecosystem.

A new era of education begins with Education 4.0 (IoT-based Educational Environment for future learning). Education 4.0 is the spine of Industry 4.0. Young minds that flourish in the Education 4.0 environment will be able to handle the complications of Industry 4.0 [8]. Education 4.0 is an open space for every stakeholder (including students, teachers, administrators, and policymakers). Education 4.0 represents an emerging technology-enabled approach that facilitates the integration of digital, intelligent, and connected technologies into teaching, learning, and institutional processes [1]. Assessment and accreditation are a primitive part of the education ecosystem [15]. It is used to provide authenticity to the education system. It is also used to maintain the quality of education in a specific environment. Education 4.0 is a completely different environment. So, assessment and accreditation parameters and methodologies used by all the nations must be upgraded accordingly [16].

Quality of Education is a societal issue that is also interrelated with government issues for policymaking. Education 4.0 will boost the education system at institution level and start the

enrichment of the education ecosystem at the grassroots level (Local Level). The impact of enrichment at the local level will automatically reflect at the national and international levels. The rest of this chapter is organized into 3 sections. The next section covers the review of the literature, and the following section illustrates the research gap obtained during the review of the literature. The last section concludes the chapter.

2.2 Systematic Literature Review

The term **Education 4.0** was first introduced by **AM Harkins** in the 2008 article titled *"Leapfrog Principles and Practices: Core Components of Education 3.0 and 4.0."* This concept emerged as a response to the rapid advancements in digital technologies and their transformative impact on education. Since its inception, **Education 4.0 (Keyword)** has gained significant traction in academic discourse, with **498 research articles** explicitly containing the phrase in their titles. A broader search on **Google Scholar** reveals **5,460 articles** that mention "Education 4.0" either in their titles or within the text, indicating its growing relevance in educational research.

2.2.1 Breakdown of Research Articles

1. **Non-Technical vs. Technical Focus**
    - **77% (385 articles)** of the available research on **Education 4.0** is **non-technical**, focusing on pedagogical frameworks, policy implications, and theoretical discussions.
    - Only **23% (113 articles)** delve into **technical aspects**, such as the integration of **Artificial Intelligence (AI), Internet of Things (IoT), and Cognitive IoT (CIoT)** in education.
2. **Scope of Literature Review**

    To ensure a **comprehensive understanding** of **Education 4.0**, this study examines:

    - **National and international education systems**
    - **AI, IoT, and CIoT applications in education**
    - **Research papers from reputed databases** (Elsevier, Scopus, Web of Science, Science Direct, ACM, IEEE)
    - **National and international reports** (e.g., UNESCO, NAAC, NIRF, QS Rankings)

2.2.2 Methodology for Systematic Literature Review

1. **Initial Collection:**
    - **113 research articles** and **20 national/international reports** were gathered for preliminary analysis.
2. **Selection Process:**
    - A **systematic filtering (Technical Research Only) for research articles** was applied to identify the most relevant and high-impact studies.
    - UNESCO, AISHE, NAAC, NIRF, QS Rankings, SCImago Ranking and THE reports were selected.
    - **68 documents** (research articles and national and international reports) were **finalized** for in-depth review.
3. **Structured Summary (Table 2.1):**
    - A **structured table** was created to summarize key aspects of each study, including:
        - **Focus Area** (e.g., smart classrooms, AI-driven learning, IoT in education)
        - **Techniques and Methods Used** (e.g., machine learning, deep reinforcement learning, blockchain)
        - **Results and Applications** (e.g., improved student engagement, automated assessments, predictive analytics)

2.3 Research Gap

Sustainable quality education is a global issue [10], [14]. The robustness, flexibility, and intelligence present in the Education 4.0 environment, make it suitable for sustainable quality education [17]. This is the preparatory stage of Education 4.0. Few global leaders have come forward to adopt Education 4.0 to date. Consequently, almost all the developing nations across the world are still using Education 3.0. The traces of Education 2.0 are also present in many countries. The research gaps explored during the review of the literature are listed below:

1. Mushrooming of higher education institutions is not required for sustainable quality education.

2. The technology used in Education 2.0 and Education 3.0 is not rich enough to maintain sustainable quality education.
3. IoT, Fog Computing, Cloud Computing, Virtual Reality (VR), Augmented Reality (AR) and Blockchain (BC) are the emerging technologies used in Education 4.0.
4. Education 4.0 has the capabilities of ubiquitous access to information.
5. Activities including Teaching, Learning, Assessment, Accreditation, etc. can be implemented more authentically and ubiquitously under Education 4.0.
6. Successful implementation of Education 4.0 is necessary for Industry 4.0.
7. IoT, Fog Computing, and Cloud Computing (IFC technology) are required at the initial levels of implementation of Education 4.0. Advanced Virtual Reality, Augmented Reality, and Blockchain technology are required at advanced stages of Education 4.0.
8. The developing nations including India will swiftly improve their quality of education to global standards by the earlier implementation of Education 4.0.

For sustainable quality education, the use of technology-enhanced teaching and learning practices is of paramount importance. Earlier implementation of Education 4.0 is required for sustainable quality education at global standards.

2.4 Technical Challenges in Education 4.0 Quality Assessment

The integration of Education 4.0 technologies into institutional quality assessment introduces several technical challenges that must be addressed to establish a reliable, scalable, secure, and intelligent quality-assurance ecosystem. Data privacy is a primary concern because IoT-enabled educational environments may generate and process sensitive student, academic, behavioural, and institutional information. Therefore, mechanisms for data minimisation, controlled access, secure processing, and privacy-preserving information exchange are essential [18]. Closely associated with privacy is educational data security, as the distributed nature of IoT and networked computing infrastructure increases the potential attack surface and requires appropriate authentication, encryption, access control, monitoring, and cyber security mechanisms [19]. The application of Artificial Intelligence (AI) introduces additional challenges related to bias, transparency, explainability, and reliability of algorithmic decisions. AI-based assessment mechanisms must therefore be designed to minimise unintended bias and provide interpretable and consistent outputs. Interoperability is another significant challenge because Education 4.0 environments may comprise heterogeneous sensors, devices, communication protocols, software platforms, databases, and institutional information systems. The proposed architecture must consequently support integration across

heterogeneous technological components and organisational boundaries. Furthermore, scalability becomes critical when the number of students, IoT devices, data sources, and participating institutions increases. A quality-assessment framework designed for a single institution should be capable of accommodating varying institutional sizes and computational workloads without unacceptable degradation in performance. Finally, real-time processing constraints arise from the continuous generation of data by distributed IoT devices, requiring efficient data transmission, processing, and decision-making with minimum latency.

These challenges demonstrate that conventional, manually driven and largely static approaches to institutional quality assessment may be insufficient for the dynamic and technology-intensive requirements of Education 4.0. They consequently provide the technological motivation for the proposed Multilayered Quality Education Ecosystem (MQEE), which adopts a layered and distributed architecture to support secure data processing, interoperability, scalable resource utilisation, intelligent analysis, and timely generation of quality-related information. The identified challenges and their corresponding design considerations form the technological basis for the development and evaluation of the proposed framework.

Table 2.1. Systematic Review of Literature

Sr. No.	Author and Year	Focus Area	Techniques and Methods Used	Results and Applications
1.	*Altameem & Altameem (2020)*	Hybridized interference bounded intuitive splitting for smart wearable systems	Cognitive-assisted IoT, interference management	Improved performance in wearable systems with reduced interference.[20]
2.	*Sangaiah et al. (2020)*	Cognitive IoT system in sustainable computing	Intelligence techniques, sustainable computing frameworks	Enhanced IoT system efficiency in sustainable environments.[15]
3.	*Huang et al. (2020)*	Wireless feedback control for industrial IoT	Variable packet length, feedback control	Optimized packet length for industrial IoT applications.[21]
4.	*Peña et al. (2020)*	DevOps for IoT systems	Continuous monitoring, system availability feedback	Improved system reliability and availability.[22]
5.	*Mahmood & Matin (2020)*	Cognitive radio-based IoT	Literature review, cognitive radio techniques	Identified trends and future directions for cognitive radio in IoT. [23]
6.	*Seng et al. (2020)*	IoT applied courseware for education	IoT design and validation, hands-on training	Effective industry-ready IoT education framework.[16]
7.	*JB et al. (2020)*	IoT-based smart classrooms	Cloud integration, IoT sensors	Enhanced campus sustainability and smart

Sr. No.	Author and Year	Focus Area	Techniques and Methods Used	Results and Applications
				learning environments.[24]
8.	*Saxena et al. (2019)*	Automated enhanced learning system using IoT	IoT-based automation, real-time feedback	Improved learning outcomes through automated systems.[25]
9.	*Fernández-Pacheco et al. (2019)*	Arduino remote laboratory with Raspberry Pi	Remote labs, IoT integration	Enabled remote experimentation and learning. [26]
10.	*Ciolacu et al. (2019)*	Education 4.0 with IoT and AI	Machine learning, early recognition systems	Supported student success through AI-driven feedback. [27]
11.	*Jayasinghe et al. (2019)*	TrustChain for privacy-preserving blockchain	Edge computing, blockchain	Secure and private data sharing in IoT.[28]
12.	*Centea et al. (2019)*	SEPT approaches for education using learning factories	Hands-on training, learning factories	Bridged the gap between education and industry needs.[29]
13.	*Abdellah et al. (2019)*	IoT traffic prediction using neural networks	Multi-step ahead prediction, neural networks	Accurate IoT traffic forecasting.[30]

Sr. No.	Author and Year	Focus Area	Techniques and Methods Used	Results and Applications
14.	*Wang et al. (2019)*	Robust localization for cognitive IoT	Mobile anchor node, spiral line algorithm	Improved localization accuracy in IoT systems.[31]
15.	*Montes & Goertzel (2019)*	Democratized AI for IoT	Distributed AI, cognitive computing	Promoted decentralized and democratized AI applications.[32]
16.	*Chen et al. (2018)*	Blended learning with immediate corrective feedback	Feedback systems, blended learning	Enhanced student engagement and understanding.[33]
17.	*Pramanik et al. (2018)*	Cognitive IoT beyond automation	AI-driven IoT, cognitive frameworks	Advanced IoT systems with cognitive capabilities.[34]
18.	*Dharur & Swaminathan (2018)*	ELK stack for IoT-powered smart buildings	ELK stack, real-time monitoring	Efficient surveillance and monitoring for smart buildings.[17]
19.	*Mahmud et al. (2019)*	QoE-aware application placement in Fog computing	Fog computing, QoE metrics	Optimized application placement for better user experience.[35]
20.	*Ali & Majeed*	IoT for smart university	IoT frameworks, smart campus	Improved campus management and student

Sr. No.	Author and Year	Focus Area	Techniques and Methods Used	Results and Applications
	(2018)	campuses	solutions	services.[36]
21.	*Gad et al. (2018)*	Iris recognition for CIoT framework	Multi-algorithmic approaches, biometrics	Secure and efficient iris recognition for IoT.[37]
22.	*Zhamanov et al. (2018)*	IoT applications in university education	IoT integration, smart education	Enhanced educational processes through IoT.[38]
23.	*Guo et al. (2018)*	IoT platform for engineering education	Secure and smart manufacturing, IoT platforms	Facilitated engineering education and research.[39]
24.	*Bahuguna et al. (2018)*	Smart learning using augmented reality	AR, Android platforms	Interactive and engaging learning experiences.[40]
25.	*Zhu et al. (2018)*	Deep Q-learning for cognitive IoT transmission scheduling	Deep Q-learning, scheduling algorithms	Optimized transmission scheduling in IoT. [41]
26.	*Roncancio et al. (2018)*	Spectral sensing for IoT applications	Radio cognitive context, spectral sensing	Improved spectrum utilization for IoT. [42]

Sr. No.	Author and Year	Focus Area	Techniques and Methods Used	Results and Applications
27.	*Verma & Sood (2018)*	IoT-based student performance evaluation	IoT frameworks, performance metrics	Automated and objective student performance assessment.[43], [44]
28.	*Banerjee & Sheth (2017)*	IoT quality control for data and applications	Quality metrics, IoT data validation	Ensured data and application quality in IoT systems.[44]
29.	*Milis et al. (2019)*	Semantically enhanced IoT-enabled control systems	Semantic technologies, IoT control systems	Enhanced interoperability and intelligence in IoT systems.[9]
30.	*Li et al. (2016)*	Distributed behaviour model orchestration in cognitive IoT	Behaviour models, orchestration techniques	Improved IoT system adaptability and performance.[45]
31.	*Sato et al. (2015)*	Feedback control theory for IoT performance evaluation	Feedback control, real-time evaluation	Effective performance monitoring for IoT systems.[46]
32.	*Senthilkumar & Arulraj (2011)*	Service quality measurement in higher education	Surveys, statistical analysis	Identified key metrics for higher education quality.[14]
33.	*Jara & Mellar (2010)*	Quality enhancement for e-learning courses	Student feedback, quality assessment	Improved e-learning course quality through feedback.[10]

Sr. No.	Author and Year	Focus Area	Techniques and Methods Used	Results and Applications
34.	*Tolley & Shulruf (2009)*	Data management systems in education	Data analytics, knowledge management	Enhanced decision-making and educational outcomes.[47]
35.	*Torki Altameem (2020)*	Smart Information System through C-IoT and Smart Wearables	Hybridized Interference Bounded Intuitive Splitting (HIBJS) algorithm	HIBJS (SNR) <1 for 100% channel uncertainty; Accuracy >97%; Reliability >98%; Energy Utilization = 70.22 (for 100 nodes) [11]
36.	*Arun Kumar Sangaiah et al. (2020)*	Use of Cognitive IoT as Intelligent Techniques	Boundary Sense Deep Learning (BSDL), Boundary Intellect Acoustic Detection (BIAD), BIVD	ResNet + BSDL (Accuracy) 92.0%; BIVD (Accuracy) 91.7%; Integration BIF (Accuracy) 100%. [15]
37.	*Kang Huang et al. (2020)*	Wireless Feedback Control for Industrial IoT (IIoT)	Wireless Networked Control System (WNCS), Age of Information, Cyberphysical Systems	IoT-based Feedback Control Systems with Variable Length Packet Control for IioT. [21]
38.	*Miguel A et al. (2020)*	IoT-based Fast & Continuous Monitoring Feedback System	Systems Process Engineering Metamodel (SPEM), Monitoring as Code (MaC), DevOps	IoT application supervision through code; Trustworthiness IoT System.[22]
39.	*M. Rezwanul*	Cognitive Radio-based	CRASN (Cognitive Radio Ad-hoc	Device communication (M2M), Security

Sr. No.	Author and Year	Focus Area	Techniques and Methods Used	Results and Applications
	Mahmood et al. (2020)	Internet of Things (CR-IoT)	Sensor Network), TCBCSS algorithm	provisioning, Energy management. [23]
40.	*Lau Gim Seng et al. (2020)*	Industry-Ready IoT Applied Courseware	IoT, AI, Over-the-air (OTA) testing, Problem-Based Learning (PBL)	IoT-enabled Smart Courseware; IoT-based Quality Education Models.[16]
41.	*Faritha Banu J et al. (2020)*	IoT and Cloud-based Smart Classroom and Campus	ARM Microcontroller, RFID security system, GPS, IoT and AI	IoT and Cloud-based smart classrooms; Automated workflow management. [12]
42.	*Amit Saxena et al. (2019)*	IoT-based Automated Enhanced Learning System	Visual, Auditory, and Kinesthetic (VAK Theory) and IoT	Learning enhancement model; Student performance improvement (5% to 42%). [25]
43.	*Atilano Fernández-Pacheco et al. (2019)*	Improving Online Education Programs on IoT	Arduino Remote Laboratory, Raspberry Pi	Remote Learning; Low-cost, efficient IoT Labs.[26]
44.	*Monica Ionita Ciolacu et al. (2019)*	IoT-enabled Education 4.0	Wearables Enhanced Learning, Education 4.0, Smartwatch, IoT, Learning Analytics	Automated assessment and feedback through wearables. [27]

Sr. No.	Author and Year	Focus Area	Techniques and Methods Used	Results and Applications
45.	*Upul Jayasinghe et al. (2019)*	Implementation of TrustChain in Edge Computing and IoT	Zero-Knowledge Proof (ZKP) algorithm, Encryption	Trustful environment for real-time IoT applications; Trust Metrics (TMs).[28]
46.	*Dan Centea et al. (2019)*	School of Engineering Practice and Technology (SEPT) Learning Factory Hub	SEPT, IoT, Industry 4.0, Experiential Learning, Learning Factory	Teaching, training, and research collaboration with Industry 4.0. [29]
47.	*Ali R. Abdellah et al. (2019)*	IoT Traffic Prediction with Neural Network	Artificial Neural Network (ANN), NARX Feedback Neural Networks, MAPE	IoT Traffic Prediction System; MAPE (2 packets/s) = 0.18%; (10 packets/s) = 6.18%. [30]
48.	*Xin Wang et al. (2019)*	Robust Localization for Cognitive IoT	Linear Fitting Algorithm, Diameter-varying Spiral Line (LDVSL) Algorithm	Accurate location finder for CIoT; Computational run time: 1654 µs (with obstacles), 2980 µs (without). [31]
49.	*Gabriel Axel Montes et al. (2018)*	Decentralized Self-Organized Cooperative (DSOC) AI-based Network	Decentralized Self-Organized Cooperative (DSOC) Network, Distributed AI	Native token for exchanging AI services; Balanced governance model. [32]
50.	*Xin Chen et al.*	Impact of Immediate	Checkable Answer Feedback	Immediate feedback improves student

Sr. No.	Author and Year	Focus Area	Techniques and Methods Used	Results and Applications
	(2018)	Corrective Feedback	(CAF)	performance by 10%. [33]
51.	*Pijush Kanti Dutta Pramanik et al. (2018)*	Use of C-IoT for AIQ (Artificial Intelligence Quotient)	IoT, Cognitive Computing, AI, Machine Learning, Cognitive Analytics	Applications: Nest Labs' Smart Thermostat, Tesla Motors' Self-driving Vehicles. [34]
52.	*Sameer Dharur et al. (2018)*	Efficient Surveillance and Monitoring using ELK Stack	Elasticsearch-Logstash-Kibana (ELK) Stack, Intel Galileo, Data Visualization	IoT-based robust surveillance and monitoring systems. [17]
53.	*Redowan Mahmud et al. (2018)*	Quality of Experience (QoE) for Fog Computing Environment and IoT	QoE-aware Application Placement Policy, Linearly Optimized Mapping, iFogSim	QoE gain: PTRR (92%), RG (88%), NRR (80%). [35]
54.	*Asim Majeed et al. (2018)*	IoT for Smart University Campuses	Educators' and Learners' Internet of Things (ELIoT), NFC, RFID, IoT	Collaboration of Big Data, Wearable Tech, AR, Cloud Computing, AI, and IoT. [36]
55.	*Ramadan Mohamed Gad et al. (2018)*	Multi-Algorithmic Approaches for Cognitive IoT (CIoT) Framework	Delta-Mean and Multi-Algorithm-Mean, Multi-Biometric Scenarios, Cognitive Healthcare IoT (CHIoT)	Iris detection accuracy: 99.4%.[37]

Sr. No.	Author and Year	Focus Area	Techniques and Methods Used	Results and Applications
56.	*Azamat Zhamanov et al. (2018)*	Implementation of IoT Applications into University Education Process	IoT-Based Flipped Classrooms, Feedback for Quality Improvement	IoT-based campuses save 60% energy.[38]
57.	*Terry Guo et al. (2018)*	IoT Platform for Engineering Education and Research (IoT PEER)	Microsoft Azure Cloud, AI, Azure WebApp, Node-RED	Machinery Health Monitoring (MHM), Intrusion Detection in Industrial Environments.[39]
58.	*Yogita Bahuguna et al. (2018)*	Smart Learning based on Augmented Reality	Unity 3D, Victoria SDK, JDK, Android Studio	AR-based Learning Platforms; 3D Modelling.[40]
59.	*Jiang Zhu et al. (2017)*	Cognitive IoT and Deep Learning	Markov Decision Process (MDP), Q Learning Algorithm, Stacked Auto-encoder Deep Learning	Q Learning reduces complexity compared to Strategy Iteration (SI) algorithm.[41]
60.	*Gina Roncancio et al. (2017)*	Radio Cognitive Context for IoT Applications	IoT, Cognitive Radio, Software-Defined Radio (SDR), Spectrum Sensing	Applications: LowPAN, TVWS in Smart Cities, Medical, Logistics. [42]
61.	*Prabal Verma & Sandeep K. Sood (2017)*	IoT-based Student Performance and Evaluation	IoT, Game Theory, RFID, Cloud Computing, Performance Evaluation Algorithm	Game-based decision-making enhances student performance evaluation.[43]

Sr. No.	Author and Year	Focus Area	Techniques and Methods Used	Results and Applications
62.	*Tanvi Banerjee et al. (2017)*	IoT Quality Control for Data and Applications	Semantic Data Quality Check, Weighted Aggregation, Fuzzy Aggregation Methods	Smart Home Monitoring System; Smart Data Collection.[44]
63.	*Georgios M et al. (2017)*	Semantically Enhanced IoT-enabled Intelligent Control Systems	SEMIoTICS, Semantic Sensor Network (SSN), Open Geospatial Consortium (OGC)	Semantic Modelling of IoT Components; Smart Campuses and Cities.[9]
64.	*Chung-Sheng Li et al. (2016)*	Distributed Behaviour Model for C-IoT	Dynamic Data-Driven Application System (DDDAS)-based Methods	Applications: Smart Grid, Atmospheric Contaminant Dispersion Monitoring.[45]
65.	*Keisuke Sato et al. (2015)*	Feedback Control Theory for Performance Evaluation of IoT Systems	Feedback Control Theory, Modelling and IoT, M2M/IoT	Applications: Smart Parking Stations, M2M Communication.[46]
66.	*N. Senthilkumar et al. (2010)*	Quality Measurement of Higher Education	SQM-HEI Model	Factors: Teaching Methodology (TM), Environmental Change in Study Factor (ECSF).[14]
67.	*Jera and Mellar (2010)*	Quality Enhancement through Feedback	Student Feedback, Student Satisfaction Survey	Feedback and surveys improve quality assurance.[10]

Sr. No.	Author and Year	Focus Area	Techniques and Methods Used	Results and Applications
68.	*Tolley and Shulruf (2009)*	Data Management System for Educational Institutions	EMIS, Assessment Tools for Teaching and Learning (asTTle), Multiple Overlapping Cohorts System	Tools for quality assessment in education. [47]

2.5 Summary

Due to the mushrooming of institutions in the last two decades, India has become the top nation in higher educational institutions. India has 4 times more institutions for young aspirants than China. This indicates that it is an alarming stage for higher educational institutions. This is the right time to halt the growing number of educational institutions in India. On the other side of this coin, less than 0.2 % of institutions are providing average quality education on global parameters and none of the Indian institutions is excellent or good in quality education on the global platform. So, there is an urgent need to shift the national focus from the number of institutions and to start focusing on the quality of education in these institutions. India must strengthen its quality monitoring and assurance system. The use of state-of-the-art quality monitoring and improvement system for every institution is the need of the hour.

India has the most fortified root system of educational institutions, now it's time to nourish the huge tree of the Higher Education system with sustainable quality education to secure a fruitful future global position in Higher Education through a sustainable quality education ecosystem. Implementation of technology-enhanced Education 4.0 is required for sustainable quality education across the globe. The use of emerging technologies including IFC, VR, AR and Blockchain is required in the education industry for sustainable quality education on global standards.

CHAPTER 3

Hidden Parameters and their impact on Education 4.0

***Chapter Briefing*— This chapter offers a comprehensive exploration of the nuanced factors influencing the delivery of quality education within the transformative framework of Education 4.0. Positioned at the intersection of technological innovation and pedagogical advancement, Education 4.0 integrates cutting-edge technologies such as Internet of Things (IoT) devices, sensors, and actuators to enable real-time and continuous assessment methodologies. This paradigm shift elevates the precision of student evaluation, thereby fostering a dynamic and adaptive learning environment. The chapter critically examines five hidden parameters—awareness, accessibility, participation, satisfaction, and academic loafing—and their pivotal role in shaping educational outcomes. Through a comparative analysis of pre- and post-implementation scenarios, the study underscores the profound impact of Education 4.0 on these parameters, demonstrating enhancements in resource accessibility, student engagement, and accountability among stakeholders. Special emphasis is placed on strategies to mitigate academic loafing to maintain an ambient and collaborative educational atmosphere. Further insights delve into the foundational pillars of educational excellence: infrastructure, learning environment, and faculty. The chapter highlights how these elements, assessed on national and international standards, interact with emerging technologies to redefine the educational experience. State-of-the-art infrastructure, coupled with well-designed curricula and competent faculty, forms the backbone of institutions striving for global competitiveness in education. By integrating the characteristics of Industry 4.0, Education 4.0 revolutionizes the approach to data acquisition, filtering, analysis, and predictive interventions. Advanced systems facilitate the seamless collection and analysis of vast educational data, optimizing learning environments and tailoring educational experiences to individual needs. This transformative framework not only enhances the efficiency of educational interventions but also fosters equitable access to resources and personalized learning pathways. The findings presented in this chapter aim to advance scholarly discourse on the interplay between technological innovations and pedagogical strategies. By dissecting hidden parameters and examining their ramifications, the chapter provides valuable insights into the integration of Education 4.0 principles, advocating for a unified approach to elevating the quality of education. Ultimately, this chapter serves as a critical resource for researchers, policymakers, and educators committed to leveraging technology for sustainable improvements in the global education landscape.**

3.1 Introduction

In recent years, the emergence of Education 4.0 has redefined the educational landscape by integrating cutting-edge technologies such as IoT devices, sensors, and actuators. These

innovations aim to enhance real-time and continuous assessment methodologies, thereby improving the overall quality of education. However, the transition to this new paradigm necessitates a deeper understanding of various underlying factors that may influence educational outcomes. This study revolves around the following research question: "How do hidden parameters such as awareness, accessibility, participation, satisfaction, and academic loafing influence the quality of education within the Education 4.0 framework?" This question guides our exploration of the pivotal role these hidden parameters play in the successful implementation of Education 4.0 and their impact on enhancing student evaluation methodologies. Infrastructure, learning environment, and faculty are the three basic criteria that national and international education evaluation agencies use to assess educational institutions [13]. These criteria are essential for ensuring that educational institutions can offer a setting that encourages learning and success for students. This study tries to offer an expert and academic assessment of these parameters. The physical resources and facilities required for teaching and learning make up an educational institution's infrastructure. These include educational spaces like classrooms, playgrounds, labs, libraries, auditoriums, and other structures. The quality of education can be significantly impacted by the infrastructure, which is a key component. An institution must have enough classrooms and buildings with the tools it needs to deliver high-quality instruction. Additionally, providing students with adequate furniture and well-maintained infrastructure can help to create a comfortable and conducive learning environment [48]. Several factors, including the learning environment, play a role in the institution's overall educational quality [49]. The learning environment's essential elements include the course syllabus, the assessment and evaluation process, the examination system, teaching–learning activities, administrative tasks, and academic activities. Students can learn the skills and knowledge they need to thrive in their careers with the aid of a well-designed curriculum that is in line with industry standards [49], [50]. Additionally, pinpointing areas where students need to improve can be aided by an efficient assessment and evaluation mechanism that measures student performance [43], [51]. An educational institution's faculty plays a key role in ensuring that it can deliver high-quality instruction. The faculty's competence, intelligence, engagement, performance, experience, and research capabilities may have a big influence on the learning results of the students [49]. Students can be guaranteed to receive individualized attention and support with sufficient faculty resources and staffing. Additionally, professors with relevant industry experience can give students the skills and knowledge they need to succeed in the workplace. Faculty members' engagement and research skills might also influence the institution's overall educational standard [50]. Figure 3.1

illustrates various direct/primitive parameters that contribute to quality assessment. This figure also illustrates that for the actual participation of stakeholders for quality assessment in the present education scenario, awareness and accessibility are also mandatory; without awareness and accessibility, participation is not possible. The educational revolution integrates the characteristics of Industry 4.0 for data acquisition, filtering, analysis, predictions, automation and many other operations, which is commonly known as Education 4.0.

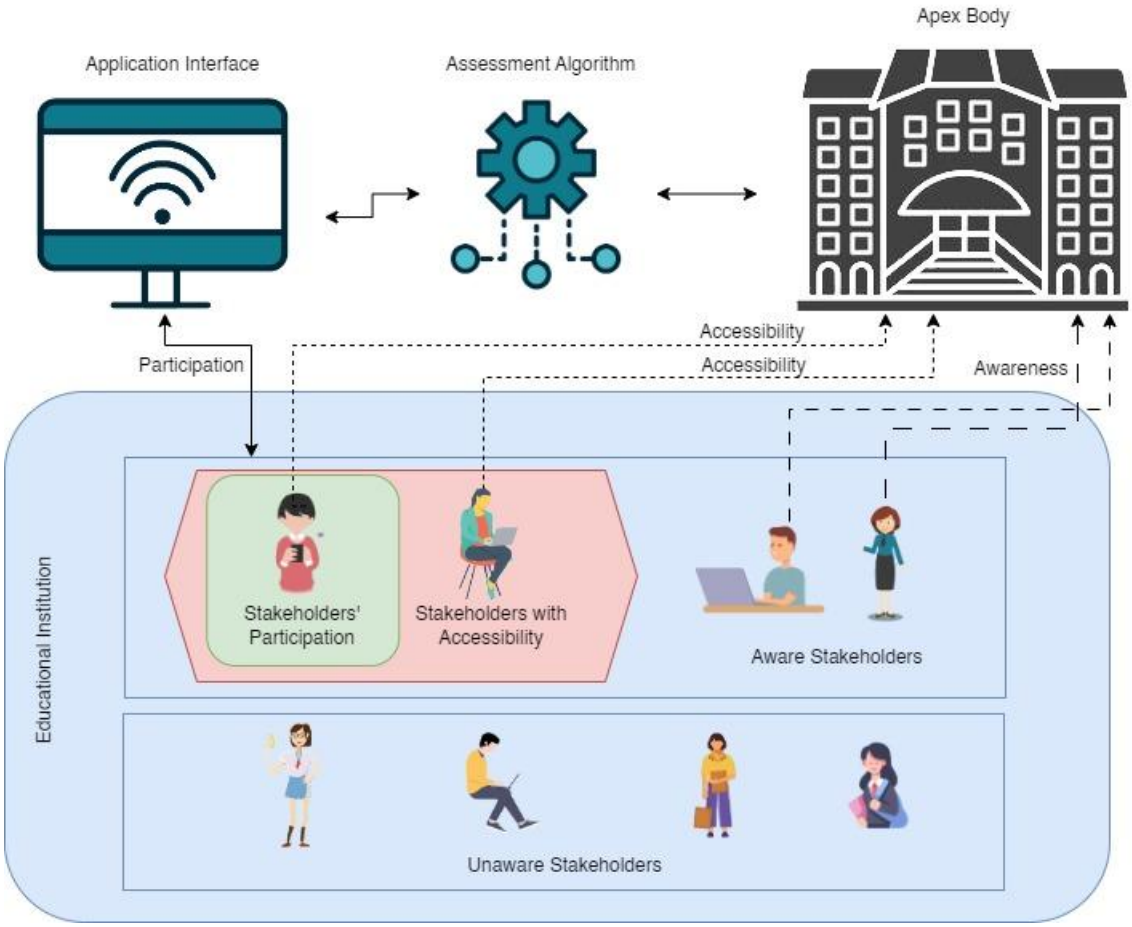


Figure 3.1. Direct/Primitive Parameters contributing to quality assessment

The integration of Internet of Things (IoT) devices, sensors, and actuators for data acquisition within an ambient educational environment, coupled with real-time and continuous data assessment, constitutes a cornerstone of Education 4.0. These advanced technologies enable the seamless collection and analysis of vast amounts of data, providing valuable insights into various educational processes. By leveraging IoT and sensor networks, educational institutions can monitor and optimize the learning environment, track student progress, and tailor educational experiences to individual needs in real time. This continuous data assessment not only enhances the accuracy and efficiency of educational interventions but also supports

dynamic and adaptive learning, making Education 4.0 a transformative approach to modern education [52], [53], [54]. Apex body is responsible for the assessment and accreditation of an educational institution. The apex body uses a comprehensive assessment algorithm for assessing an institution; this assessment algorithm relates to an application interface to make the assessment and accreditation process user-friendly for both stakeholders and the apex body. The stakeholders participated in the assessment and accreditation process through the application interface. All the stakeholders are subdivided into subgroups, i.e., the first sub-group consists of unaware stakeholders, who do not know about the assessment and accreditation process; this sub-group did not participate in the assessment and accreditation process. The second major sub-group consists of aware stakeholders who are aware of the assessment and accreditation process; this sub-group is further divided into three sub-groups, i.e., aware stakeholders who do not have access to the assessment and accreditation process, and the other sub-group consists of the aware stakeholders who have access to the assessment and accreditation process, but did not participate knowingly or unknowingly in the assessment and accreditation process. The last sub-group is of the aware stakeholders who have access to the assessment and accreditation process and participated in the assessment and accreditation process [55]. Although these parameters contribute a lot to quality education, some other parameters are also responsible for quality education. In many earlier studies on quality education, many hidden parameters were explored. As this study focuses on the Education 4.0 environment, the hidden parameters that are significantly improved by the incorporation of IoT devices, sensors, and actuators for real-time assessment are considered for further evaluation. Education 4.0 is a completely new environment that only affects the outer space of educational infrastructure, without hindering the internal workings in the inner space. To investigate the hidden parameters that influence how well education is delivered in the Education 4.0 context, the purpose of this study is to determine if integrating IoT devices, sensors, and actuators for real-time evaluation will have an impact on educational quality. The study attempts to offer an in-depth understanding of how technology might be used to enhance education in the Education 4.0 environment by analysing these hidden factors. Figure 3.2 illustrates various indirect/hidden parameters that affect quality education under Education 4.0.

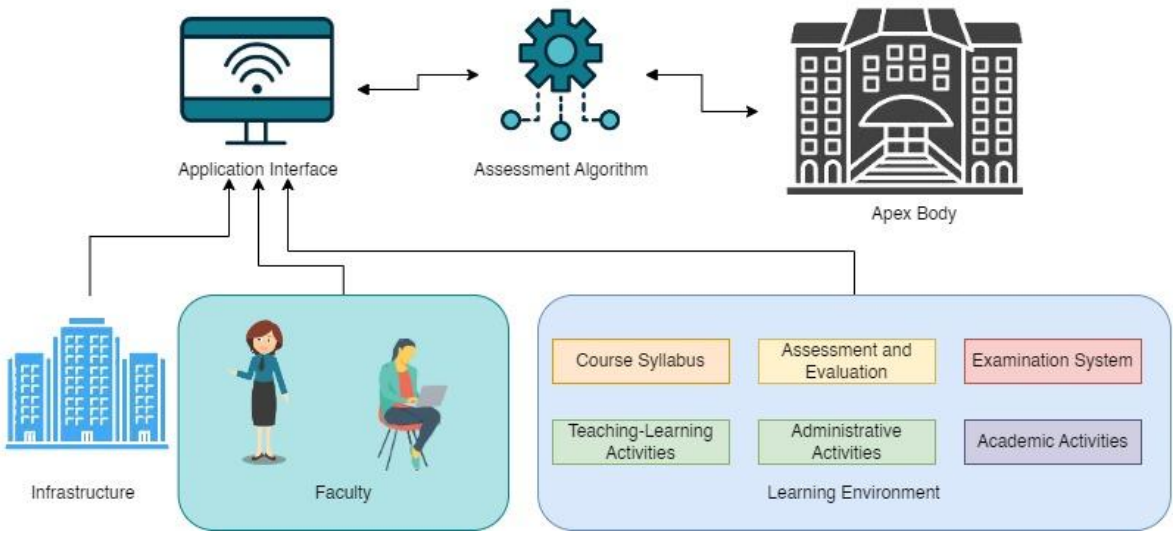


Figure 3.2. Direct/Primitive Parameters for Assessment

3.2 Education 4.0

Education 4.0 is a modern educational approach that aims to incorporate the technological breakthroughs of Industry 4.0 into the learning process. This innovative framework utilizes Internet of Things (IoT) devices, sensors, and actuators to establish a captivating and flexible learning environment. The main characteristics of Education 4.0 encompass:

- ***Real-Time and Continuous Assessment:*** Education 4.0 integrates Internet of Things (IoT) devices and sensors to enable the collection and assessment of data in real-time and continuously. This enables instructors to promptly assess student development and make informed judgments based on data to customize educational experiences according to individual requirements. Continuous evaluation improves the precision and effectiveness of educational interventions, fostering flexible and responsive learning environments [46], [56].
- ***Enhanced Accessibility:*** The implementation of IoT technology in Education 4.0 enhances the availability of educational resources. Students could retrieve educational resources from any place and at any moment, thereby eliminating conventional obstacles to learning. This enhanced accessibility facilitates the connection between conventional and digital learning settings, hence ensuring equal learning opportunities for all students [3].
- ***Personalized Learning Experiences:*** Education 4.0 facilitates tailored learning experiences by incorporating new technology. The real-time data obtained from IoT devices enables the tailoring of curriculum and learning paths to cater to the distinct requirements of individual

students. This customization boosts student involvement and optimizes learning results by specifically targeting individual strengths and limitations.

- ***Collaborative Learning Environments:*** Education 4.0 promotes collaborative learning by utilizing digital platforms that enable students and teachers to engage and cooperate with one another. These platforms facilitate diverse collaborative activities, such as group projects and peer assessments, fostering a more engaged and captivating learning experience.
- ***Smart Infrastructure:*** Smart infrastructure is a fundamental component of Education 4.0. IoT-enabled devices and smart systems are installed in educational institutions to enhance the physical learning environment. This encompasses intelligent classrooms, automated administrative procedures, and sophisticated resource management, all of which enhance efficiency and create a favorable learning environment [57], [58].
- ***Faculty Development and Engagement:*** Education 4.0 highlights the significance of faculty proficiency and involvement. It facilitates continuous professional development for educators, providing them with the necessary skills and expertise to successfully incorporate technology into their teaching methods. To fully utilize the capabilities of Education 4.0 technologies, it is crucial to have faculty members who are actively involved and highly skilled [52], [59], [60].

High-quality education is a fundamental aspect of any civilization. To ensure the delivery of high-quality education, it is essential to consider a variety of variables that have an impact on the educational environment. The quality of education is, however, adversely impacted by several additional, less obvious issues as well. This study's major objective is to identify the unobservable factors that are influenced by the Education 4.0 environment. The term "Education 4.0" refers to a cutting-edge setting where Internet of Things (IoT) gadgets, sensors, and actuators are used to enable real-time and continuous assessment, which affects many little-noticed elements for educational institutions. Infrastructure, learning environment, and teachers make up the three key elements that directly influence outstanding education. The equipment and environments required for teaching and learning make up the infrastructure of an educational institution [49], [61]. The availability of a variety of facilities, such as classrooms, playgrounds, labs, libraries, auditoriums, and other necessary buildings, is crucial for facilitating high-quality instruction in educational institutions. These facilities are essential to making it possible for instruction to be effective. To establish a welcoming and comfortable learning environment, it is crucial to maintain infrastructure and furnish classrooms with the

appropriate equipment, in addition to having an appropriate number of buildings and classrooms. The detailed flowchart of the investigation methodology is illustrated in Figure 3.3. This study initially investigates the pre-Education 4.0 scenario, identifying fundamental and hidden parameters that influence the quality of education. By examining these parameters, we aimed to understand the underlying factors that impacted educational outcomes before the implementation of Education 4.0. These identified parameters were then applied to the post-Education 4.0 scenario to assess their effects within the new educational paradigm. Through rigorous analysis, we explored the mathematical relationships among these parameters, leading to the development of a comprehensive mathematical model. This model incorporates the identified hidden parameters, offering a robust framework for understanding and enhancing educational quality in the post-Education 4.0 context.

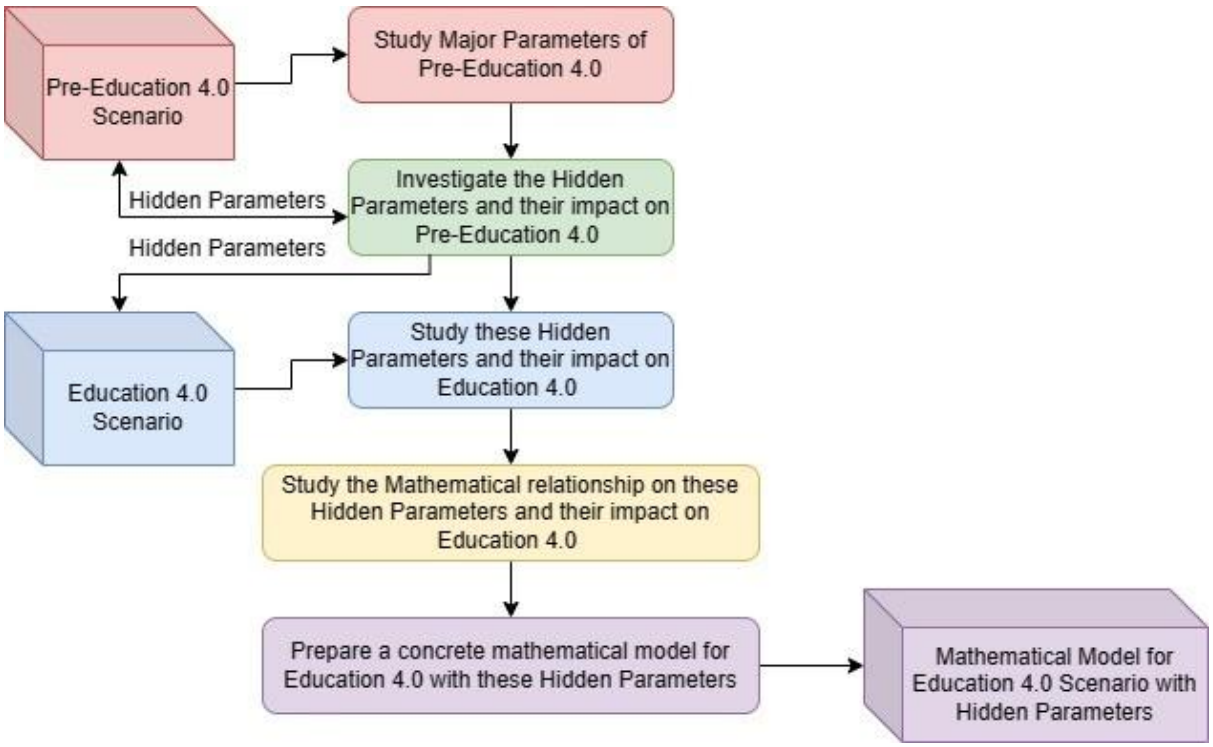


Figure 3.3. Flowchart of investigation methodology

The course syllabus, evaluation and assessment procedures, examination systems, teaching and learning procedures, administrative procedures, and academic procedures are important elements of the learning environment. Students can acquire the skills and knowledge essential to succeed in their particular professions by creating a professionally developed curriculum that complies with industry standards. Furthermore, a valid system of assessment and evaluation that monitors student performance can point out areas where students need to develop [62]. An institution's faculty has a big impact on its capacity to

deliver high-quality instruction. The competence, intelligence, engagement, performance, experience, and research talents of the faculty may have a considerable impact on the quality of training they provide. Making sure that students receive customized attention and support is doable with sufficient faculty resources and staffing. Students can benefit from the knowledge and skills that professors with relevant industry experience can offer to be successful in their chosen profession. The faculty's level of involvement and research skills may also influence the institution's overall academic standards. The quality of education is influenced by several unsaid elements in addition to the obvious ones. In prior studies on high-quality education, many of these hidden characteristics were examined. However, we will focus only on the unobserved factors that are influenced by the Education 4.0 environment in this study. One way that Education 4.0 has improved the education sector is through real-time and continuous assessment, which influences many unspoken elements for educational institutions.

It also examines the vital contributions of all campus stakeholders, including students, faculty members, and administrative staff, to the assessment and accreditation processes within the Education 4.0 framework. Each group's role and impact on these processes are crucial for a comprehensive understanding of how Education 4.0 can be effectively implemented and sustained. Detailed descriptions of the characteristics and responsibilities of these stakeholders, as provided in the Introduction section, underscore their importance in fostering a collaborative and data-driven educational environment. By integrating the perspectives and efforts of these diverse groups, this research aims to enhance the overall efficacy and robustness of assessment and accreditation under the Education 4.0 paradigm. This study considers the five hidden parameters for exploration, i.e., awareness, accessibility, participation, satisfaction, and academic loafing [63], [64]. Awareness about the assessment and accreditation process is a crucial hidden parameter that affects the quality of education. In the Education 4.0 environment, real-time and continuous assessment enables students to become aware of their academic progress and areas of improvement. This helps them to take corrective measures and improve their learning outcomes. Another unobserved factor that influences the quality is the accessibility in terms of taking part in the assessment and accreditation process.

3.3 Hidden Parameters

3.3.1 Introduction to Hidden Parameters

Hidden parameters refer to subtle, often overlooked factors that significantly influence the quality of education. In the context of Education 4.0, which leverages IoT devices, sensors,

and actuators to facilitate real-time and continuous assessment, understanding these hidden parameters is crucial for enhancing student evaluation methodologies. This study identifies and scrutinizes five key hidden parameters: awareness, accessibility, participation, satisfaction, and academic loafing.

3.3.2 Selection of Hidden Parameters

The five hidden parameters were chosen based on their critical impact on the educational process and their relevance within the Education 4.0 framework:

- Awareness: knowledge of the assessment and accreditation process.
- Accessibility: ability to access educational resources and participate in assessment activities.
- Participation: engagement in the assessment and accreditation processes.
- Satisfaction: stakeholder contentment with the assessment and accreditation process.
- Academic Loafing: irregularities and lack of effort in academic activities.

These parameters were selected because they are pivotal to the successful implementation and functioning of Education 4.0, impacting the overall quality of education.

3.3.3 Measurement with Technology Devices

These hidden parameters are measured using a range of technological devices and methods that provide real-time and continuous data:

- IoT Devices and Sensors: used to track and monitor student activities and engagement levels.

  Example: sensors can measure the time students spend on educational platforms, indicating their participation and engagement.
- Learning Management Systems (LMSs): collect data on student access to resources, submission of assignments, and participation in online discussions.

  Example: LMS logs can provide data on student accessibility to learning materials and their active participation in course activities.
- Biometric Devices: monitor physiological responses to gauge emotional engagement and satisfaction.

  Example: wearable devices that track heart rate variability and skin conductance to infer levels of stress and engagement.

- Feedback Systems: surveys and feedback tools used to measure stakeholder satisfaction with the assessment and accreditation processes.

  Example: online surveys can gather data on student and faculty satisfaction levels regarding the educational environment and processes.

3.3.4 Prior Research on Hidden Parameters

Several studies have explored these hidden parameters in various educational contexts:

- Awareness and Participation: studies have shown that increased awareness of assessment processes leads to higher levels of participation and engagement among students [65], [66], [67].
- Accessibility: research indicates that better accessibility to educational resources enhances learning outcomes and reduces educational disparities [48], [55], [68].
- Satisfaction: student and faculty satisfaction has been linked to improved educational experiences and outcomes [69], [70].
- Academic Loafing: this phenomenon has been studied extensively, with findings suggesting that accountability mechanisms can mitigate its effects [63], [64], [71], [72].

3.3.5 Other Hidden Parameters in Literature

In addition to the selected parameters, other hidden factors discussed in the literature include self-efficacy, metacognitive strategies and social presence. These additional parameters were not included in this study due to the focus on factors that can be directly influenced and measured through the integration of IoT and real-time assessment technologies within Education 4.0.

3.3.6 Reason for Choosing These Parameters

The chosen hidden parameters were selected to provide a comprehensive understanding of the nuanced aspects influencing educational quality in the Education 4.0 environment. The hidden parameters selected for this study awareness, accessibility, participation, satisfaction, and academic loafing were chosen based on their profound impact on educational quality, as evidenced by prior research and theoretical frameworks.

- Awareness: Awareness of the assessment and accreditation processes is crucial as it directly affects students' engagement and motivation. Studies by [73], [74], [75] have demonstrated that increased awareness leads to higher student participation and better academic performance.

- Accessibility: Accessibility ensures that educational resources are available to all learners, thereby reducing disparities in educational outcomes. Research indicates that enhanced accessibility through digital platforms significantly improves learning effectiveness and equity [76], [77].
- Participation: Active participation in learning activities and assessment processes is linked to improved learning outcomes. According to [65], [78], participation fosters a sense of belonging and enhances collaborative learning, which are essential components of Education 4.0 [24], [79], [80].
- Satisfaction: Stakeholder satisfaction, including students, faculty, and administrative staff, is a key indicator of the success of educational interventions. Researchers found that satisfaction correlates with increased retention rates and positive educational experiences [69], [70].
- Academic Loafing: This parameter, often overlooked, refers to reduced effort in group settings, which can detrimentally affect learning quality. Studies such as [63], [71] highlight the need for accountability mechanisms to mitigate academic loafing and promote active participation. These parameters were selected due to their substantial influence on the dynamics of Education 4.0, and their selection is supported by a wealth of literature [64], [72] emphasizing their relevance in enhancing educational outcomes.

By focusing on awareness, accessibility, participation, satisfaction, and academic loafing, this study aims to address key areas that are critical for enhancing educational outcomes through technological interventions. These parameters are well-supported by prior research, ensuring that the findings of this study can contribute meaningfully to the existing body of knowledge and offer practical insights for the effective implementation of Education 4.0.

Students can access instructional resources at any time and from any location in the Education 4.0 environment using IoT devices and sensors. By bridging the traditional and digital learning gap, this expands students' access to higher education. Moreover, the other hidden factor that influences how well education is delivered is participation in the assessment and accreditation processes. Real-time and continuous evaluation is a feature of the Education 4.0 environment that encourages student engagement. Their engagement and academic results are enhanced because of this. Further, stakeholders' satisfaction with the assessment and accreditation process is one additional parameter that needs exploring under Education 4.0. Before the actual implementation of Education 4.0 at the institutional level, it is necessary to

ensure satisfaction among stakeholders about Education 4.0. Similarly, the impact of academic loafing (irregularities in teaching–learning process, administration and other educational aspects) directly aligns with stakeholders' accountability. In the context of Education 4.0, irregularity is defined as any deviation from the minimum required value of a specified parameter within a designated time period and the specific area of the educational environment. In the context of Education 4.0, accountability is defined as the ability of stakeholders to achieve the minimum required value of a specified parameter within a designated time period and specific area of the educational environment. In essence, if any stakeholder or group of stakeholders meets this minimum required value, their accountability is affirmed. Conversely, failure to meet the minimum required value constitutes an irregularity attributed to the stakeholder or group. Therefore, by improving accountability among stakeholders, academic loafing can be reduced in an ambient educational environment [65].

The hidden constructs considered in the proposed framework represent complex educational and behavioural phenomena that may not be directly observable through a single measurable variable. Therefore, their operationalization is based on the integration of multiple relevant indicators and contextual parameters. In the proposed framework, sensor-generated and digital interaction data are considered as supplementary behavioural indicators that may assist in identifying patterns associated with the underlying constructs. Such indicators should not, however, be interpreted as direct or complete representations of psychological constructs such as learner satisfaction or academic loafing. Their interpretation requires appropriate validation, contextual analysis, and consideration of measurement uncertainty and individual variability [81]. Further, all data acquisition and processing within the framework should be governed by appropriate privacy, consent, and ethical principles. The relationships identified among the measured variables are interpreted primarily as associative patterns, and causal conclusions should only be established where supported by an appropriate causal research design and sufficient empirical evidence.

3.4 Impact of hidden parameters on Education 4.0

This section provides a comparative analysis of the characteristics of pre-Education 4.0 and post-Education 4.0, as detailed in Table 3.1, and examines the impact of these pre- and post-implementation scenarios of Education 4.0 on the education industry, summarized in Table 3.2. The pre-Education 4.0 scenario pertains to the state of the education industry before the adoption of Education 4.0, while the post-Education 4.0 scenario represents the actual education industry scenario under a simulation environment. This section also includes an

examination of the impact of hidden parameters under these scenarios. The results of the pre-Education 4.0 scenario were obtained from prior research, which highlights the significance of awareness, participation, accessibility, and satisfaction with assessment and accreditation [50]. The subsequent section of this chapter provides a detailed explanation of the justification for post-Education 4.0. The pre-Education 4.0 scenario, as observed in previous research, indicated a lack of clear understanding of the assessment process enforced by the governing, affiliating, examining, and accreditation bodies among stakeholders, primarily students and teachers [49], [82]. Consequently, special programs were required to increase awareness among stakeholders, as they needed to participate in various surveys and provide feedback to these apex bodies for assessment purposes [83]. In the post-Education 4.0 scenario, real-time assessment data are automatically collected by IoT devices, sensors, and actuators, eliminating the need for stakeholders to be aware of the assessment process. Even if stakeholders are not aware of the assessment process, they still serve as a source of data for these devices and sensors [84], [85]. Therefore, awareness does not play a significant role in the post-Education 4.0 scenario. The use of IoT devices ensures that data is collected regardless of stakeholders' knowledge of the assessment process, making it a more efficient and streamlined approach to assessment. In the pre-Education 4.0 scenario, the participation of stakeholders in the assessment process was limited to those who were aware of it due to the direct correlation between awareness and participation. This resulted in low participation rates. However, in the post-Education 4.0 scenario, participation is no longer dependent on awareness but rather on the functioning of IoT devices in the institution. As long as the IoT devices are properly working, any stakeholder present in the institution during a specific time interval (ΔT) will automatically participate in the real-time assessment. Table 3.2 outlines the anticipated changes in key educational parameters as influenced by the shift from traditional education methods (pre-Education 4.0) to modern, technology-enhanced approaches (post-Education 4.0).

Table 3.1. Characteristics of pre-Education 4.0 and post-Education 4.0 scenarios

Characteristic	Pre-Education 4.0	Post-Education 4.0
Teaching Approach	Traditional classroom-based learning with limited technological usage	Blended learning approach with a focus on technology integration
Learning Environment	Conventional classroom settings with limited access to digital tools	Interactive and adaptive learning environments with digital resources
Curriculum	Static and standardized curriculum	Dynamic and personalized curriculum tailored to

Design	delivery	individual needs
Assessment Methods	Emphasis on exams and standardized tests	Diverse assessment methods including project-based assessments
Teacher's Role	Mainly as knowledge providers and instructors	Facilitators of learning, mentors, and guides for student-centered learning
Student Engagement	Passive learning with limited interaction	Active participation, collaboration, and engagement through technology
Skills Development	Focus on traditional academic skills	Emphasis on critical thinking, problem-solving, digital literacy, and adaptability
Lifelong Learning	Limited emphasis on continuous learning beyond formal education	Encouragement of lifelong learning and upskilling for future readiness

Table 3.2. Impact on hidden parameters under pre- and post-Education 4.0 scenarios

Parameters	Pre-Education 4.0	Post-Education 4.0
Awareness	Very Low	Very High
Participation	Very Low	Very High
Accessibility	Very Poor	Very Good
Satisfaction	Low	May be improved
Academic Loafing as Accountability	Very High	Very Low

Note: $Academic\ Loafing \propto \frac{1}{Accountability}$, the values in this table represent Academic Loafing

Table 3.3 summarizes the types of data collected with technological devices in Education 4.0, along with examples and their relationships to hidden parameters, such as participation, awareness, satisfaction, academic loafing, and accessibility.

Achieving complete coverage of all areas of the campus through IoT devices, sensors, and actuators, along with proper connectivity between stakeholders and these devices, can lead to 100% participation under the post-Education 4.0 scenario [65]. On the other hand, accessibility remains challenging under the pre-Education 4.0 scenario, as the mechanism used by apex bodies requires extra effort from stakeholders [86]. Furthermore, accessibility is interrelated with previous parameters, i.e., awareness and participation, and is also influenced by external parameters, i.e., application interface, assessment algorithm and apex body, leading to similar results as earlier parameters. Similarly, under the post-Education 4.0 scenario, 100% accessibility can be achieved by fulfilling the previously discussed conditions. The next two parameters, namely satisfaction and academic loafing, are intertwined with a crucial aspect of Education 4.0, which is the real-time irregularity detection and alert generation framework [87]. This framework is a fundamental component of the Education 4.0 environment and is capable of detecting all sorts of irregularities in real-time and generating specific alerts for the respective stakeholders. As mentioned earlier, satisfaction is relatively low in the pre-Education 4.0 scenario. However, the implementation of the real-time irregularity detection and alert generation framework has the potential to improve satisfaction levels in the post-Education 4.0 scenario. Additionally, accountability, which is also lacking in the pre-Education 4.0 scenario, can be improved through the mentioned framework. Any irregularities caused by any stakeholder can be detected and reported in real-time, ultimately minimizing such occurrences with time and adaptability.

Table 3.3. Types of data collected

Types of Data Collected	Examples	Related Hidden Parameters
Activity Data	Logins, time spent on educational platforms, completion of assignments, and participation	Participation: measures student engagement in educational activities.

	in forums.	Accessibility: frequency of access to learning resources.
Performance Data	Test scores, assignment grades, progress reports.	Awareness: informs students about progress and areas needing improvement. Satisfaction: higher performance data leads to increased satisfaction.
Behavioral Data	Attendance records, participation in class discussions, submission patterns.	Participation: captures extent and consistency of student engagement. Academic Loafing: indicates irregular participation patterns.
Biometric Data	Heart rate, skin conductance, facial expressions.	Satisfaction: reflects the emotional and psychological state of students. Academic Loafing: changes in biometric data indicate disengagement.
Feedback Data	Survey responses, feedback forms, peer reviews.	Satisfaction: measures stakeholders' contentment with educational processes. Awareness: highlights areas needing more information or support.
Environmental Data	Classroom temperature, lighting conditions, noise levels	Accessibility: optimal conditions enhance accessibility and comfort. Satisfaction: contributes to higher satisfaction levels.

This part elaborates on the impact of hidden parameters on Education 4.0 and illustrates the elaborative picture of pre-Education 4.0 and post-Education 4.0 scenarios. Figure 3.4 illustrates the mathematical model of the pre-Education 4.0 scenario, and Figure 3.5 illustrates the mathematical model of the post-Education 4.0 scenario. In these two models, U and U' define the set of stakeholders in pre-Education 4.0 and post-Education 4.0 scenario. $S_{\text{Awareness}}$, $S_{\text{Participation}}$, and $S_{\text{Accessibility}}$ are the set of stakeholders for awareness, participation and accessibility for the pre-Education 4.0 scenario. $S'_{\text{Awareness}}$, $S'_{\text{Participation}}$, and $S'_{\text{Accessibility}}$represents the same parameters for the post-Education scenario. S'_{Present} is the set of present stakeholders at time ΔT. α and α' are the sets of unaware stakeholders in pre-Education 4.0 and absent stakeholders in post-Education 4.0 scenario, respectively. The pre- and post-Education 4.0 scenarios are represented by Equations (1) and (2) and Equations (3) and (4), respectively.

(1)

$$where\ \alpha\ is\ set\ of\ unaware\ stakeholders\ in\ Pre - Education\ 4.0\ \ scenario, and\ S_{Awareness} \cap \alpha = \emptyset$$

$$S_{Participation} \in S_{Accessibility} \in S_{Awareness} \quad (2)$$

$where\ S_{Participation} \leq S_{Accessibility} \leq S_{Awareness}$

$$U'(\Delta T) = S'_{Present} + \alpha' \quad (3)$$

$where\ \alpha' is\ a\ set\ of\ absent\ stakeholders\ in\ the\ Post-Education\ 4.0\ scenario\ at\ time\ \Delta T$

$$S'_{Present} = S'_{Accessibility} = S'_{Participation} = S'_{Awareness} \quad (4)$$

$$if\ U = U'(\Delta T)\ then\ \alpha > \alpha' \quad (5)$$

Equation (5) represents the pre- and post-Education 4.0 scenario of a similar institution; then, the number of unaware stakeholders is greater than the number of absent stakeholders at time ΔT.

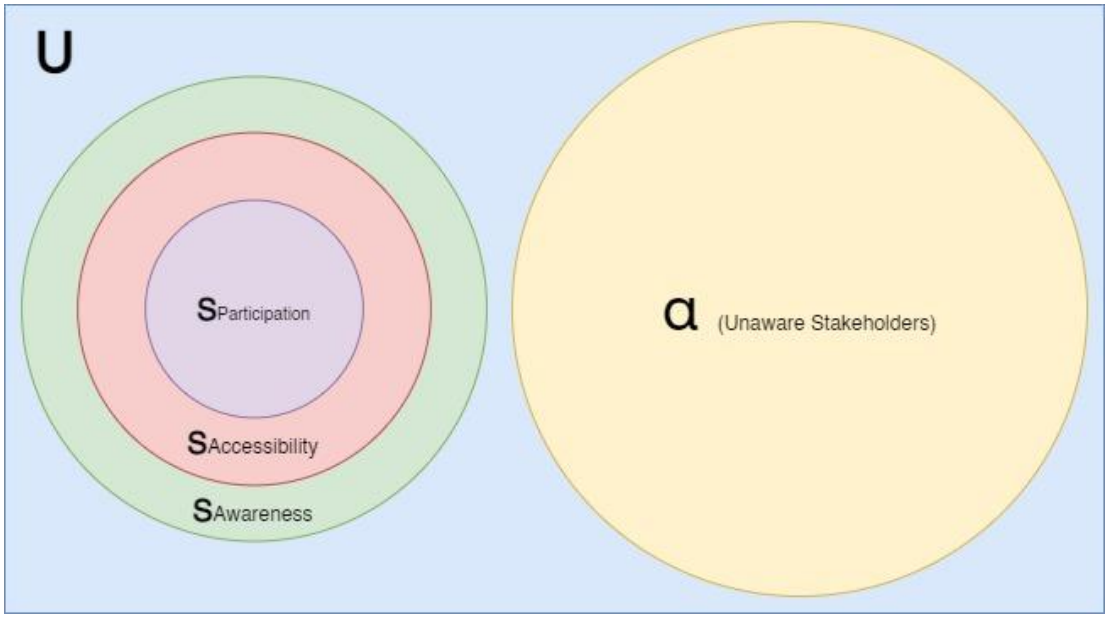


Figure 3.4. Pre-Education 4.0 Mathematical Scenario

Equations (1)– (5) are clearly illustrated in Figures 3.4 and 3.5. In Figure 3.4, the impact of awareness and accessibility on participation is clearly visible under the pre-Education 4.0 scenario. Further, Figure 3.5 clearly illustrates the non-significance of awareness, accessibility and even participation under post-Education 4.0 scenario, and no special efforts are required for participation in the assessment and accreditation process; the required data are automatically acquired under Education 4.0 scenario [55].

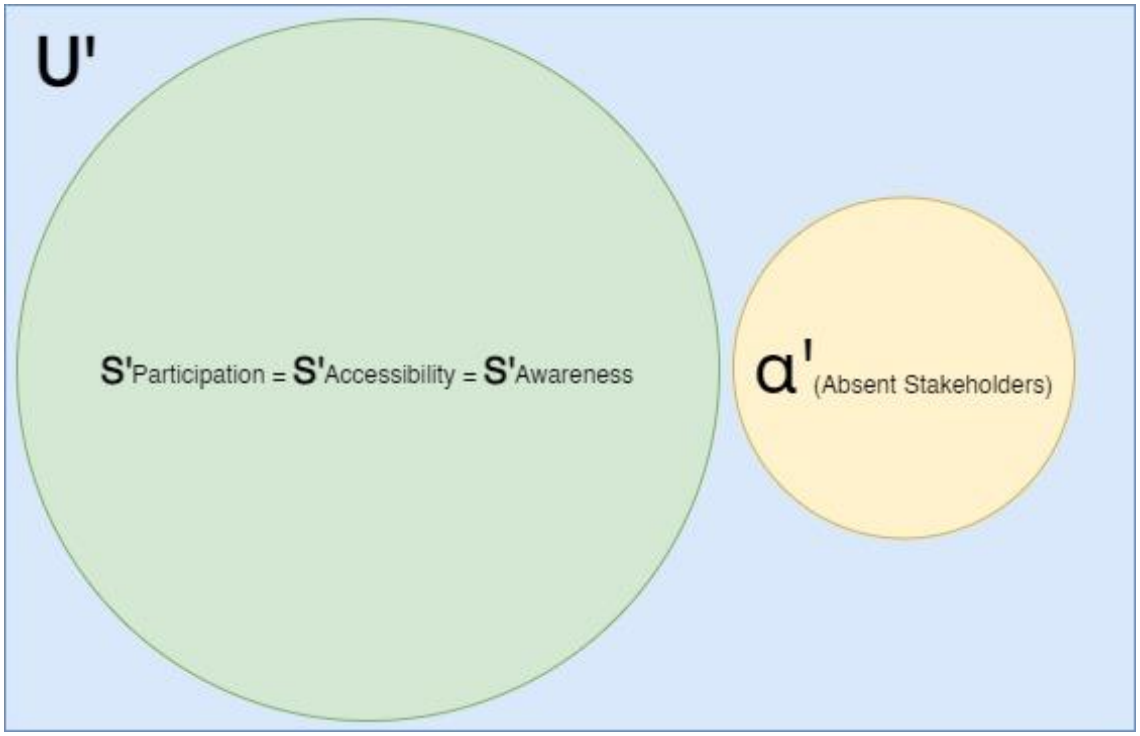


Figure 3.5. Post-Education 4.0 Mathematical Scenario

Further, academic loafing is inversely proportional to accountability. That means we can reduce academic loafing among stakeholders by improving accountability among them. Furthermore, accountability is inversely proportional to irregularities among stakeholders. Irregularity is any act or activity executed by any of the stakeholders that crosses the defined threshold limits for a particular parameter under evaluation, e.g., to conduct a lecture in any time interval ΔT, the presence of a specific stakeholder s is required in a specific classroom c; the deviation on any parameters in this example is considered an irregularity on account of the stakeholder s.

$$S'_{AL} \propto \frac{1}{S'_{Accountability}} \tag{6}$$

$where\ S'_{AL} is\ academic\ loafing\ among\ stakeholders, S'_{Accountability} is\ accountablity.$

$$S'_{Accountability} \propto \frac{1}{\sum_{i=0}^{n} IR_{Count}} \tag{7}$$

$where\ n\ is\ the\ number\ of\ stakeholders, IR_{Count}\ is\ the\ irregularity\ count, and\ n \leq U'$

From Equations (6) and (7)

$$S'_{AL} \propto \frac{1}{S'_{Accountability} \propto \frac{1}{\sum_{i=0}^{n} IR_{Count}}} \quad (8)$$

Therefore, from Equation (6)-(8)

$$S'_{AL} \propto \sum_{i=0}^{n} IR_{Count} \quad (9)$$

Hence, we can conclude that academic loafing can be reduced by reducing stakeholders' irregularities. Further, low academic loafing also means high accountability among stakeholders. Finally, by improving participation, accessibility, awareness, and accountability, satisfaction may be improved.

Building on the chapter's emphasis on Education 4.0 as a learner-centred and technology-enabled approach, this study brings attention to the often-overlooked factors that quietly shape the quality of education. The research identifies five key hidden variables—awareness, accessibility, participation, satisfaction, and academic loafing—and demonstrates their strong influence on teaching–learning outcomes beyond traditional measures of quality. By examining these variables before and after the implementation of Education 4.0, the study shows how real-time data, continuous assessment, and smart technologies help students become more aware, gain easier access to learning resources, participate more actively, and experience higher levels of satisfaction. At the same time, the study highlights how academic loafing and related irregularities can be detected and reduced through data-driven monitoring and accountability mechanisms. One of the important outcomes of this research is the clear, measurable link established between academic loafing and student engagement patterns. By integrating these hidden variables into assessment and accreditation processes, the study offers a more holistic and realistic framework for evaluating educational quality in the Education 4.0 environments, ultimately supporting better decision-making and more meaningful improvements in teaching and learning.

3.5 Summary

The culmination of this research underscores the pivotal role played by infrastructure, learning environment, and faculty in delineating the caliber of education, emphasizing their intricate interplay in shaping the educational landscape. Moreover, the study illuminates the significance of numerous hidden factors such as awareness, accessibility, participation, satisfaction, and academic loafing, which intricately contribute to the overall educational

experience. Through a meticulous placement of these variables within both pre- and post-Education 4.0 scenarios, this study offers a nuanced understanding of their differential impacts across these distinct epochs. By juxtaposing the dynamics of awareness, accessibility, and participation, our research sheds light on the evolving nature of educational excellence, highlighting the shifting paradigms in the post-Education 4.0 era. Furthermore, our investigation establishes a quantifiable correlation between irregularities and academic loafing, unraveling the complexities underlying student engagement and performance. The theoretical and managerial implications of this study provide a pathway for the improvement of the assessment and accreditation process in both pre- and post- Education 4.0 scenarios. By identifying avenues for enhancing satisfaction levels within the post-Education 4.0 paradigm, this study paves the way for targeted interventions aimed at maximizing student fulfillment and academic achievement. The findings of this study are poised to significantly enhance the implementation of Education 4.0 by addressing key aspects of the assessment and accreditation processes within this advanced educational paradigm. Specifically, the mathematical solutions developed and analyzed in this research offer robust frameworks for the integration and optimization of diverse data acquisition algorithms. These algorithms are crucial for capturing, processing, and analyzing the extensive datasets characteristic of the Education 4.0 environments. By providing precise and scalable solutions, this study not only facilitates the seamless integration of data-driven methodologies but also ensures the reliability and efficiency of accreditation systems, ultimately contributing to the broader adoption and success of Education 4.0 initiatives. These findings not only yield actionable insights for optimizing educational efficacy across diverse domains but also underscore the imperatives of holistic evaluation encompassing hidden parameters. As such, the proposed framework provides an initial technological approach for supporting institutional quality assessment and accreditation in the context of Education 4.0 and may be further evaluated and extended through future research, providing a comprehensive framework for understanding and enhancing educational quality in an ever-evolving landscape. While this study has provided valuable insights into the impact of Education 4.0 on educational quality through the lens of hidden parameters, there are several avenues for future research and development that warrant exploration. Future work could expand the scope to include additional hidden parameters that may influence educational quality in the Education 4.0 environments. For instance, exploring cultural factors, socio-economic influences, and personal motivations could provide a more comprehensive understanding. Future studies could also utilize advanced data analytics techniques, such as machine learning and predictive modeling, to extract more nuanced

patterns and insights from the vast amounts of data collected by IoT devices and sensors. This could enhance personalized learning experiences and optimize educational interventions. Further, strategies could be developed and tested to enhance stakeholder engagement and accountability within the Education 4.0 environments. This could involve participatory action research methodologies to co-create solutions with students, educators, administrators, and policymakers. By addressing these future research directions, the field of Education 4.0 can continue to evolve, offering transformative opportunities to enhance educational quality, accessibility, and equity in a rapidly changing digital landscape.

CHAPTER 4

Validation of Hidden Parameters: A Systematic Study

***Chapter Briefing*— This chapter investigates the Quality Education Ecosystem (QEE) and its critical role in establishing sustainable quality education globally, analysing challenges faced by leading nations such as the United States, United Kingdom, Germany, Canada, China, and India. Despite India's extensive higher education infrastructure, the study reveals its limited success in meeting global benchmarks. Essential hidden parameters like academic loafing, awareness, participation, accessibility, and satisfaction are identified as pivotal to QEE's inner layer, impacting its efficacy. Academic loafing—a phenomenon where stakeholders exert reduced efforts in collective settings—emerges as a key challenge. To address these issues, the chapter introduces the Multilayered Quality Education Ecosystem (MQEE), a framework integrating Cognitive IoT solutions to enhance monitoring, assessment, and accreditation processes in the Education 4.0 environments. The MQEE holistically addresses both intellectual quotient (IQ) and emotional quotient (EQ), fostering cognitive and socio-emotional growth while emphasizing ground-level implementation of emerging technologies like IoT and AI. Significant contributions include unveiling hidden elements within the QEE, proposing MQEE as a global solution, addressing academic loafing, and enhancing participation and accountability. By emphasizing further exploration of concealed layers and the importance of EQ in education, the chapter provides a pathway for transformative advancements in global education systems within the Education 4.0 framework.**

4.1 Introduction

Sustainable quality education ecosystem is a fundamental requirement of every nation. The global leaders in quality education such as the United States (US), United Kingdom (UK), Germany, Canada, and China are also facing challenges in providing a sustainable quality education ecosystem [88]. More than 80% of institutions of all the nations including the global leaders are struggling to provide the average quality of education to young aspirants on a global platform. Only 0.2% of Indian institutions that participated in Webometric University Ranking-2019 touched the scale of average quality education Countries arranged by a number of Universities in Top Ranks, Ranking Web of Universities: More than 28000 institutions ranked). It was observed that more than 51649 educational institutions are presently imparting higher education in India. The present infrastructure of Indian Higher

Education is one of the largest in the world regarding the number of colleges, universities, and stand-alone Institutions. India has even more infrastructure (in terms of the number of higher educational institutions) than the other 4 most populated nations of the world together i.e. China, the US, Indonesia, and Brazil. India and China together hold 25% of the world's post-secondary population i.e. about 40 million enrolments. The (Quacquarelli Symonds) QS-World University Ranking-2020 recognized the quality of research executed by Indian faculty during the year 2019. India is listed among the top three nations of the world in citations per faculty which is on par with the US and China (QS World University Rankings 2020: Top Global Universities | Top Universities, n.d.). University Grants Commission (UGC), All India Council for Technical Education (AICTE), National Assessment and Accreditation Council (NAAC), Bar Council of India (BCI), Indian Council of Agricultural Research (ICAR), National Council for Teacher Education (NCTE), Dental Council of India (DCI), Medical Council of India (MCI), Pharmacy Council of India (PCI), Central Council of Homoeopathy (CCH), Central Council of Indian Medicine (CCIM), and many other apex bodies are working for the assessment and improvement of quality education in India in their respective domains. More than half a dozen education commissions are deployed in India to generate intellectual reports on higher education [89]. All India Survey on Higher Education (AISHE) is the largest national-level survey conducted and it is one of the biggest national surveys done among all the other countries. These apex bodies including AISHE, National Institutional Ranking Framework (NIRF), National Board of Accreditation (NBA), and others are working for the improvement of a quality education system for higher education in India. For a sustainable quality education system adequate infrastructure, intellectual faculty, and a healthy environment for learning are required. 51649 higher educational institutions, the world's best research-oriented and intellectual faculty, and more than two dozen domain-specific national level apex bodies for the assessment and monitoring accomplished the quality education system in India. Although the Government of India is strengthening all three walls of this system still 98.8% of the education system fails to touch the global parameters of quality education [90]. The present education system is not reachable to the rural areas [91], which may be one of the reasons behind low-quality education in India. The performance of the present Indian Education System on global parameters indicates the requirement for exploration in the Quality Education Ecosystem (QEE) [92]. The present study unveiled many novel things that were affecting the present education ecosystem directly or indirectly but were unnoticed so far. Restructuring of present education ecosystem for the Education 4.0 environment by empowering it with emerging technology is the main

motivation behind this study. Improvised education ecosystem, and the use of emerging technology like IoT, and AI for monitoring, assessment, and accreditation at the ground level are some of the key advantages of this study.

4.1.1 Requirement and Contribution

Quality Education Ecosystem is an integral part of every educational institution, the components mentioned in Figure 4.1 only reveal the outer shell of QEE that might be the prerogative of the state or central government in India. This outer shell of the QEE of the Indian Education System is robust, whereas the inner layer of this ecosystem is still very delicate and needs more care and protection (in terms of the government laws to grow) [93].

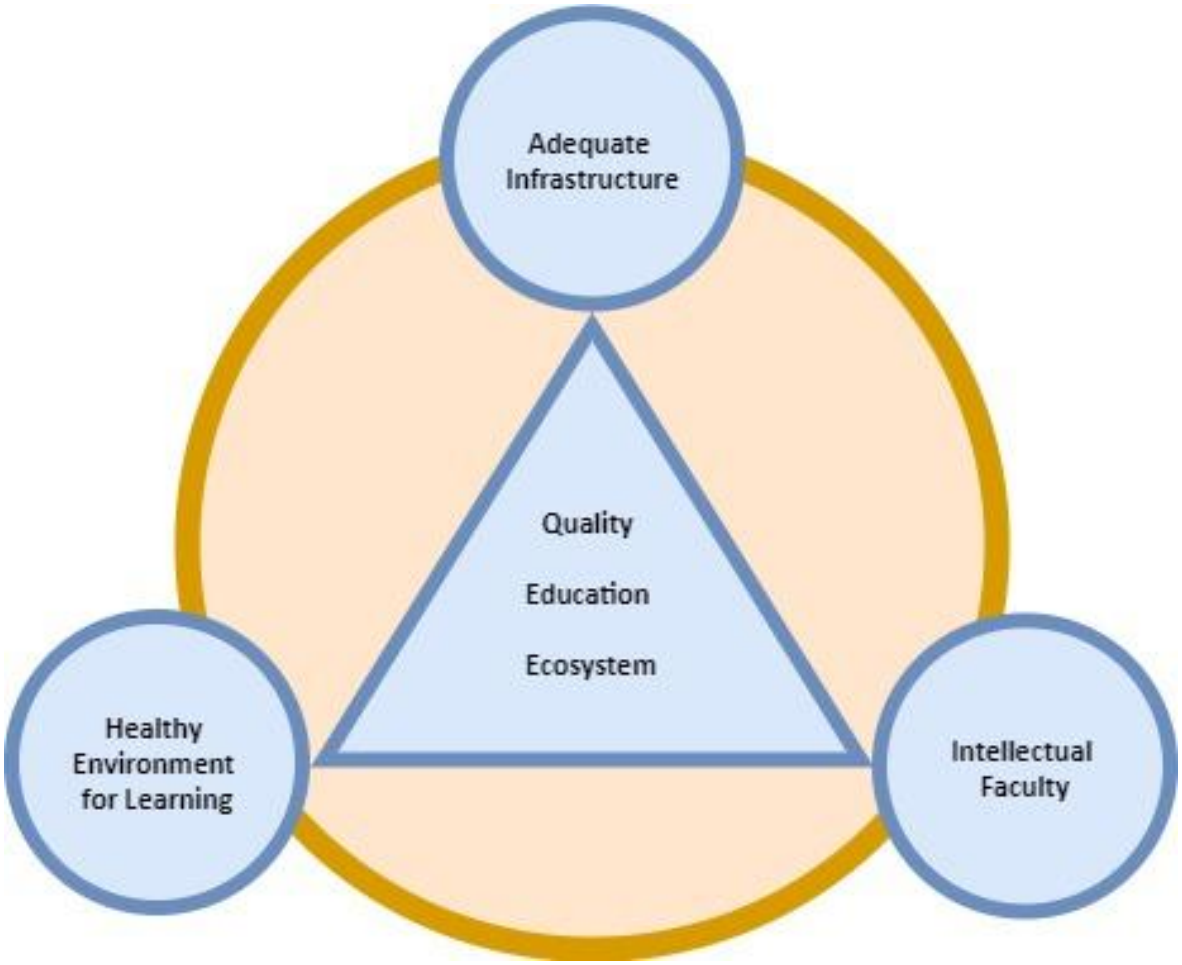


Figure 4.1. Quality Education Ecosystem (QEE) with components

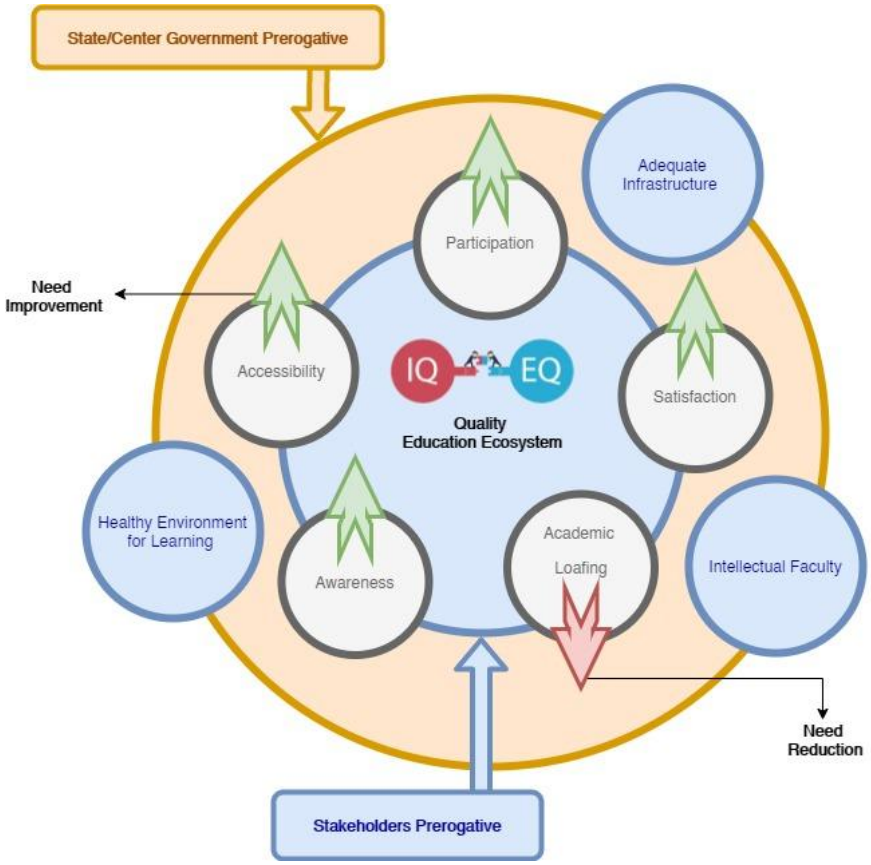


Figure 4.2. Multilayered Quality Education Ecosystem (MQEE)

A survey conducted to check the ground-level reality of QEE unfolds the main hidden rudiments of QEE. This survey explored many new factors in the quality education ecosystem. Figure 4.2 illustrates the broader view of the Multilayered-Quality Education Ecosystem. The outer layer is the prerogative of the state/centre government and is handled by the apex bodies of higher education in India. Whereas the inner layer is the prerogative of all institutions and stakeholders of this entire ecosystem including students, teachers, non-teaching staff, administration, and management. Both quantitative and qualitative aspects constitute the outer layer of MQEE, whereas the inner layer deals with only the qualitative aspects of MQEE. A weaker inner layer results in a weaker quality education ecosystem. Awareness, Participation, Accessibility, Satisfaction, and Academic Loafing constitute the inner layer of MQEE. The implementation of the Multilayered Quality Education Ecosystem at the ground level will achieve sustainable quality education on global parameters. The MQEE is the quickest and most effective remedial solution to diminishing quality education in India. This term academic loafing is derived from social loafing during this study. Social loafing is the tendency for individuals to expend less effort when working collectively than when working individually [94]. Social loafing is very common but very difficult to trace [95]. As academics are also a major and important part of society social loafing affects

academicians which results in academic loafing. "Academic Loafing is the tendency for the individual teacher as well as students to expend less effort towards quality education as their individual-efforts are not evaluated on any level of assessment, only collective efforts are evaluated for quality education".

More than 993 Universities, 39931 Colleges, and 10725 Stand Alone Institutions by 2019 made India the top country in the world in terms of the number of universities and colleges [96]. In July-2019, India participated with 3944 colleges and universities in the webometric university ranking survey-2019 and became the top participator in this survey [90]. China being the most populated country has 1736 fewer colleges and universities than India and the United States of America, one of the leading countries in the world, has 687 fewer institutions than India. So, India is nowhere lagging in terms of the number of institutions, yet it faces problems regarding sustainable education. Sustainable quality education is one of the persistent problems for all nations across the world. In the United States, the top performer in the higher education sector in webometric university ranking has 92.08% of its institutions below average quality. 96.44% of the institutions that participated across the world in webometric assessment have below-average quality. In India, only 0.2% of the institutions are providing average quality on global parameters. So, it is the need of the hour to stop the mushrooming of institutions in India and focus on the quality of education in the existing infrastructure [97].

As per QS-World University Ranking-2020, India is among the top three nations in *'Citation per faculty'* behind China and the United States of America which indicates the disposal of the better position of qualitative/quantitative parameters of research work executed in Indian institutions. But, on the other hand, India's global 'Academic Reputation' is even below the average global academic reputation of world education [98] which clearly illustrates that *the world's best faculty in research is not providing the average quality education to their students*. Academic loafing might be the reason behind this, and it needs to be explored on the ground level. NAAC [99] and AICTE [100] are among the leading government organizations for affiliation of colleges and universities in India. Both these organizations together are designated as "the top affiliating bodies on the national level" in the world. AISHE is the largest national-level survey conducted among all the other national surveys conducted across the globe. All these apex bodies dedicated to affiliation and assessment of higher education are using state-of-the-art technology for the same. The impact of technology might be diluted because of improper ground-level implementation. Adequate infrastructure,

the best research-oriented faculty, and domain-specific assessment agencies enabled the quality education ecosystem in India. The mushrooming of institutions is neither required nor does it improve the quality of education in India [101]. The proposed MQEE supports holistic growth in the present education system by including EQ as an essential part of quality education along with IQ. EQ is equally important as IQ for successful career growth and social appearance [102]. The exploration of the quality education ecosystem and unveiling other concealed layers are areas of future investigation. The main contributions of this study include:

- It explores various factors that require immediate improvement on the ground level for quality education and further explores the hidden factors that are required to complete the quality education ecosystem.
- It elaborates the relationship between quality education and various other variables that affect quality education.
- The proposed multilayered C-IoT based education model for assessment and accreditation fosters the Education 4.0 environment. The use of cognitive-IoT and public/private reporting eradicates the IoT-Big Data problem in the Education 4.0 environment.
- Feedback-Data preprocessing through Bidirectional Weighted Sum (BWS) method, and incremental abstraction method, enhance the scalability and flexibility of the education model.
- The proposed trust algorithm improves the level of trust in terms of transparency among stakeholders.

4.2 Methodology

A sequence of methods is deployed to redesign a robust education model for sustainable quality education. In this section, an attempt has been made to explore various hidden parameters that need immediate improvement for the betterment of sustainable quality education and for removing obstacles in building a quality education ecosystem. Various methodologies used in this study are discussed in detail under the following sub-sections:

4.2.1 Restructuring Education Ecosystem with Five-Step Improvement Model

Restructuring of education ecosystem is the need of the hour. Figure 4.3 illustrates the various steps involved in restructuring the quality education ecosystem. Subsequently, the conceptual and comprehensive models are proposed at various levels of its implementation.

For the exploration of the quality education ecosystem case studies on the Indian education system are considered, and sample data obtained from surveys has been evaluated with the help of various statistical tools. We examined the outcomes of the survey for quality education and checked the correlation between quality education and various other dependent variables as one of the main objectives of this study. Five variables (Awareness, Participation, Satisfaction, Academic loafing, and Accessibility) that affect the assessment of quality education are considered for this research. From a sample of 2798 individuals, 2200 individuals were selected through a stratified convenience sampling method to ensure the representation of relevant subgroups based on their availability and willingness to participate. Although stratification improves the representation of different categories within the study population, the non-probability nature of convenience sampling may introduce selection bias. Therefore, the findings should be interpreted primarily within the context of the sampled population and research setting, and caution should be exercised when generalising the results to a wider population or to institutions operating under substantially different conditions. The response rate of this survey was found to be above 62.78%. From a sample of 2798 individuals, 2200 individuals from 27 different states and union territories across India were selected, the selected individuals were either pursuing or had completed education under courses at various levels like undergraduate (UG), Postgraduate (PG), Master of Philosophy (M.Phil.), Doctor of Philosophy (Ph.D.) or Postdoctoral (Postdoc). Himachal Pradesh, Punjab, Kerala, Haryana, Delhi, Gujarat, and Chandigarh were the main participating states/ Union Territories (UTs), the selected sample covered both government & private Colleges & Universities from Rural, Urban and Metropolitan areas of India. Not more than 100 responses from any single state/UT have been considered for this survey. The states/UTs with less than 50 responses were not considered for this survey.

The Bidirectional Weighted Sum (BWS) method was used to integrate the result on boundaries for obtaining the valuable solution to provide additional support for the relationships identified through correlation analysis. While correlation analysis indicates the direction and strength of association between variables, BWS is used to further examine and interpret these relationships within the context of the proposed framework. Thus, BWS is not intended to replace or benchmark established statistical techniques such as correlation, regression, or SEM; rather, it serves as a supporting mechanism that provides an additional analytical perspective for strengthening the interpretation of the observed relationships. The conclusions of the study are therefore based on the combined interpretation of the relevant

analytical results and are not dependent solely on BWS. BWS is a more efficient and accurate method in comparison with the traditional percentage outcome method. A detailed illustration and comparison of the BWS method are given in the subsequent section of this chapter. Evaluation of the correlation between y (quality education) and various other variables (x) like awareness, participation, satisfaction, academic loafing, etc. was done using standard correlation techniques. The results were further used to analyse the different parameters (x) for a better quality of education (y). The Bidirectional Weighted Sum boundaries analysis method has been used to check the resultant solution for two extreme boundaries for various variables. Further, a scatter diagram and Karl Pearson's Coefficient of Correlation have been used to check the correlation of various variables with quality education (y).

The above methodological implementation consolidates five steps improvement model for a robust ecosystem. This model suggests the sequence of actions that results in a robust quality education ecosystem. The awareness and accessibility improve participation and reduce academic loafing that leads to satisfaction. Bagchi defined student satisfaction as the difference between student perception and expectation [103]. This model involves each

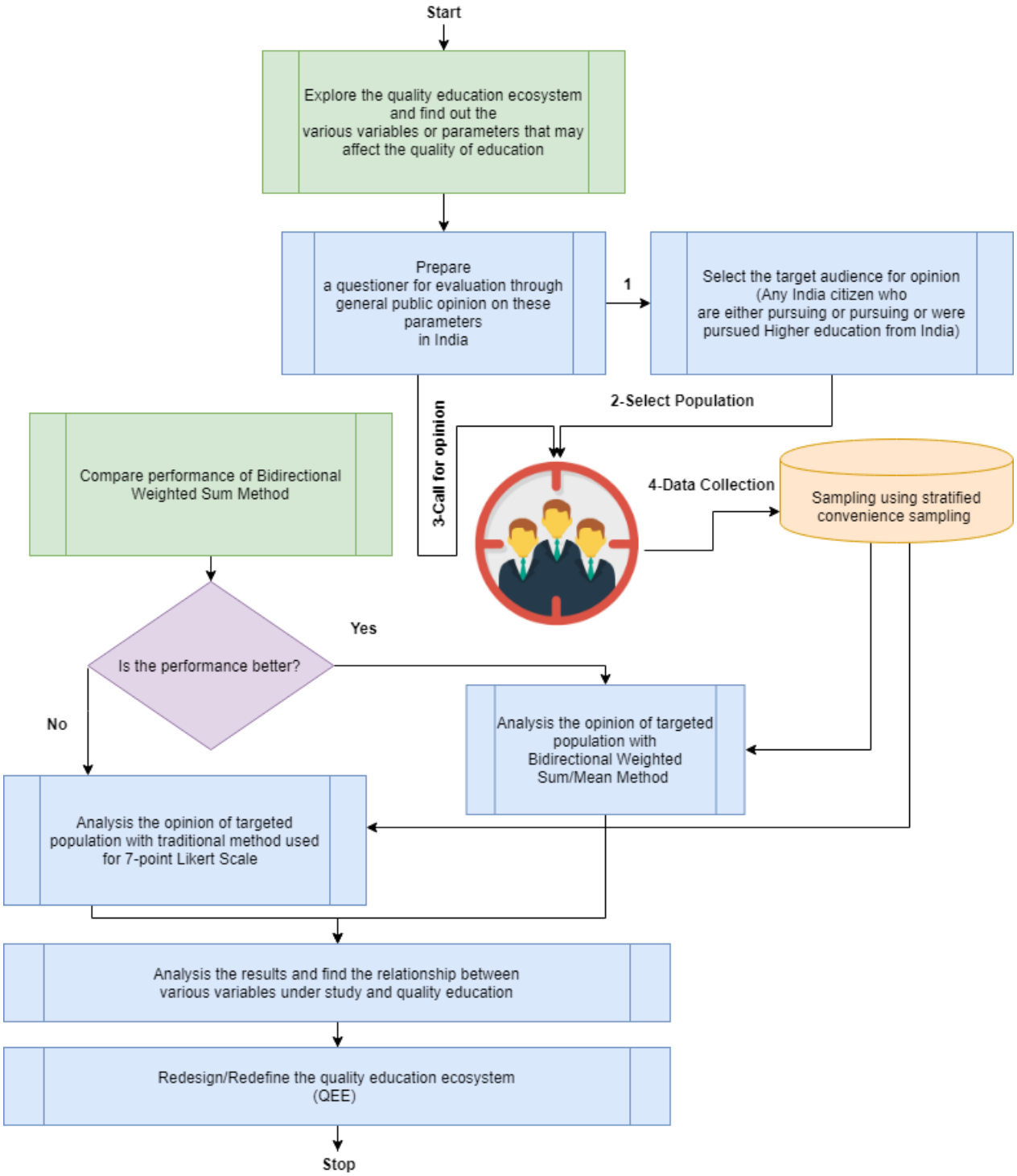


Figure 4.3. Flow Chart of the methodology used for restructuring of Quality Education Ecosystem

stakeholder in quality management which reduces the gap between perception and expectation. Reduction in academic loafing and enhancement in satisfaction are the cumulative results of the first three steps. The proper implementation of the first three steps enforces a behavioural change in every stakeholder, and the positive impact of the first three steps automatically improves the concrete results of the last two steps. So, the policymakers need only converge their focus on the first three steps, and it will subsequently result in improving all five factors of the quality education ecosystem. Proper reporting and appropriate corrective action on any observable irregularity in the education ecosystem may also decrease academic loafing and increase satisfaction. Reporting and alerts are discussed in the subsequent sections of this chapter. The sequential implementation of this model enforces maximum results with comparatively less effort.

4.2.2 Bidirectional Weighted Sum method for boundary value analysis (BWS)

The Bidirectional Weighted Sum method for boundary value analysis (BWS) is used to obtain precise results. The neutral value of the 7-point Likert Scale is *'Neither Agree nor Disagree'*. We can consider this point as the origin (O) of the Likert Scale because the outcomes under this point neither support the positive side (Agree) nor approve of the negative side (Disagree). This origin is providing two independent directions one towards the positive side i.e. Somewhat Agree, Agree, and Strongly Agree and the other one towards the negative side i.e. Somewhat Disagree, Disagree, and Strongly Disagree. The negative and positive weights are assigned as shown in Figure 4.10. The bidirectional weighted sum maintains the significance of the 7-point Likert Scale. If the researcher processes the data further and calculates the sum of the percentage for the negative PS^{-ve} (Disagree) and positive PS^{+ve} (Agree) sides of this question, then the result will be obtained as follows:

$$(PS)^{+ve} = \sum_{i=1}^{3} Pi \quad (1)$$

$$(PS)^{-ve} = \sum_{i=1}^{3} Ni \quad (2)$$

$where\ 1 \leq i \leq 3\ for\ 7-Point\ Likert\ Scale\ and\ 1 \leq i \leq 2\ for\ 5-Point\ Likert\ Scale$

The values of $(PS)^{-ve}$ & $(PS)^{+ve}$ have been evaluated in Figure 4.5 as 44.8% and 44.5% respectively. In this example $(PS)^{-ve} > (PS)^{+ve}$ converges the resultant to some extent towards the negative side. But we cannot consider extreme values (Strongly Agree/Strongly Disagree) and the middle value (Somewhat Agree/Somewhat Disagree), as it misleads the significance of the Likert Scale over closed-ended questions (Yes/No). So, the researcher needs some other technique to get precise results.

$$Bidirectional\ Weighted\ Sum\ (BWS)^{+ve} = \sum_{i=1}^{3} Pi \quad (3)$$

$$Bidirectional\ Weighted\ Sum\ (BWS)^{-ve} = \sum_{i=1}^{3} Ni \quad (4)$$

$where\ 1 \leq i \leq 3\ for\ 7-Point\ Likert\ Scale\ and\ 1 \leq i \leq 2\ for\ 5-Point\ Likert\ Scale$

$$BWS = (BWS)^{+ve} + (BWS)^{-ve} \quad (5)$$

$$if\ BWS > 0 \quad (6)$$

$\{then\ boundary\ value\ is\ converged\ towards\ positive\ side\ and\ the\ final\ result\ is\ Agree\}$

$$if\ BWS = 0 \quad (7)$$

$\{then\ boundary\ value\ is\ not\ converged\ towards\ any\ side\ and\ the\ final\ result\ is\ Neither\ Agree\ nor\ Disagree\}$

$$if\ BWS < 0 \quad (8)$$

$\{then\ boundary\ value\ is\ converged\ towards\ negative\ side\ and\ the\ final\ result\ is\ Disagree\}$

Note: $The\ greater\ positive\ value\ means\ greater\ degree\ of\ positivity\ (Agree)and\ the\ greater\ negative\ value\ means\ greater\ degree\ of\ negativity\ (Disagree)$

$$(BWS)^{+ve} = \sum_{i=1}^{3} Pi \tag{9}$$

$$(BWS)^{-ve} = \sum_{i=1}^{3} Ni \tag{10}$$

Correlation coefficient (ρ^{xy}) has been evaluated for each variable as:

$$\rho^{xy} = \frac{n(\sum(BWS(x)BWS(y)) - (\sum BWS(x))(\sum BWS(y))}{\sqrt{[n\sum BWS(x)^2 - (\sum BWS(x))^2]}[\sqrt{[n\sum BWS(y)^2 - (\sum BWS(y))^2]}} \tag{11}$$

4.3 Incremental abstraction model

As we move upward the density of data is also increasing and problems may arise due to big data. So, to avoid such problems the level of abstraction is also increased as the data move from one layer to the other in the upward pyramid. The incremental abstraction method is suitable for continuously arriving at real-time raw data [104], [105]. The level of abstraction will increase as the data is moving on the upper side of the layered structure. The incremental abstraction model with its various report components is shown in Figure 4.4.

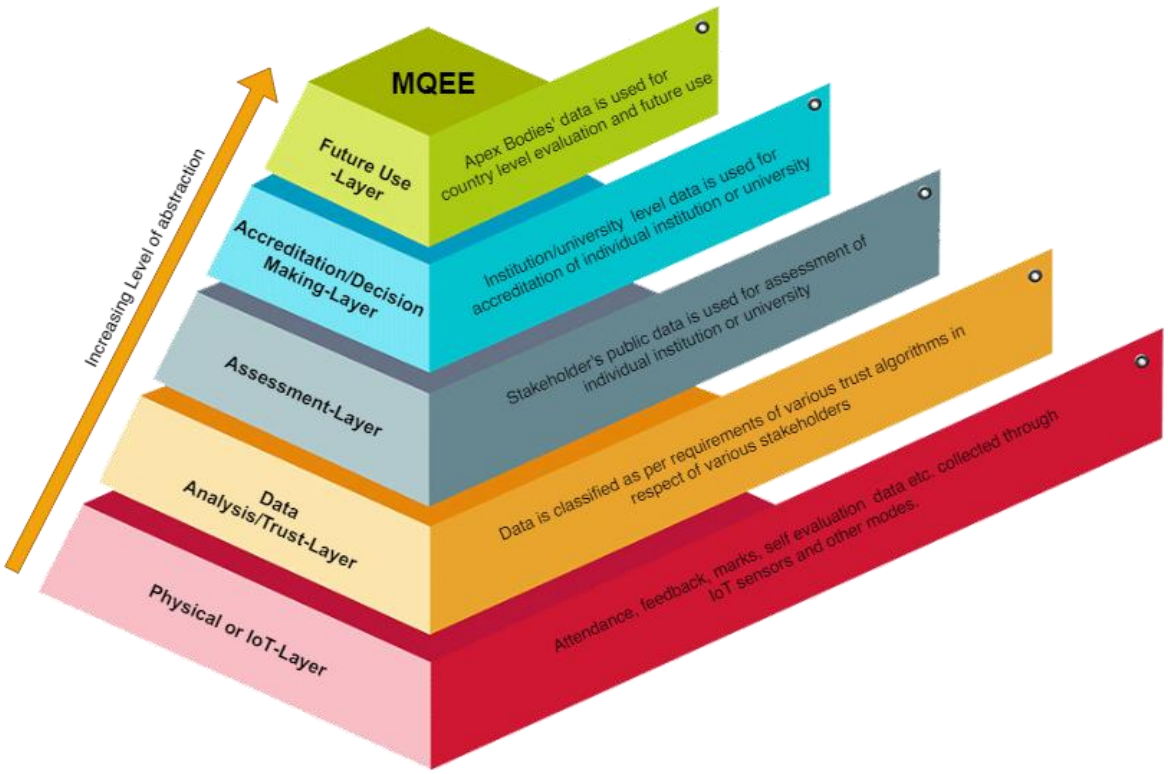


Figure 4.4. Incremental abstraction model with various reports generated at different layers of the quality education ecosystem

The physical or IoT-Layer is rich in raw data while the heterogeneous data from various resources make this layer denser for data. The data analysis/trust layer pre-processed the heterogeneous data through BWS and Big Dansing is deployed for data cleaning [106]. Further, the data is segregated as per the requirement of various reports generating trust algorithms by using the distributional profile of multiple word categories (DPWC) [107]. The outputs of this layer can be further bifurcated as the data in public and private reports. The private data is used by this layer to transmit the data for application purposes for stakeholders' reporting and alerts. Only the public data will be transmitted to the assessment-layer. The assessment layer will use these heterogeneous clusters of abstract data for its assessment. At the assessment layer, the clustered data is further classified into public and private assessment report. The private assessment will further be used for application purposes for institution-level reporting and alerts while the public data will be transmitted to the accreditation layer. The accreditation layer will hold only the concrete dataset from various other layers and use this concrete dataset for

accreditation and policy making. No special abstraction method is used for abstraction in this model the concrete reports (Minimum required data for analysis) are supplied to the next higher level for analysis. Data abstraction in various reports as per the requirement of assessment and accreditation level are serving as abstraction method.

One of the key outcomes of this study is the development of the Incremental Abstraction Model, which offers a practical and intuitive way to handle the growing volume and complexity of data in the Education 4.0 environments. As data moves upward through the layered structure of the proposed ecosystem, it naturally becomes denser and more diverse, increasing the risk of Big Data–related challenges. To address this, the model gradually increases the level of abstraction at each successive layer, ensuring that raw data is meaningfully refined rather than simply accumulated. At the base, the IoT layer continuously generates large amounts of real-time, heterogeneous data. As this data progresses upward, it is cleaned, filtered, and organized using structured analytical techniques, transforming it into information that is easier to interpret and use. Only the most relevant and purpose-specific data is passed on to higher layers, where it supports assessment, reporting, and accreditation activities. By delivering concise, decision-ready datasets instead of overwhelming volumes of raw information, the Incremental Abstraction Model improves efficiency, scalability, and reliability. As a result, this model serves as a major deliverable of the study, providing a clear and scalable framework for real-time data management, informed decision-making, and effective quality assurance within Education 4.0 ecosystems.

4.3.1 Data Privacy, Security and Incremental Abstraction

In the proposed framework, the use of IoT-enabled technologies may involve the collection of student-related personal, behavioural and academic data. Therefore, privacy and security are considered important aspects of the proposed architecture [18]. The framework is designed to ensure that the collection and processing of such data remain purpose-specific, controlled, and limited to the requirements of educational quality assessment and accreditation. An important privacy-preserving feature of the proposed framework is the Incremental Abstraction Model, which is applied across the different layers of the proposed MQEE architecture. Under this approach, detailed and potentially

sensitive data are primarily collected, processed, and analysed at the institutional level. The raw or granular information is therefore not required to be transmitted beyond the institution unless specifically authorised and necessary for a defined purpose. At each successive layer of the framework, the data are progressively transformed into higher-level, aggregated, and more meaningful information. Consequently, only the concrete and relevant information required for assessment, accreditation, and further quality analysis is transferred to the next higher layer or the concerned apex/assessment body. This layered abstraction reduces the unnecessary exposure of student-level information and helps minimise privacy risks during inter-institutional data transmission and analysis. For example, student-level IoT observations may initially be processed within the institution to generate appropriate academic, behavioural, environmental, or quality-related indicators. Instead of transferring the underlying individual-level observations, the subsequent layer may receive only the aggregated indicators or institutional-level evidence required for quality assessment. Thus, the proposed architecture supports the principle of data minimisation and purpose limitation, while retaining the information necessary for institutional evaluation. The Incremental Abstraction Model also contributes to cyber security by reducing the volume and sensitivity of information transmitted between different architectural layers [19]. Combined with access control, authentication, secure communication, encryption, data retention policies, and institutional governance mechanisms, it provides an additional layer of protection for sensitive educational information.

The proposed framework does not envisage unrestricted transmission of students' personal data to external or apex bodies. Rather, it follows a layered, privacy-aware data processing approach, in which sensitive information remains predominantly within the institutional boundary and only the required level of abstracted information is communicated to higher-level assessment and accreditation authorities. The final implementation of these mechanisms would, however, remain subject to applicable legal, ethical, institutional, and regulatory requirements.

4.4 Evaluation and Analysis

Generally, for better survey results such as 5-points or 7-points, Likert Scales have been recommended. While evaluating the results using these Likert Scales the outcomes in percentage were received for all 5 or 7 points but in some cases, this method of percentage outcomes cannot provide the precise result for a question (yes/no). Further, this technique is unable to provide the results in terms of the most positive and most negative (boundaries: best and worst impact) impact of the question on the respective variable. The following example illustrates the result of 330 outcomes of a survey question on the 7-point Likert Scale on some random values in Figure 4.5 the respective chart and the percentage outcomes of all 7-points did not help the researcher in deciding whether the participants agreed or disagreed in response to this question as a precise solution (negative/positive) cannot be claimed by this method. Figure 4.6 examines the same data under the proposed *Bidirectional Weighted Sum method for boundary value analysis (BWS)* to obtain precise results.

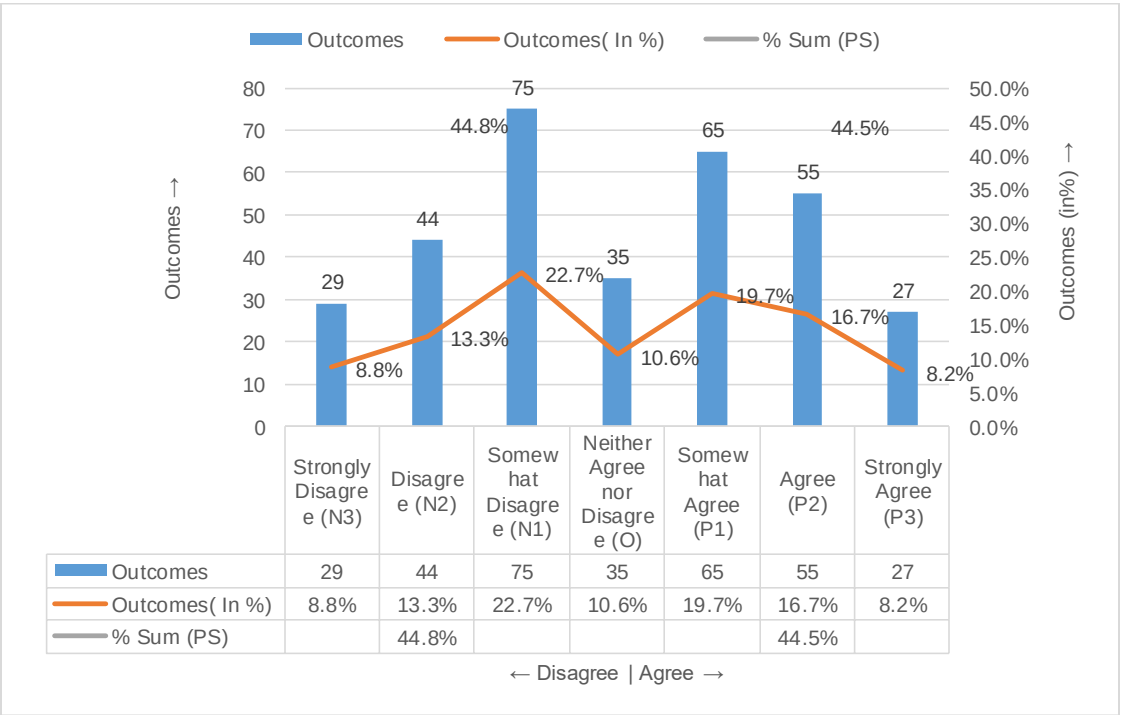
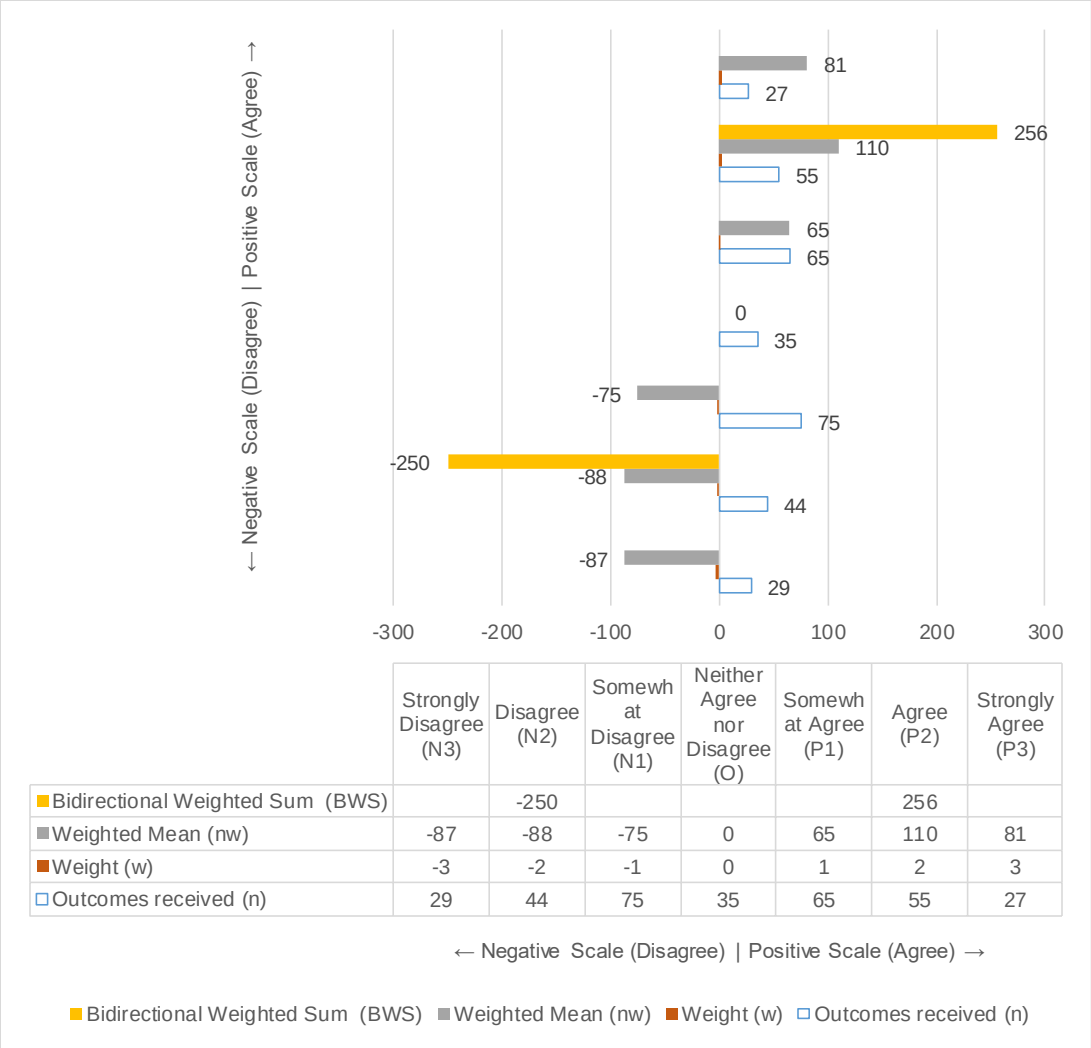


Figure 4.5. Statistical illustration of 7-point Likert scale with percentage outcomes

The values of (BWS)+ve & (BWS)-ve have been evaluated in Figure 4.6 as 256 and -250 respectively.

$$BWS = (256) + (-250)$$
$$= 6 \quad (12)$$

The positive value of BWS indicates the overall boundary value is converged towards the positive side, and the result is positive i.e. Agree. Although in Figure 4.5 the resultant percentage value of the positive side is less than that of the negative side the boundary value analysis through the bidirectional weighted sum Figure 4.6 contradicts it and provides the actual value. As the bidirectional weighted sum for the boundary value analysis method gives accurate and precise results for survey questions analysis, this research will use this method for analysing the questions in respect of various variables considered for this research. For more accuracy instead of weighted sum, weighted mean may also be used. The sample data of 2200 individuals were selected by a stratified convenience sampling method from 2798 individuals. The data collected has been further classified into two categories i.e. various variables *(x)* that may affect quality education (i.e. Awareness, Participation, satisfaction, Accessibility, and Academic Loafing) and quality education *(y)*. The responses received (5- and 7-point Likert scale) were further classified as positive, negative, and neutral impact. The Bidirectional weighted sum (BWS) has been applied to the data to study the negative *(i.e. BWS^{-ve})*, positive *(i.e. BWS^{+ve})* impact, and the concrete impact *(i.e. BWS(x)* and *BWS(y))* (resultant impact of negative and positive responses) for more accurate and precise results.



	Strongly Disagree (N3)	Disagree (N2)	Somewhat Disagree (N1)	Neither Agree nor Disagree (O)	Somewhat Agree (P1)	Agree (P2)	Strongly Agree (P3)
Bidirectional Weighted Sum (BWS)		-250				256	
Weighted Mean (nw)	-87	-88	-75	0	65	110	81
Weight (w)	-3	-2	-1	0	1	2	3
Outcomes received (n)	29	44	75	35	65	55	27

Figure 4.6. Statistical illustration of a 7-point Likert scale with Bidirectional Weighted Sum (BWS) method for boundary value analysis

$$= 311 + 1234 + 567 = 2112$$

$$= (-1368) + (-738) + (-128) = -2234$$

$$\text{BWS} = (2112) + (-2234)$$

$$= -122 \qquad (13)$$

Similarly, BWS for each question was calculated for a precise result. Four questions in respect of each variable i.e. Awareness, Participation, satisfaction, Accessibility, Academic Loafing, and Quality Education have been selected from the survey questionnaire. The Bidirectional Weighted Sum method for a survey question related to satisfaction is tabulated for illustration in Table 4.1:

Table 4.1. 1 Bidirectional Weighted Sum *(BWS) method*

Options	Classification	Frequency (f)	Bidirectional Weight (w)	(fw)	BWS		Resultant BWS
Highly Dissatisfied	-ve (N)	456	-3	-1368	BWS -ve	-2234	-122
Dissatisfied		369	-2	-738			
Somewhat Dissatisfied		128	-1	-128			
Neither Satisfied nor Dissatisfied	Neutral (O)	130	0	0			
Somewhat Satisfied	+ve (P)	311	1	311	BWS +ve	2112	
Satisfied		617	2	1234			
Highly Satisfied		189	3	567			
Total		2200					

Based on the above discussion and illustration, the differences between the percentage outcome method and the BWS method are tabulated as:

Table 4.2. 2 Comparison table between percentage outcome method and BWS method

	Percentage outcomes Method	***BWS Method***
Suitable for 5-point Likert Scale	√	√
Suitable for 7-point Likert Scale	√	√
Boundary Value Analysis	X	√
Complexity for m-point Likert Scale	$O(mN)$	$O((m-1)N)$
Significance of Neutral decision (i.e. neither agree nor disagree)	√	X
Extreme values and their subsequent values have the same significance	√	X
Concrete result possibility (Agree or Disagree)	X	√
Accuracy	Low	High

On the basis of the survey conducted, the five parameters of the inner layer and the respective outcomes of the BWS method are mentioned in Table 4.3. The classification of data for five different variables i.e. Awareness, Participation, Satisfaction, Accessibility, and Academic Loafing, and the respective correlation coefficient for Quality Education is tabulated in Table 4.3. Awareness, Participation, satisfaction, and Accessibility were found to be the variables that have a positive correlation with quality education. Awareness (82.63%), Participation (94.24%), Satisfaction (92.13%), and Accessibility (98.27%) correlated with the quality of education which means that all these variables are directly proportional to quality education with at most 7.93% average variation.

$$Quality\ Education \propto Awareness, Participation, Satisfaction\ and\ Accessibility \quad (14)$$

Table 4.3. Correlation table between quality education (y) and variables under study i.e. Awareness, Participation, satisfaction, Accessibility, and Academic Loafing (x)

Variable	$\boldsymbol{BWS\ (x)}$			$\boldsymbol{BWS\ (y)}$			$\boldsymbol{Correlation\ coefficient\ (\rho^{xy})}$	***Correlation***
	$\boldsymbol{(BWS)^{-ve}}$	$\boldsymbol{(BWS)^{+ve}}$	$\boldsymbol{BWS^{x}}$	$\boldsymbol{(BWS)^{-ve}}$	$\boldsymbol{(BWS)^{+ve}}$	$\boldsymbol{BWS^{Y}}$		
Awareness	-1909	291	-1618	-3980	180	-3800	0.826303	**Positive**
	-1514	874	-640	-2234	2112	-122		

	-1742	504	-1238	-3346	1124	-2222		
	-4480	489	-3991	-4242	-320	-4562		
Participation	-1909	291	-1618	-3346	1124	-2222	0.94244	
	-1742	504	-1238	-2234	2112	-122		
	-4480	489	-3991	-4242	-320	-4562		
	-3767	230	-3537	-3980	180	-3800		
Satisfaction	-2234	2112	-122	-2234	2112	-122	0.92133	
	-3624	583	-3041	-3346	1124	-2222		
	-4480	489	-3991	-3980	180	-3800		
	-3767	230	-3537	-4242	-320	-4562		
Accessibility	-2130	70	-2060	-2234	2112	-122	0.982729	
	-4480	489	-3991	-3980	180	-3800		
	-3793	256	-3537	-3346	1124	-2222		
	-4566	194	-4372	-4242	-320	-4562		
Academic loafing	-194	4566	4372	-3980	180	-3800	-0.99351	**Negative**
	-320	4242	3922	-3346	1124	-2222		
	-66	4657	4591	-4242	-320	-4562		
	-256	3793	3537	-2234	2112	-122		

The scatter diagram in Figure 4.7 indicates the positive correlation between variables (Awareness, Participation, Satisfaction, and Accessibility) and Quality education.

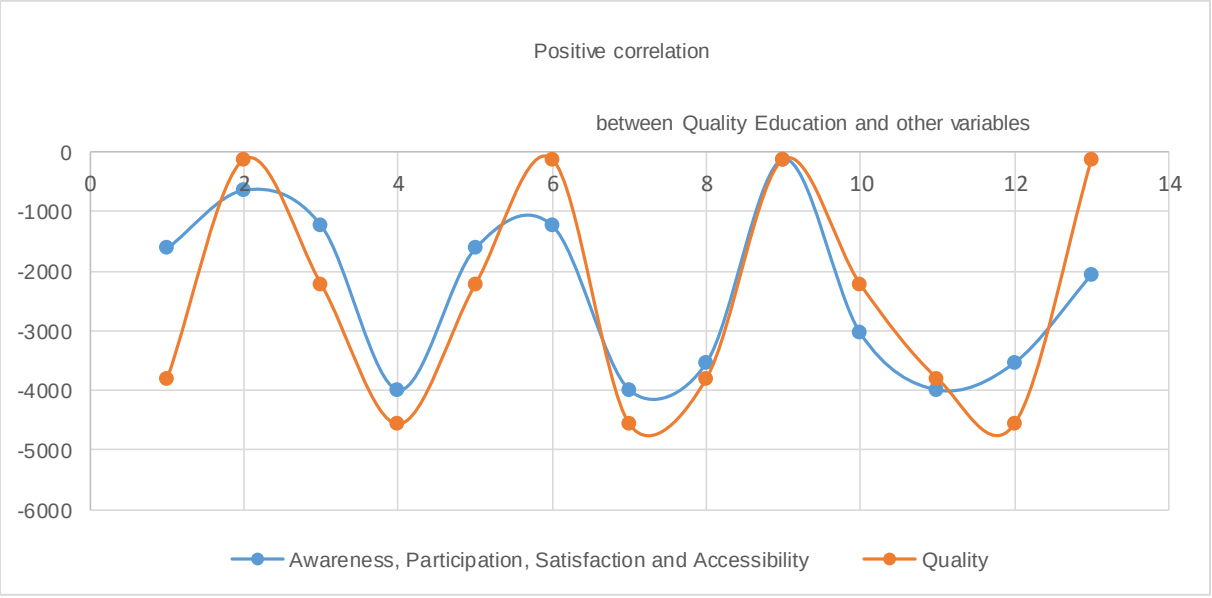


Figure 4.7. Scatter Diagram between different variables under study (Awareness, Participation, Satisfaction, and Accessibility) and Quality Education shows a positive correlation between quality education and various other variables under study

The average correlation between quality education and all these four variables is 91.82%. So, the government can enrich higher education policies by enriching awareness, participation, satisfaction, and accessibility among all stakeholders. As all these

rudiments are directly proportional to quality, in turn, it will improve the overall quality of education. The improvisation in all these rudiments will also strengthen the inner layer of the proposed Multilayered-Quality Education Ecosystem.

AISHE claims to reach 37.3 million students out of 37.4 million students across India during 2019 [96], which is above 99% but on the ground level, the situation is completely contradictory. 68.8% of participants who participated in this survey had not even heard of the biggest survey conducted on higher education in India i.e. AISHE. 86.8% of students never participated in any education survey like AISHE, student satisfaction, or any other quality education survey. Only 3.3% of students regularly participated in AISHE and 2.1% regularly participated in student satisfaction surveys (conducted by NAAC or other agencies) [108]. So, unawareness and poor participation in the quality assessment are two major factors behind the low quality of education in India. 96.8% of stakeholders including students, teachers, and non-teaching members of higher education systems are willing to participate in quality assessment. Further 86.7 % of participants also agreed that active participation of all stakeholders i.e. students, teachers, and non-teaching staff is required for sustainable quality education (principle of total participation). The government must put some steps forward in order to bring awareness to all stakeholders about the quality assessment and to also improve the participation of all stakeholders in the same. For accessibility [109] and satisfaction, the survey concludes that 84.5% of stakeholders are not in direct contact with their respective apex education bodies like UGC, AICTE, NAAC, BCE, ICAR, NCTE, DCI, MCI, PCI, CCH, and CCIM, etc., although they must be in direct contact with their respective apex bodies. Only 36.6% of students are satisfied with the quality of education at their respective institutions. More than 70% of students are not satisfied with the employable skills acquired by them at UG or PG level. 87.2% of students are not satisfied with the education system that evaluates only one aspect of intelligence i.e. IQ-Intelligence Quotient and are willing to introduce another important factor of intelligence i.e. EQ (Emotional Quotient) in the education system. United Nations International Children's Emergency Fund (UNICEF) recently reported that 'By 2030 more than 50% of India students are not on the right track of acquiring education and skills that are required to employment' [110], and 87.7% of students agree with UNICEF's report about Indian Education System. So, by improving

accessibility by establishing direct contact between every stakeholder and their respective apex education bodies, the government may improve accessibility. The introduction of an EQ evaluation system in higher education is one more important factor for quality improvement [102]. Awareness, Participation, and accessibility will lead to satisfaction of all stakeholders which will result in quality education in India. One other factor i.e. Academic Loafing or Loafing in Academics is an untouched term that has a very high significance [111] and negatively correlates (-99.35%) with quality education. i.e. Academic Loafing is inversely proportional to quality education with at most 0.65% variation. The scatter diagram in Figure 4.8 indicates the negative correlation between quality education and academic loafing.

$$Quality\ Education\ \propto \frac{1}{Academic\ Loafing} \tag{15}$$

So, to improve the quality of education academic loafing must be decreased in the education sector.

The increasing level of academic loafing is one of the main reasons behind substandard quality education [112] in India. The assessment of individual stakeholders of the higher education system at the ground level will reduce academic loafing as a result, quality education will increase in higher education institutions. Academic Loafing in teachers can be mitigated by continuous individual assessment and 95.2% of participants agree with this statement. The participants also agree that the quality of education can be increased pragmatically by reducing academic loafing in teachers and students. All stakeholders including administration, management, teachers, students, and non-teaching staff unintentionally indulge in academic loafing. Unawareness, non-participation, and unemployable skill sets, which are some of the indicators that indicate academic loafing, are also present in students. QS-World University Ranking is the ranking system that evaluates citations per faculty of a country and indicates the research level of the faculty members of the respective country, declared India as one of the top 3 nations in this category [98]. Academic loafing is one of the major factors behind the persistence of low-quality education by the world's best faculty members in India.

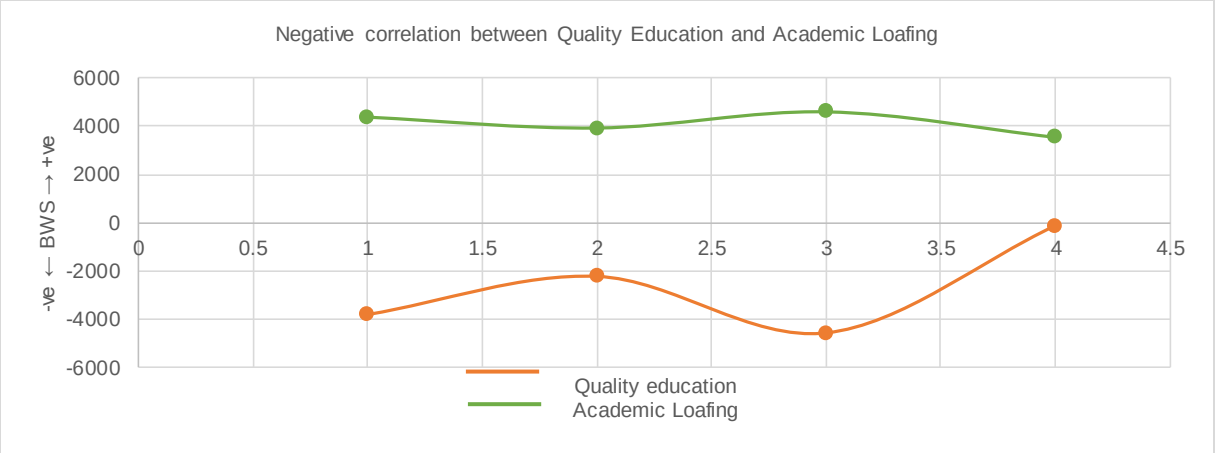


Figure 4.8. Scatter Diagram between Academic Loafing and Quality Education showing a negative correlation between Quality education and Academic Loafing

From table-4.2 the value of (ρ^{xy}) i.e. correlation coefficient for all five variables is not equal to zero.

$$(\rho^{xy}) \neq 0 \tag{16}$$

$$(\rho^{xy})\ for\ all\ variables\ is\ between -1\ and +1\ so\ there\ must\ be\ some\ correlation\ between\ x\ and\ y$$

The main results obtained during this research indicate that Bidirectional Weighted Sum *(BWS)* method for boundary value analysis is more suitable for precise and accurate results as compared to a 5-point or 7-point Likert Scale. It was also observed that Awareness, Participation, Satisfaction, Accessibility, and Academic Loafing are the main variables that are affecting the quality of education at the higher education level in India, and these variables constitute the inner layer of the quality education ecosystem. Awareness, Participation, Satisfaction, and Accessibility are all four variables that have a positive correlation with quality education. This indicates that all these variables are affecting the quality of education in India directly. So, for improving the quality of education, the government must improve all these factors. The only variable under study i.e. Academic Loafing has a negative correlation with quality education. This indicates that the variable Academic Loafing is affecting the quality of education inversely [64]. So, again, to improve the quality of education, the government must reduce this factor.

Total participation (i.e. all stakeholders including students, teachers, non-teaching staff, administration, and management) must be acquired for assessment of quality education. The intelligence or quality of education must not be assessed only based on IQ evaluation at UG/PG or higher levels of education, but it should also include the other major factor of intelligence i.e. EQ (emotional intelligence) [113], [114]. 96.8 % of stakeholders including students, teachers, and non-teaching staff are willing to give their active and regular participation for quality education in India but, due to a lack of state-of-the-art technology and easily accessible methods at ground level, they are unable to give their contribution in this area. E-participation is one of the solutions which provides open access to university, administration, government, and other facilities to the students [115]. So, E-participation can also be considered an effective tool to achieve total participation. The integration of quality assurance systems in every institution is mandatory [116] and implementation of this quality assurance system on state-of-the-art technology enhances all the parameters of quality assurance.

4.5 Hidden Parameters as Outcomes and Deliverables of the Study

A major outcome and key deliverable of this study is the systematic identification, measurement, and integration of critical hidden parameters within the Quality Education Ecosystem (QEE) that decisively influence educational quality in the Education 4.0 context. The research establishes awareness, accessibility, participation, satisfaction, and academic loafing as the core latent variables constituting the inner layer of the ecosystem, which directly governs the effectiveness of the outer layer comprising infrastructure, faculty, and the learning environment. Through the application of the Bidirectional Weighted Sum (BWS) method, these hidden parameters are quantitatively validated, revealing strong individual associations with quality education—awareness (82.63%), satisfaction (92.13%), participation (94.24%), accessibility (98.27%), and academic loafing (99.35%). Collectively, these parameters demonstrate an average association of 93.32% with educational quality, underscoring their decisive role. The findings further indicate that enhanced awareness and total participation serve as key drivers for improving accessibility and satisfaction, while significantly mitigating the detrimental effects of academic loafing. The proposed C-IoT–based Multilayered Quality Education

Ecosystem (MQEE) translates these hidden parameters into actionable components through data preprocessing, incremental abstraction, and continuous monitoring. By uncovering and operationalizing these concealed layers, the study delivers a holistic, data-driven framework that strengthens assessment, accreditation, and quality assurance processes, offering a sustainable pathway for improving educational quality at institutional, national, and global levels.

From a quality assessment perspective, the present study adopts an inclusive stakeholder-centric approach, wherein all students enrolled in the institution are considered integral participants in the quality evaluation process. Students constitute the primary and most influential stakeholder group in higher education ecosystems, and their engagement levels directly reflect the effectiveness of pedagogical and institutional interventions. However, for the purpose of quantitative modeling and empirical analysis, it is neither methodologically robust nor statistically valid to always assume absolute participation (100%) across all stakeholders.

Accordingly, the study employs a minimum attendance threshold of 75% as a scientifically and regulatorily justified benchmark for effective participation in quality assessment. This threshold is widely recognized and enforced across universities, autonomous colleges, and regulatory and accrediting bodies in India, including provisions under UGC regulations and institutional ordinances, where a minimum of 75% attendance is typically mandated for course completion, examination eligibility, and academic progression—excluding programs offered under distance or open learning modes. In several institutions and professional programs, this requirement is even higher; however, 75% remains the most commonly accepted and operationally standardized norm across the Indian higher education system.

Based on this regulatory convergence and practical feasibility, the Improvement Factor (i) after the implementation of Education 4.0 is defined within the bounded interval:

$$75\% \leq i \leq 100\%$$

This interval represents the realistic range of stakeholder engagement and participation achievable under institutional constraints while maintaining academic validity. The lower bound ensures compliance with minimum regulatory standards for meaningful participation, whereas the upper bound reflects the aspirational objective of full engagement facilitated by Education 4.0 interventions.

The mathematical formulation and quantitative illustration of the improvement in participation, accessibility, awareness, satisfaction, and the corresponding reduction in academic loafing—modeled through the defined Improvement Factor—are systematically presented in Table 4.4, thereby providing an empirical foundation for the proposed framework.

Table 4.4. Minimum and Maximum Impact on Quality Education in respect of Awareness, Accessibility and Participation under Education 4.0

Parameter	**Correlation with Quality education (In %)**	**Improvement factor *i* after implementation of Education 4.0 (In %)**	**Minimum impact on Quality Education. (In %)**	**Maximum impact on Quality Education (In %)**
Awareness	82.63	$75\% \leq i \leq 100\%$	61.97	82.63
Accessibility	98.27	$75\% \leq i \leq 100\%$	73.7	98.27
Participation	94.24	$75\% \leq i \leq 100\%$	70.68	94.24

4.6 Summary

The Bidirectional Weighted Sum (BWS) method for the 5-point/7-point Likert Scale method for boundary value analysis gives accurate and precise results. This method is also helpful to illustrate the best, worst, and concrete effects as opposed to other methods. To overcome the problem of diminishing quality in education the implementation of the C-IoT-based Multilayered-Quality Education Ecosystem (MQEE) at the ground level is mandatory. Data preprocessing at the initial level and increasing the level of abstraction

on each layer mitigate the impacts of Big Data in the Education 4.0 environment. In this study, it was concluded that every stakeholder must work on the inner layer of this ecosystem to enhance the quality of education. Further, it was found in this analysis that total participation and awareness are mandatory to improve accessibility and satisfaction among stakeholders so that there is a lessening of the devastating impact of academic loafing. It was also observed that the vigorous education ecosystem of any nation results in sustainable quality education. The improvisation of the inner layer of the ecosystem will diversify the impact of the already robust outer layer of the Quality Education Ecosystem (i.e. Adequate Infrastructure, Intellectual Faculty, and a Healthy Environment for learning). The overall enhancement of the Quality Education Ecosystem improves the overall quality of education on the global parameters. Awareness (82.63%), Satisfaction (92.13%), Participation (94.24%), Accessibility (98.27%), and academic loafing (99.35%) were found to be associated with quality education with an average association of 93.32%. Exploration of the hidden layers of the present education ecosystem and the proposed technologically enhanced C-IoT based model for the improvement of quality education are the main contributions of this study. Although the proposed model recommends an automated reporting system for quality improvement, the necessary action on reports is still under stakeholders' purview. Such limitations need further improvement in the near future. Policy makers' acceptance and proper implementation at the grassroots level are the main managerial implications of this study. The C-IoT-based proposed model can further be elaborated for other education areas like courseware designing and automated evaluation through Virtual and Augmented Reality (VAR). C-IoT can further be used in self-regulated learning and health monitoring of stakeholders in educational institutions etc. BWS can also be used for boundary value analysis in AI-based applications for decision-making. The incremental data abstraction techniques like public/private data classification can be vibrantly used in many other areas like health care, human resource management, and total quality management.

CHAPTER 5

Multilayered-Quality Education Ecosystem (MQEE): A Proposed novel solution for assessment and accreditation for Education 4.0

***Chapter Briefing*— This chapter introduces the Multilayered-Quality Education Ecosystem (MQEE), a transformative framework leveraging Cognitive IoT (C-IoT) technologies to address challenges in sustainable quality education within the Education 4.0 environment. The proposed model integrates IoT, Fog Computing, and Cloud Computing to manage heterogeneous data and enable real-time sensing, preprocessing, analysis, and actionable insights for stakeholders. With its layered structure, the framework ensures transparency through public and private reporting components, which feed into university-level assessments and accreditation processes. Innovations such as Historical Adversity Approximation (HAA) and Fog computing-based Vulnerable Data Set (VDS) classification further enhance predictive capabilities for irregularities. By fostering 21st-century skills and aligning with Industry 4.0 demands, MQEE provides intelligent monitoring, irregularity detection, and real-time reporting, ensuring a sustainable and technologically advanced ecosystem. This comprehensive approach supports global standards in education, minimal human intervention, and effective decision-making, emphasizing policymakers' acceptance and grassroots implementation for broader applicability across educational domains, including courseware design, automated evaluation through Virtual and Augmented Reality (VAR), and stakeholder health monitoring.**

5.1 Introduction

On the basis of the survey and various outcomes of the survey mentioned under chapter 4, the use of state-of-the-art technology at the grassroots level is of paramount importance for improvement in quality education. IoT, which is used by many organizations [117], is a network of physical objects used for real-time communication [118].

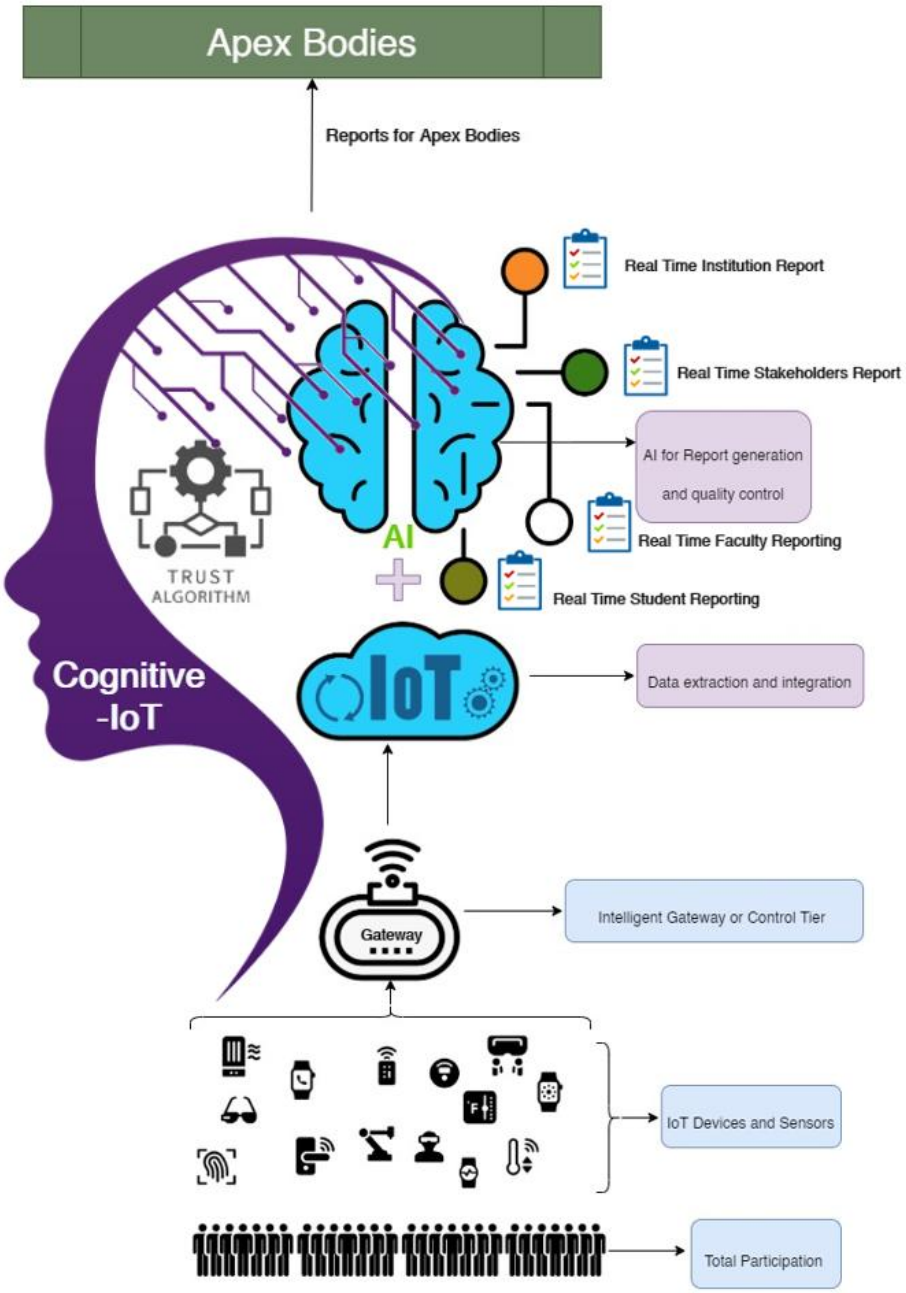


Figure 5.1. Conceptual C-IoT based proposed model

IoT environment (IoT devices, sensors, and mobile devices) is enabled to foster quality and reduce delay [119] so, IoT for real-time data collection and Artificial Intelligence (AI) for data analysis or the combination of both IoT and AI i.e., Cognitive-IoT [120] is proposed in this chapter for conceptualization of the C-IoT based framework for Education 4.0. The proposed implementation model is a C-IoT based model in order to have a complete and robust quality education ecosystem. The use of C-IoT also manages the IoT-Big Data's lacunas which are caused by a huge amount of heterogeneous data in real-time [121] by using an incremental abstraction model. The proposed framework is suitable for the Education 4.0 environment. Education 4.0 is the emerging necessity for the functioning of Industry 4.0 manpower [122]. The education sector also needs to increase its potential to meet the requirement of quality needed for functioning of Industry 4.0 [123]. Figure 5.1 illustrates this conceptual model.

The ground-level implementation of this model will start repairing the current education model's drawbacks at the grassroots level and eventually affect every layer of the education ecosystem. C-IoT can also handle scalability and flexibility problems [124]. The proposed C-IoT-based model will provide ubiquitous access to information in real-time. The ground-level implementation model and the primary part of the conceptual model are illustrated in Figure 5.1. All the stakeholders are sensed through IoT devices in a real-time environment for data collection.

The outcomes of the various algorithms serve as inputs for the report generation system. Effective data analysis is possible in a smart environment using AI and deep learning techniques [125]. The AI-based report generation will generate a comprehensive report for each stakeholder i.e. student, teacher, and administrative staff. All the reports are text-based as most data collected by IoT devices is text-based [126]. All the reports have two major components i.e. public and private. The private component of the report is used by the respective stakeholder for self-evaluation and improvement, whereas the public component is transferred to the next level for more comprehensive analysis at higher levels. Both public and private reports use data abstraction and data hiding methods [127] to increase transparency and trust. The private component of the report will decrease the level of academic loafing and improve the level of satisfaction among various

stakeholders. Figure 5.2 illustrates the complete layered structure of the proposed multilayered conceptual framework. The Physical/IoT layer and Data analysis/Trust layer are implemented at the grassroots level. In the present study, the term "trust" is used in a conceptual and operational sense to describe the increased transparency, traceability, and reduced dependence on direct human intervention in the proposed framework. The use of automated data collection, processing, and monitoring is expected to support more transparent and consistent institutional assessment processes. However, trust is not treated as an independent measurable construct in this study, and no separate trust model, index, or quantitative metric has been developed. Therefore, references to trust in the proposed framework should be understood within the context of transparency and reduced manual intervention rather than as a formally measured research variable. Figure 5.1 illustrated the case of a single institution; similarly, the other institutions are also generating institution-level reports. Therefore the public part of each report will serve as input to the next layer i.e. the assessment layer at the university level. Each university will further produce a public and private assessment report. The public report will serve as input for the accreditation layer. Every stakeholder will get the related report at different levels of the proposed model to recognize their respective efforts. The structure of a specific report depends on the specific institution category e.g. the reports of engineering institutions will differ from pharmaceutical or management institutions. The accreditation layer is a decision-making-layer. It will help the policymakers to provide ranking and grading to an individual institution or university. The further extension of the proposed model may also achieve the Global Reporting Initiative for sustainability in education [128].

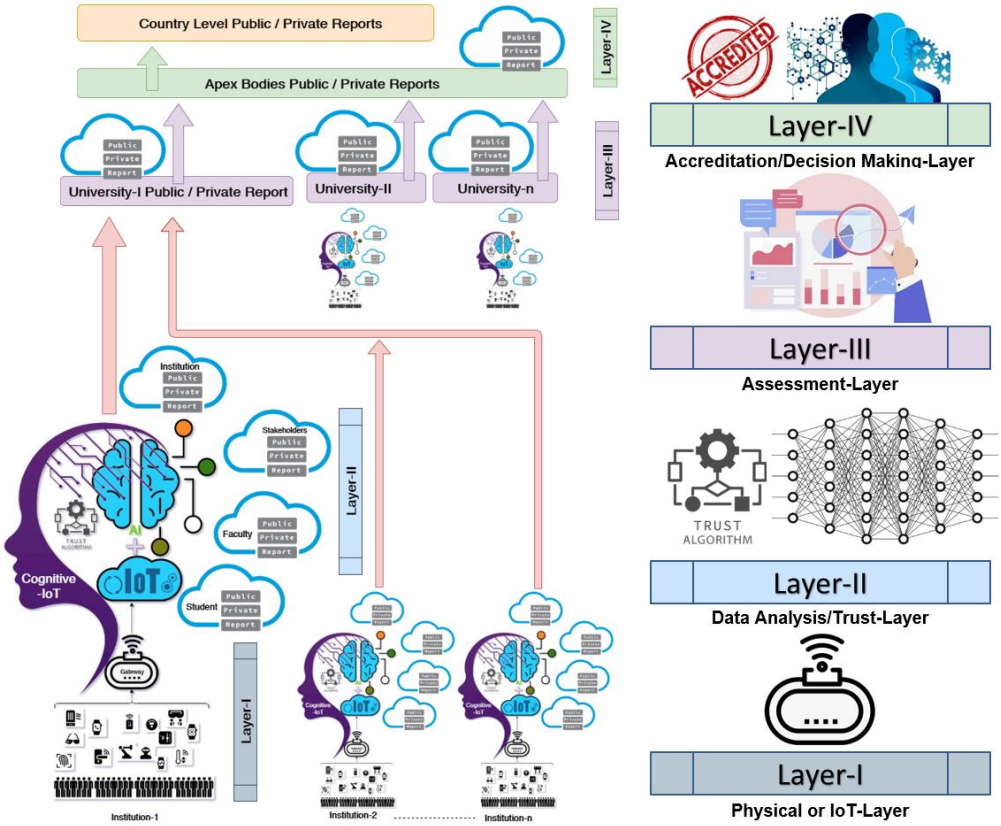


Figure 5.2. C-IoT based multilayered conceptual model for Education 4.0

Maintaining global standards in education and a technology-inspired sustainable education ecosystem are the priority goals of every nation. The present educational institutions need to enrich enough information and technology infrastructure that can inculcate 21st-century skills in the students. The growth of future innovation and production requires 21st-century skilled people [129]. Further, an established and technologically rich educational environment is essential for Industry 4.0 revolution. Factually, Technology enabled monitoring, assessment, and accreditation in the educational institution under Education 4.0 revolution are required for the holistic growth of learners and educators. Furthermore, minimal human intervention for ubiquitous monitoring and assessment in the educational institution has often been ignored to provide effective education. In Education 4.0 environment, ubiquitous monitoring, assessment, and accreditation will be easily carried out using IFC technology creating a resolute background for the same. Moreover, the framework can also be enhanced by generating real-time alerts and reports against any irregularity in educational

environment. Effective monitoring and assessment through IFC technology under the Education 4.0 environment has opened a new chapter for future educational institutions. The real-time reporting for any irregularity to the concerned authority in educational environment, will help to improve the educational environment on global standards. The recent developments and utilization of IoT devices, mobile internet, Technologies like IoT; Fog Computing; Cloud computing (IFC), Deep Learning, and AI have changed the scenario of data perception, data transmission, and information storage in many areas of life, including education sector [58], [130], [131], [132]. In the present scenario using IoT devices, it has become possible to sense and transmit various types of data in real-time. The massive growth in neural networks and AI technology results in reliable and accurate information acquisition, transmission, and prediction. The numerous opportunities in IFC computing and emerging requirements of Education 4.0 stability are the major inspiration behind the presented research. Influenced by these facts, the main contributions of this chapter are listed below:

1. This chapter emphasizes utilization of IoT; Fog Computing; Cloud Computing (i.e. IFC Computing) for intelligent monitoring and irregularity detection for real-time reporting to the concerned authorities for minimal damage in the educational environment.
2. Fog computing nodes are used for the classification of data accumulated by various IoT devices mainly in two classes i.e. Vulnerable Data Set (VDS) and Invulnerable Data Set (IDS) based on a set of threshold limits (SoTL).
3. Historical Adversity Approximation (HAA) is deployed to assess SoTL for real-time prediction of irregularities in an educational environment.
4. An irregularity prediction mechanism is offered to generate real-time alerts in respect of any irregularity in the educational institution and consequently, reporting to the concerned authority for in-time corrective actions.

5.2 C-IoT Based Proposed Model

Real-time assessment is one of the key challenges in the implementation of Education 4.0. Real-time assessment of every stakeholder including students, teachers, and administrative staff is of paramount importance for Education 4.0 [8]. Accuracy in

the assessment process of an educational institution directly depends upon the accuracy during data acquisition. The main motivation behind this chapter is to explore the most suitable technological integration for the implementation of Education 4.0 and to propose a suitable framework for assessment and irregularity detection for Education 4.0.

The chapter recommends the involvement of sensor-based data acquisition methods (IoT), data classification and integration methods over fog nodes, assessment, and irregularity detection methods over the cloud nodes for the implementation of the Education 4.0 environment. In brief IFC (IoT, Fog, and Cloud Computing) technological integration is recommended for the implementation of Education 4.0. Further C-IoT-based assessment and irregularity detection methods are also recommended in the chapter. Figure 5.3 illustrates the IFC based Proposed Layered Architecture for Assessment and irregularity detection for the ambient education environment under Education 4.0.

This proposed framework illustrates the conceptual model of an IoT-enabled campus under Education 4.0. IFC technology is the spine of the proposed model. IFC technological integration is proposed under this model for assessment and irregularity detection. All three technologies, i.e. IoT, Fog, and Cloud, constitute the following three layers of the proposed framework:

1. Physical Layer or IoT Layer.
2. Fog Layer.
3. Cloud Layer.

The subsequent subsections provide a detailed illustration of each layer along with the construction, implementation scenario, significance, outputs, etc. All 3 layers are committed to the execution of a predefined task to fulfill the aims of the proposed framework.

Firstly, Physical Layer or IoT Layer constitutes numerous physical devices including Mobile Phones, Smart-Watches, RFID Embedded ID cards, Sensors, Video surveillance cameras, Raspberry Pi, Actuators, and other IoT-enabled devices for real-time data acquisition [133]. The extracted data from IoT Layer is pre-processed with the local fog nodes at Fog Layer. The Fog layer is responsible for all data pre-processing activities

including classification, filtering, and abstraction [134]. The classified data is further filtered and abstracted over the local fog nodes under information mining. The filtered and abstracted information over the local fog nodes is further disseminated to the cloud layer for analysis and decision-making. Numerous data analysis algorithms are executed over the cloud layer for decision-making and irregularity detection. All the 3 layers are discussed in detail under the following subsections:

5.2.1 Physical Layer or IoT Layer

Numerous sensors, actuators, IoT enabled devices constitute the Physical or IoT Layer. All physical devices are broadly characterized under two main categories, i.e., movable and immovable. All wearable devices including smart-watches and RFID Embedded ID cards come under movable devices. Whereas stationary devices including video surveillance cameras, raspberry pi, actuators, and some other IoT-enabled stationary devices are categorized as immovable devices [135]. The detailed elaboration of movable and immovable devices is mentioned in Table 5.1.

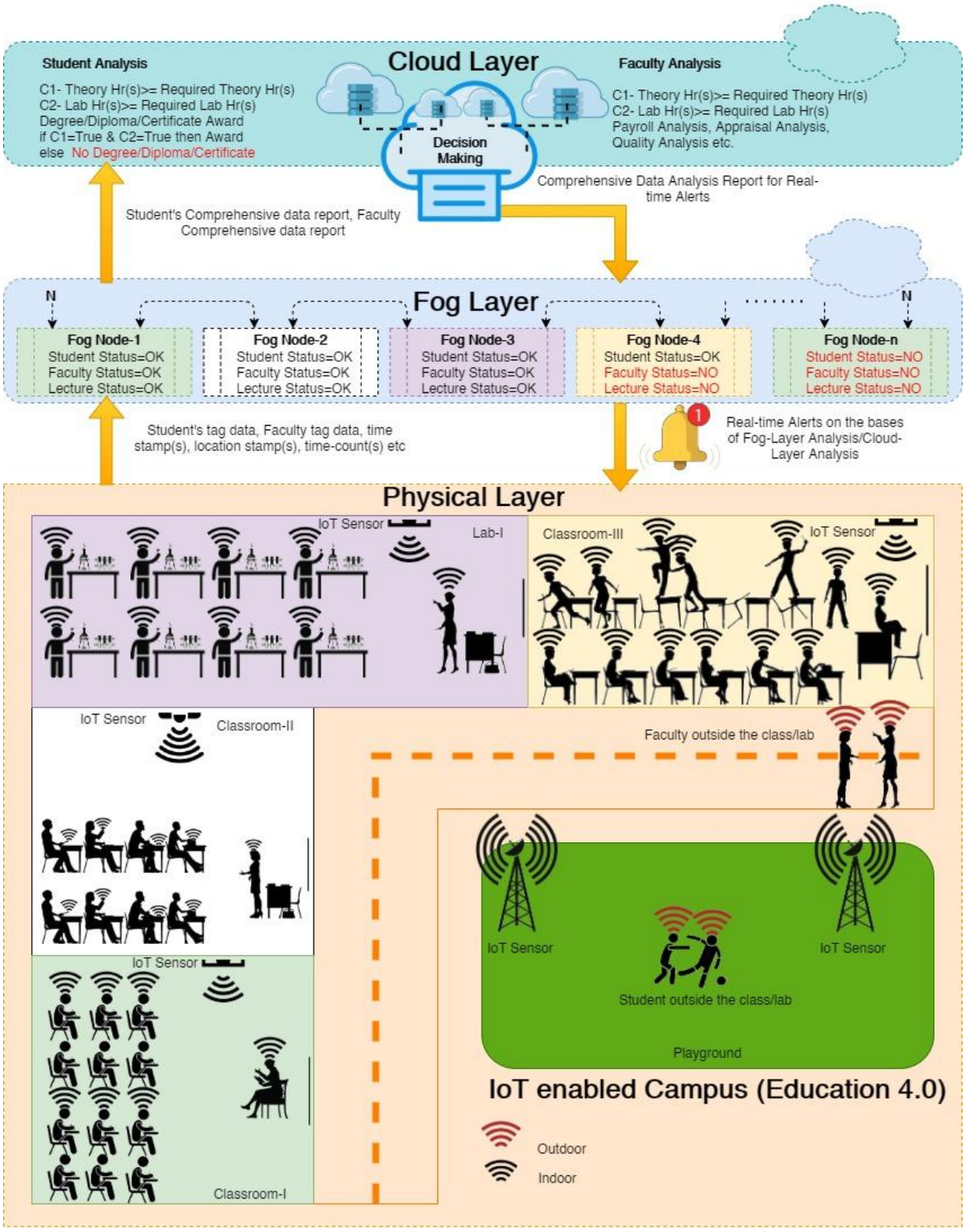


Figure 5.3. IFC based Proposed Layered architecture for Assessment and irregularity detection for the ambient education environment under Education 4.0

Table 5.1. Movable and immovable devices used under the Education 4.0 environment. C-Communication; F-File Transfer; S-Sensing, A-Actuation, FD-Fitness Data, AD-Activity Data, ED –Environment Data, √ Applicable, ×- Not-Applicable

	Device	Communication	Used for				Extracted Data		
			C	F	S	A	FD	AD	ED
Movable Devices	Mobile Phone	FDMA, TDMA, CDMA, GPS, Wi-Fi, and Bluetooth, etc.	√	√	√	×	√	√	√
	Smartwatch	Bluetooth, Wi-Fi, GPS, etc.	√	√	√	×	√	√	√
	RFID Embedded ID Cards	RFID	√	×	√	×	×	√	×
	IoT enabled devices	LPWANs, Wi-Fi, Bluetooth, Zigbee, Z-Wave, Sigfox, and RFID, etc.	√	√	√	√	√	√	√
	VR/AR Devices	3DOF, 6DOF, GPS, Wi-Fi, etc.	√	√	√	×	×	√	×
Immovable Devices	Video Surveillance Cameras	Internet Protocol (IP) and LAN	√	√	√	×	×	√	√
	Raspberry PI	Wi-Fi, Bluetooth, micro-HDMI, Ethernet, and GPS, etc.	√	√	√	√	√	√	√
	Actuators	WSAN	√	×	×	√	×	√	√
	IoT enabled devices	Wi-Fi, Bluetooth, Zigbee, Z-Wave, Sigfox, and RFID, etc.	√	√	√	√	√	√	√

Various devices proposed at the physical layer and their uses are listed below:

- Mobile Phones of every stakeholder registered with the institution database are used to check the real-time location (Geographical time stamp) of stakeholders.
- Smart-watches and fitness bands are deployed to check the health-related data of stakeholders.
- RFID Embedded ID Cards are used to check the real-time geographical location of stakeholders [136].
- Courseware is a specially designed (institution-specific) hardware/software that contains all the digital information about various courses running in the

institution. It is used to check the various aspects of courses and the other assessment and accreditation activities related to courses [137].

- Thermistors, Resistance temperature detectors, and Thermocouples are used to acquire temperature data from various places including classrooms, labs, offices, libraries, workshops, etc. [138]
- A psychrometer and Hair tension moisture sensors are deployed to check the moisture and humidity data from various places [139].
- Photoresistor and Photodiode are used to collect ambient light intensity data from various places [140].
- Hydrophone and Geophone are deployed to monitor the level of noise [141].
- Hydrostatic pressure sensors and optical sensors are used to check pressure levels in labs [142].
- Doppler radar and Occupancy sensors are deployed to observe the motion of stakeholders in classrooms, labs, offices, corridors, passages, etc. [143]
- Active-ultrasonic motion sensors, Passive-infrared motion sensors, Active-radar sensors, and Passive-infrared sensors (PIR) are used as motion sensors with surveillance cameras [144].
- Gyroscope IoT sensors including Accelerometer and Heading indicator sensors are deployed at various sports locations to check the motion of stakeholders w.r.t. the stationary objects [145].
- Chemical IoT sensors including Electrochemical Breathalyzer and an Electronic nose are deployed to check the air and water purity [146].Click or tap here to enter text.
- Image IoT sensors like Active-pixel sensors and Charge-coupled devices are used along with surveillance cameras for image monitoring [147].Click or tap here to enter text.
- Along with all these IoT sensors linear actuators, motors, relays, solenoids are also deployed for various other purposes [148].

5.2.1.1 Data Perception Layer (DPL)

The sensation (perception/responsiveness) of data in the proposed smart campus/institution is monitored and collected under this layer. The classification of various stakeholders as students, faculty, and administrative staff becomes indispensable to identify in real-time. Conspicuously, IoT devices and sensors are embedded in the ID Cards, wearables, and various other geographical areas of the campus [149]. The various stakeholders are characterized by their respective embedded ID cards and their presence is ensured by the respective location-stamp and timestamp. Numerous sensors and actuators are available commercially to sense and react to real-time data. A brief overview of such sensors and actuators has been illustrated in Table 5.1 along with their respective characteristics. Further, other data related to the ambient environment (inner and outer temperature of the classrooms, humidity level, pressure and availability of oxygen, etc.) are acquired using a temperature sensor, humidity sensor, pressure sensors, and gas sensors [150]. The time-stamp and location-stamp are acquired using GPS/GNSS sensors [151]. The acquired data which is mentioned above is then transferred to the currently available local fog computing nodes like routers, switches, Raspberry Pi, and other smart fog devices. The acquired data is transmitted using wireless communication protocols like Bluetooth LE, SigFox, RFID, ZigBee, NFC, Z-Wave, WiFi, etc. over the HTTP (Hypertext Transfer Protocol) and MQTT (Message Queuing Telemetry Transport) [9]. Various IoT communication technologies and protocols used for various vendible applications are illustrated in Table 5.2 [152]. Further, SSL i.e. Secure Socket Layer is used to protect the wireless communication channel [76]. Correspondingly, to store data on fog nodes authentication and mapping techniques are used [153]. For effective temporal analysis, the data is stored on fog nodes in a time-synchronized manner using location-stamp and timestamp.

Table 5.2. IoT communication technology and protocols [152]

Characteristics	**6LoWPAN**	**Bluetooth LE**	**Cellular**	**NFC**	**RFID**	**SigFox**	**ZigBee**	**Z-Wave**
Common Applications	Monitor and Control via internet	Wireless headsets, Audio Applications	M2M	Payment, Access	Tracking, Inventory, Access	Street Lighting Energy meters	Home industry monitoring and controlling	Home Monitoring and Control
Data Rate	250 kbps	1 Mbps	40kbps	100 bps (UL), 600 bps (DL)	106 212 or 424 kbps	NA	250 kbps	100 kbps
Features	Commonly Used Internal Access	Low power version available	Longer Range	Security	Low Cost	Long Battery life (up to 20 years) Low Cost	Mesh Network	Simple Protocol
Frequency Bands	868 MHz(EU) 915MHz(USA) 2.4GHz(Global)	2.4 GHz	Common Cellular bands	125 KHz, 13.56 MHz, 860 MHz	125 KHz, 13.56 MHz, 902-928 MHz	868MHz(EU) 902MHz(USA)	2.4 GHz	868 MHz-908 MHz
Modulation Type	BPSK O-QPSK	TDMA	BPSK OFDM	ASK	FSK PSK	UNB DBPSK (UL), GFSK (DL)	BPSK/BPSK O-QPSK	BFSK
Network	WPAN	WPAN	WNAN	P2P Network	Proximity	LPWAN	WPAN	WPAN
Power	(1-2 years	30 mA	High Power	50 mA	Ultra-low	10 mW-	30 mA	2.5 mA

	lifetime on batteries) Low power consumption	Low Power	Consumption	low power Very Low	Power	100 mW	Low Power	Low power consumption
Security	AES	E0 Stream AES-128	RC4	RSA AES	RC4	Partially addressed	AES	AES-128
Spreading	DSSS	FHSS	DSSS	GSMA	DSSS	DSSS	DSSS	No
Standard	IEEE 802.15.4	IEEE 802.15.1	3GPP and GSMA, GSM/GPRS/EDGE (2G), UMTS/HSPA (3G), LTE (4G)	ISO/IEC 14443 A&B,JIS X-6319-4	RFID	SigFox	IEEE 802.15.4	Z-Wave
Range	Short Range 10-100 m	Short Range ~15-30 m	Several km	Short Range 0-10 cm m 10 cm-1 m	Short Range Up to 200 m	Long Range 10km (URBAN) 50km (RURAL)	Short Range 10-100 m	30 m (indoors) 100 m (outdoors)
Topology	Star Mesh Network	Star-Bus Network	NA	P2P Network	P2P Network	Start Network	Star, Mesh Cluster Network	Mesh Network

5.2.1.2 Data Classification Layer (DCL)

DCL is the Data Classification Layer. The data collected over the data perception layer is transmitted over the fog computing nodes. The stakeholder's fitness-oriented data (temperature, heart rate, and blood pressure), environment-oriented data (inner and outer temperature of the classrooms, humidity level, pressure and availability of oxygen, etc.), and stakeholder's activity data (timestamp, location-stamp, embedded ID cards, and bio-stamp) are stored on the fog nodes in heterogeneous form. The acquired data in real-time is transmitted over fog nodes and they are further specifically classified into four different datasets i.e. Stakeholder Fitness Dataset (SFD), Campus Environment Dataset (CED), Stakeholder Activity Dataset (SAD), and Course Authenticity Dataset (CAD). These datasets have been defined in detail in the subsequent sections.

i. Stakeholder Fitness Dataset (SFD): The fitness-related data instances for each stakeholder in real-time constitute the SFD. The various instances of Stakeholder Fitness Dataset (SFD) are body temperature, heart rate, oxygen measure (SpO2) and blood pressure, etc. [154]. Such datasets are assimilated using various IoT-enabled sensors and actuators integrated with smartwatches and embedded ID cards as wearable IoT. Features have been extracted from these datasets by using a cross-modality search. The use of cross-modality search on datasets improves the efficiency of data assessment [155]. This dataset has been integrated to check the real-time fitness status of all the stakeholders.
ii. Campus Environment Dataset (CED): The environment-oriented and geographical data values for each predefined geographical cluster like classrooms, labs, grounds, open areas, auditoriums, etc. constitute the CED. This dataset shows the ambient environmental conditions of various geographical clusters. The various instances of Campus Environment Dataset are indoor and outdoor temperature level, humidity level, pressure, noise, and availability of oxygen (air quality), etc. Such datasets are acquired using various sensors like temperature sensors, pressure sensors, gas sensors, and humidity sensors. Various data elements are integrated to check the ambient environmental conditions of the campus. The Campus Environment Dataset

is also integrated with Stakeholder Fitness Dataset for more accurate results. The environmental features have been extracted by using SAX (Symbolic Aggregate approximation) [156]. SAX ensures effective feature extraction over the Campus Environment Dataset (CED).

iii. Stakeholder Activity Dataset (SAD): The activity-oriented data values for each stakeholder in real-time constitute the SAD. The various instances of stakeholder Activity Datasets are location-stamp, timestamp, biometric-stamp, etc. Proximity sensors, bio-sensors, and GPS/GNSS sensors are used to sense stakeholders' activity data values. Various data elements are integrated to check the real-time stakeholder activities. A hidden state Conditional Random Field framework has been deployed for effective data analysis [157].

iv. Course Authenticity Dataset/Courseware (CAD/CW): The course-oriented data values in real-time constitute the CAD/CW. This dataset is neither sensed by any sensor nor generated by any IoT devices. Rather it is developed by the respective institution as per the courses running, time-stamps and location-stamps, student-stamp, teacher-stamp and duration-stamp, etc. timestamp is the duration of the daily class, and the location-stamp is the geographical-location of the campus associated with the respective course and time. The student-stamp is the embedded ID(s) & biometric identity of all the students associated with that class, similarly, the teacher-stamp is the embedded ID & biometric identity of the associated teacher and duration-stamp is the total number of hours allocated to the course and the number of hours completed by the students on a specific timestamp at real-time.

All the data extraction techniques are illustrated in Figure 5.4. An educational institution is a complex environment so the collection and integration of data is a very challenging task. In a real-time environment of educational institutions, the collection of falsified data instances is also possible. It is necessary to pre-process the collected data to protect it from falsified data that leads to inaccurate results. Maximum likelihood (ML) or maximum a posteriori (MAP) are used iteratively under Expectation-Maximization (EM) algorithm in the initial step of data pre-processing [158], [159]. The log-likelihood corrects the falsified data. Further Kalman filter is used for the smoothing of the EM

algorithm [160]. E-step and M-step under Kalman Filter make the falsified data correct for accurate result calculation.

Maximum likelihood estimates as:

$$\hat{\sigma}_v^2 = \frac{1}{N}\sum_{k=1}^{N}(Z_k - \hat{x}_k)^2$$

Where $\hat{x}_k$ are scalar output estimators and Z_k are scalar measurements.

The noise variance estimates as:

$$\hat{\sigma}_w^2 = \frac{1}{N}\sum_{k=1}^{N}\left(\hat{x}_{k+1} + \hat{F}\hat{x}_k\right)^2$$

Where $\hat{x}_k$ and $\hat{x}_{k+1}$ are scalar state estimators.

Updated model coefficient $\hat{F}$ is calculated as:

$$\hat{F} = \frac{\sum_{k=1}^{N}(\hat{x}_{k+1} - \hat{F}\hat{x}_k)}{\sum_{k=1}^{N}\hat{x}_k^2}$$

After the initial pre-processing of data through the EM algorithm, the extracted data is again analyzed by the LBN for efficacious data cataloguing [161].

A set of threshold limits (SoTL) is used for the LBN model. SoTL is useful for the classification of data with respect to threshold limits.

Definition 1. *SoTL (Set of threshold limits) is defined as the set of allowed threshold values of all the variables like minimum and maximum room temperature allowed for students of a specific age group, body temperature, timestamps, and location-stamps, etc. over a time frame* ΔT.

Conceptually the SoTL is very useful for data classification. Based on defined threshold limits the data set is effortlessly classified into two different data sets i.e. vulnerable and invulnerable.

Data Classification

The Stakeholder Fitness Dataset (SFD), Campus Environment Dataset (CED), Stakeholder Activity Dataset (SAD), and Course Authenticity Dataset/Courseware (CAD/CW) over a time frame ΔT for its respective SoTL set classifies the pre-processed and filtered data into two different data sets i.e. Vulnerable Data Set (VDS) and Invulnerable Data Set (IDS). Each of these data sets is discussed below in detail.

1. ***Vulnerable Data Set (VDS):*** VDS is the set of those data instances that are susceptible to an individual stakeholder or a group of stakeholders. This data set leads to severe issues under various conditions, i.e., a sudden increase in the temperature of a specific classroom affects a group of stakeholders that includes a set of students, teachers, and other officials or lab workers sharing the same location-stamp. On the other hand, the increase in temperature of a particular stakeholder only affects that stakeholder. But in both cases, the acquisition of such data elements requires immediate actions to prevent major damage. A special analysis approach is required to handle this type of dataset.
2. ***Invulnerable Data Set (IDS):*** IDS is the set of those data values that are under threshold limits. This data set is safe and invulnerable and doesn't require any special action or analysis approach. The normal body temperature and normal classroom temperature don't affect any individual stakeholder or a group.
3. LBN model based on the conditional probability table for the classification of datasets is used where VDS and IDS classes are related to the invulnerability of an individual stakeholder. Let V_i indicate the vector associated with i^{th}considerable parameter for vulnerability check. All the considerable parameters are identical. Based on all the (n) mutually unrelated considerable parameters for vulnerability check for each stakeholder the conditional discrete probability table for classification is drawn that converts the probability into two values i.e. 0 and 1. Consequently, the results of the discrete conditional probability table divide the dataset into two different sets i.e., VDS and IDS. For (n) mutually unrelated considerable parameters 2^n different probability values have been calculated. For instance, 3 mutually unrelated parameters (ABC) are tabulated as:

Table 5.3. Discrete conditional probability table for mutually unrelated parameters (ABC), VDS- Vulnerable Dataset; IDS- Invulnerable Dataset; D-Discrete Probability and P-Probability

ABC	$P_0(A_0B_0C_0)$	$P_1(A_0B_0C_1)$	$P_2(A_0B_1C_0)$	$P_3(A_0B_1C_1)$	$P_4(A_1B_0C_0)$	$P_5(A_1B_0C_1)$	$P_6(A_1B_1C_0)$	$P_7(A_1B_1C_1)$
VDS	0.9	0.7	0.2	0.8	0.3	0.5	0.1	0.6
IDS	0.1	0.3	0.8	0.2	0.7	0.5	0.9	0.4
$(VDS)_D$	1	1	0	1	0	0	0	1
$(IDS)_D$	0	0	1	0	1	0	1	0
	VDS	VDS	IDS	VDS	IDS	Neutral (VDS)	IDS	VDS

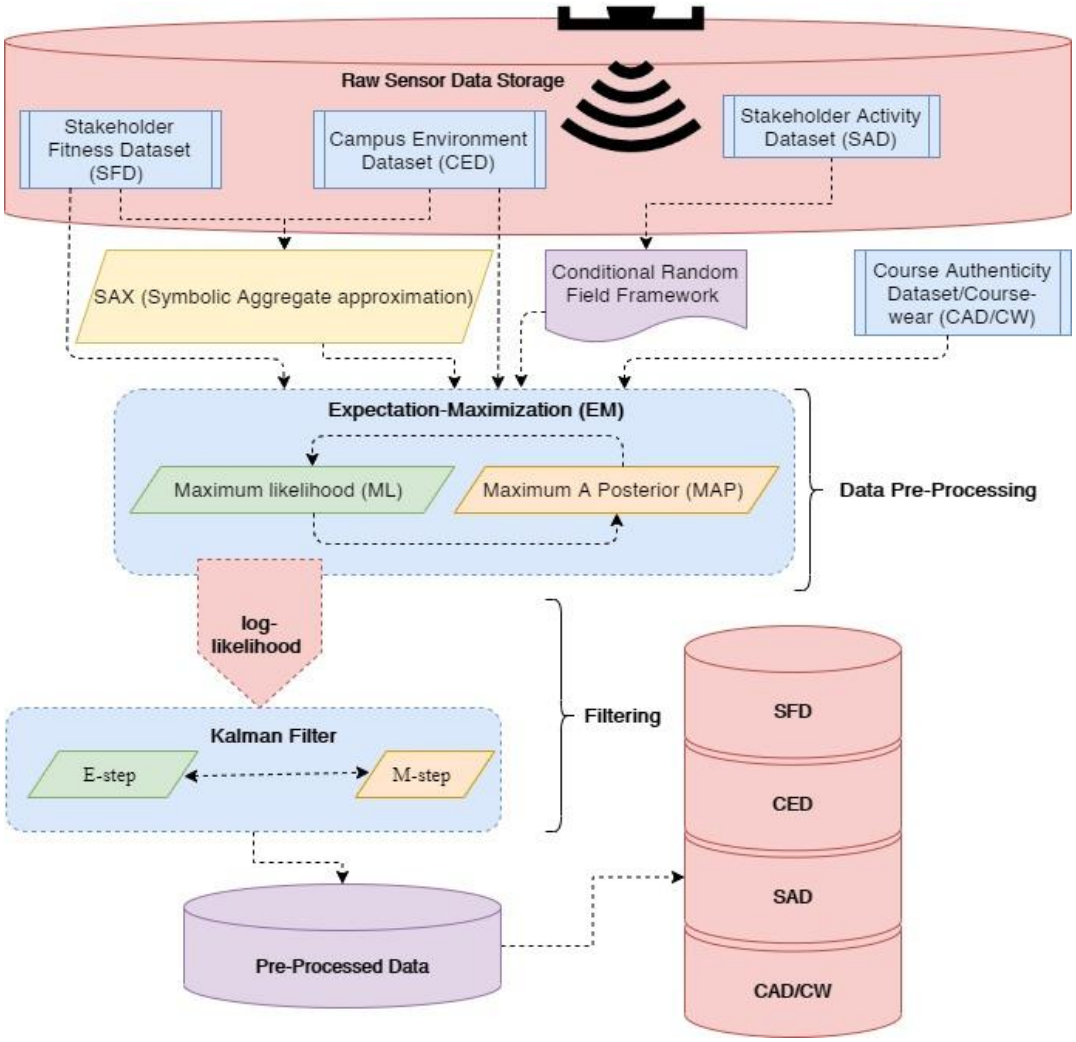


Figure 5.4. Data Extraction, Pre-Processing and Filtering

The datasets $(VDS)_D$ and $(IDS)_D$ represent the discrete Vulnerable and Invulnerable datasets respectively. The Neutral result value is considered as VDS as the Neutral result represents the threshold value of IDS and has an equal probability to come under VDS or IDS at any point in time. To avoid the risk of ignored vulnerable parameters all the neutral values are considered as VDS.

The VDS and IDS are converted into $(VDS)_D$ and $(IDS)_D$ respectively based on the following probability check parameters:

$(VDS)_D$, $(IDS)_D$ =1 if VDS, IDS >=0.6

$(VDS)_D$, $(IDS)_D$ =0 if VDS, IDS <0.6

$(VDS)_D$, $(IDS)_D$ =Neutral if VDS, IDS =0.5

$P_{iabc} = P_i(A_a B_b C_c)$

$where\ 0 \leq i < 2^N\ and\ N\ is\ number\ of\ considerable\ parameters$

$and\ a, b, c\ is\ 0,1$

The joint probability for j^{th}stakeholder can be calculated as:

$$P_j(C_k) = \sum_{i=0}^{i<2^N} P_{i(abc)}$$

Where, $C_k$is the VDS and IDS classes.

5.2.1.3 Information Mining & Abstraction Layer (IMAL)

IMAL is the Information Mining and Abstraction Layer. IMAL Layer is devoted to mining valuable data from various stakeholders' datasets. Precisely, the presented framework is intended to provide real-time assessment and monitoring services for various stakeholders associated with an educational institution. Conspicuously, Temporal Data Mining (TDM) is used to extract valuable data instances for monitoring and reporting [162]. The extracted data segments are further analyzed in-depth to check the vulnerability areas of every stakeholder. In the form of time-series notation for the formation of data segments Temporal Data Mining (TDM) is an effectual method.

Definition 2. *Temporal Chunk(TC): Given SoTL (Set of threshold limits) assessment of data instances in the time frameΔT, then Temporal Chunk (TC) is exemplified as a combination of data instances to every considerable parameter analogous to every occurrence of time $t \in \Delta T$ and is symbolized as* $(t_1, v_1)(t_2, v_2)(t_3, v_3)(t_4, v_4) \dots\dots\dots\dots\dots (t_n, v_n)$

Data abstraction is necessary for a real-time data collection scenario. Temporal Chunk (TC) is an effective formulation for data abstraction. It nullifies the data with no potential change and only selects the data that shows some potential change and contributes to detailed analysis. The temporal chunks are also important for predicting vulnerable areas for each stakeholder and the formation of detailed reports about all vulnerable issues encountered during the monitoring of a stakeholder. Figure 5.5 illustrates the Temporal Chunk (TC) in an educational environment.

Definition 3. *Historical Adversity Approximation (HAA): For a given temporal Chunk (TC) for a time frameΔt, Historical Adversity Approximation (HAA) is a quantifiable aspect based on SoTL measure of various parameters for a particular stakeholder or stakeholder group. Mathematically Historical Adversity Approximation (HAA) is calculated as:*

$$HAA = \frac{1}{n}(w_1 \times SoTL_1 + w_2 \times SoTL_2 + w_3 \times SoTL_3 + \cdots \dots\dots\dots + w_n \times SoTL_n$$

$w_1, w_2, w_3, \dots\dots, w_n$ are the respective weights for i^{th} parameter i.e. $SoTL_i$.

Historical Adversity Approximation represents the vulnerability measure of various data items based on SoTL that helps in the estimation of vulnerability impact on an individual stakeholder or group of stakeholders. The large value of Historical Adversity Approximation (HAA) indicates vulnerable circumstances for a stakeholder or group of stakeholders whereas the small value indicates invulnerable circumstances. The important characteristic of HAA is to detect irregularities in the education environment around individual stakeholders. Consequently, corrective action can be taken at the early stages of irregularities and unavoidable and harmful situations in educational institutions can be controlled at the early stages. Further Map-Reducing Function is used for data

abstraction. Apache Hadoop and Spark are some of the well-known platforms for the use of Map Reducing for distributed data computation [163]. Map Reducing is one of the most effective parallel programming platforms. Figure 5.6 illustrates the detailed procedure of the Historical Adversity Approximation (HAA) measure for stakeholder or stakeholder group vulnerability.

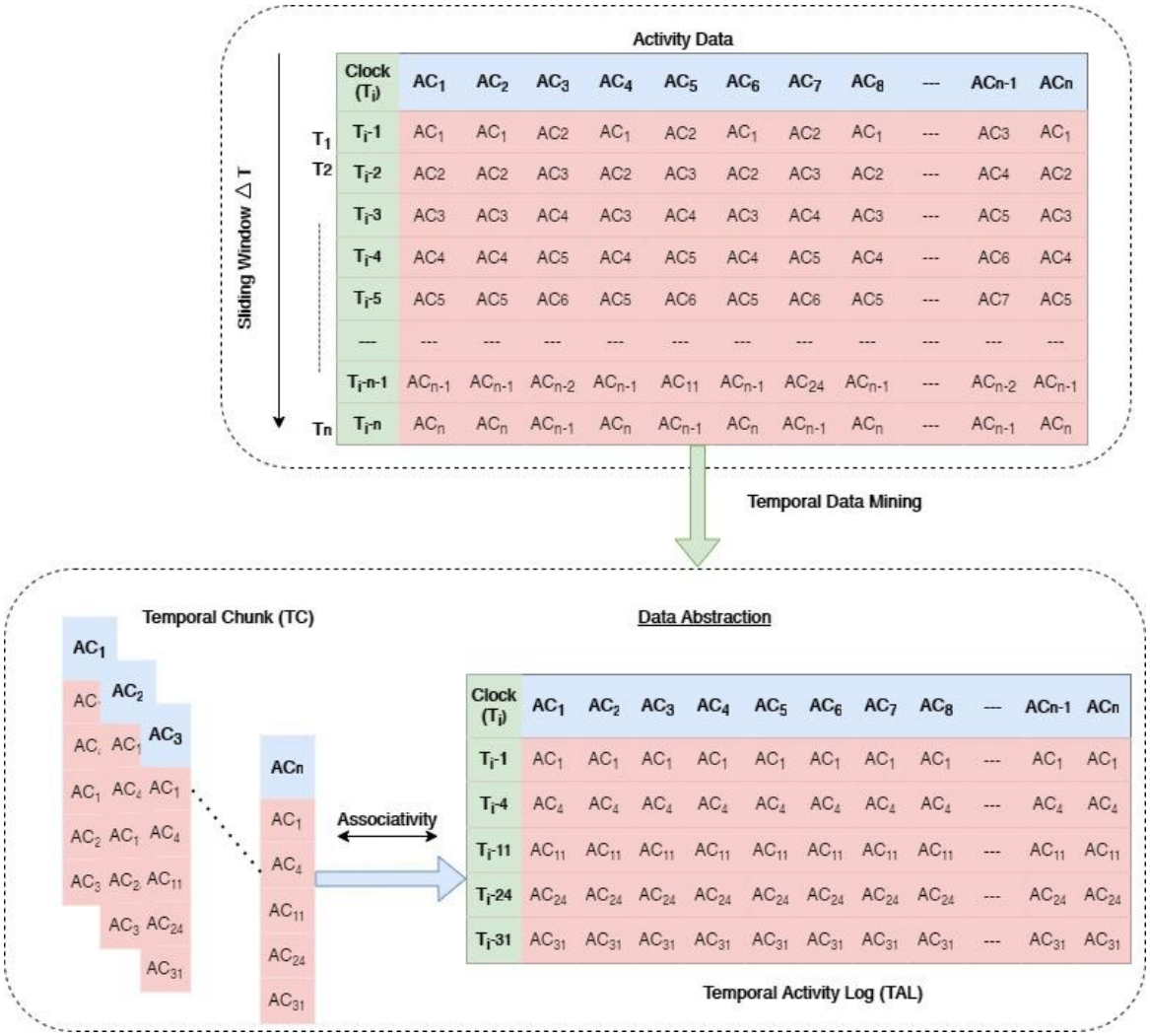


Figure 5.5. Temporal Chunk (TC) for Institutional data

5.2.1.4 Predictive Decision-Making Layer (PDML)

PDML is the Predictive Decision-Making Layer. PDML is a fog computing-inspired novel model for various stakeholders in the educational institute. The Historical Adversity Approximation (HAA) based educational severity is predicted with the help of Deep Learning-based M-Bi-LSTM. The M-Bi-LSTM architecture is an amalgamation of three robust techniques of deep learning involving Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), and Bi-Directional Long Short Term Memory (Bi-LSTM) [164]. The design of the presented model is symbolized in Figure 5.7. CNN is used to forecast the adverse data instances by classified datasets (Only Image Data) of Historical Adversity Approximation (HAA), the datasets other than images are classified through RNN and GRU. The extracted adverse data is pooled into the Bi-LSTM. Bi-LSTM uses these extracted data instances for sequential learning. Every projected dataset is deliberated as distinct objects by Bi-LSTM. To analyze every possible pattern locally, for a time frame ΔT based on Temporal Chunk (TC), CNN and RNN read the respective clusters of predicted adverse values. The extracted patterns are pooled further to Rectified Linear Unit (ReLU) and with Gated Recurrent Unit (GRU) which are the non-linear functions for pattern transformation [164], [165]. Further, the max-pooling function is used to change the transformed patterns into feature vectors. Finally, the feature vectors are analyzed to predict the next adverse event for a stakeholder or group of stakeholders by Bi-LSTM. The step-by-step detailed illustration of the proposed model is elaborated below.

5.2.1.4.1 Adaptive Optimization Unit (AOU)

Adaptive Optimization Unit (AOU) classifies the input dataset into various categories like text, audio, video, and image data and also pools this data to their respective units for the extraction of adverse data. The text and audio datasets are further processed by RNN whereas the video and image datasets are processed by CNN for better performance of M-Bi-LSTM [166].

5.2.1.4.2 Recurrent Neural Network (RNN) and Convolutional Neural Network (CNN)

Recurrent Neural Network (RNN) and Convolutional Neural Network (CNN) are the two robust techniques of deep learning [167]. The input dataset affects the performance of RNN and CNN. CNN gives the best performance for video and image datasets whereas RNN is the best-suited algorithm for text and audio datasets. For small educational institutions data where the number of stakeholders is small (<1000), either RNN or CNN can be used but as

the no. of stakeholders increases the use of a single algorithm decreases the performances of the overall model. For unanimous best performance, both RNN and CNN with AOU are proposed in this model.

5.2.1.4.3 Rectified Linear Unit (ReLU) and Gated Recurrent Unit (GRU)

Rectified Linear Unit (ReLU) and Gated Recurrent Unit (GRU) are used with Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) as non-linear functions for pattern transformation respectively. The convolutional layers are entrenched at the top to read the patterns of a local dataset. ReLU and GRU are used with their respective neural network techniques to convert the local to universal configuration vectors. Further, the universal configuration vectors are transmitted for adversity prediction to the presented M-Bi-LSTM model.

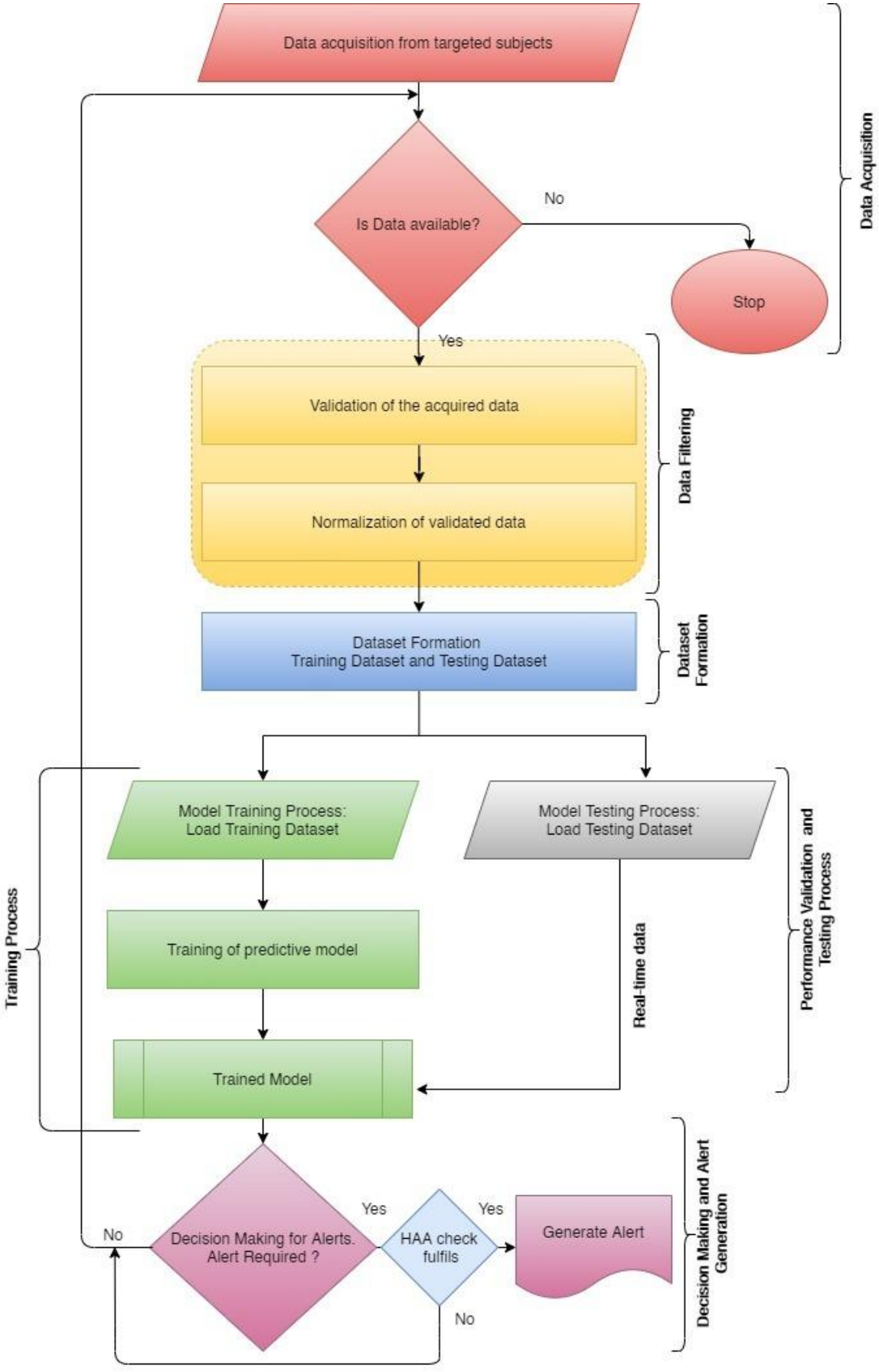


Figure 5.6. Complete process for Alert Generation using HAA estimation

5.2.1.4.4 Multi-layered Bi-Directional Long Short-Term Memory (M-Bi-LSTM)

The proposed M-Bi-LSTM network is a combination of 4 data processing layers. These 4 layers of M-Bi-LSTM represent a deep neural network. The primary layer of the proposed module is connected with the captured input and behaves like a layer of memory cells. The second and third layers of the model are used for forward learning and backward learning respectively. The last layer is used for irregularity prediction in terms of outcome probability.

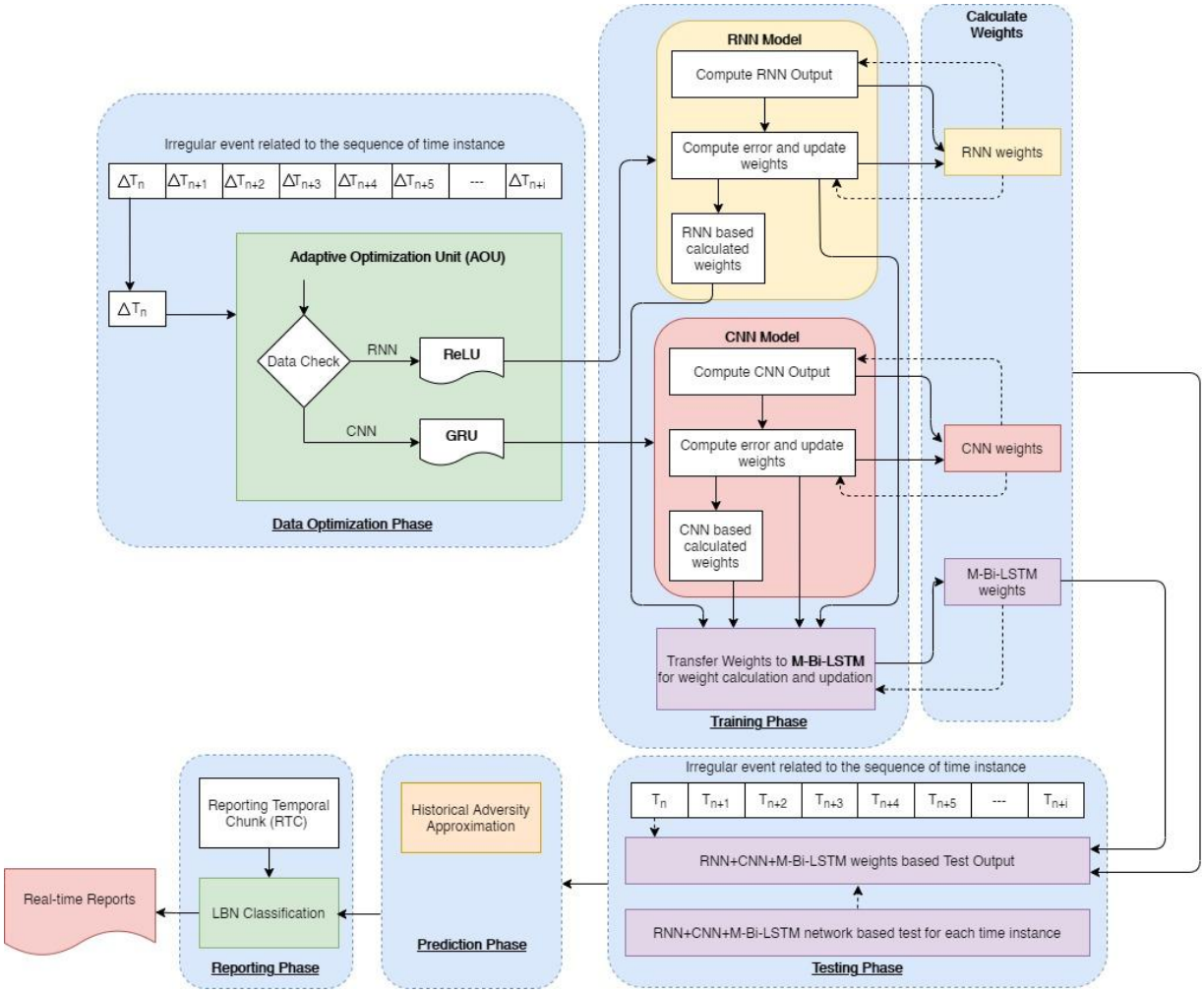


Figure 5.7. M-Bi-LSTM inspired Adversity Prediction and reporting model

A major outcome and novel deliverable of this study is the development of the M-Bi-LSTM model, a multi-layer bidirectional long short-term memory network specifically designed for data classification and prediction within the Education 4.0 environments. To the best of the researcher's knowledge, this is the first application of an M-Bi-LSTM architecture for handling educational data characterized by hidden parameters, real-time inputs, and complex temporal dependencies. The proposed M-Bi-LSTM consists of four dedicated data-processing layers, forming a deep neural network capable of capturing both short-term and long-term

patterns. The initial layer directly interfaces with the captured input data and functions as a memory cell layer, enabling effective retention of contextual information. The second and third layers perform forward and backward learning, respectively, allowing the model to analyze data sequences in both temporal directions and thereby improve classification accuracy. The final layer translates the learned representations into probabilistic predictions of irregularities, providing a robust and interpretable outcome measure. By integrating bidirectional learning with multi-layer memory processing, the M-Bi-LSTM delivers a scalable and intelligent predictive framework, marking a significant methodological contribution and reinforcing the study's novelty in data-driven assessment and quality assurance under the Education 4.0 paradigm.

5.2.2 FOG LAYER

The extracted data from the physical layer are pre-processed over local fog nodes. Data pre-processing, data filtering, and data classification are the major activities executed under fog nodes [168]. Symbolic Aggregate Approximation (SAX) and the Conditional Random Field Framework are deployed at the initial level of data pre-processing [169]. The acquired data from Physical Layer i.e., IoT Layer is classified under various sets. The Stakeholder Fitness Dataset (SFD), Campus Environment Dataset (CED), Stakeholder Activity Dataset (SAD), and Course Authenticity Dataset (CAD) are the main datasets deployed for assessment and accreditation. A brief illustration of these datasets is mentioned below:

1. Stakeholder Fitness Dataset (SFD) constitutes the past history and real-time fitness status of every stakeholder.

2. Campus Environment Dataset (CED) covers various factors of the campus environment including, temperature, humidity, air pressure, noise, etc.

3. Stakeholder Activity Dataset (SAD) includes the location stamp, timestamp, biometric timestamp, etc.

4. Course Authenticity Dataset/Course-Ware (CAD/CW) comprises all the information in respect of courses running in the institutions including name, course, course code, students enrolled under the course, duration of the course, assessment and accreditation constituents, etc. Course Authenticity Dataset (CAD) is also termed as Course-Ware (CW) [16].

All these pre-processed, filtered and classified datasets are further used for the assessment and accreditation process. The subsequent section illustrates the assessment, reporting, and irregularity detection process executed over the cloud layer.

5.2.3 CLOUD LAYER

Real-time assessment, reporting, and irregularity detection have been executed over the cloud node. For assessment, SoTL (Set of Threshold Limits) is deployed to predict major irregularities in each dataset in real-time. Table 5.2 illustrates the SoTL table for two variables associated with SFD Dataset.

Definition 1: *Set of Threshold Limits (SoTL) are the sets of all threshold values of various variables including the minimum required values, maximum acceptable values, etc. e.g. under SFD, minimum and maximum heartbeat level, oxygen saturation level, body temperature, etc., are included.*

As mentioned in Table 5.4, various other variables and datasets have separate SoTL. Based on respective SoTL value assessment, irregularity detection, and alarm generation have been executed. RNN, CNN, and M-Bi-LSTM are deployed over the cloud node for executing all these activities [169].

5.2.3.1 Assessment

The classified data from the fog layer is evaluated on the cloud layer on the basis of their respective SoTL dataset. Under assessment, various dataset integration is used. e.g. courseware dataset is integrated with the student activity dataset for the academic assessment. The stakeholder fitness dataset is integrated with the campus environment dataset for real-time assessment of stakeholders' fitness etc. Dataset integration from various resources also boosts the quality of assessment. The following are the main assessment activities proposed during this study:

a. Stakeholders' Fitness Assessment has been executed based on various fitness-related parameters. HIoT (Healthcare Internet of Things) is deployed for fitness assessment [170]. Stakeholder Fitness Dataset and Campus Environment Datasets are integrated for stakeholders' fitness assessment. This assessment initiates various fitness-related irregularity detections and corresponding alarming. Stakeholders Fitness Assessment is very useful to take preventive actions to control the spreading of contagious/epidemic/pandemic diseases.

b. Students' Course Assessment has been executed on the basis of various courseware parameters. Stakeholders' Activity Dataset and Courseware Dataset are integrated for Students' Course Assessment. The corresponding alarming and irregularities detection initiates after accomplishing the Students' Course Assessment. This assessment helps students to complete their theory and lab hours, course credits, etc. Early detection of irregularities will decrease student dropout and consequently the result and education quality will also improve. Students' Course Assessments have a greater impact on various components including quality, satisfaction and irregularity detection, etc.

Table 5.4. SoTL table for Body Temperature and Heartbeat Level under Stakeholder Fitness Dataset (SFD)

$f(x) = 0$ Indicates invulnerable state and $f(x) = 1$ indicates the vulnerable state

Variable	Age Group	Min-Value	Max-Value	Vulnerable dataset	
Body Temperature	0-2 Year	94.5 °F	99.1 °F	$f(x) = \begin{cases} 1, \\ 0, \end{cases}$	$94.5\ °F < x > 99.1°F$ $94.5\ °F \geq x \leq 99.1°F$
	3-10 Year	96.6 °F	98.0 °F	$f(x) = \begin{cases} 1, \\ 0, \end{cases}$	$96.6\ °F < x > 98.0°F$ $96.6\ °F \geq x \leq 98.0°F$
	11-65 Year	95.3 °F	98.4 °F	$f(x) = \begin{cases} 1, \\ 0, \end{cases}$	$95.3\ °F < x > 98.4°F$ $95.3\ °F \geq x \leq 98.4°F$
	Over 65 Year	96.0 °F	97.4 °F	$f(x) = \begin{cases} 1, \\ 0, \end{cases}$	$96.0\ °F < x > 97.4°F$ $96.0\ °F \geq x \leq 97.4°F$
Heartbeat Level	0-1 Year	100 bpm	160 bpm	$f(x) = \begin{cases} 1, \\ 0, \end{cases}$	$100\ \text{bpm} < x > 160\ \text{bpm}$ $100\ \text{bpm} \geq x \leq 160\ \text{bpm}$
	1-3 year	90 bpm	150 bpm	$f(x) = \begin{cases} 1, \\ 0, \end{cases}$	$90\ \text{bpm} < x > 150\ \text{bpm}$ $90\ \text{bpm} \geq x \leq 150\ \text{bpm}$
	3-5 year	80 bpm	140 bpm	$f(x) = \begin{cases} 1, \\ 0, \end{cases}$	$80\ \text{bpm} < x > 140\ \text{bpm}$ $80\ \text{bpm} \geq x \leq 140\ \text{bpm}$
	5-12 year	70 bpm	120 bpm	$f(x) = \begin{cases} 1, \\ 0, \end{cases}$	$70\ \text{bpm} < x > 120\ \text{bpm}$ $70\ \text{bpm} \geq x \leq 120\ \text{bpm}$
	12-18 year	60 bpm	100 bpm	$f(x) = \begin{cases} 1, \\ 0, \end{cases}$	$60\ \text{bpm} < x > 100\ \text{bpm}$ $60\ \text{bpm} \geq x \leq 100\ \text{bpm}$

c. Stakeholders' Working Hours Assessment has been executed on the basis of Stakeholders' Activity parameters. Stakeholders' Activity Dataset and Courseware Dataset are integrated for Stakeholders' Working Hours Assessment. The real-time working hours assessment has a greater impact on employee retention and in-time course completion. The real-time working hours assessment will also eradicate human errors in calculating stakeholders' working hours.

d. Stakeholders' (Excluding Students) Payroll Assessment has been executed on the basis of Stakeholders' Activity parameters. Students are excluded from this assessment as they are not part of the payroll system. Stakeholders' Payroll Assessment will be executed after stakeholders' Working Hours Assessment. Stakeholders' Working Hours Assessment is associated with their payroll history including their salary components and allowances etc. for Stakeholders' Payroll Assessment.

e. Stakeholders' (Excluding Students) Appraisal Assessment has been executed on the basis of Stakeholders' Activity parameters. Working hours, Payroll, Quality, Performance, Feedback, etc. are the major components that affect Stakeholder's Appraisal Assessment. The proposed Appraisal Assessment is a transparent system and has zero human errors and human bias.

f. Stakeholders' Quality Assessment has been executed on the basis of Stakeholders' Activity parameters. Quality is a component that depends on two major factors i.e. the inputs (efforts) made by stakeholders in terms of working hours and the outputs in terms of results. The M-Bi-LSTM based predictive algorithm is used to predict the outputs or results of various stakeholders [169]. On the basis of the predictive results and actual results, the quality will be calculated.

g. Stakeholders' Performance Assessment is an administrative component. Stakeholders' Activity Dataset, Campus Environment Dataset, Stakeholders Fitness Dataset, and courseware dataset are integrated for the assessment of stakeholders' Performance. Based on stakeholders' inputs (efforts) the predictive algorithm is used to predict the performance assessment of individual stakeholders. The performance of different stakeholders has different impacts e.g. Performance assessment of students will impact their results and academic performance whereas the performance of faculty and non-teaching staff members will impact their salary and appraisal etc.

The proposed assessment process, various irregularities generated w.r.t. assessment, alarm generation, and finally, the process of accreditation is illustrated in Figure 5.8. Various predictive algorithms are used for the assessment process. All the activities discussed so far under this section and subsequently discussed are interrelated and depend on one another. The previous activity in this list either initiates the next activity or has some impact on the next activity. The subsequent subsection explores irregularity detection.

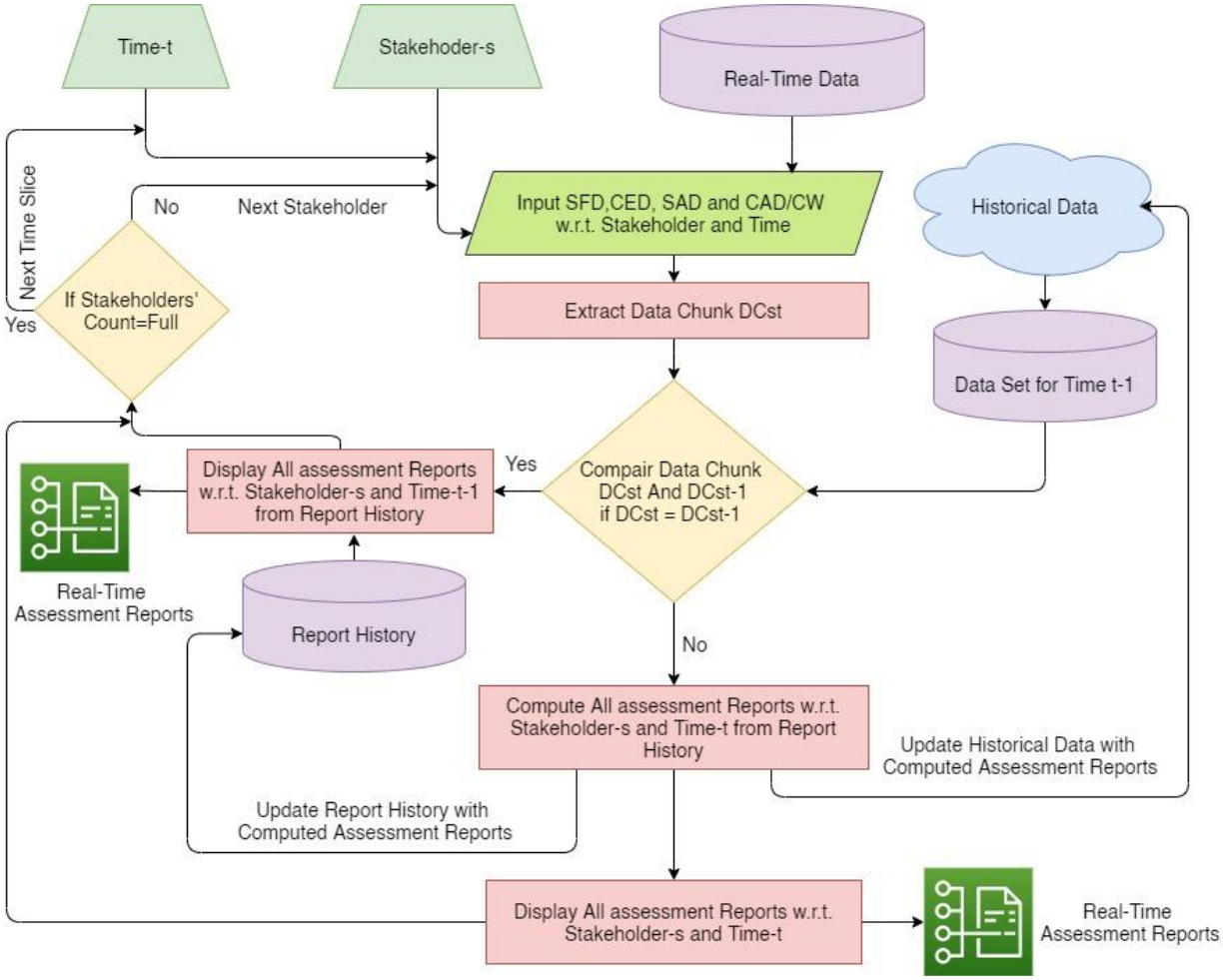


Figure 5.8. Assessment under Education 4.0

5.2.3.2 Irregularity Detection

After an assessment, it is possible to identify various types of irregularities in the ambient educational environment [171]. Various types of assessments have positive as well as negative outcomes for stakeholders. The positive outcomes or assessments are always in the favor of stakeholders. Whereas the negative outcomes or assessments are due to some kind of irregularity in the system or stakeholders' activities. For example under students' course assessment if the requisite number of working hours is not completed by a particular student then it shows the irregularity w.r.t. that particular student and timely corrective action is required for improvement. On the other hand, if a group of students or an entire class is not completing the requisite number of working hours then in this particular case it may be an irregularity on the faculty part or administrative part. All possible irregularities are detected through various irregularity prediction algorithms. Some of the irregularity detection algorithms are efficient enough to work independently, whereas some others are integrated with another algorithm to explore the exact irregularity. Figure 5.9 illustrates the proposed

irregularity detection mechanism. Various irregularity detection algorithms are explored in the results and discussion section.

This study presents an original and forward-looking contribution to Education 4.0 through the development of a real-time irregularity detection algorithm designed for an ambient, technology-enabled educational ecosystem. Unlike most existing studies, which primarily emphasize assessment outcomes and post hoc performance evaluation, the proposed approach focuses on the continuous, real-time identification of irregularities arising from both stakeholder activities and systemic processes—an area that remains largely unexplored in contemporary educational research. In this framework, assessment outcomes are treated as meaningful indicators of system performance: positive outcomes reflect effective engagement and compliance, while negative outcomes signal the presence of underlying irregularities. For instance, when an individual student fails to meet the required academic engagement, the issue can be addressed through timely, student-level intervention. Conversely, when similar patterns are observed across an entire class or cohort, the irregularity may point to instructional or administrative shortcomings. The proposed algorithm is capable of distinguishing between these contexts by employing intelligent prediction mechanisms, operating both independently and in integrated forms, to accurately identify the source of deviation. By embedding this detection process within a real-time Education 4.0 environment, the study enables proactive monitoring, early intervention, and continuous quality improvement. To the best of the researcher's knowledge, this work represents a novel and pioneering effort, establishing a new direction for intelligent educational monitoring and governance within the Education 4.0 paradigm.

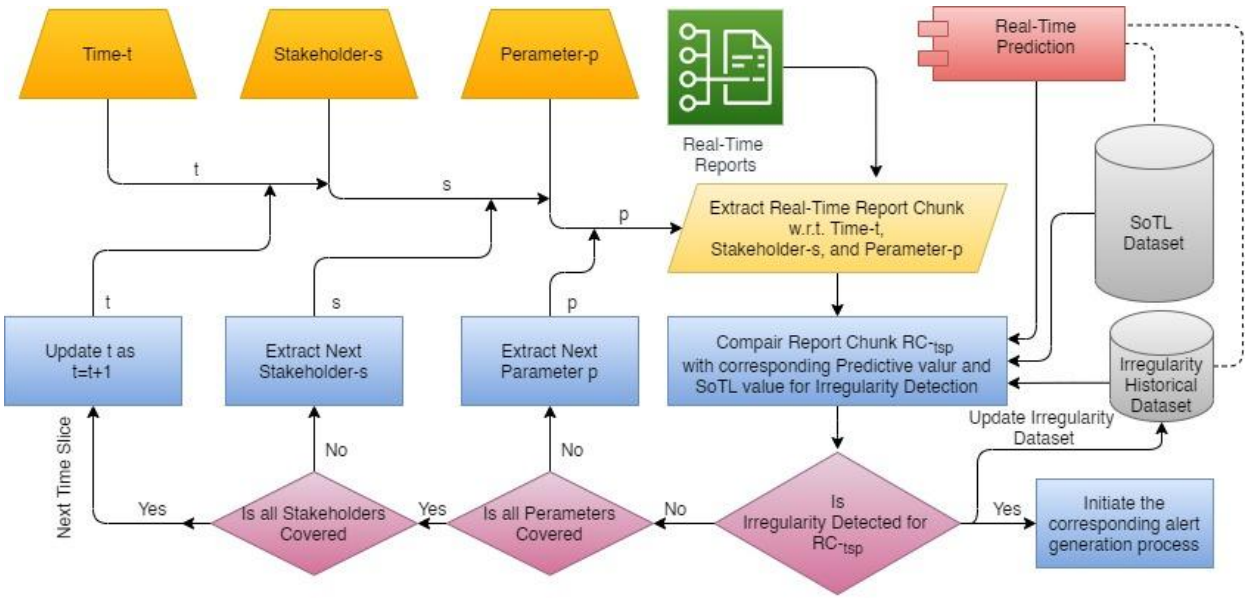


Figure 5.9. Irregularity Detection under Education 4.0

5.2.3.3 Alarm Generation

The positive and negative impacts of the assessment section require proper management [172]. The positive assessment is deployed for motivation, whereas the negative assessment is deployed to alert an individual stakeholder or a group of stakeholders for in-time predictive action. The real-time alarming is very useful to avoid numerous harmful effects of any type of irregularity. In continuation to the example discussed under the previous subsection i.e. irregularity detection, if a particular student is lagging behind in his/her course credits then the alarm generation will remind that individual about this irregularity. This alarming will make the individual aware and may help the individual to improve their credits. On the other hand, for group issues, the corresponding alert will be given to the respective faculty member as well as the corresponding administrative official for in-time corrective action. The positive assessment will also play a significant role in the improvement of quality. All alerts are based on some predictive analysis. The predictive analysis will help the individual to track their performance based on their current input scenario as well as the required inputs on their behalf to achieve their target. Positive Motivation, Improvement in quality, and performance are some of the hidden aspects of real-time alarm generation that are not quantified but will be observed after the implementation of the proposed system in an ambient educational environment [64].

5.3 Application Layer for Institution and Apex Bodies

The application layer of the presented framework depends upon numerous parameters such as the implementing country; Education Policy of the country; University; Institution; Data Requirements of Policymakers, University, and Institution; Courses and curriculum of the Institution, and many other stakeholders' levels requirements. All these parameters need to be fixed by policymakers or at the university level. Consequently, the format of various reports and alerts can be designed for a particular institution associated with that university or policymakers. Designing and development of application layer is a top-down approach. The requirements at the policy makers' level affect the requirements of the university. Consequently, Institutions, Departments, and courses are affected. The application layer of the presented framework may be explored as a separate case study, which is associated purely with the education domain. The various key points that need to be addressed under any specific case study are listed below:

- Requirements need to be collected from all the stakeholders by using a top-down approach, starting from the policy makers' level before implementation.
- Dataset needs to be classified in a manner that fulfills all the requirements using a bottom-up approach, starting from the institution level.
- Parameters for each report need to be studied and segregated under two categories i.e. public and private.
- Public/private parameters and the reports associated with public/private parameters need to be submitted to the concerned stakeholder.
- Based on the dataset, the corresponding IoT infrastructure needs to be deployed at the institution level for the collection of data in real-time.
- Web-based or Mobile based applications need to be developed for alerts and reporting purposes.
- Corresponding security mechanisms need to be developed for data security in a web/mobile environment.

User (stakeholders) friendly mobile or web applications will enhance the productivity of the presented framework at the application level. Real-time interaction between the framework and stakeholders is implemented over the application layer. The interaction between stakeholders is also implemented over the application layer.

5.4 Summary

Sustainable education is a global concern. The reflection of Industry 4.0 unveils a novel revolutionary chapter in the current education industry i.e. Education 4.0. Under Education 4.0 environment automated data collection, monitoring, classification, and prediction have been observed as a necessity for future development in the education domain. Conspicuously, this research proposes an IFC technology for provisioning an effective monitoring and reporting environment for our educational institutions. The three major paradigms of IFC technology i.e. fog computing, IoT, and cloud computing are deployed for effective monitoring and reporting under an ambient educational environment. Specifically, during this analysis, IoT has been deployed for concurrent data acquisition in real-time. The information acquired from the previous step is classified into vulnerable and invulnerable clusters constructed on the probabilistic measure of SoTL. Alerts and the corresponding reporting procedure have been deployed for real-time alerts and reports to be delivered to the concerned stakeholder or group of stakeholders for timely corrective actions. Based on comprehensive analysis, it can be safely stated that the presented framework is outperforming the other contemporary technologies for educational monitoring and reporting under the Education 4.0 environment. The presented framework is useful for automated real-time assessment and accreditation under the Education 4.0 environment. The use case presented in this study is supportive in numerous areas where assessment, appraisal, accreditation, rewards, etc. are applicable on a performance basis. In terms of anticipated classification performance, comparable Fog/IoT-enabled frameworks employing Bi-LSTM and hybrid CNN-LSTM classifiers for real-time monitoring and anomaly/irregularity detection have reported classification accuracy in the range of approximately 95%-97.8% with precision values above 98%, and the proposed M-Bi-LSTM based VDS/IDS classification mechanism is expected to achieve performance within a similar range once empirically validated. Similarly, by processing and classifying data at the fog layer rather than routing every transaction to the cloud, the proposed framework is expected to substantially reduce latency and response time; comparable fog-based architectures have reported inference and response latencies ranging from a few milliseconds to under a few hundred milliseconds per data sample, against markedly higher latencies observed in purely cloud-centric designs. Furthermore, the automated, layered public-private reporting mechanism is expected to considerably improve reporting efficiency over manual and periodic institutional assessment practices by shortening the turnaround time between irregularity detection, alarm generation, and stakeholder notification. These anticipated benchmarks for accuracy, precision, latency, response time, classification performance, and

reporting efficiency are drawn from comparable fog/IoT-based Bi-LSTM classification studies in the literature and will require empirical validation through pilot deployment of the proposed MQEE framework in a live institutional setting, which is identified as an important direction for future work. From a future research perspective, elaborative IoT networks for education institutions and various security concerns within the educational domain are essential research areas to be considered. In addition to this, AI-based automated accreditation of educational institutions by various apex bodies (Accreditation agencies) is an additional research dimension that needs to be addressed in the future for a robust education ecosystem.

CHAPTER 6

Algorithms for monitoring and trust building in Education 4.0

***Chapter Briefing*— Education 4.0, a revolutionary concept shaped by Industry 4.0, is transforming the education sector through the integration of technologies such as IoT, AI, and Big Data Analytics. This chapter focuses on algorithmic approaches to monitoring and trust building, emphasizing the automation of assessment and accreditation processes within educational institutions. By leveraging IoT-enabled devices for real-time data collection and AI algorithms for intelligent analysis, the framework ensures transparency, efficiency, and data-driven decision-making. A two-phased accreditation model evaluates crucial parameters like stakeholder fitness, campus environment, activity tracking, and course authenticity, employing grading mechanisms ranging from 1.5 to 4.0 CGPA and D to A++ grades for benchmarking. The automated system detects irregularities, generates alerts, and streamlines the accreditation process, offering significant advantages such as reduced human intervention and improved resource utilization. Policymakers and educators benefit from this innovative framework, which fosters trust, collaboration, and systemic improvement. Future research directions include expanding IoT networks, developing robust security measures, and creating AI-driven accreditation systems to address emerging challenges and ensure sustainable practices. By adopting these technologies, the framework exemplifies a paradigm shift in assessment and accreditation, setting new benchmarks for innovation and adaptive education ecosystems.**

6.1 Introduction

The use of new technology in education has seen major modifications and developments in recent years. Our lives, our workplaces, and our educational systems have all undergone radical change because of the fourth industrial revolution, or Industry 4.0 [123]. The notion of "Education 4.0," which was created to characterize the incorporation of cutting-edge technologies like the Internet of Things (IoT), Artificial Intelligence (AI), and Big Data Analytics into the education sector, has gained popularity [173]. By utilizing these technologies to better the teaching-learning process, as well as the assessment and accreditation of students, Education 4.0 strives to increase the quality and effectiveness of education [128]. A vital part of the educational system, assessment and accreditation allow educational institutions to monitor students' performance and progress while also ensuring that the standard of instruction being delivered is upheld. The manual data gathering and analysis used in traditional assessment and certification processes takes a lot of time and resources

[174]. Automation of this process is possible, increasing its effectiveness and efficiency with the use of IoT and AI technologies [175]. This study suggests an IoT-enabled smart approach to assessment and accreditation, complete with an automated monitoring and alarm generation algorithm, to solve the shortcomings of conventional evaluation and accreditation procedures. This chapter's aim is to examine the possibility of an IoT-enabled smart approach to assessment and accreditation and to analyse its efficacy and efficiency in comparison to more conventional evaluation and accreditation procedures. To improve the evaluation and certification process, this chapter will give a general introduction to Education 4.0, IoT technologies, and AI algorithms. As well as presenting the findings of a comparison of this approach with conventional assessment and accreditation processes, it will also talk about the design and implementation of an IoT-enabled smart approach to assessment and accreditation.

The term "Education 4.0" refers to the incorporation of cutting-edge technologies like IoT, AI, and Big Data Analytics into the educational system [169]. By improving the teaching-learning process, student assessment, and accreditation, this integration attempts to raise the quality and efficacy of education. A paradigm shift from the conventional teacher-centric method to a learner-centric approach, where students are given the authority to take control of their learning path, is represented by Education 4.0 [176]. The incorporation of IoT into Education 4.0 offers the chance to gather and examine data regarding numerous facets of the teaching-learning process. Students' performance, attendance, and activity data can all be gathered using IoT sensors [135]. The learning preferences and patterns of students can then be deduced from the analysis of this data by AI systems. The proposed assessment and accreditation scenario for Education 4.0 is demonstrated in Figure 6.1.

Devices may connect to and communicate with one another through the internet thanks to a technology called the Internet of Things (IoT) [8]. IoT technology offers a wide range of uses in many industries, including education. IoT sensors can be utilized in Education 4.0 to gather information on numerous facets of the teaching-learning process. For instance, sensors can be used to keep tabs on attendance, locate pupils, and gather usage information for learning tools like computers and books. The application of IoT technology in education offers the chance to gather data in real time that can then be analysed by AI algorithms to reveal insights about the preferences and learning styles of specific students.

A technology known as Artificial Intelligence (AI) enables machines to carry out tasks that would ordinarily need human intelligence [177]. A key component of Education 4.0 is the

use of AI algorithms to analyse the massive amounts of data gathered by IoT sensors and produce insights that can be applied to improve teaching-learning processes, student assessment, and accreditation [7]. The process of assessment and accreditation is another area in which AI algorithms are used in education 4.0. AI systems can analyse student performance and progress data to produce insights and suggestions for administrators and teachers. To support students' learning, this can help identify areas where they are having difficulty and offer focused interventions.

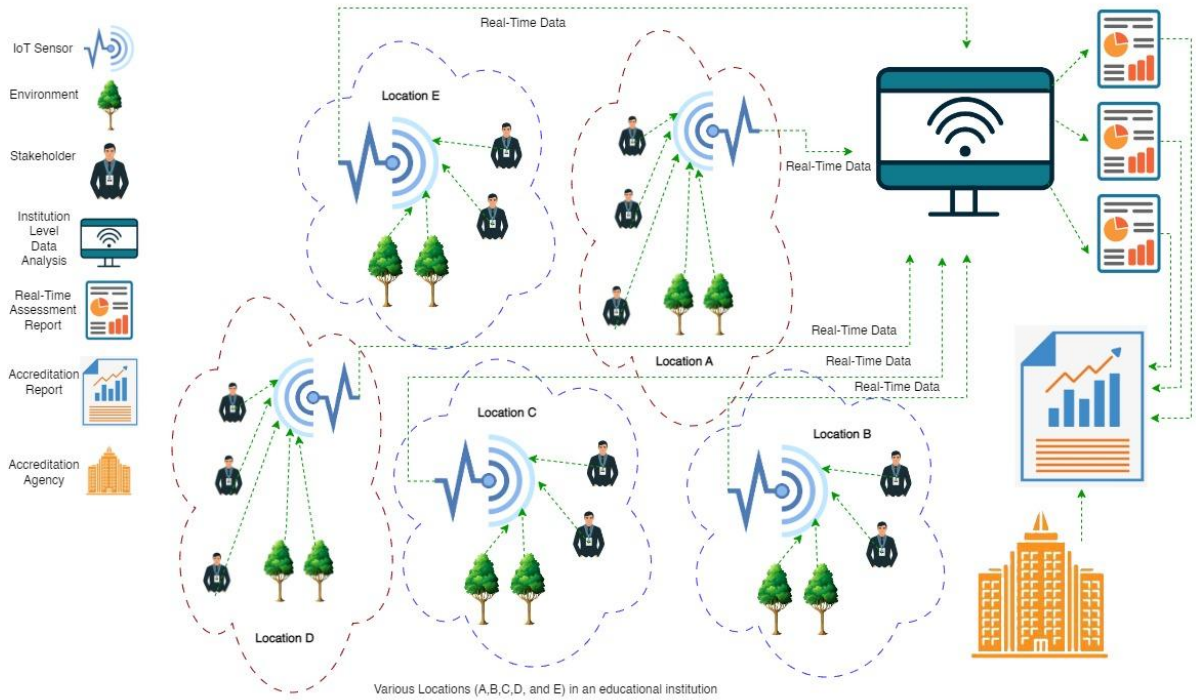


Figure 6.1. Real-Time Assessment and Accreditation Scenario in Education 4.0

The content and level of difficulty of the learning materials can be adjusted by these systems to the student's comprehension level by using data on the learning styles and preferences of specific students. Finally, decision-making in educational institutions can be assisted by AI algorithms. AI algorithms can be used, for instance, to analyse data on student performance and pinpoint locations where funding should be distributed to assist student learning [178], [179]. This could aid in maximizing resource usage and enhancing educational institutions' general effectiveness. To sum up, AI algorithms are a crucial component of Education 4.0 because they give us the skills to analyse the enormous amounts of data produced by IoT sensors and produce insights that can be used to improve teaching-learning processes as well as student assessment and accreditation. Given the immense potential of AI in education, it is expected that in the years to come this field will continue to experience innovation and

development. The main objectives of this study are to design an algorithmic approach for assessment and accreditation under the Education 4.0 environment, further, to design such algorithms which will help the education industry to monitor all the stakeholders and detect all sorts of irregularities observed by the IoT infrastructure present in the institution without any human intervention. This chapter primarily presents the proposed algorithms and their conceptual application within the MQEE framework. The detailed implementation and simulation-based evaluation of these algorithms, including their performance parameters and experimental results, are presented in the subsequent chapter.

6.2 Datasets for Assessment and Accreditation

Various IoT devices, sensors, and actuators are deployed to acquire input data for real-time and continuous assessment. This study focuses on the two major components i.e., assessment and accreditation. All the stakeholders are assessed on the basis of their fitness, and accountability in the institution. On the other hand the accreditation of the institution is granted on the basis of Fitness of the stakeholders inside the institution and Teaching-Learning Environment in the institution. To cover these two components, Stakeholders' Fitness, Environment of Campus, Stakeholders' Activities and Authenticity of Stakeholders' courses are required. Further, all the assessment and accreditation are associated with stakeholders so identification of stakeholder in respect of Fitness, Environment, Activity and Courses is of paramount importance. So, keeping all these things under consideration, the following input datasets are considered for this study.

1. Stakeholder Fitness Dataset
2. Campus Environment Dataset
3. Stakeholder Activity Dataset
4. Stakeholder Identification Dataset
5. Course Authenticity Dataset/Course Ware

In this section, the relevance of various datasets is illustrated. The first dataset discussed is the Stakeholder Fitness Dataset (SFD) [169]. This dataset is associated with all the stakeholders, including students, teachers, non-teaching staff members, and anyone else who is associated with the institution. As the students and teachers are the major stakeholders of the institution, and their fitness may be affected by any other stakeholder in this institution who are in connection with students and teachers therefore to ensure the fitness of the major stakeholders, the fitness of other stakeholders including the non-teaching, administrative and management is

also important. Therefore, the input data scenario is customized for each stakeholder, and they all are participating in this dataset. Table 6.1 provides a detailed description of the variables associated with the SFD.

In this study under the stakeholders Fitness Dataset (SFD), only three parameters are considered i.e., Body Temperature, Heartbeat Level, and Blood Pressure. All the parameters are used for a basic fitness check. The minimum and maximum values are for the age group of 15 years to 65 years; this age group is associated with Higher Education as all types of stakeholders. The vulnerable function f(x) is used to check the vulnerable values associated with respective Stakeholders' Fitness variables [180], [181]. The vulnerable function f(x) may be changed as per the individual stakeholder and geographical location of this campus.

Table 6.1. Stakeholder Fitness Dataset (SFD)

Variable	**Minimum Value**	**Maximum Value**	**Vulnerable values**
Body Temperature	95.3 °F	98.4 °F	$f(x) = \begin{cases} 1, & 95.3\ °F < x > 98.4°F \\ 0, & 95.3\ °F \geq x \leq 98.4°F \end{cases}$
Heartbeat Level	60 bpm	100 bpm	$f(x) = \begin{cases} 1, & 60\ \text{bpm} < x > 100\ \text{bpm} \\ 0, & 60\ \text{bpm} \geq x \leq 100\ \text{bpm} \end{cases}$
Blood Pressure	80 mmHg	120 mmHg	$f(x) = \begin{cases} 1, & 80\ \text{mmHg} < x > 120\ \text{mmHg} \\ 0, & 80\ \text{mmHg} \geq x \leq 120\ \text{mmHg} \end{cases}$

The second dataset is the Campus Environment Dataset (CED), which is entirely associated with real-time environment variables [169]. This dataset helps to monitor the real environment of the institution, and based on the input values, many corrective activities have been initiated to provide a healthy teaching-learning environment for every stakeholder associated with the institution. The campus-environment is affected by many parameters and to include all the parameters in these initial stages of Education 4.0 makes this environment more complex. So, to keep things simple at the initial stages of Education 4.0's assessment and accreditation only four parameters that affect the teaching-learning environment are considered for this study. Table 6.2 provides a detailed description of the variables associated with the CED. In this table 4 campus environment variables are illustrated with their minimum and maximum values. The minimum and maximum values associated with each variable may be changed as per the geographical location of the institution. Similar to Table 6.1, the vulnerable function f(x) is used to check the vulnerable values associated with respective Environmental variables [182], [183]. The vulnerable function f(x) may be changed as per the geographical location of this campus. The use of predefined threshold values in the proposed framework is necessary

for the formal representation, illustration, and simulation of the proposed algorithms. Since the framework integrates multiple parameters related to institutional performance, environmental conditions, student behaviour, infrastructure, and quality indicators, threshold values provide reference points for classifying and interpreting the corresponding measurements during algorithmic processing. However, a single set of threshold values cannot be considered universally applicable to all educational institutions. Institutional characteristics, geographical and climatic conditions, available infrastructure, student population, resource availability, academic practices, and the criteria prescribed by the concerned assessment or accreditation agency may influence the appropriate threshold for a particular parameter. Therefore, the threshold values used in the present study are considered reference values for simulation and feasibility analysis rather than fixed universal standards.

In an actual institutional deployment, these thresholds would be calibrated using institution-specific baseline data, historical observations, relevant contextual parameters, and the quality indicators prescribed by the concerned assessment or accreditation agency. Such adaptive configuration would enable the proposed framework to maintain its applicability across institutions with different operational and environmental conditions while avoiding the assumption of a uniform threshold for all educational institutions.

Table 6.2. Campus Environment Dataset (CED)

Variable	**Minimum Value**	**Maximum Value**	**Vulnerable values**
Temperature	15℃	30℃	$f(x) = \begin{cases} 1, & 15\,℃ < x > 30℃ \\ 0, & 15\,℃ \geq x \leq 30℃ \end{cases}$
Humidity Level	60 gm^{-3}	120 gm^{-3}	$f(x) = \begin{cases} 1, & 60\ gm^{-3} < x > 120\ gm^{-3} \\ 0, & 60\ gm^{-3} \geq x \leq 120\ gm^{-3} \end{cases}$
Air Pressure	100 millibars	1050 millibars	$f(x) = \begin{cases} 1, & 100 \text{ millibars} < x > 1050 \text{ millibars} \\ 0, & 100 \text{ millibars} \geq x \leq 1050 \text{ millibars} \end{cases}$
Noise Level	50 decibels	90 decibels	$f(x) = \begin{cases} 1, & 50 \text{ decibels} < x > 90 \text{ decibels} \\ 0, & 50 \text{ decibels} \geq x \leq 90 \text{ decibels} \end{cases}$

The Stakeholder Activity Dataset is the third dataset, which is associated with the real-time position of the stakeholder in the institution [169]. Based on the position of one or more stakeholders on the campus at a specific point in time, the activities of the stakeholders are decided by various algorithms illustrated in the subsequent sections of the chapter. Table 6.3 covers the location dataset. For systematically geographical segregation of institutional

environment, the entire campus is divided into some blocks, where each block may contain one or more buildings. In table 6.3 four such blocks are illustrated i.e., Electronic and Communication Engineering (ECE), Computer Science Engineering (CSC), Commerce and Business Management (CBM), Architecture (ARC). Moreover, the different places of a building are marked with a specific Location ID and on a specific Location ID many other IoT devices are installed for real-time monitoring, and a specific Device ID is assigned to all the devices. Based on the data received from a particular Device ID it is easier to find the location of a Stakeholder in the campus. Further, the IoT devices, sensors, actuators, and smart devices are classified into two categories i.e. Movable and Immovable devices [136]. Movable devices are generally associated with stakeholders like their Radio Frequency Identification (RFID)-enabled ID (Identity Document) cards and smart wearable devices. The other category of devices is fixed or immovable. The movable devices are generally the stakeholders' data sender. On the other side, the immovable devices are the stakeholders' data receivers. Therefore, whenever a particular stakeholder comes in the range of any immovable device, the location of that device is punched with the stakeholders' dataset. On the basis of this location and the values of stakeholders' associated Time-Table ID, the activity of respective stakeholders can be calculated. The next section of this chapter illustrates this in detail along with the corresponding algorithms associated with this dataset.

Table 6.3. Location Dataset (LDS)

Block ID	**Block**	**Location ID**	**Location**	**Device ID**	**Device**	**Device Type**
4579	ECE	83907142	Lecture Hall-102	TT85479	TempTrack1000	Immovable
1245	CSE	25670918	Hardware Lab-VI	SS32568	SoundSense2000	Immovable
6587	CBM	17463289	Basketball Ground Block II	HP32157	HumidProbe3000	Immovable
1245	CSE	98247360	Software Lab-V	AP95478	AirPress4000	Immovable
3657	ARC	74591823	Lecture Hall-415	ES32547	EnviroSense5000	Immovable
6587	CBM	60948725	Auditorium-II	CT65214	ClimaTrack6000	Immovable
1245	CSE	31259876	CS-Dean Office	AS74578	Atmosphere7000	Immovable

The fourth dataset is the Stakeholder Identification Dataset, which is a non-real-time dataset used in this study. This dataset consists of values such as Name, Course, Identification Number, Job Role, etc. This dataset helps the IoT devices to identify the stakeholder. Multiple

parameters may be added to this dataset to identify the stakeholder as per the requirement of a specific institution. For demonstration purposes in Table 6.4, 20 stakeholders are illustrated. All these values are neither associated with any institutions nor with any stakeholder, for demonstration purposes these random values are used in this study. Here in this table, each stakeholder holds a unique stakeholder ID, Types of stakeholders are also defined in the table, further, each stakeholder is associated with any one of the departments. Moreover, a unique ID Card No. and Smart Device No. are also associated with the individual stakeholder. Similar Course ID is assigned to Students associated with similar courses. Courses ID Set may be assigned to faculty members associated with more than one course as in the case of 1st record. Finally, a unique Time-Table ID is issued to all the stakeholders. The students enrolled in similar courses and non-teaching stakeholders associated with similar departments and job roles may have similar Time-Table IDs. The fields in the Stakeholder Identification Dataset may be increased as per the requirements e.g., stakeholders' mobile no, email Id, address, and other personal/professional details may also be added in this table as per the requirement of the application-level module.

Finally, the Course Authenticity Dataset/Courseware is another non-real-time dataset used in the study. This dataset includes information about the various courses currently running in the respective institution. This dataset includes Course Name, Course Code, Students associated with the course, Theory and practical hours associated with the course, Minimum and Maximum credits required for the course, etc. This dataset helps to check the attendance and performance of the stakeholders associated with the respective course. Table 6.5 covers the various elements of this dataset. Like the Stakeholder Identification dataset in Table 6.4, this dataset may also be improved as per the requirement of the application module. The Time Stamp, Location Stamp, and Faculty IDs associated with each course are related to the timetables covered earlier in this section. Student Set is the set of students' IDs enrolled under a particular subject. All the remaining fields of this table are self-explanatory.

In a nutshell, this study utilizes various datasets to provide a holistic view of the institution's stakeholders' activities, environments, and performance. These datasets help to monitor and improve the teaching-learning environment for all the stakeholders associated with the institution. By analysing the data from these datasets, the study aims to improve the stakeholders' overall experience and performance, leading to a better learning outcome. The subsequent section of this study covers all the major assessment algorithms used in this input

scenario for assessment in terms of monitoring and irregularity detection in Education 4.0 [62], [184].

Table 6.4. Stakeholder Identification Dataset (SID)

Stakeholder ID	Department	ID Card No	Smart Device No.	Course ID/Set	Time-Table ID
FAC9832412	CSE	IC745836	SW786547	C-21547, C-45789	TT-21547-1
ADM7869024	ECE	IC328951	SW643215	C-45789	TT-45789-1
NT4658390	DNO	IC912657	SW123789	NULL	TT-8547-4
VIS2015739	CBM	IC567218	SW875612	C-91236	TT-91236-1
STU9235601	CSE	IC823694	SW589732	C-21547	TT-21547-2
STU3482157	ARC	IC469832	SW346891	C-75324	TT-75324-1
FAC6812943	ECE	IC126589	SW986532	C-38679	TT-38679-1
NT5210038	VCO	IC874532	SW451236	NULL	TT-8373-3
STU7902461	MCE	IC259873	SW192837	C-59471	TT-59471-1
ADM3045962	SUP	IC935684	SW726534	NULL	TT-8557-5
VIS6178025	ASE	IC684723	SW687345	C-82463	TT-82463-1
FAC1483296	ASE	IC317596	SW259673	C-82463	TT-82463-2
NT8750943	RGO	IC987234	SW964385	NULL	TT-8787-4
STU9264053	ARC	IC536189	SW513742	C-75324	TT-75324-2
ADM6917503	DSW	IC273845	SW327916	NULL	TT-8777-8
VIS2913845	ARC	IC941782	SW971824	C-75324	TT-75324-3
NT6203958	DSW	IC672391	SW647523	NULL	TT-4578-9
STU8290456	CBM	IC385729	SW385294	C-91236	TT-91236-2
FAC3145962	EEE	IC124789	SW219465	C-21547	TT-21547-3
VIS5318075	EEE	IC768543	SW736289	C-21547	TT-21547-4

Note: "STU" denotes students, "FAC" denotes faculty, "NT" denotes non-teaching staff, "ADM" denotes administrative staff, and "VIS" denotes visiting staff. The next 7 digits are randomly generated for each stakeholder ID. Timetable signifies the time frame associated with a particular group of students and their respective group of teachers and other supporting staff.

Table 6.5. Course Authenticity Dataset/Course Ware (CAD/CW)

Course	Course ID	Subject	Min-Theory (Hrs)	Min-Practical (Hrs)	Max-Theory (Hrs)	Max-Practical (Hrs)	Min-Credits (T)	Min-Credits (P)	Max-Credits (T)	Max-Credits (P)	Time Stamp	Location Stamp	Faculty ID	Code	Name	Type	Student Set
Course-1	C-21547	S-1	60	40	100	50	3	1	4	2	T1	L1	F1	1.1	N1	C	SS1
		S-2	60	40	100	50	3	1	4	2	T2	L1	F2	1.2	N2	C	SS1
		S-3	60	40	100	50	3	1	4	2	T3	L1	F3	1.3	N3	C	SS1
		S-4	60	40	100	50	3	1	4	2	T4	L1	F4	1.4	N4	C	SS1
		S-5	60	0	100	0	3	0	4	0	T5	L1	F1	1.5	N5	E	SS1
		S-6	60	0	100	0	3	0	4	0	T6	L2	F5	1.6	N6	E	SS1
Course-2	C-45789	S-1	60	40	100	50	3	1	4	2	T1	L2	F2	2.1	N7	C	SS2
		S-2	60	40	100	50	3	1	4	2	T2	L2	F3	2.2	N8	C	SS2
		S-3	60	40	100	50	3	1	4	2	T3	L3	F1	2.3	N9	C	SS2

Note: S-Subject; T-Time Stamp; L-Location Stamp; F-Faculty ID, N-Name; C-Core; E-Elective; SS-Student Set

6.3 Assessment Algorithms

In this section of the study, various algorithms for assessment in Education 4.0 are discussed with their implementation and use case. The following monitoring and irregularity detection algorithms are implemented over various datasets discussed in the previous section:

1. Fitness monitoring and irregularity detection algorithm (FMIDA).
2. Environment monitoring and irregularity detection algorithm (EMIDA).
3. Course authenticity monitoring and irregularity detection algorithm (CAMIDA).
4. Employee monitoring and irregularity detection algorithm (EPMIDA).

Table 6.6 illustrates the various algorithms, along with the datasets used and applications of these algorithms. All these algorithms play an important role in accreditation and in output layers, especially for alert generation in respect of every irregularity detection.

Table 6.6. Assessment Algorithms

Algorithm	Dataset(s) Used	IoT devices and Sensors Used	Application(s)

FMIDA	SFD	Temperature Sensor, Heart Rate Sensor, Blood Pressure Sensor.	Fitness-Related Alert Generation on Output Layers
EMIDA	CED	Temperature Sensor, Air Pressure Sensor, Noise Sensor, Humidity Sensor	Environment-Related Alert Generation on Output Layers
CAMIDA	LDS, CAD/CW	Any Sensor emitting information about a particular stakeholder.	Course Authenticity and its related Alert Generation on Output Layers
EPMIDA	LDS, CAD/CW	Any Sensor emitting information about a particular stakeholder.	Employee Payroll and its related Alert Generation on Output Layers

6.3.1 Fitness monitoring and irregularity detection algorithm (FMIDA)

This algorithm specifically uses Stakeholder Fitness Dataset illustrated in Table 6.1. On the basis of various vulnerability detection functions f(x) this algorithm monitors the health of an individual stakeholder and generates seeds for respective alerts. This algorithm produces the real time fitness assessment report of all the stakeholders s present in the institution on a time instance ΔT. This real-time data for a specific stakeholder is known as data chunk. Further, this algorithm also produces irregularities detected by SFD and generates irregularities detection count for accreditation algorithms. A report history is generated after every time instance ΔT and the respective changes are saved in the corresponding report history of an individual stakeholder.

Algorithm 1: Fitness monitoring and irregularity detection algorithm (FMIDA)

1 $S_{id} \leftarrow Stakeholder\ ID,$

$\Delta T \leftarrow Current\ Time\ Instance,$

$SFD \leftarrow Stakeholder\ Fitness\ Dataset,$

$R_{his} \leftarrow Report\ History,$

$D_{chunk} \leftarrow Data\ Chunk$

$S_{set} \leftarrow Stakeholder\ Set$

$Div_{id} \leftarrow Device\ ID$

$D_{set} \leftarrow Device\ Set\ with\ ready\ state$

$S_{count} \leftarrow 1,$

$\Delta T \leftarrow t,$

$S_{id} \leftarrow s$

2 **if** $\Delta T \neq Null$ **then**

3 $Get\ D_{set}\ for\ \Delta T$

4 **while** $D_{set} = d$ **do**

5 $Get\ S_{set(dt)}\ for\ D_{set} = d\ and\ \Delta T = t$

6 $Get\ S_{set(t-1)} \forall\ s \in S_{set(dt)}\ from\ R_{his(t-1)}$

7 **While** $S_{set(dt)} = s$ **do**

8 **if** $S_{set(dt)} \neq S_{set(t-1)}\ for\ s\ and\ t$

9 $Get\ f(x)_{BT}\ for\ S_{set(dt)}\ from\ SFD$

10 $Get\ f(x)_{HR}\ for\ S_{set(dt)}\ from\ SFD$

11 $Get\ f(x)_{BP}\ for\ S_{set(dt)}\ from\ SFD$

12 $Update\ R_{his}\ for\ s$

13 **If** $f(x)_{BT} \mid f(x)_{HR} \mid f(x)_{BP} = 1$

14 $Enable\ Irregularity\ Detected\ IR = 1\ for\ s\ and\ S_{BT}, S_{HR}, and\ S_{BP}$

15 **Call Algorithm 6** $for\ s\ and\ \Delta T$

16 $Update\ s\ to\ next\ s$

17 $IR_{count(FDS)} = IR_{count(FDS)} + 1$

18 **Call Algorithm 6** $to\ Generate\ Assessment\ Report\ for\ s\ and\ t$

19 $Goto\ 7$

20 **end**

21 **Call Algorithm 6** $to\ Generate\ Assessment\ Report\ for\ s\ and\ t$

22 $Update\ s\ to\ next\ s$

23 $Goto\ 7$

24 **end**

25 **Call Algorithm 6** $to\ Generate\ Assessment\ Report\ for\ s\ and\ t$

26 $Update\ s\ to\ next\ s$

27 $Goto\ 4$

28 **end**

39 $Goto\ 2$

30 **end**

31 $Update\ IR_{count(FDS)}\ for\ Accreditation\ Algorithm$

32 $Goto\ 2$

33 **else**

34 ***end***

Note: Refer Legend Table 6.9 for symbols used in this algorithm

6.3.2 Environment monitoring and irregularity detection algorithm (EMIDA)

This algorithm specifically uses Environment Dataset (EDS) and Location Dataset (LDS) illustrated in Table 6.2 and Table 6.3 respectively. On the basis of various vulnerability detection functions f(x) illustrated in Table 6.2, this algorithm monitors the Environment of various locations of the institution and generates seeds for respective alerts. This algorithm produces the real time environment assessment report of all the locations l of the institution at a time instant ΔT. Further, this algorithm also produces irregularities detected by EDS and generates irregularities detection count for accreditation algorithms.

Algorithm 2: Environment monitoring and irregularity detection algorithm (EMIDA)

1 $L_{id} \leftarrow Location\ ID,$
$\Delta T \leftarrow Current\ Time\ Instance,$
$EDS \leftarrow Environment\ Dataset,$
$R_{his} \leftarrow Report\ History$
$Div_{id} \leftarrow Device\ ID$
$D_{set} \leftarrow Device\ Set\ with\ ready\ state$
$L_{count} \leftarrow 1,$
$\Delta T \leftarrow t,$
$Div_{id} \leftarrow d$
$L_{id} \leftarrow l$
2 ***if*** $\Delta T \neq Null$ ***then***
3 $Get\ D_{set}\ for\ \Delta T$
4 ***while*** $D_{set} = d$ ***do***
5 $Get\ L_{id}\ as\ l\ for\ d\ and\ \Delta T = t$
6 $Get\ f(x)_{TP}\ for\ l\ from\ EDS$
7 $Get\ f(x)_{AP}\ for\ l\ from\ EDS$
8 $Get\ f(x)_{NL}\ for\ l\ from\ EDS$
9 $Get\ f(x)_{HL}\ for\ l\ from\ EDS$
10 $Update\ R_{his}\ for\ l$

11 | | $Get\ l_{t-1}\ from\ R_{his(t-1)}\ for\ l$
12 | | ***if*** $l_t \neq l_{t-1}$
13 | | | ***If*** $f(x)_{TP} \mid f(x)_{AP} \mid f(x)_{NL} \mid f(x)_{HL} = 1$
14 | | | | $Enable\ Irregularity\ Detected\ IR = 1\ for\ l\ and\ l_{TP}, l_{AP}, l_{NL} and\ l_{HL}$
15 | | | | ***Call Algorithm 6*** $for\ l\ and\ t$
16 | | | | $Update\ l\ to\ next\ l$
17 | | | | $IR_{count(EDS)} = IR_{count(EDS)} + 1$
18 | | | | ***Call Algorithm 6*** $to\ Generate\ Assessment\ Report\ for\ l\ and\ t$
19 | | | | $Update\ R_{his}\ for\ l$
20 | | | | $Goto\ 5$
21 | | | ***end***
22 | | | ***Call Algorithm 6*** $to\ Generate\ Assessment\ Report\ for\ l\ and\ t$
23 | | | $Update\ l\ to\ next\ l$
24 | | | $Goto\ 5$
25 | | ***end***
26 | | $Goto\ 2$
27 | ***end***
28 | $Update\ IR_{count(EDS)}\ for\ Accreditation\ Algorithm$
29 | $Goto\ 2$
30 ***else***
31 ***end***

Note: Refer Legend Table 6.9 for symbols used in this algorithm

6.3.3 Course Authentication Monitoring and irregularity detection algorithm (CAMIDA)

This algorithm specifically uses the Course Authenticity Dataset/Course ware (CAD/CW), Stakeholder Identification Dataset (SID) and Location Dataset (LDS) illustrated in Table 6.5, Table 6.4, and Table 6.3 respectively. On the basis of these datasets, irregularities may be detected in respect of students and Faculty members, this algorithm monitors the authenticity of various courses running in the institution and generates seeds for respective alerts. This algorithm produces the real time course authentication assessment report of all the courses running in the institution at a time instant ΔT. Further, this algorithm also produces

irregularities detected by CAD/CW and generates irregularities detection count for accreditation algorithms.

Algorithm 3: Course Authenticity monitoring and irregularity detection algorithm (CAMIDA)

$L_{id} \leftarrow Location\ ID,$
$\Delta T \leftarrow Current\ Time\ Instance,$
$SID \leftarrow\ Stakeholder\ Identification\ Dataset,$
$CAD/CW \leftarrow\ Course\ Authenticity\ Dataset/Course\ ware\ ,$
$LDS \leftarrow\ Location\ Dataset,$
$R_{his} \leftarrow Report\ History$
$Div_{id} \leftarrow Device\ ID$
$D_{set} \leftarrow Device\ Set\ with\ ready\ state$
$S_{set} \leftarrow Stakeholder\ Dataset$
$L_{count} \leftarrow 1,$
$\Delta T \leftarrow t,$
$Div_{id} \leftarrow d$
$L_{id} \leftarrow l$
$S_{id} \leftarrow s$
if $\Delta T \neq Null$ ***then***
    $Get\ D_{set}\ for\ \Delta T$
    while $D_{set} = d$ ***do***
        $Get\ L_{id}\ as\ l\ for\ d\ and\ \Delta T = t\ from\ LDS$
        $Get\ S_{set}\ for\ l,\quad and\ \Delta T = t$
        $Get\ Sub_{set} \leftarrow Sub_{id}\ \forall\ S_{set}\ where\ L_{id} = l\ and\ \Delta T = t$
        $Get\ Course_{set} \leftarrow Course_{id}\ \forall\ S_{set}\ where\ L_{id} = l\ and\ \Delta T = t$
        $Get\ Faculty_{set} \leftarrow Faculty_{id}\ \forall\ Course_{set}\ where\ L_{id} = l\ and\ \Delta T = t$
        if $Faculty_{set}Count \neq 1\ for\ Faculty_{set}$
            $Get\ Faculty_{id} \in Faculty_{set}\ where\ l = TimeTable_l\ and\ t = TimeTable_t$
            if $Faculty_{id} = Null$
                $Enable\ Irregularity\ Detected\ IR = 1\ for\ Faculty_{id}$
                Call Algorithm 6 $for\ Faculty_{id}, l\ and\ t$
                $Update\ d\ to\ next\ d$
                $IR_{count(CAD/CW)} = IR_{count(CAD/CW)} + 1$

17 **Call Algorithm 6** to
$Generate\ Assessment\ Report\ for\ Faculty_{id}, l\ and\ t$
18 $Update\ R_{his}\ for\ Faculty_{id}, l\ and\ t$
19 $Goto\ 5$
20 **end**
21 **else**
22 $Get\ S_{setPresent} \in S_{set}\ where\ l = TimeTable_l\ and\ t = TimeTable_t$
23 $Mark\ Attendance\ Status = 1\ \forall\ S_{setPresent}$
24 $Update\ Subject\ Credits\ and\ Course\ Credits\ \forall\ S_{setPresent}\ with\ time\ \Delta T$
25 $Update\ d\ to\ next\ d$
26 **Call Algorithm 6** $toGenerate\ Assessment\ Report\ \forall\ S_{setPresent}, l\ and\ t$
27 $Update\ R_{his}\ \forall\ S_{setPresent}, l\ and\ t$
28 $Update\ IR_{count(CAD/CW)}\ for\ Accreditation\ Algorithm$
29 $Goto\ 5$
30 **end**
31 **end**
32 $Get\ Faculty_{setIR}\ from\ Faculty_{set}\ \forall\ Course_{set}\ where\ L_{id} \neq l\ and\ \Delta T \neq t$
33 $Enable\ Irregularity\ Detected\ IR = 1\ \forall\ Faculty_{setIR}$
34 **Call Algorithm 6** $\forall\ Faculty_{setIR}, l\ and\ t$
35 $IR_{count(CAD/CW)} = IR_{count(CAD/CW)} + count(Faclut y_{setIR})$
36 $Get\ S_{setPresent} \in S_{set}\ where\ l = TimeTable_l\ and\ t = TimeTable_t$
37 $Mark\ Attendance\ Status = 1\ \forall\ S_{setPresent}$
38 $Update\ Subject\ Credits\ and\ Course\ Credits\ \forall\ S_{setPresent}\ with\ time\ \Delta T$
39 $Update\ d\ to\ next\ d$
40 **Call Algorithm 6** $to\ Generate\ Assessment\ Report\ \forall\ S_{setPresent}, l\ and\ t$
41 $Update\ R_{his}\ \forall\ S_{setPresent}, l\ and\ t$
42 $Update\ IR_{count(CAD/CW)}\ for\ Accreditation\ Algorithm$
43 $Goto\ 5$
44 **end**
45 $S_{setAbsent} \in S_{set}\ where\ l = TimeTable_l\ and\ t = TimeTable_t\ and \nexists\ S_{setPresent}$
46 $Enable\ Irregularity\ Detected\ IR = 1\ \forall\ S_{setAbsent}$
47 **Call Algorithm 6** $\forall\ S_{setAbsent}, l\ and\ t$

48 $IR_{count(CAD/CW)} = IR_{count(CAD/CW)} + count(S_{setAbsent})$

49 $Mark\ Attendance\ Status = 0\ \forall\ S_{setAbsent}$

50 $Update\ d\ to\ next\ d$

51 $\boldsymbol{Call\ Algorithm\ 6}\ to\ Generate\ Assessment\ Report\ \forall\ S_{setAbsentt}, l\ and\ t$

52 $Update\ R_{his}\ \forall\ S_{setAbsent}, l\ and\ t$

53 $Update\ IR_{count(CAD/CW)}\ for\ Accreditation\ Algorithm$

54 $Goto\ 5$

55 ***else***

56 $Goto\ 2$

57 ***end***

Note: Refer Legend Table 6.9 for symbols used in this algorithm

6.3.4 Employee monitoring and irregularity detection algorithm (EPMIDA)

This algorithm specifically uses the Stakeholder Identification Dataset (SID) and Location Dataset (LDS) illustrated in Table 6.4, and Table 6.3 respectively. On the basis of these data sets, irregularities may be detected in respect of employees of the institution. This algorithm monitors the accountability of all the employees in the institution and generates seeds for respective alerts. This algorithm produces the real time employee monitoring assessment report of all the employees of the institution at a time instant ΔT. Further, this algorithm also produces irregularities detected by EPM i.e., employee. It also generates irregularities detection count for accreditation algorithms.

In a nutshell, all these 4 algorithms produce an assessment report for the individual stakeholder for fitness and accountability, and all the individual location of the institution for environment. Further, these algorithms also support the other algorithms mentioned under the subsequent sections of this chapter. The next section uses the irregularity detection count for the accreditation of the institution.

Algorithm 4: Employee monitoring and irregularity detection algorithm (EPMIDA)

1 $L_{id} \leftarrow Location\ ID,$

$\Delta T \leftarrow Current\ Time\ Instance,$

$SID \leftarrow\ Stakeholder\ Identification\ Dataset,$

$LDS \leftarrow\ Location\ Dataset,$

$R_{his} \leftarrow Report\ History$

$Div_{id} \leftarrow Device\ ID$

$D_{set} \leftarrow Device\ Set\ with\ ready\ state$

$S_{set} \leftarrow Stakeholder\ Dataset$

$L_{count} \leftarrow 1,$

$\Delta T \leftarrow t,$

$Div_{id} \leftarrow d$

$L_{id} \leftarrow l$

$S_{id} \leftarrow s$

2 $\boldsymbol{if}\ \Delta T \neq Null\ \boldsymbol{then}$

3 $Get\ D_{set}\ for\ \Delta T$

4 $\boldsymbol{while}\ D_{set} = d\ \boldsymbol{do}$

5 $Get\ L_{id}\ as\ l\ for\ d\ and\ \Delta T = t\ from\ LDS$

6 $Get\ S_{set}\ for\ l, \quad and\ \Delta T = t$

7 $Get\ S_{setPresent} \in S_{set}\ where\ l = TimeTable_l\ and\ t = TimeTable_t\ and\ S_{type} \nexists STD$

8 $S_{setAbsent} \in S_{set}$ $where\ l = TimeTable_l\ and\ t = TimeTable_t\ and \nexists S_{setPresent}\ and\ S_{type} \nexists STD$

9 $Enable\ Irregularity\ Detected\ IR = 1\ \forall\ S_{setAbsent}$

10 $\boldsymbol{Call\ Algorithm\ 6}\ \forall\ S_{setAbsent}, l\ and\ t$

11 $IR_{count(EMP)} = IR_{count(EMP)} + count(S_{setAbsent})$

12 $Update\ Employee\ Payroll\ \forall\ S_{setPresent}\ with\ time\ \Delta T_{+ve}$

13 $Update\ Employee\ Payroll\ \forall\ S_{setAbsent}\ with\ time\ \Delta T_{-ve}$

14 $Enable\ Irregularity\ Detected\ IR = 1\ for\ S_{setAbsent}$

15 $\boldsymbol{Call\ Algorithm\ 6}\ for\ S_{setAbsent}, l\ and\ t$

16 $Update\ d\ to\ next\ d$

17 $\boldsymbol{Call\ Algorithm\ 6}\ to\ Generate\ Assessment\ Report\ for\ S_{setPresent}, l\ and\ t$

18 $\boldsymbol{Call\ Algorithm\ 6}\ to\ Generate\ Assessment\ Report\ for\ S_{setAbsent}, l\ and\ t$

19 $Update\ R_{his}\ for\ S_{setPresent}, l\ and\ t$

20 $Update\ R_{his}\ for\ S_{setAbsent}, l\ and\ t$

21 $Goto\ 5$

22 $\boldsymbol{end}$

23 $\boldsymbol{else}$

24 *Goto* 2

25 ***end***

Note: Refer Legend Table 6.9 for symbols used in this algorithm

6.4 Accreditation Algorithms

The present accreditation scenario is not continuous and real-time. Further, it involves many parameters for accreditation. Under Education 4.0 the continuous and real-time accreditation is also possible [99]. But the institution scenario is ideal most of the time e.g., if a class is going on in a lecture hall so the number of students present in that lecture hall, faculty present in the lecture hall, the fitness parameters of all the stakeholders present in that lecture hall and the environment variables of this lecture hall remain almost constant during the lecture time. So, continuous assessment of all the stakeholders is justified because only the changes observed by various IoT devices and sensors are considered for various types of assessments [185]. On the outer side the accreditation involves all the stakeholders, locations, courses, and all the parameters associated with these objects. So, the overall process is very cumbersome for real-time. Further, in real-time the rank of grade associated with the accreditation system also changes on different time frames of the institution. So, instead of real-time accreditation with all the parameters, intervallic accreditation is recommended. Moreover, the accreditation agency considers a number of institutions to provide a specific rank to an individual institution. So, the real-time framework at institution level is not possible. Therefore, this study recommends two-phase accreditation process. Under Phase-I the institution performs accreditation based on the existing accreditation and possible accreditation under the Education 4.0 environment, using limited parameters in real-time like Self-Study-Report or the Internal Quality Assurance Report [99]. In second phase of accreditation on the basis of first phase, the historical data and the other external parameters the external agency conducts this accreditation process as per their set norms. This section covers only the Phase-I accreditation. The phase-I accreditation is based upon the three major metrics i.e., Fitness, Environment and Accountability. All these metrics contribute to assessment as per the criterion mentioned under Table 6.7. Further, Table 6.8 proposes the Real-time grading system for Phase I accreditation process.

Table 6.7. Proposed Accreditation Criterion

Criterion (C)	**Criterion Weight in**	**Stakeholder Type**	**Weightage in**	**Overall Contribution**	**CGPA Contribution** $\alpha = \frac{w \times total\ CGPA}{100}$

	percentage (w_i)		**percentage** (w_j)	$w = \frac{w_i \times w_j}{100}$	
Fitness	25	Student	40	10	0.40
		Faculty	40	10	0.40
		Other Stakeholders	20	5	0.20
Environment	25	All Stakeholders	100	25	1.00
Accountability	50	Student	40	20	0.80
		Faculty	40	20	0.80
		Other Stakeholders	20	10	0.40
	Total			**100**	**4.00**

Table 6.8. Proposed grading system for phase-I accreditation

Grading	**CGPA**	**Status**
A++	3.51 - 4.00	Accredited
A+	3.26 - 3.50	Accredited
A	3.01 – 3.25	Accredited
B++	2.76 – 3.00	Accredited
B+	2.51 – 2.75	Accredited
B	2.01 - 2.50	Accredited
C	1.51-2.00	Accredited
D	<=1.50	Non- Accredited

The fitness criterion for accreditation is calculated on the basis of various irregularities detected by different fitness parameters in respect of different stakeholders. Equations 1 to 4 propose the fitness calculation method.

$$C_{Fitness(STD)} = \left[\alpha_{Fitness(STD)} \times \left(1 - \frac{IR_{count(FDS-STD)}}{S_{Count(STD)}}\right)\right] \quad (1)$$

Where STD is Student, FDS is Fitness Dataset, IR is irregularity for time

$\Delta T = t$, $\alpha_{Fitness}$ is CGPA Contribution of fitness

$$C_{Fitness(FAC)} = \left[\alpha_{Fitness(FAC)} \times \left(1 - \frac{IR_{count(FDS-FAC)}}{S_{Count(FAC)}}\right)\right] \quad (2)$$

Where FAC is Faculty for time $\Delta T = t$

$$C_{Fitness(OTR)} = \left[\alpha_{Fitness(OTR)} \times \left(1 - \frac{IR_{count(FDS-OTR)}}{S_{Count(OTR)}}\right)\right] \quad (3)$$

Where OTR is Other Stakeholders except students and faculty members for time $\Delta T = t$

$$C_{Fitness} = C_{Fitness(STD)} + C_{Fitness(FAC)} + C_{Fitness(OTR)} \quad (4)$$

Equation 5 is used for environment criterion calculation.

$$C_{Environment} = \left[\alpha_{Environment} \times \left(1 - \frac{IR_{count(EDS)}}{l_{Count}}\right)\right] \quad (5)$$

Where EDS is Environment Dataset for time $\Delta T = t$,

$\alpha_{Environment}$ is CGPA Contribution of environment

Equation 6 to equation 8 are used for Accountability calculation.

$$C_{Accountability(STD)} = \left[\alpha_{Accountability\,(STD)} \times \left(1 - \frac{IR_{count\left(\frac{CAD}{CW}-STD\right)}}{S_{Count(STD)}}\right)\right] \quad (6)$$

Where CAD/CW is Course authenticity dataset / courseware,

$\alpha_{Accountability}$ is CGPA Contribution of Accountability

$$C_{Accountability(FAC)} = \left[\alpha_{Accountability(FAC)} \times \left(1 - \frac{IR_{count\left(\frac{CAD}{CW}-FAC\right)}}{S_{Count(FAC)}}\right)\right] \quad (7)$$

$$C_{Accountability(OTR)} = \left[\alpha_{Accountability\,(OTR)} \times \left(1 - \frac{IR_{count(EMP-OTR)}}{S_{Count(OTR)}}\right)\right] \quad (8)$$

Where EMP is Employee other than Faculty members

$$C_{Accountability} = C_{Accountability(STD)} + C_{Accountability(FAC)} + C_{Accountability(OTR)} \quad (9)$$

Equation 10 is used to calculate the overall CGPA score for an institution.

$$C \leftarrow Total_{CGPA} = C_{Fitness} + C_{Environment} + C_{Accountability} \quad (10)$$

The proposed accreditation algorithm for Phase-I accreditation is based on the principle that CGPA of an institution is inversely proportional to the irregularity detection count that means fewer irregularities detected by Algorithms 1 to 4 lead to a good CGPA score, and a higher irregularity detection count leads to a poor CGPA [186]. Therefore, for good CGPA score

institution must focus on all the three criteria i.e., Fitness, Environment and Accountability. Algorithm 5 illustrates the accreditation process for Phase-I accreditation.

Algorithm 5: Accreditation Algorithm (ACCA)

$\Delta T \leftarrow Current\ Time\ Instance,$
$SFD \leftarrow Stakeholder\ Fitness\ Dataset,$
$EDS \leftarrow Environment\ Dataset,$
$SID \leftarrow Stakeholder\ Identification\ Dataset,$
$LDS \leftarrow Location\ Dataset,$
$CAD/CW \leftarrow Course\ Authenticity\ Dataset/Course\ wear,$
$S_{set} \leftarrow Stakeholder\ Set$
$IR \leftarrow Irregularity\ Detection$
$EMP \leftarrow Employee$
$STD \leftarrow Student$
$FAC \leftarrow Faculty$
$OTR \leftarrow Employee\ other\ than\ Faculty$
$L_{set} \leftarrow Location\ Set$
$\Delta T \leftarrow t,$
if $\Delta T \neq Null$ **then**
  $Get\ IR_{count(FDS)} \forall S_{set}\ for\ \Delta T \leftarrow t$
  $Get\ IR_{count(EDS)} \forall L_{set}\ for\ \Delta T \leftarrow t$
  $Get\ IR_{count(CAD/CW)} \forall S_{set}\ for\ \Delta T \leftarrow t$
  $Get\ IR_{count(EMP)} \forall S_{set} \nexists S_{set(STD)}\ for\ \Delta T \leftarrow t$
  $Get\ S_{count(STD)}\ from\ S_{set}\ for\ t$
  $Get\ S_{count(FAC)}\ from\ S_{set}\ for\ t$
  $Get\ S_{count(EMP)}\ from\ S_{set}\ for\ t$
  $Get\ S_{count(OTR)}\ from\ S_{set}\ for\ t$
  $Get\ l_{count}\ from\ L_{set}\ for\ t$
  $Set\ \alpha \leftarrow Fitness, Environment, Accountability\ ref - Table\ 7$
  $Calculate\ individual\ accreditation\ reports\ for\ all\ three\ criteria$
  ***Call Algorithm* 6** $to\ generate\ individual\ accreditation\ reports$
  $calculate\ CGPA\ ref - Equation\ 1\ to\ Equation\ 10$
  ***Call Algorithm* 6** $to\ generate\ accreditation\ report\ with\ CGPA$

17 $calculate\ Grade\ ref - Table\ 8$

18 ***Call Algorithm 6*** $to\ generate\ accreditation\ report\ with\ Grade$

19 $update\ t\ to\ next\ \Delta T$

20 $Goto\ 2$

21 ***else***

22 ***end***

Note: Refer Legend Table 6.9 for symbols used in this algorithm

In a nutshell equation(s) 1 to 10 are used in Algorithm 5 for Phase-I accreditation. The subsequent section of this chapter explores another essential component of the Education 4.0 environment i.e., Output Scenario or Application Layer.

6.4.1 Output Scenario for Education 4.0

This sub-section presents the output scenario or application layer scenario for Education 4.0. The algorithms, namely Algorithm 1 to 4, detect irregularities and generate assessments, while Algorithm 5 generates an accreditation report.

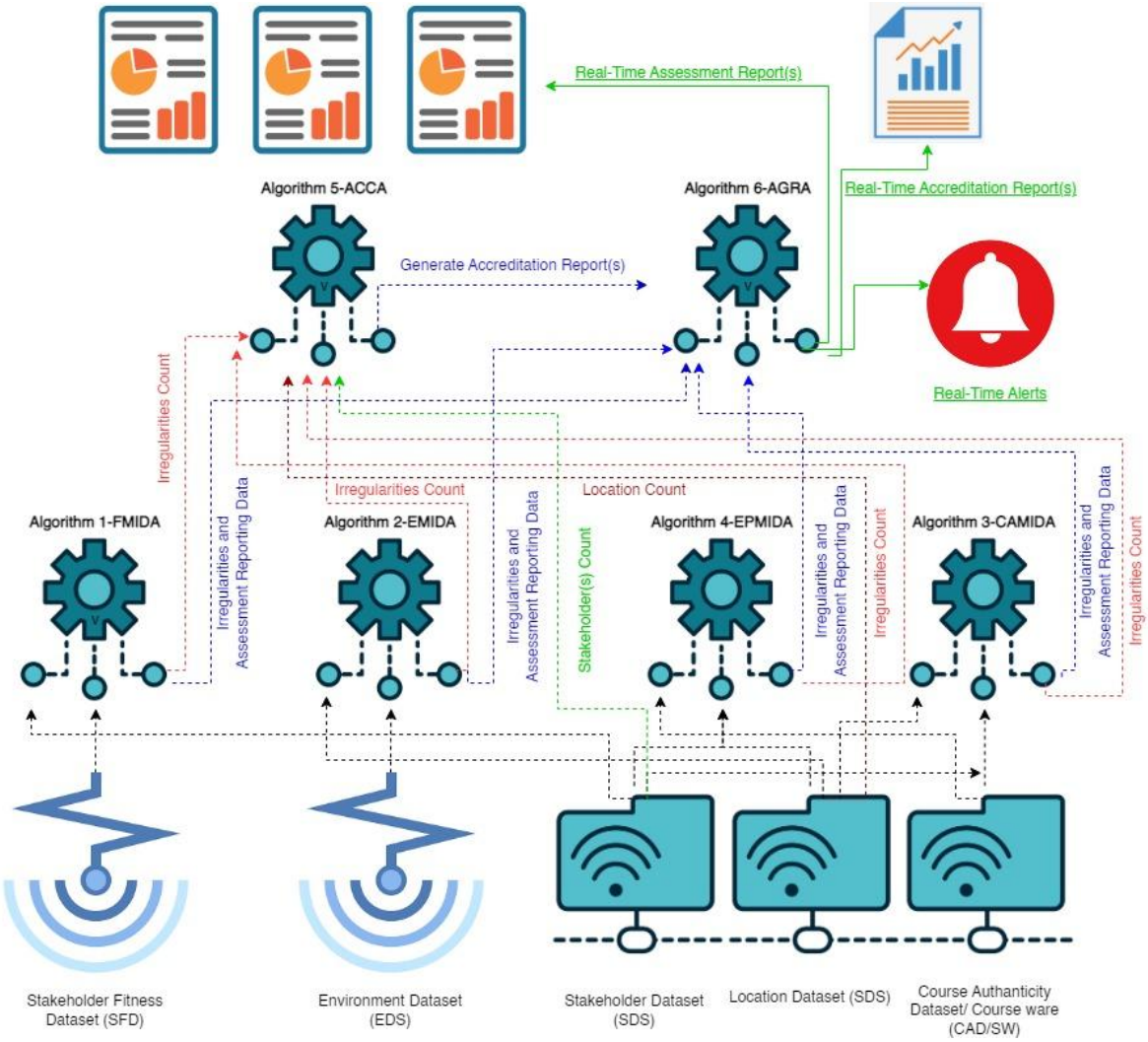


Figure 6.2. Algorithmic Scenario for Assessment and Accreditation under Education 4.0

The irregularities and assessments generated by these algorithms are then displayed to the relevant stakeholders for prompt and effective action to be taken on the application layer. It is crucial that each detected irregularity in this study is communicated to the respective stakeholder through an output scenario. The overall working of all the algorithms discussed in the chapter is illustrated in Figure 6.2. In addition, Algorithm 6 is utilized whenever any of the previously discussed algorithms detect an irregularity. This algorithm is responsible for generating alerts that are sent to the concerned stakeholder. The output scenario and algorithm 6 facilitate communication and quick resolution of issues, ensuring that the Education 4.0 system operates smoothly and effectively. In a nutshell, the output scenario and Algorithm 6 play significant roles in the Education 4.0 system. They ensure that irregularities are promptly detected and communicated to the relevant stakeholders for a quick solution. These

components facilitate the efficient functioning of the system and enhance its overall effectiveness. The output scenario may also be improved as per the requirements of institution.

Algorithm 6: Alert Generation and Reporting Algorithm (AGRA)

$\Delta T \leftarrow Current\ Time\ Instance,$

$SFD \leftarrow Stakeholder\ Fitness\ Dataset,$

$EDS \leftarrow Environment\ Dataset,$

$SID \leftarrow Stakeholder\ Identification\ Dataset,$

$LDS \leftarrow Location\ Dataset,$

$CAD/CW \leftarrow Course\ Authenticity\ Dataset/Course\ wear,$

$S_{set} \leftarrow Stakeholder\ Set$

$\alpha \leftarrow CGPA\ contribution$

$IR \leftarrow Irregularity$

$EMP \leftarrow Employee$

$STD \leftarrow Student$

$FAC \leftarrow Faculty$

$OTR \leftarrow Employee\ other\ than\ Faculty$

$L_{set} \leftarrow Location\ Set$

$Div_{set} \leftarrow Device\ Set$

$l_{count} \leftarrow Location\ Count$

$S_{count} \leftarrow 1,$

$\Delta T \leftarrow t,$

if $\Delta T \neq Null$ ***then***

  if $\boldsymbol{IR = ture}$

    $Get\ s\ for\ S_{set} for\ IR\ and\ t$

    $Get\ \ l\ for\ L_{set} for\ IR\ and\ t$

    $Get\ d\ from\ Div_{set}\ \ for\ IR\ and\ t$

    $Generate\ respective\ alert\ for\ s, l, and\ d\ for\ time\ t$

  else if $\boldsymbol{Assessment\ Report = ture}$

    $Get\ s\ for\ S_{set} for\ Assessment\ Report\ and\ t$

    $Get\ \ l\ for\ L_{set} for\ Assessment\ Report\ and\ t$

    $Get\ d\ from\ Div_{set}\ \ for\ Assessment\ Report\ and\ t$

    $Generate\ respective\ Assessment\ Report\ for\ s, l, and\ d\ for\ time\ t$

13 | ***else if Accreditation Report = ture***

14 | | $Get\ s\ for\ S_{set} for\ Accreditation\ Report\ and\ t$

15 | | $Get\ \ l\ for\ L_{set} for\ Accreditation\ Report\ and\ t$

16 | | $Get\ d\ from\ Div_{set}\ \ for\ Accreditation\ Report\ and\ t$

17 | | $Generate\ respective\ Accreditation\ Report\ for\ s, l, and\ d\ for\ time\ t$

18 | ***else***

19 | | $update\ \Delta T\ for\ next\ t$

20 | | $goto\ 2$

21 ***else***

22 ***end***

Note: Refer Legend Table 6.9 for symbols used in this algorithm

Table 6.9. Legend Table for Algorithm 1 to 6

Symbol	Meaning	Elaboration
←	Left Arrow	Value on the right-hand side of this arrow is assigned to the variable present in the left-hand side of this arrow.
Δ	Delta	Specifically used for a Time Interval T
=	Equal to	Used as logical equal to, for checking logical expression for a conditional statement
≠	Not Equal to	Used as logical not equal to, for checking logical expression for a conditional statement
∀	For All	Applicable for all the items present in the right-hand side of this symbol
∄	There Does Not Exist	The items present on the left-hand side do not exist in the set of items present on the right-hand side of this symbol
∈	Element Of	The items present on the left-hand side are the element of the set of items present on the right-hand side of this symbol
|	Or	Used as logical or, for checking logical expression for a conditional statement

6.5 Summary

Education 4.0 represents a crucial development for the future of the education industry. One of the fundamental requirements of this approach is the implementation of real-time and continuous assessment, which can be facilitated using IoT devices, sensors, and actuators. By

monitoring key parameters such as stakeholders' fitness, campus environment, and course authenticity, these technologies can generate valuable data that can be used to produce real-time assessment reports for a wide range of stakeholders. This chapter has outlined various algorithms for monitoring, irregularity detection, assessment, and accreditation, which have demonstrated a high degree of efficiency in producing real-time reports. These assessments cover four key parameters: fitness, environment, courses, and employees. Moreover, a two-phased accreditation approach has been recommended, with phase-I accreditation executed in real-time over a limited set of parameters, and phase-II accreditation executed periodically based on accreditation agency guidelines. Phase-I accreditation is based on three broader parameters: fitness, environment, and accountability. The principle of fewer irregularities for better accreditation is the basis of this approach, with the accreditation CGPA ranging from 1.50 to 4.00 and grades ranging from D to A++. The accreditation CGPA and grades are adopted from a prestigious Indian assessment and accreditation agency NAAC (National Assessment and Accreditation Council). The implementation of these strategies can help to ensure that Education 4.0 is grounded in accurate, reliable, and up-to-date information, which is essential for fostering better learning outcomes and supporting the development of high-quality educational programs.

CHAPTER 7

MQEE Implementation and Performance Analysis

Chapter Briefing— **This chapter provides a detailed exploration of the implementation and performance analysis of the Multilayered Quality Education Ecosystem (MQEE) model, emphasizing the logistical, financial, and technical dimensions integral to its success. The research underscores the reliance on physical IoT devices, fog computing infrastructure, and cloud systems, which necessitate substantial upfront investments and meticulous planning for large-scale deployment. To mitigate operational complexities and financial constraints, simulation methodologies are employed, leveraging tools such as iFogSim to evaluate the framework under controlled conditions. This approach enables researchers to model data flow, resource utilization, and system efficiency before committing to physical infrastructure investments. Insights from simulations serve as a foundation for validating the financial feasibility, scalability, and technical robustness of the MQEE model. The chapter also references existing literature to substantiate financial projections and deployment timelines, emphasizing modular and scalable system designs that facilitate smoother transitions from prototype implementations to comprehensive deployments. By synthesizing validated frameworks with simulation-based findings, the MQEE model offers a promising avenue for integrating IoT and AI-driven analytics into education systems, aligning with the overarching goals of Education 4.0.**

7.1 Introduction

The implementation of the proposed MQEE model entails significant logistical, financial, and technical considerations, particularly given its reliance on physical Internet of Things (IoT) devices, fog computing infrastructure, and cloud-based systems. These components demand substantial initial funding for experimentation and prototype development. Furthermore, customized software applications or web-based platforms would be required at the institutional, university and governing body/apex body levels to facilitate seamless integration and operational functionality. This requirement reflects the need for extensive resource allocation and strategic planning for both prototype-level deployment and subsequent large-scale implementation.

The time needed to achieve full deployment also poses a notable constraint. For example, in the scenario of a single university governed by an apex body overseeing 10–15 affiliated colleges, the estimated timeline for complete implementation could span two to three years.

This projection encompasses the phases of planning, resource acquisition, prototype testing, and iterative refinements based on initial feedback. To circumvent these challenges, the study employs simulation methodologies as an alternative to physical implementation for initial experimentation. Simulation platforms such as iFogSim are utilized to model and evaluate the MQEE framework. iFogSim provides a robust environment for simulating IoT, fog, and cloud computing systems, enabling researchers to test and validate the model's efficacy under controlled conditions. By using simulation, it becomes possible to gather valuable insights into the operational dynamics of the MQEE model, including data flow, resource utilization, and system performance, without the immediate need for physical infrastructure [187].

7.1.1 Feasibility and Validation of MQEE Model: Financial, Logistical, and Technical Perspectives

The financial implications of implementing IoT-enabled systems in educational institutions have been extensively addressed in the existing literature. Alam et al. (2021) report that establishing an IoT infrastructure in higher education settings necessitates, on average, a 25% increase in budgetary allocation compared to traditional systems. These insights highlight the importance of strategic resource optimization and phased deployment to manage financial burdens effectively.

To address the practical limitations of direct deployment, simulation tools such as iFogSim have gained prominence. Validated across numerous studies, iFogSim has demonstrated its efficacy in accurately modelling resource allocation and system performance in IoT-fog computing environments. For instance, Gupta et al. (2020) report an accuracy exceeding 90%, confirming iFogSim as a reliable tool for preliminary experimentation and theoretical validation [188].

In terms of deployment timelines, Zhang and Li (2019) estimate an average duration of 2 to 4 years for the full implementation of IoT-based frameworks in medium-sized educational institutions [189]. These projections closely align with the anticipated timeline for the deployment of the proposed Multilayered Quality Education Ecosystem (MQEE), affirming the practical feasibility of the model.

Scalability remains a crucial determinant of success for IoT frameworks in education. Banerjee et al. (2022) emphasize that modular and scalable system designs can reduce integration challenges by 15–20%, thereby facilitating smoother transitions from pilot implementations to full-scale deployments [44].

The MQEE model proposed in this study represents a comprehensive and forward-looking approach to the monitoring, evaluation, and enhancement of educational systems through the integration of IoT, fog computing, and AI-driven analytics. Despite inherent financial, logistical, and temporal constraints, the use of simulation environments such as iFogSim provides a cost-effective and efficient platform for validating theoretical constructs and optimizing deployment strategies [187]. By synthesizing validated technical frameworks and simulation-based insights, this research offers a robust foundation for advancing IoT-enabled education systems within the scope of Education 4.0 [190].

7.2 iFogSim: A Simulation Framework for IoT-Fog-Cloud implementation

iFogSim is a widely adopted, Java-based simulation toolkit developed by Gupta, Dastjerdi, Ghosh, and Buyya (2017) for modelling and evaluating IoT-Fog-Cloud (IFC) environments [191]. Designed as an extension of the CloudSim framework, iFogSim enables researchers to simulate the behaviour of distributed computing paradigms in edge-centric networks where latency, energy consumption, and network congestion are key performance indicators. The toolkit supports resource management, application module placement, latency-aware service orchestration, and data flow modelling, making it highly suitable for experimentation in Education 4.0 and smart learning ecosystems [187], [192].

iFogSim simulates the interaction of physical and logical components within an IFC architecture, including:

- IoT devices (e.g., sensors, actuators)
- Fog nodes (e.g., gateways, edge servers)
- Cloud data centres
- Application modules

The simulation workflow involves defining application topologies using Directed Acyclic Graphs (DAGs), where vertices represent processing modules and edges denote data flows or dependencies. This abstraction allows researchers to evaluate how application performance is affected by various module placement strategies and network hierarchies [193].

7.2.1 Utilization in Research: Evaluating Performance and Scalability

From a research perspective, iFogSim plays a critical role in the design, validation, and optimization of IFC-based architectures. It allows simulation of:

- Resource allocation and scheduling algorithms
- Energy consumption patterns across edge, fog, and cloud layers
- Latency-sensitive task execution in heterogeneous environments
- Network usage and data transmission costs

Studies such as those by Gupta et al. (2017) and Mahmud et al. (2018) have leveraged iFogSim to develop and evaluate novel fog-aware scheduling and placement algorithms, reporting improvements in latency up to 45% and network congestion reduction by 30% in comparison to cloud-only deployments [192], [193].

Further, Baccour et al. (2020) employed iFogSim to analyse the performance of AI-integrated IoT-fog systems in smart campus settings. Their results highlighted that dynamic fog orchestration led to better resource utilization and reduced SLA violations, especially under fluctuating workloads [194].

7.2.2 Relevance to Education 4.0 and MQEE Implementation

In the context of Education 4.0, iFogSim enables simulation of real-time monitoring, adaptive learning environments, and predictive analytics, which are central to models like the Multilayered Quality Education Ecosystem (MQEE). By modelling sensors (e.g., attendance, performance tracking), fog nodes (e.g., on-campus servers), and cloud layers (e.g., institutional databases), iFogSim provides a realistic and cost-effective environment to assess the feasibility of such systems before real-world deployment [132], [195], [196].

The ability to simulate heterogeneous data flows, module migrations, and failure scenarios allows researchers to pre-emptively identify bottlenecks and optimize resource provisioning for robust, scalable implementations.

7.3 Simulation Environment

Given the diverse infrastructural layouts and geographical contexts of educational institutions, a single, static architecture for the implementation of the Multilayered Quality Education Ecosystem (MQEE) is neither feasible nor recommended. To address this variability, a dynamic and customizable framework has been developed using the iFogSim simulation platform, enabling the flexible construction of institution-specific components. It is important to clarify that the iFogSim based implementation represents simulation-based feasibility and performance evaluation rather than real-world institutional validation. The results obtained from simulation are therefore interpreted within the assumptions and

parameter settings of the simulated environment. Factors such as real network variability, sensor failures, heterogeneous hardware, privacy requirements, user behaviour, and institutional interoperability may differ in actual deployment. These aspects have consequently been identified as limitations and important considerations for future real-world implementation and field validation. Figure 7.1 illustrates the design of a scalable infrastructure model tailored for Education 4.0. Institutions can adapt and configure their unique setups based on this foundational environment. In the example depicted, the simulated infrastructure includes four blocks, each comprising five classrooms, one library, one playing area, one auditorium, and two toilet blocks. Additionally, each classroom, block, library, and playing area is equipped with two surveillance cameras. The framework also supports the customization of students, teachers, and non-teaching staff profiles. While this environment provides a flexible baseline, it does not represent a fully scalable solution applicable to every institution, as the number and type of physical amenities may vary significantly across campuses. To overcome this limitation, the development of a customized, web-based application is proposed. Such a tool would enable institutions to independently configure and manage each block, building, classroom, or facility according to their specific needs and infrastructural characteristics, thereby enhancing the practical applicability and adaptability of the MQEE framework.

```
package Education;
* Simulation of Scalable Infrastructure for Education 4.0
 * @author Anil Verma
 */
public class EducationInfrastructure {
public static void creatInfrastructure(){
                    static List<FogDevice> fogDevices = new
ArrayList<FogDevice>();
                    static List<Sensor> sensors = new ArrayList<Sensor>();
                    static List<Actuator> actuators = new ArrayList<Actuator>();
                    static int numOfBlocks=4;
                    static int numOfClassroomsPerBlock=5;
                    static int numOfLibrariesPerBlock=1;
                    static int numOfPlayingAreasPerBlock=1;
                    static int numOfAuditoriumPerBlock=1;
                    static int numOfStudentsPerClass=10;
                    static int numOfEmployeesTeaching=10;
                    static int numOfEmployeesNTeaching=5;
                    static int numOfCamerasPerClassroom=2;
                    static int numOfCamerasPerBlock=2;
                    static int numOfCamerasPerLibrary=2;
                    static int numOfCamerasPerPlayingArea=2;
                    static int numOfCamerasPerToilet=0;
                    static int numOfToiletPerBlock=2;
```

Figure 7.1. Scalable Simulation Environment

To facilitate a comprehensive understanding of the layered architecture within a single Block of the proposed MQEE, a sample topology has been constructed. The topologies, depicted in Figure 7.2 (a) and 7.2 (b), serve as a representative model to elucidate the structural design of the complete MQEE framework.

In this illustrative topology, the first layer comprises IoT devices deployed across various institutional amenities, including the Auditorium, Library, Playing Area, Toilets, and Classrooms. Within each amenity, all associated sensors and actuators are interconnected via a central switch. These switches, in turn, are linked to individual fog devices, each corresponding to a specific amenity. In the full MQEE deployment, the intermediary switches shown in the sample topology are functionally replaced by fog nodes, which perform data preprocessing and local computation. These fog nodes across amenities are integrated into a higher-level proxy server, identified in the topology as the Block (Proxy Server). This proxy server acts as a central node for each block and is responsible for coordinating data flow and processing at the block level. Subsequently, each block-level proxy server is connected to the

cloud node, enabling centralized storage, analytics, and inter-block communication. The architecture ensures that all blocks within an institution are seamlessly connected via the proxy server, which ultimately interfaces with the cloud. This hierarchical design enhances scalability, real-time responsiveness, and fault tolerance within the MQEE infrastructure. The foundational three-layered IoT–Fog–Cloud (IFC) architecture is depicted in Figure 7.3 [58]. In this hierarchical model, devices categorized under levels 2 and 3 correspond to IoT devices and gateway nodes, which operate at the edge of the network and are responsible for data generation and initial transmission [197]. The fog layer is represented by level 1, comprising intermediate processing units that handle latency-sensitive tasks closer to the data source [198]. At the top of the hierarchy, level 0 constitutes the cloud layer, offering centralized processing, storage, and global coordination capabilities. A comprehensive description of each hierarchical level is provided in Table 7.1.

Each component within these topologies is generated either through JSON-based configuration or manually using the Fog Topography Creator GUI provided in the iFogSim framework. The structure and attributes of the JSON configuration for the Cloud Node are illustrated in Figure 7.3, while a detailed explanation of each component parameter is presented in Table 7.2. This JSON object defines the configuration parameters for a cloud-level fog device in an iFogSim simulation [199]. Each field plays a critical role in how the device behaves within the simulated IoT-Fog-Cloud (IFC) environment. The Cloud node, fog nodes (including Classroom, Library, Auditorium, Playing Area, Toilet, Block, etc.), proxy server, and switches are defined following a consistent structure, like that of the Cloud node, with varying parameter values tailored to their respective roles. In the simulation environment, each of these components is configured using a uniform JSON schema, allowing for scalable and modular deployment. The complete configuration details for some of the Cloud and Fog nodes used in the simulation are presented in Table 7.3. In addition, IoT devices, including sensors and actuators, can be defined in a similar manner using either JSON configuration files or the Fog Topography Creator GUI. However, the structure and parameters of these components differ from those used for fog and cloud nodes [200]. The key components of sensors and actuators are illustrated in Figures 7.4 and 7.5, respectively. Detailed descriptions of these components are provided in Table 7.3 for sensors and Table 7.4 for actuators. Furthermore, to establish connectivity between different IoT, Fog, or Cloud devices within the simulation topology, network links can be defined using either JSON configuration files or the Fog Topography Creator GUI [193]. The structure and parameters of a typical network link

are illustrated in Figure 7.6, with detailed descriptions of each component provided in Table 7.6. The complete configuration details for some of the IoT sensor nodes used in the simulation are presented in Table 7.7.

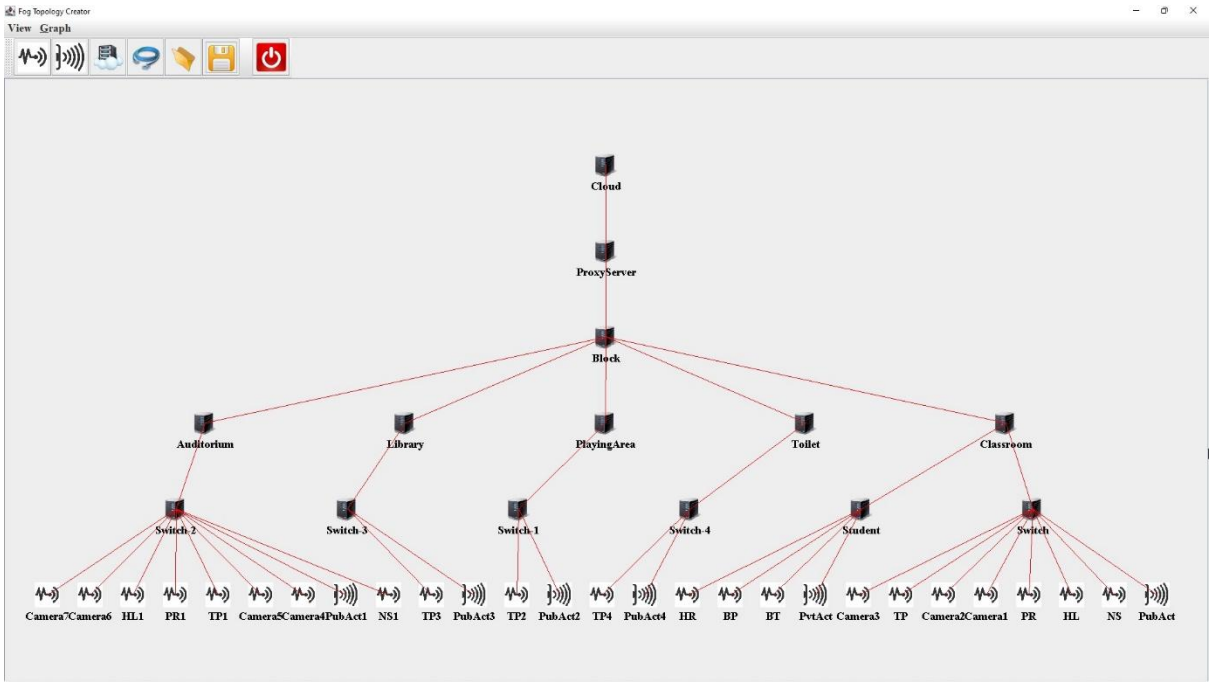


Figure 7.2(a). Basic Topology of a Single Block

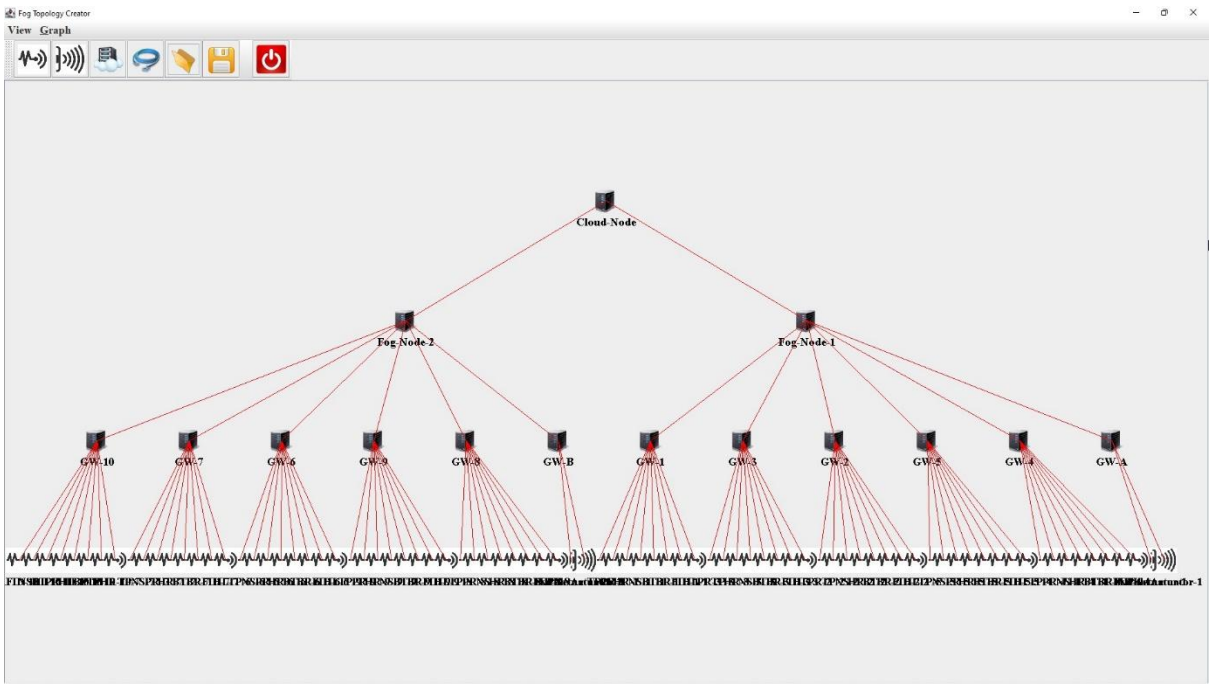


Figure 7.2(b). Three-layered IoT–Fog–Cloud (IFC) topology

Table 7.1. Description of different Levels in IFC topology

Level	Device Type	Characteristics
0	**Cloud Node**	Highest-level device; most powerful; centralized storage and processing; high latency
1	**Proxy Server / Gateway**	Mid-level fog nodes; interface between cloud and local fog devices; moderate resources
2	**Building-level Fog Node**	Located at institutions or buildings; handles multiple edge devices
3	**Edge/IoT Devices** (e.g., Smart Cameras, Sensors, Classroom Controllers)	Closest to the physical environment; low latency; limited resources

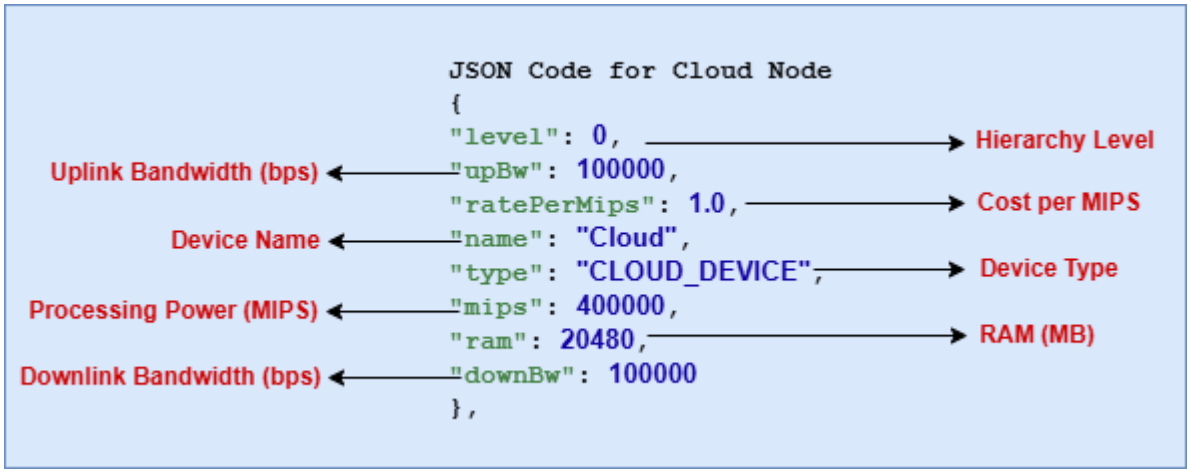


Figure 7.3. Different Components of Cloud Node JSON

Table 7.2. Detailed description of various components of Cloud Node JSON

Field	Description
"level": 0	**Hierarchy Level**: Indicates the device's position in the fog computing hierarchy. 0 typically represents the **cloud node**, the topmost layer with the most computing resources and storage capabilities. In iFogSim, higher numbers (e.g., 1, 2...) are used for fog nodes or edge devices located closer to sensors/actuators.
"upBw": 100000	**Uplink Bandwidth (bps)**: Defines the **maximum data transfer rate (in bits per second)** from the cloud node to its parent (or to fog devices if it's the root). High uplink bandwidth ensures fast data transmission to other devices in the topology.
"ratePerMips": 1.0	**Cost per MIPS**: Represents the **monetary cost of processing power**, i.e., how much it costs to use one MIPS (Million Instructions Per Second) of processing. A value of 1.0 suggests a cost unit per MIPS, which is useful in cost-aware simulations or economic modelling.
"name": "Cloud"	**Device Name**: A unique identifier for the device. In this case, "Cloud" explicitly states that this node acts as the cloud server in the topology. This helps distinguish devices in

	logs, debugging, or visualization.
"type": "FOG_DEVICE"	**Device Type**: Denotes the type of node. Even though it is the cloud node, it is still treated as a FOG_DEVICE in iFogSim because all computation-capable devices (fog nodes, cloud nodes) extend the same base class. The actual behaviour is determined by other attributes like level, not this label alone.
"mips": 400000	**Processing Power (MIPS)**: Indicates the **total available processing capacity** of the device in MIPS (Million Instructions Per Second). A value of 400000 suggests this cloud node can perform a very large number of computations per unit time — appropriate for a centralized, powerful server.
"ram": 20480	**RAM (MB)**: Denotes the **amount of memory** available in the cloud node. 20480 MB equals 20 GB of RAM, which is reasonable for a powerful cloud server. This value is used by iFogSim to model memory-intensive applications and resource allocation.
"downBw": 100000	**Downlink Bandwidth (bps)**: Specifies the **data transmission capacity from the cloud node to its child devices** (e.g., fog nodes, proxy servers). A high value like 100000 bps ensures efficient data transfer to lower-tier nodes in the network.

Table 7.3. Description of some of the institutional amenities represented with Fog/Cloud Node in the simulation

Parameter	Cloud Node	Proxy Server	Block Node	Classroom Node	Library Node	Switch
Level	0	1	2	3	3	4
upBw (bps)	100000	20000	10000	10000	10000	10000
downBw (bps)	100000	20000	10000	10000	10000	10000
ratePerMips	1.0	1.0	1.0	0.1	0.1	0.1
Name	Cloud	Proxy Server	Block	Classroom	Library	Switch-1
Type	CLOUD	FOG	FOG	FOG	FOG	FOG
Mips	400000	80000	40000	40000	40000	40000
ram (MB)	20480	10240	2048	1024	1024	1024

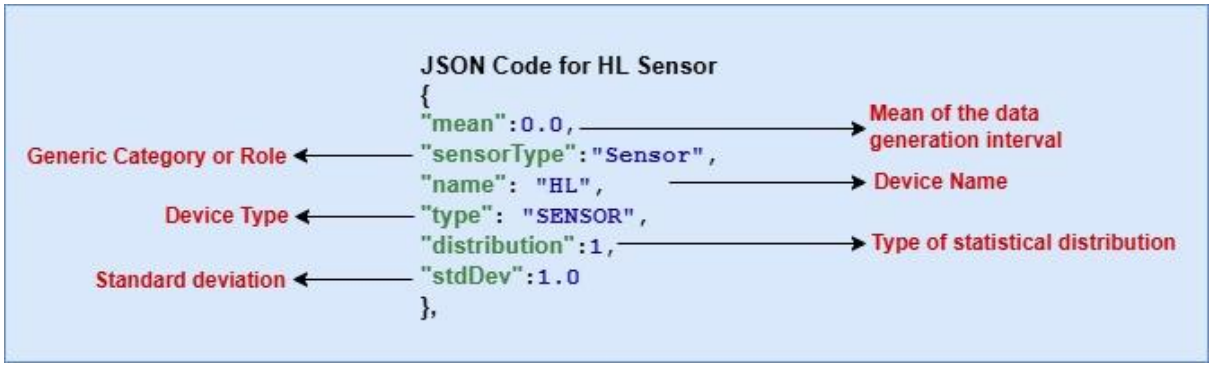


Figure 7.4. Different Components of IoT Sensor JSON

Table 7.4. Detailed description of various components of IoT devices/sensor JSON

Field	Description
"mean": 0.0	**Mean of the data generation interval (in seconds)** for the sensor. In stochastic models (e.g., Gaussian distribution), this defines the **average time** between two consecutive data emissions. A value of 0.0 suggests this might be **overridden by another timing mechanism** or is a placeholder.
"sensorType": "Sensor"	The **generic category or role** of the device. "Sensor" indicates it is a data-generating entity typically connected to a fog device. This may be used for classification or logical grouping.
"name": "HL"	A **unique identifier** or short name for the sensor. "HL" could stand for something like **"Humidity Level"**, depending on the simulation context. This name is used in the simulation to refer to the sensor instance.
"type": "SENSOR"	Specifies the **device type**. In iFogSim, "SENSOR" differentiates it from other entities like "ACTUATOR", "FOG_DEVICE", etc. This is critical for behaviour modeling, tuple routing, and event handling.
"distribution": 1	Refers to the **type of statistical distribution** used for modelling the inter-arrival time of data packets (tuples) from the sensor. A value of 1 typically refers to a **Gaussian (Normal) distribution**, but this depends on the simulation engine's implementation.
"stdDev": 1.0	**Standard deviation** for the Gaussian distribution. Along with "mean", it determines the **variability or spread** in the data generation interval. A stdDev of 1.0 indicates moderate fluctuation around the mean interval.

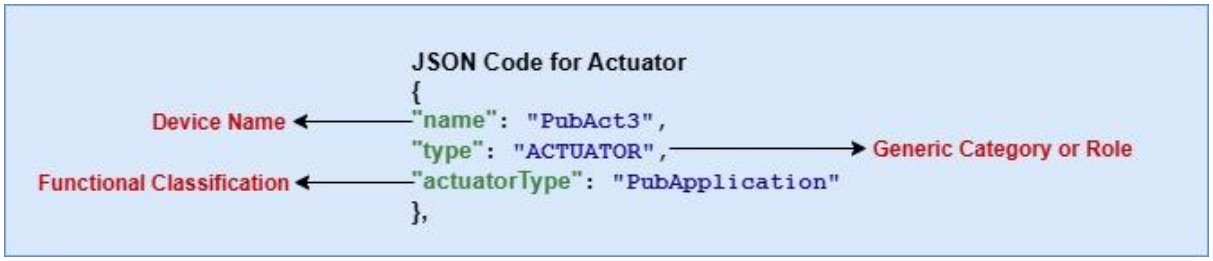


Figure 7.5. Different Components of IoT Actuator JSON

Table 7.5. Detailed description of various components of IoT devices/actuator JSON

Field	Description
"name": "PubAct3"	This is the **unique identifier** or label for the actuator within the simulation environment. The name "PubAct3" could indicate its association with a **public area**, **application module**, or **specific task** such as a publishing action or display trigger.
"type": "ACTUATOR"	Specifies the **role of the component**. In iFogSim, "ACTUATOR" indicates that this device is **responsible for executing actions** based on the outputs of application modules (e.g., controlling a camera, updating a display, triggering alarms). Actuators typically respond to control signals sent from fog/cloud processing units.
"actuatorType": "PubApplication"	Defines the **functional classification** of the actuator. "PubApplication" suggests that this actuator is associated with a **publishing application**, possibly to **display notifications**, **control an output device**, or **interface with user-level services** in a smart campus or education setting. This field guides how tuples (data packets) are handled when sent to this actuator.

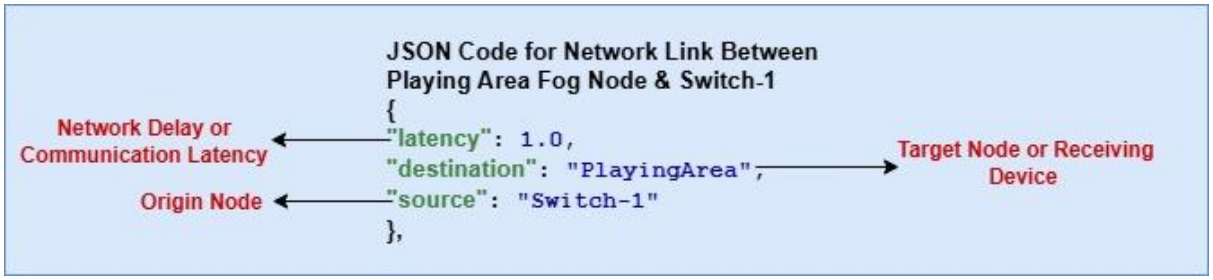


Figure 7.6. Different Components of Network Link JSON between two IoT/Fog/Cloud devices

Table 7.6. Detailed description of various components of Network Link between Playing Area Fog node and Network Switch-1

Field	Description

"latency": 1.0	Specifies the **network delay** or **communication latency** (in milliseconds or seconds, depending on the simulation context) between the source and destination nodes. A value of 1.0 indicates a **low-latency link**, suitable for near-real-time communication—essential in applications such as surveillance, smart classrooms, or interactive educational systems.
"destination": "PlayingArea"	Denotes the **target node** or receiving device in the connection. In this case, "PlayingArea" represents a **fog node** assigned to monitor or manage the physical playing area, possibly collecting data from sensors or sending commands to actuators.
"source": "Switch-1"	Denotes the **origin node** from which data is transmitted. "Switch-1" represents a **network switch or intermediary fog node** that links multiple local devices (e.g., sensors, actuators) to higher-level processing layers. This node acts as a hub in the topology for routing data efficiently.

7.4 Incremental Abstraction Reporting for different Levels of MQEE

As discussed in earlier chapters, the implementation of the Multilayered Quality Education Ecosystem (MQEE) framework is supported by an Incremental Abstraction Reporting Mechanism. This section presents the various types of reports generated upon completion of the simulation environment and the execution of the algorithms introduced previously. Based on data acquired from sensors deployed at the IoT layer, the simulation yields three distinct types of reports:

1. IoT Level Private Reports
2. Fog Level Public Reports
3. Cloud Level Public Reports

The IoT Level Private Reports are intended to identify localized vulnerabilities or irregularities at the physical layer. These reports enable precise detection of the stakeholder, building, or classroom responsible for a given anomaly. Classified as Level 2-1 reports, they are generated by IoT gateways (Level 2) and serve as input for higher-level (Level 1) reporting. These reports are detailed and distributed across Level 2 devices within the network. Information from these reports is displayed on Personal Application Modules, allowing stakeholders to receive real-time alerts. For example, if a student's body temperature exceeds a predefined threshold, the system will notify the student via a mobile or web application developed by the institution. A sample Level 2-1 Private Report generated during the simulation is illustrated in Figure 7.7(a)-Figure 7.7(d).

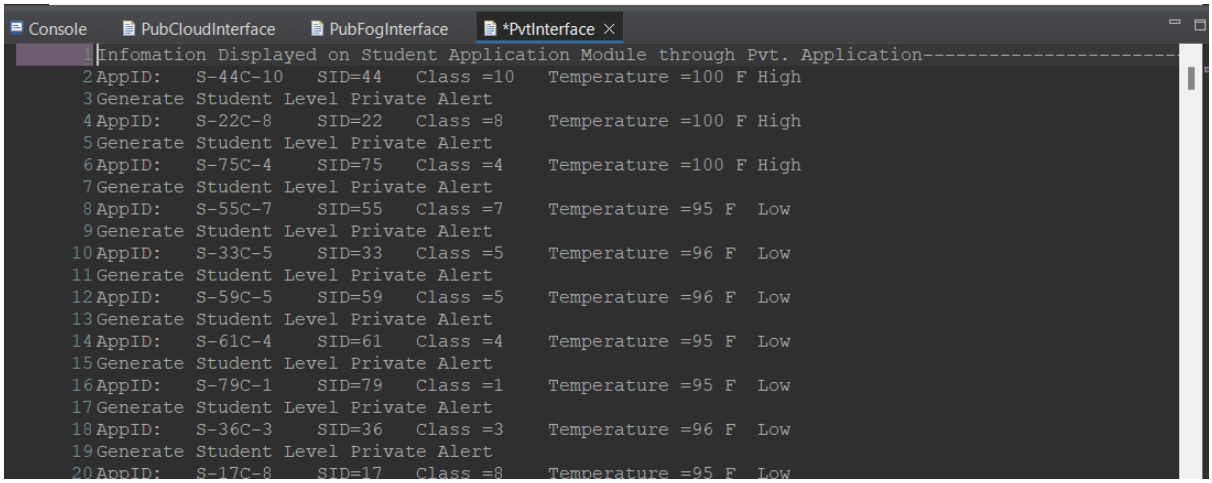


Figure 7.7(a). IoT Level Private Report Simulating Body Temperature irregularities

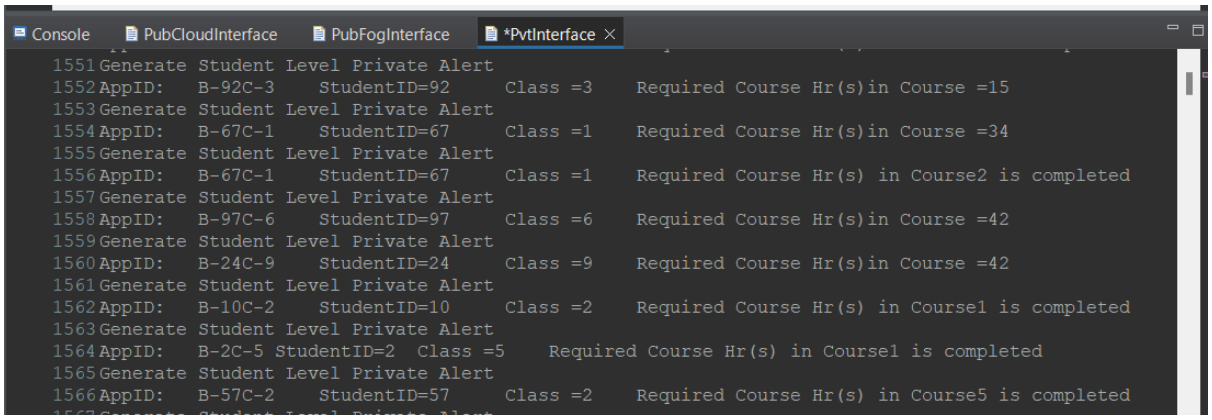


Figure 7.7(b). IoT Level Private Report Simulating Required Course Hr(s) irregularities and completion report

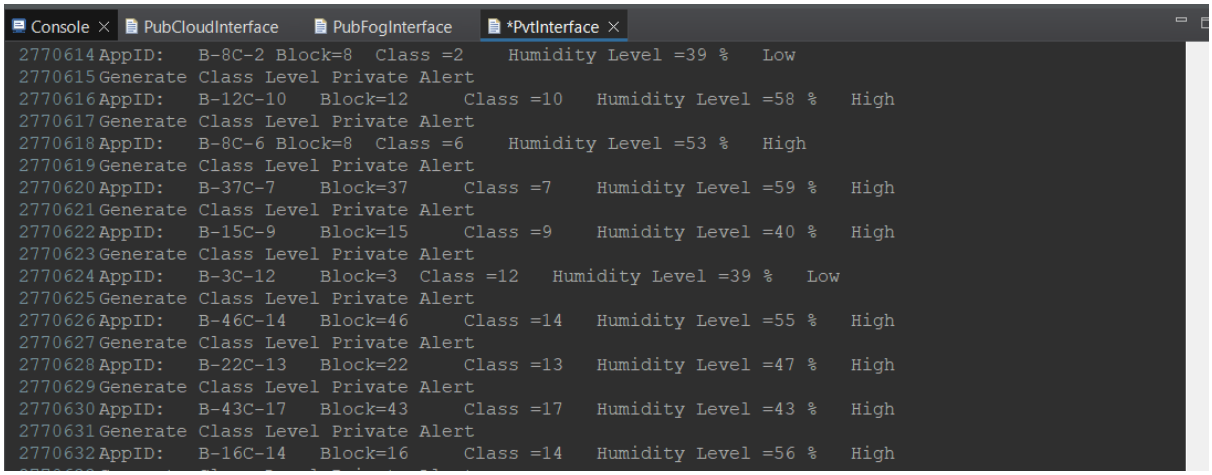


Figure 7.7(c). IoT Level Private Report Simulating Humidity Level irregularities

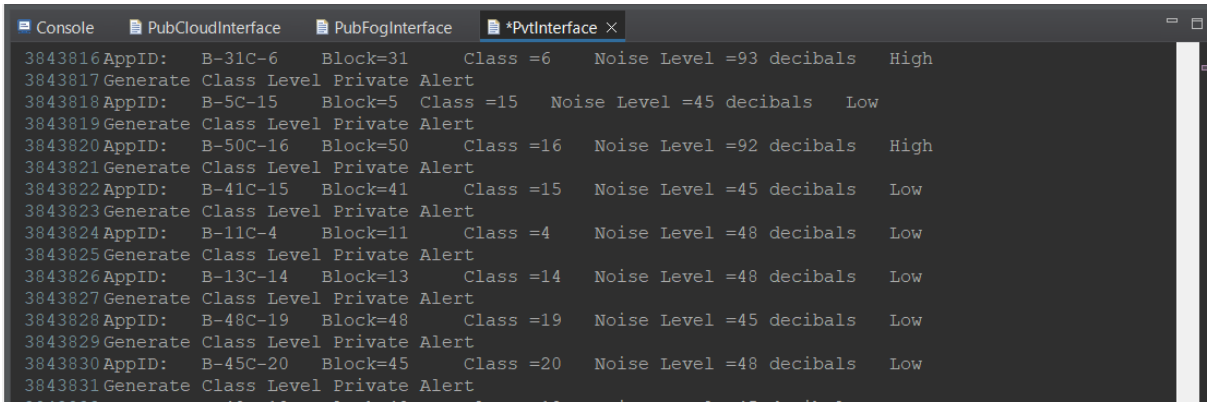


Figure 7.7(d). IoT Level Private Report Simulating Noise Level irregularities

The Fog Level Public Reports, referred to as Level 1-1 reports, are generated using data received from Level 2. While much of the original sensor data is retained, it is abstracted for broader interpretation. These reports are publicly accessible to authorized personnel such as faculty in-charges, administrators, or deans. They provide summarized insights across multiple classrooms or blocks, facilitating decision-making at the intermediate management level. An example of a Level 1-1 Public Report produced during the simulation is shown in Figure 7.8.

Finally, the Cloud Level Public Reports, designated as Level 1-0 reports, represent the highest level of abstraction in the reporting hierarchy. These reports are compiled using data from the Fog Level (Level 1) and primarily contain statistical summaries, such as the total number of detected irregularities or vulnerabilities across the institution. This level of reporting supports institutional assessments and strategic planning by summarizing key trends in performance, safety, and compliance. These reports are typically made available to institutional heads or university-level authorities. A representative Level 1-0 Public Report generated during the simulation is presented in Figure 7.9.

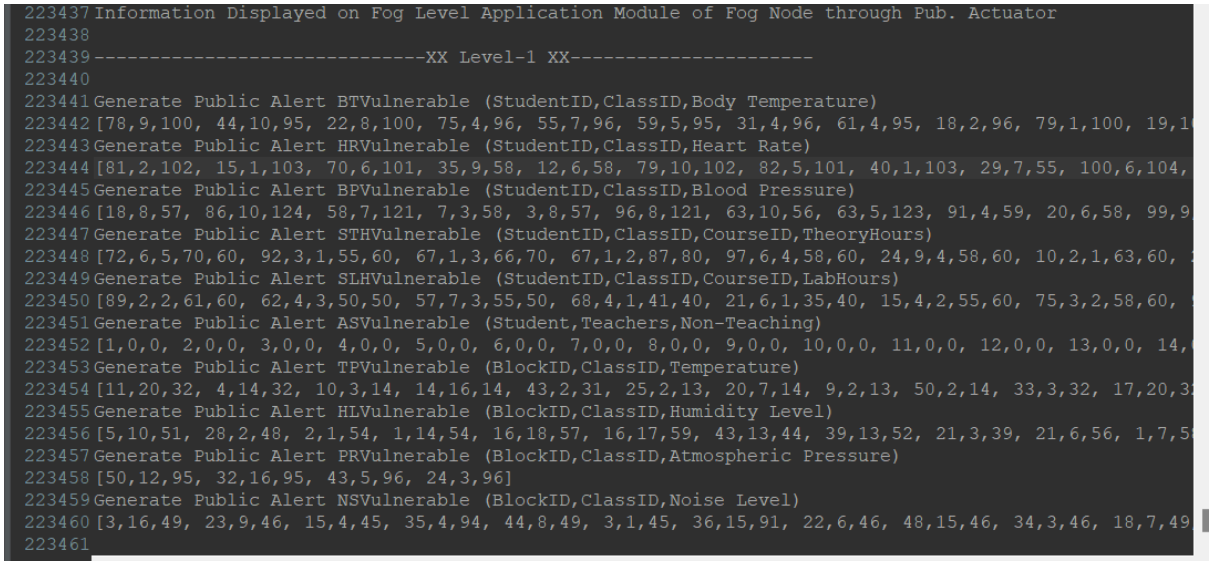


Figure 7.8. Fog Level Public Report showing various vulnerable areas

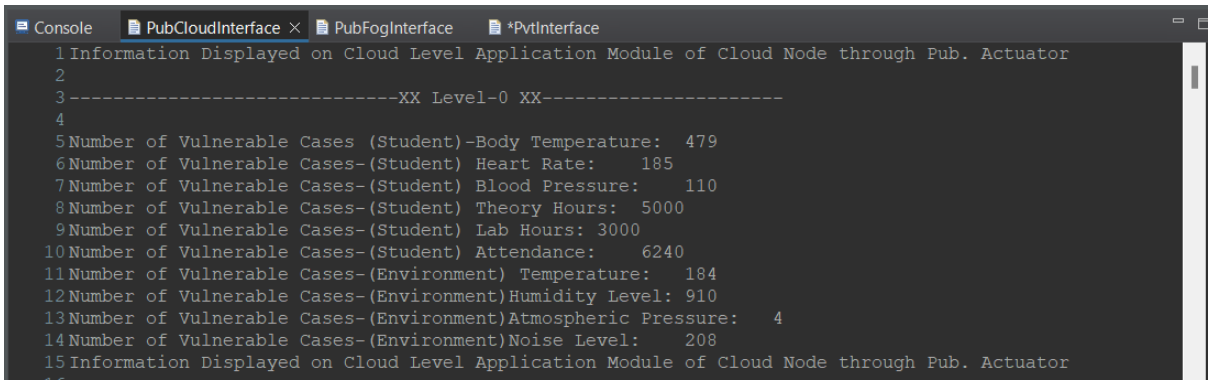


Figure 7.9. Cloud Level Public Report showing number of vulnerable cases

7.5 Performance Analysis and Recommendations

The assessment and accreditation in this environment can be processed in two different ways, i.e., Real time as we generated all the reports in the previous section of this chapter. Or intervallic i.e., after a fixed interval of time. Both the Real time and intervallic scenario of assessment and accreditation are illustrated in the subsequent section of this chapter.

7.5.1 Real-Time/Intervallic Assessment and Accreditation

Education 4.0 represents a transformative shift in the educational paradigm, driven by the convergence of IoT, artificial intelligence, and real-time data analytics. One of its most significant capabilities is the ability to support real-time assessment and accreditation, enabling institutions to evaluate performance, compliance, and quality indicators continuously and instantaneously. As outlined in the preceding sections, data from educational institutions is collected through a network of IoT devices, sensors, and actuators, strategically deployed across various functional areas. This includes classrooms, laboratories, administrative blocks, and other academic and non-academic zones. To facilitate systematic processing and analysis, the collected data is classified into four distinct categories, i.e., SFD, CED, SAD, and CAD/CW. These categories, previously discussed in detail, form the foundation of real-time monitoring and reporting mechanisms within the MQEE framework. The real-time assessment and accreditation architecture, illustrated in Figure 7.10, integrates both live data feeds and historical datasets from multiple institutions. This hybrid approach enables the application of predictive and diagnostic algorithms to detect potential irregularities in the educational environment. For instance, deviations in classroom attendance, sensor-based environmental anomalies, or drops in student performance patterns can be flagged for immediate review. A key feature of this model is its ability to generate real-time alerts based on identified anomalies, allowing stakeholders to initiate preventive or corrective actions well before issues escalate. For example, if environmental sensors detect poor ventilation in a classroom, or if student feedback data reveals persistent dissatisfaction with teaching quality, appropriate interventions can be automatically recommended or triggered [56]. Despite its advantages, the real-time assessment framework presents substantial challenges in terms of computational load and resource consumption [48], [191], [201]. Maintaining continuous data acquisition, processing, and reporting demands significant computing power and may lead to resource inefficiencies, especially in low-demand periods or smaller institutions with limited infrastructure. To address this limitation, the following section introduces an intervallic (periodic) assessment model, inspired by existing accreditation workflows. This model offers a cost-effective and resource-optimized alternative, balancing technological advancement with practical implementation feasibility. Instead, the real-time outputs such as predictions, assessments, irregularity detections, and alerts are stored in dedicated datasets, rather than being acted upon in real-time. This design approach offers a significant computational advantage. By deferring the processing of real-time data until the initiation of the formal accreditation process, the system avoids unnecessary computational overhead that would otherwise be incurred in an ambient and stable educational environment. These dedicated data

repositories, rich with event-driven insights, are later integrated with the institution's historical accreditation datasets when the accreditation cycle is triggered by the respective apex body. The structure and components of this intervallic assessment and accreditation model are illustrated in Figure 7.11.

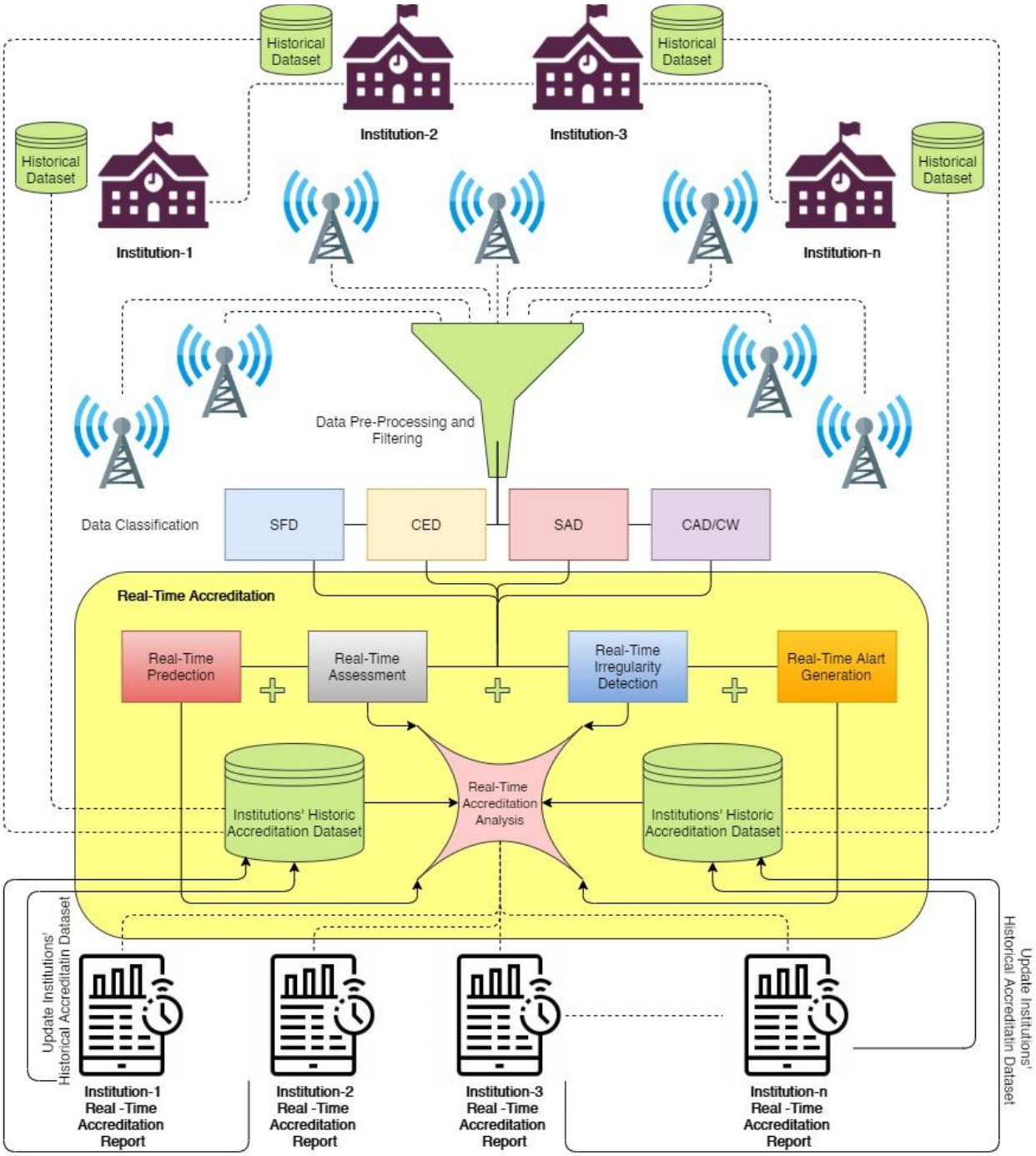


Figure 7.10. Real-Time Assessment and Accreditation under Education 4.0

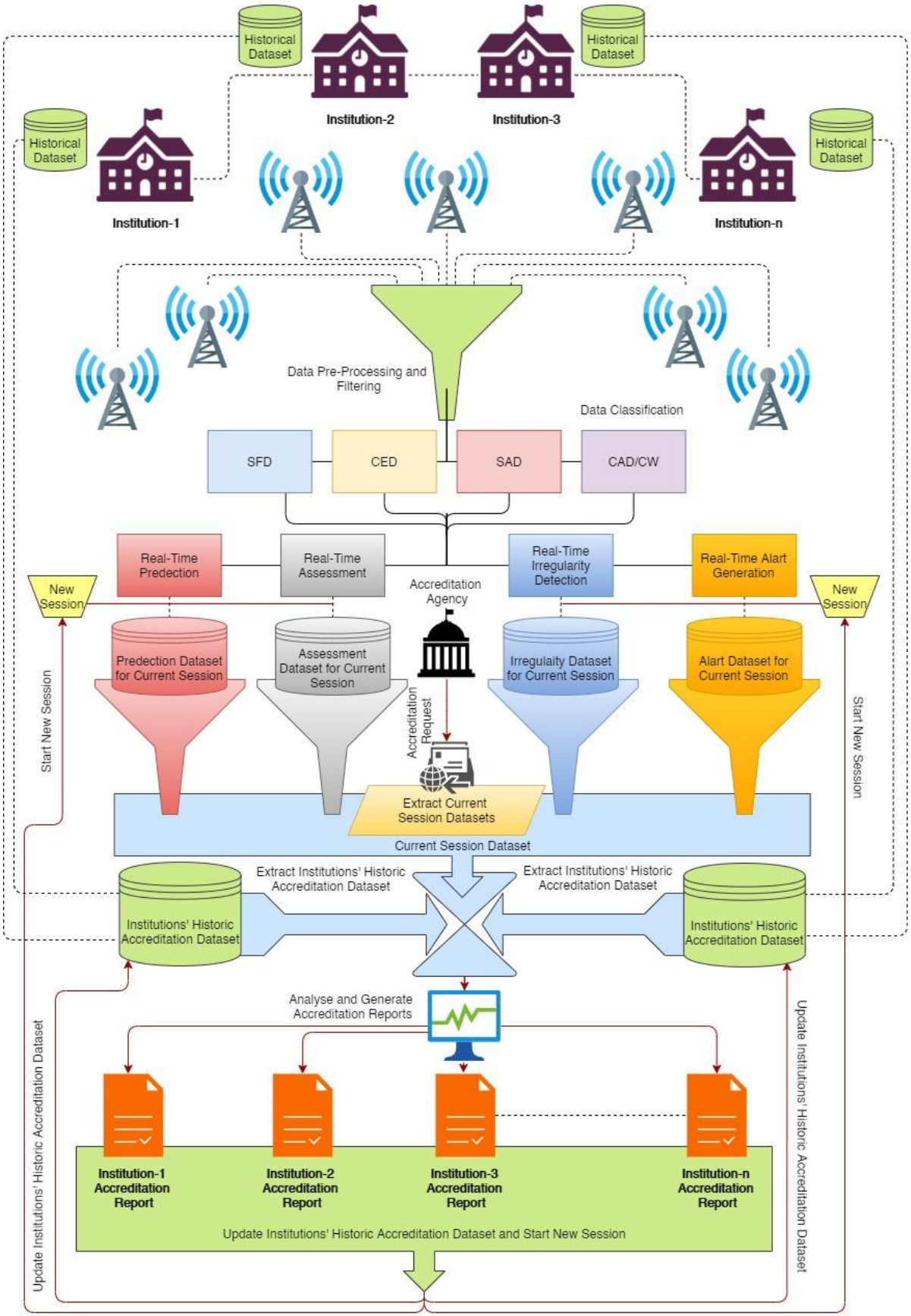


Figure 7.11. Intervallic Assessment and Accreditation under Education 4.0

Once the process is initiated in accordance with the policies of the accreditation agency, the stored real-time data is analyzed alongside historical datasets, allowing for the preparation of a comprehensive and up-to-date accreditation report. Subsequently, these new reports are appended to the historical record, ensuring continuous data enrichment and readiness for future assessment cycles. The intervallic approach described herein presents a robust and resource-efficient alternative to continuous real-time evaluation. It ensures the benefits of data-driven decision-making and quality assurance while maintaining computational sustainability within the Education 4.0 infrastructure.

One of the most important and innovative outcomes of this study is the development of the M-Bi-LSTM model, a novel deep learning architecture designed specifically for data classification and prediction in Education 4.0 settings. To the best of the researcher's knowledge, this model has not been previously used for analyzing educational data that involves hidden parameters and continuously generated real-time inputs. The proposed M-Bi-LSTM is built with four interconnected processing layers that work together as a deep neural network. The first layer directly receives the input data and acts as a memory layer, helping the model retain important information over time. The second and third layers learn from the data in both forward and backward directions, allowing the model to understand patterns more comprehensively rather than relying on a single flow of information. The final layer converts this learned knowledge into probability-based predictions of irregularities. By combining memory, bidirectional learning, and probabilistic prediction, the M-Bi-LSTM model offers a powerful and flexible tool for intelligent decision-making. As such, it stands out as a key deliverable of this research and a significant step forward in applying advanced deep learning techniques to education-focused data analytics.

7.5.2 Performance Evaluation over simulation environment

The performance evaluation of the proposed framework for real-time reporting, irregularity detection, and alert generation was carried out through a detailed simulation across the previously described environment. The evaluation was conducted over ten discrete time intervals, simulating the system's behavior in a continuous time iteration model to closely reflect real-world operational dynamics. The simulation aimed to assess the computational efficiency and response time of each layer—IoT, Fog, and Cloud—under sustained operational conditions [43], [183].

The results indicate that the IoT layer required significantly more time for data collection, irregularity detection, and private reporting, primarily due to the heterogeneity and distributed nature of IoT devices and the volume of data generated by sensors [184], [197], [202]. In contrast, the fog nodes and the cloud node demonstrated relatively low latency and faster processing, attributed to their higher computational capabilities and centralized data handling. The time consumed by each component—across the IoT, Fog, and Cloud layers—is visually represented in Figure 7.12(a) and Figure 7.12(b). As shown in Figure 7.12(a), IoT nodes equipped with various sensors exhibit significantly higher processing times compared to fog and cloud nodes. This discrepancy highlights the computational limitations of edge-level devices and the overhead of real-time local processing.

Furthermore, Figure 7.12(b) presents a focused comparison of the 10th simulation iteration, where a noticeable reduction in processing time is observed across all layers, particularly in the fog and cloud layers, when compared to the 1st simulation iteration. This reduction may be attributed to increased system optimization, improved data routing efficiencies, and reduced sensor-side computation demands over time. For a more granular analysis, a comprehensive tabular representation of the computation times across all IoT devices, the fog node, and the cloud node is provided in Table 7.7. This data supports a detailed understanding of layer-specific computational performance, enabling further insights into the scalability and responsiveness of the proposed MQEE framework under Education 4.0.

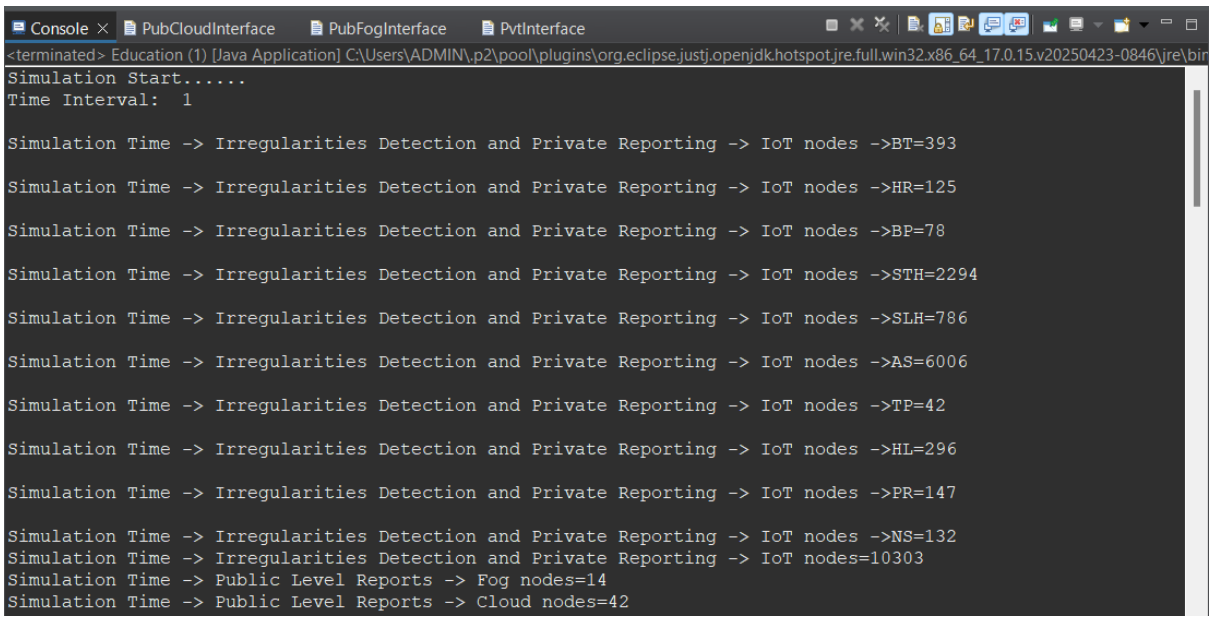


Figure 7.12(a). Time (in milliseconds) taken by various devices during 1st simulation iteration

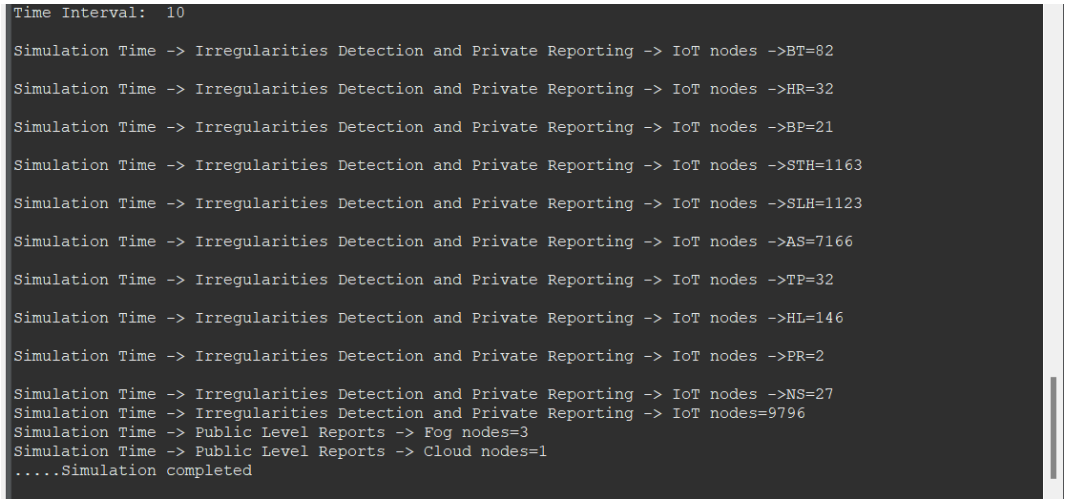


Figure 7.12(b). Time (in milliseconds) taken by various devices during 10th simulation iteration

Table 7.7. Time (in milliseconds) taken by all the IoT devices, Fog node and Cloud node

Time Interval	BT	HR	BP	STH	SLH	AS	TP	HL	PR	NS	Total IoT Nodes	Fog Node Reports	Cloud Node Reports
1	393	125	78	2294	786	6006	42	296	147	132	10303	14	42
2	127	28	22	1092	1015	4608	84	421	2	75	7475	10	3
3	257	31	22	885	523	5175	39	160	1	27	7123	3	2
4	83	31	28	902	1662	4719	267	175	1	30	7899	4	1
5	83	30	23	1282	509	5721	30	526	2	28	8236	3	1
6	82	29	20	1269	907	4569	32	144	1	32	7086	3	1
7	78	30	18	1124	485	6735	36	159	2	27	8697	3	2
8	2367	32	24	1195	1522	4734	31	144	1	32	10082	3	1
9	100	31	20	1432	479	4784	33	147	1	28	7055	3	1
10	82	32	21	1163	1123	7166	32	146	2	27	9796	3	1

7.6 Summary

This chapter presented a comprehensive overview of the iFogSim-based simulation environment developed for the implementation of the proposed Multilayered Quality Education Ecosystem (MQEE). Emphasis was placed on establishing a scalable and cost-efficient simulation model grounded in solid research insights to support early-stage development and experimentation. The chapter detailed the simulation topology design, including the creation and deployment of various nodes across the IoT–Fog–Cloud (IFC) architecture. Each component—IoT devices, sensors, actuators, switches, gateways, proxy servers, fog nodes, and the cloud node—was defined through structured JSON configuration files, enabling a modular and reproducible simulation setup. Additionally, the structure and purpose of network links connecting different layers were described using dedicated JSON formats, completing the overall network topology. A key focus was the layer-wise deployment of devices within the MQEE framework, aligned with Education 4.0 objectives. The

simulation environment demonstrated how different device layers interact to support real-time data processing, event detection, and report generation. The chapter also elaborated on the multi-level reporting structure, highlighting the generation and flow of Level 2-1 Private Reports (IoT layer), Level 1-1 Public Reports (Fog layer), and Level 1-0 Cloud Reports (Cloud layer). These reports serve as the foundation for monitoring, analyzing, and responding to irregularities within the institutional environment. Furthermore, the chapter critically examined two key evaluation models: real-time and intervallic assessment and accreditation. While real-time processing offers immediate responsiveness, it was observed to be computationally intensive, particularly at the IoT layer. In contrast, the intervallic model, inspired by current accreditation practices, was recommended for its resource efficiency and scalability, enabling meaningful evaluation with reduced computational overhead. Finally, the performance evaluation of the framework was conducted across multiple time intervals, showcasing the system's efficiency in irregularity detection, reporting, and alert generation. Simulation results demonstrated that IoT nodes incurred the highest processing times, while fog and cloud layers maintained low latency, validating the layered abstraction approach. This chapter not only validated the feasibility of the MQEE framework through simulation but also laid the groundwork for its practical adoption in the Education 4.0 environments by recommending optimal configurations and reporting mechanisms for quality assurance and accreditation.

CHAPTER 8

Conclusion and Future Scope

***Chapter Briefing*— This chapter concludes this thesis by presenting the requirements, objectives, methodology used, results and recommendations for the proposed framework. It further presents an objective-wise mapping of the study and a dedicated discussion of the study's limitations, and highlights the future scope of the presented framework for various domain-specific and other applications.**

8.1 Conclusion

Education 4.0 marks the evolution of a dynamic, interconnected, and limitless teaching-learning ecosystem that leverages emerging technologies to personalize and optimize educational experiences. Within this new paradigm, assessment and accreditation remain vital processes for ensuring and enhancing the quality of education. However, the current assessment and accreditation mechanisms adopted by most nations are largely intervallic, rigid, and insufficiently equipped to meet the continuous and data-driven demands of Education 4.0. This study addresses the critical need for a robust, intelligent, and adaptive assessment and accreditation system aligned with the Education 4.0 framework. Specifically, it seeks to answer the following research questions:

- How can a C-IoT-based novel solution be designed to support assessment and accreditation in Education 4.0?
- What intelligent trust mechanisms can be developed using C-IoT for reliable monitoring in Education 4.0?
- How does the proposed framework perform across various quality parameters under simulated educational environments?

To answer the first research question, this study begins with a thorough exploration of existing assessment and accreditation systems to identify structural limitations and contextual gaps. The findings reveal that many critical yet often overlooked factors particularly the three foundational pillars of the education ecosystem: infrastructure, faculty, and learning environment play a significant role in determining educational quality. These elements are fully integrated into the proposed solution to create a holistic assessment model. The study further investigates and leverages cutting-edge technologies including the Internet of Things

(IoT), Fog Computing, Cloud Computing, Edge and Grid Computing, Artificial Intelligence (AI), Machine Learning (ML), and Blockchain. Based on experimental trials and feasibility analysis, the IoT-Fog-Cloud (IFC) architecture is selected as the most suitable technological stack for implementing the proposed model. This leads to the formulation of the Cognitive IoT (C-IoT)-based Multi-layered Quality Education Ecosystem (MQEE) a scalable and intelligent architecture designed to support Education 4.0 with real-time monitoring, contextual responsiveness, and system-level transparency. Addressing the second research question, the study introduces a suite of intelligent algorithms for ubiquitous monitoring, irregularity detection, alert generation, assessment, and accreditation. These algorithms are powered by customized M-Bi-LSTM (Multilayered Bidirectional Long Short-Term Memory) machine learning models to enable predictive accuracy, contextual analysis, and pattern recognition. By automating the entire lifecycle from data acquisition to trust-driven accreditation decisions the framework significantly reduces human involvement, thereby minimizing bias and error. Collectively, these algorithms are referred to as the Trust Algorithm, as they ensure reliability, transparency, and accountability within the education quality assurance process. To answer the third research question, the performance of the proposed MQEE framework is evaluated using the iFogSim simulation toolkit. iFogSim provides a cost-effective, realistic platform to simulate the behaviour of large-scale IoT, fog, and cloud-based networks without requiring physical deployment. The simulation environment facilitates the evaluation of the system's ability to perform data classification, vulnerability detection, real-time alert generation, and predictive assessment.

Moreover, the framework is tested for both real-time and intervallic assessment and accreditation scenarios, providing valuable insights into its adaptability and efficiency. The results suggest that while real-time reporting offers rapid responsiveness and operational awareness, intervallic accreditation structured and triggered by historical and cumulative data proves more effective for resource optimization and policy-driven compliance. Consequently, a hybrid model is recommended: employing real-time mechanisms for continuous assessment and leveraging intervallic strategies for formal accreditation processes.

In a nutshell, this study presents a technologically advanced, AI-empowered, and resource-efficient framework that redefines how quality assurance is conceptualized and executed in the Education 4.0 landscape. The C-IoT-based MQEE architecture offers a viable path forward for institutions seeking to embrace smart, autonomous, and transparent educational ecosystems.

8.2 Usefulness and Practical Significance of the Study

The present research offers substantial practical value by translating the principles of Education 4.0 into an implementable, data-driven framework for assessment, quality assurance, and accreditation. A key contribution of the study is the development and application of a novel M-Bi-LSTM–based framework, which enables intelligent classification and prediction of complex, real-time educational data influenced by hidden parameters. This framework supports informed decision-making by accurately identifying patterns, trends, and irregularities within dynamic learning environments.

The study further introduces an Incremental Abstraction Model to effectively address Big Data challenges by progressively transforming raw, heterogeneous data into meaningful, decision-ready information. This model ensures that stakeholders at different levels institutions, assessment bodies, and accreditation agencies receive concise and relevant reports aligned with their specific requirements, thereby enhancing efficiency, scalability, and reliability in evaluation processes.

Another major practical outcome is the development of real-time irregularity detection algorithms capable of identifying deviations in stakeholder behavior and system performance within an ambient Education 4.0 ecosystem. By enabling early detection and timely corrective interventions, these algorithms promote continuous quality improvement, transparency, and accountability. Collectively, the proposed real-time assessment and accreditation framework integrates Cognitive-IoT, advanced analytics, and layered data abstraction, shifting quality assurance from a retrospective, periodic exercise to a proactive and continuous process. The study therefore delivers actionable models and tools that are directly applicable to institutions, accreditation agencies, and policymakers seeking sustainable and globally aligned quality education systems.

Major Usefulness of the Study

1. Provides a novel M-Bi-LSTM–based framework for intelligent classification and prediction of real-time educational data.
2. Enables effective management of Big Data through the Incremental Abstraction Model, ensuring meaningful and scalable reporting.
3. Supports real-time detection of irregularities, facilitating early intervention and continuous improvement in educational processes.

4. Strengthens assessment and accreditation systems through data-driven, automated, and transparent mechanisms.
5. Enhances stakeholder accountability, participation, and engagement within the Education 4.0 environments.
6. Assists institutional leaders and policymakers in evidence-based planning and decision-making.
7. Offers a flexible and transferable framework adaptable to other domains such as healthcare, human resource management, and total quality management.

Objective-wise Mapping of the Study

To clearly demonstrate how each research objective has been addressed in the present study, Table 8.1 maps every objective to the corresponding methodological approach, the chapter/section in which it is treated, and the key outcome achieved.

Table 8.1. Objective-wise mapping of the study

S.No	Research Objective	Approach Adopted in the Study	Chapter Reference	Key Outcome
1	To design a C-IoT based novel solution for assessment and accreditation for Education 4.0.	Literature review, Research Gap, Conceptual Design, Detailed Design and iFogSim based Simulation.	Chapters 2-4	Design of the Cognitive IoT (C-IoT)-based Multi-layered Quality Education Ecosystem (MQEE).
2	To develop a C-IoT based trust algorithm for monitoring and trust building in Education 4.0.	Design of the Trust Algorithm suite, covering ubiquitous monitoring, irregularity detection, alert generation, assessment, and accreditation, powered by customized M-Bi-LSTM models and secure Incremental Abstraction	Chapter 5-6	M-Bi-LSTM based Solution, Incremental Abstraction Model, Various assessment, accreditation, and irregularity detection

		Model.		algorithms.
3	To evaluate the performance of the proposed framework on various quality parameters.	Simulation of the MQEE framework using the iFogSim toolkit under real-time and intervallic scenarios; comparative performance analysis of data classification, vulnerability detection, and predictive assessment.	Chapter 7	Validated hybrid model recommendation combining real-time assessment with intervallic accreditation.

8.3 Limitations of the Study

While the proposed framework demonstrates significant potential for real-time assessment and accreditation in Education 4.0, the present study is bounded by certain limitations that distinguish the results demonstrated here from the areas identified for future work in the next section:

1. **Simulation-based validation:** The framework's performance has been evaluated using the iFogSim simulation toolkit rather than a physical IoT–Fog–Cloud deployment; consequently, real-world factors such as network latency variance, hardware heterogeneity, and live institutional data noise are not fully captured in the present results.
2. **Domain scope of empirical validation:** The MQEE framework and Trust Algorithm have been empirically validated specifically for the assessment and accreditation use case in Education 4.0; applicability to other domains such as healthcare or human resource management, discussed in Section 8.4, remains conceptual and has not been empirically tested in this study.
3. **Data integrity mechanisms:** The present study focuses on trust-driven monitoring and irregularity detection; blockchain-based immutable record-keeping for accreditation data, though proposed as a future enhancement, has not been implemented or evaluated in the current framework.
4. **Scale of simulation scenarios:** The iFogSim-based evaluation was conducted under defined network configurations and scenario sizes; performance at the scale of large, multi-campus institutional deployments has not been independently verified.

These limitations do not diminish the contributions of the study; rather, they delineate its present scope and provide the motivation and foundation for the future research directions outlined in Section 8.4.

8.4 Future Scope

The proposed C-IoT-based framework demonstrates high adaptability and broad applicability across multiple domains, making it especially valuable for future real-world deployments and interdisciplinary research. Its core design is particularly well-suited for real-time assessment in diverse educational environments aligned with the vision of Education 4.0, offering seamless integration of continuous evaluation, automated reporting, and trust-based accreditation. Beyond academia, the framework can be leveraged in the development of

intelligent courseware platforms for both technical and non-technical disciplines, enabling real-time learner evaluation, adaptive content delivery, and personalized academic support. In organizational settings, it holds promise for human resource management, particularly in large institutions where manual oversight mechanisms are insufficient. The system's ability to autonomously monitor activities, detect irregularities, and generate alerts positions it as a valuable solution for enterprise-level personnel evaluation and decision-making [178], [203], [204]. Furthermore, the architecture aligns well with Smart City and IIoT applications, where large-scale infrastructure monitoring, reliability assurance, and event-based alerting are critical [76], [205]. The framework's potential also extends to public and private sector policymaking, offering a data-driven foundation for developing intelligent, transparent, and adaptive policies. Looking ahead, future research could focus on integrating blockchain technology to enhance data integrity and provide immutable accreditation records [206], [207], [208]. The adoption of federated learning techniques could ensure data privacy in distributed educational networks, while cross-institutional accreditation systems may enable benchmarking and collaborative quality improvement across institutions. The development of AI-powered intervention mechanisms for early detection and support of at-risk learners, coupled with edge AI deployment, can further enhance real-time responsiveness, especially in resource-constrained environments. Additionally, extending the framework's accessibility through mobile platforms and LMS integration would improve practical usability. Finally, aligning the system with national and international accreditation standards and digital education policies could facilitate its formal adoption by educational bodies and regulatory authorities. In essence, this study not only provides a solid foundation for quality assurance under Education 4.0 but also opens a wide range of opportunities for innovation and scalability across educational, industrial, civic, and governance domains.

REFERENCES

[1] A. Elragal and A. Habibipour, "Operationalizing education 4.0: A structured method for course materials and assessment alignment," *Front. Educ.*, vol. 10, 2025.

[2] H. Ş. Okumuş, S. Birgün, and Y. Şahin, "University 4.0 readiness in the digital age: An entropy-based multi criteria assessment of Turkish universities," *Discov. Educ.*, vol. 5, no. 1, Art. no. 114, 2026.

[3] R. C. Dorf, "Educational Technology," *IEEE Transactions on Education*, vol. 12, no. 1, pp. 50–52, 1969, doi: 10.1109/TE.1969.4320439.

[4] A. Benešová and J. Tupa, "Requirements for Education and Qualification of People in Industry 4.0," *Procedia Manuf.*, vol. 11, no. June, pp. 2195–2202, 2017, doi: 10.1016/j.promfg.2017.07.366.

[5] M. Maria, F. Shahbodin, and N. C. Pee, "Malaysian higher education system towards industry 4.0 - Current trends overview," *AIP Conf. Proc.*, vol. 2016, pp. 0–7, 2018, doi: 10.1063/1.5055483.

[6] C. A. Bonfield, M. Salter, A. Longmuir, M. Benson, and C. Adachi, "Transformation or evolution?: Education 4.0, teaching and learning in the digital age," *High. Educ. Pedagog.*, vol. 5, no. 1, pp. 223–246, 2020, doi: 10.1080/23752696.2020.1816847.

[7] M. I. Ciolacu, L. Binder, P. Svasta, I. Tache, and D. Stoichescu, "Education 4.0 - Jump to Innovation with IoT in Higher Education," *SIITME 2019 - 2019 IEEE 25th International Symposium for Design and Technology in Electronic Packaging, Proceedings*, no. October, pp. 135–141, 2019, doi: 10.1109/SIITME47687.2019.8990825.

[8] A. Verma, A. Singh, E. Lughofer, X. Cheng, and K. Abualsaud, "Multilayered-quality education ecosystem (MQEE): an intelligent education modal for sustainable quality education," *J. Comput. High. Educ.*, no. 0123456789, 2021, doi: 10.1007/s12528-021-09291-1.

[9] G. M. Milis, C. G. Panayiotou, and M. M. Polycarpou, "SEMIoTICS: Semantically Enhanced IoT-Enabled Intelligent Control Systems," *IEEE Internet Things J.*, vol. 6, no. 1, pp. 1257–1266, 2019, doi: 10.1109/JIOT.2017.2773200.

[10] M. Jara and H. Mellar, "Quality enhancement for e-learning courses: The role of student feedback," *Comput. Educ.*, vol. 54, no. 3, pp. 709–714, 2010, doi: 10.1016/j.compedu.2009.10.016.

[11] T. Altameem and A. Altameem, "Hybridized interference bounded intuitive splitting for smart wearable system using cognitive assisted Internet of Things," *Comput. Commun.*, vol. 151, no. January, pp. 428–436, 2020, doi: 10.1016/j.comcom.2019.12.047.

[12] F. B. J, R. R, S. M, and G. M. N R, "IoT based Cloud Integrated Smart Classroom for smart and a sustainable Campus," *Procedia Comput. Sci.*, vol. 172, no. 2019, pp. 77–81, 2020, doi: 10.1016/j.procs.2020.05.012.

[13] M. Wang, “Research on Construction of the Internal Quality Assurance System of Assessment-Based Diagnosis and Reformation in Higher Vocational Colleges,” *2019 IEEE Eurasia Conference on IOT, Communication and Engineering, ECICE 2019*, no. 9, pp. 518–521, 2019, doi: 10.1109/ECICE47484.2019.8942780.

[14] N. Senthilkumar and A. Arulraj, “SQM-HEI – determination of service quality measurement of higher education in India,” *Journal of Modelling in Management*, vol. 6, no. 1, pp. 60–78, 2011, doi: 10.1108/17465661111112502.

[15] A. K. Sangaiah, J. S. A. Dhanaraj, P. Mohandas, and A. Castiglione, “Cognitive IoT system with intelligence techniques in sustainable computing environment,” *Comput. Commun.*, vol. 154, no. January, pp. 347–360, 2020, doi: 10.1016/j.comcom.2020.02.049.

[16] L. G. Seng, K. L. K. Wei, and S. J. Narciso, “Effective industry ready IoT Applied Courseware - Teaching IoT Design and Validation,” *IEEE Global Engineering Education Conference, EDUCON*, vol. 2020-April, pp. 1579–1583, 2020, doi: 10.1109/EDUCON45650.2020.9125366.

[17] S. Dharur and K. Swaminathan, “Efficient surveillance and monitoring using the ELK stack for IoT powered Smart Buildings,” *Proceedings of the 2nd International Conference on Inventive Systems and Control, ICISC 2018*, no. Icisc, pp. 700–705, 2018, doi: 10.1109/ICISC.2018.8398888.

[18] Z. Tang, C. Zeng, and Y. Zeng, “Research on data security in industry 4.0 manufacturing industry against the background of privacy protection challenges,” *Int. J. Comput. Integr. Manuf.*, vol. 38, no. 5, pp. 636–648, 2025.

[19] B. Wibowo et al., “Cyber resilience to digital threats for education institutions 4.0,” *Int. J. Manage. Sci. Appl.*, vol. 4, no. 1, pp. 35–45, 2025.

[20] T. Altameem and A. Altameem, “Hybridized interference bounded intuitive splitting for smart wearable system using cognitive assisted Internet of Things,” *Comput. Commun.*, vol. 151, pp. 428–436, Feb. 2020, doi: 10.1016/j.comcom.2019.12.047.

[21] K. Huang, W. Liu, Y. Li, A. Savkin, and B. Vucetic, “Wireless Feedback Control with Variable Packet Length for Industrial IoT,” *IEEE Wireless Communications Letters*, vol. 2337, no. c, pp. 1–1, 2020, doi: 10.1109/lwc.2020.2998611.

[22] M. A. L. Peña, J. Díaz, J. E. Pérez, and H. Humanes, “DevOps for IoT Systems : Fast & Continuous Monitoring Feedback of System Availability,” vol. 4662, no. c, 2020, doi: 10.1109/JIOT.2020.3012763.

[23] M. Rezwanul Mahmood and M. A. Matin, *Current Research Trends on Cognitive Radio Based Internet of Things (IoT)*. Springer International Publishing, 2020. doi: 10.1007/978-3-030-42573-9_2.

[24] A. Adel, “The Convergence of Intelligent Tutoring, Robotics, and IoT in Smart Education for the Transition from Industry 4.0 to 5.0,” *Smart Cities*, vol. 7, no. 1, pp. 325–369, Jan. 2024, doi: 10.3390/smartcities7010014.

[25] A. Saxena, K. Shinghal, R. Misra, and A. Agarwal, "Automated Enhanced Learning System using IOT," *Proceedings - 2019 4th International Conference on Internet of Things: Smart Innovation and Usages, IoT-SIU 2019*, pp. 1–5, 2019, doi: 10.1109/IoT-SIU.2019.8777711.

[26] A. Fernández-Pacheco, S. Martin, and M. Castro, "Implementation of an arduino remote laboratory with raspberry pi," *IEEE Global Engineering Education Conference, EDUCON*, vol. April-2019, pp. 1415–1418, 2019, doi: 10.1109/EDUCON.2019.8725030.

[27] M. I. Ciolacu, L. Binder, P. Svasta, I. Tache, and D. Stoichescu, "Education 4.0 - Jump to Innovation with IoT in Higher Education," *SIITME 2019 - 2019 IEEE 25th International Symposium for Design and Technology in Electronic Packaging, Proceedings*, no. October, pp. 135–141, 2019, doi: 10.1109/SIITME47687.2019.8990825.

[28] U. Jayasinghe, G. M. Lee, Á. MacDermott, W. S. Rhee, and K. Elgazzar, "TrustChain: A Privacy Preserving Blockchain with Edge Computing," *Wirel. Commun. Mob. Comput.*, vol. 2019, 2019, doi: 10.1155/2019/2014697.

[29] D. Centea, I. Singh, and M. Elbestawi, "SEPT Approaches for Education and Training using a Learning Factory," *Procedia Manuf.*, vol. 31, pp. 109–115, 2019, doi: 10.1016/j.promfg.2019.03.018.

[30] A. R. Abdellah, O. A. K. Mahmood, A. Paramonov, and A. Koucheryavy, "IoT traffic prediction using multi-step ahead prediction with neural network," *International Congress on Ultra Modern Telecommunications and Control Systems and Workshops*, vol. 2019-Octob, pp. 1–4, 2019, doi: 10.1109/ICUMT48472.2019.8970675.

[31] X. Wang, Z. Qian, X. Wang, and L. Huang, "Robust localization for cognitive IoT via the mobile anchor node based on the diameter-varying spiral line," *IEEE Access*, vol. 7, pp. 28487–28497, 2019, doi: 10.1109/ACCESS.2019.2901745.

[32] G. A. Montes and B. Goertzel, "Distributed, decentralized, and democratized artificial intelligence," *Technol. Forecast. Soc. Change*, vol. 141, no. November, pp. 354–358, 2019, doi: 10.1016/j.techfore.2018.11.010.

[33] X. Chen, L. Breslow, and J. DeBoer, "Analyzing productive learning behaviors for students using immediate corrective feedback in a blended learning environment," *Comput. Educ.*, vol. 117, no. September 2017, pp. 59–74, 2018, doi: 10.1016/j.compedu.2017.09.013.

[34] P. K. D. Pramanik, S. Pal, and P. Choudhury, *Beyond Automation: The Cognitive IoT. Artificial Intelligence Brings Sense to the Internet of Things*. 2018. doi: 10.1007/978-3-319-70688-7_1.

[35] R. Mahmud, S. N. Srirama, K. Ramamohanarao, and R. Buyya, "Quality of Experience (QoE)-aware placement of applications in Fog computing environments," *J. Parallel Distrib. Comput.*, vol. 132, pp. 190–203, 2019, doi: 10.1016/j.jpdc.2018.03.004.

[36] M. Ali and A. Majeed, “How Internet-of-Things (IoT) Making the University Campuses Smart ?,” pp. 646–648, 2018, doi: 10.1109/CCWC.2018.8301774.

[37] R. Gad *et al.*, “Iris Recognition Using Multi-Algorithmic Approaches for Cognitive Internet of things (CIoT) Framework,” *Future Generation Computer Systems*, vol. 89, pp. 178–191, 2018, doi: 10.1016/j.future.2018.06.020.

[38] A. Zhamanov, Z. Sakhiyeva, R. Suliyev, and Z. Kaldykulova, “IoT smart campus review and implementation of IoT applications into education process of university,” *2017 13th International Conference on Electronics, Computer and Computation, ICECCO 2017*, vol. 2018-Janua, pp. 1–4, 2018, doi: 10.1109/ICECCO.2017.8333334.

[39] T. Guo, D. Khoo, M. Coultis, M. Pazos-Revilla, and A. Siraj, “Poster abstract: IoT platform for engineering education and research (IoT PEER)-applications in secure and smart manufacturing,” *Proceedings - ACM/IEEE International Conference on Internet of Things Design and Implementation, IoTDI 2018*, no. c, pp. 277–278, 2018, doi: 10.1109/IoTDI.2018.00038.

[40] Y. Bahuguna, A. Verma, and K. Raj, “Smart learning based on augmented reality with android platform and its applicability,” *Proceedings - 2018 3rd International Conference On Internet of Things: Smart Innovation and Usages, IoT-SIU 2018*, pp. 1–5, 2018, doi: 10.1109/IoT-SIU.2018.8519853.

[41] J. Zhu, Y. Song, D. Jiang, and H. Song, “A new deep-q-learning-based transmission scheduling mechanism for the cognitive internet of things,” *IEEE Internet Things J.*, vol. 5, no. 4, pp. 2375–2385, 2018, doi: 10.1109/JIOT.2017.2759728.

[42] G. Roncancio, M. Espinosa, M. R. Pérez, and L. C. Trujillo, “Spectral sensing method in the radio cognitive context for IoT applications,” *Proceedings - 2017 IEEE International Conference on Internet of Things, IEEE Green Computing and Communications, IEEE Cyber, Physical and Social Computing, IEEE Smart Data, iThings-GreenCom-CPSCom-SmartData 2017*, vol. 2018-Janua, pp. 756–761, 2018, doi: 10.1109/iThings-GreenCom-CPSCom-SmartData.2017.116.

[43] P. Verma and S. K. Sood, “Internet of Things-based student performance evaluation framework,” *Behaviour and Information Technology*, vol. 37, no. 2, pp. 102–119, 2018, doi: 10.1080/0144929X.2017.1407824.

[44] T. Banerjee and A. Sheth, “IoT Quality Control for Data and Application Needs,” *IEEE Intell. Syst.*, vol. 32, no. 2, pp. 68–73, 2017, doi: 10.1109/MIS.2017.35.

[45] C. S. Li, F. Darema, and V. Chang, “Distributed behavior model orchestration in cognitive internet of things solution,” *Int. J. Inf. Manage.*, pp. 1–11, 2016, doi: 10.1016/j.ijinfomgt.2016.03.012.

[46] K. Sato, Y. Kawamoto, H. Nishiyama, N. Kato, and Y. Shimizu, “A modeling technique utilizing feedback control theory for performance evaluation of IoT system in real-time,” *2015 International Conference on Wireless Communications and Signal Processing, WCSP 2015*, pp. 0–4, 2015, doi: 10.1109/WCSP.2015.7341303.

[47] H. Tolley and B. Shulruf, “From data to knowledge: The interaction between data management systems in educational institutions and the delivery of quality education,”

Comput. Educ., vol. 53, no. 4, pp. 1199–1206, 2009, doi: 10.1016/j.compedu.2009.06.003.

[48] M. Farhan *et al.*, "A Real-Time Data Mining Approach for Interaction Analytics Assessment: IoT Based Student Interaction Framework," *Int. J. Parallel Program.*, vol. 46, no. 5, pp. 886–903, 2018, doi: 10.1007/s10766-017-0553-7.

[49] V. V. Silaeva and V. P. Semenov, "Internal Education Quality Assurance through Standardization of Educational Organization Management System," *Proceedings of the 2018 International Conference "'Quality Management, Transport and Information Security, Information Technologies'", IT and QM and IS 2018*, pp. 70–73, 2018, doi: 10.1109/ITMQIS.2018.8525083.

[50] A. Verma, A. Singh, E. Lughofer, X. Cheng, and K. Abualsaud, "Multilayered-quality education ecosystem (MQEE): an intelligent education modal for sustainable quality education," *J. Comput. High. Educ.*, no. 0123456789, 2021, doi: 10.1007/s12528-021-09291-1.

[51] M. Ciolacu, A. F. Tehrani, R. Beer, and H. Popp, "Education 4.0-Fostering student's performance with machine learning methods," *2017 IEEE 23rd International Symposium for Design and Technology in Electronic Packaging, SIITME 2017 - Proceedings*, vol. 2018-Janua, pp. 438–443, 2017, doi: 10.1109/SIITME.2017.8259941.

[52] C. A. Bonfield, M. Salter, A. Longmuir, M. Benson, and C. Adachi, "Transformation or evolution?: Education 4.0, teaching and learning in the digital age," *High. Educ. Pedagog.*, vol. 5, no. 1, pp. 223–246, 2020, doi: 10.1080/23752696.2020.1816847.

[53] A. Hariharasudan and S. Kot, "A scoping review on Digital English and Education 4.0 for Industry 4.0," *Soc. Sci.*, vol. 7, no. 11, 2018, doi: 10.3390/socsci7110227.

[54] H. Kuper, "Industry 4.0: changes in work organization and qualification requirements—challenges for academic and vocational education," *Entrepreneurship Education*, vol. 3, no. 2, pp. 119–131, 2020, doi: 10.1007/s41959-020-00029-1.

[55] M. A. Varghese, "Development of collegiums of quality assessors for the Indian National Assessment & Accreditation Council (NAAC)," *2011 International Workshop on Institutional and Programme Accreditation: Connections and Opportunities - Proceedings, IWIPA 2011*, 2011, doi: 10.1109/IWIPA.2011.6221137.

[56] I. Udrea, V. I. Gheorghe, and A. M. Dogeanu, "Optimizing Greenhouse Design with Miniature Models and IoT (Internet of Things) Technology—A Real-Time Monitoring Approach," *Sensors*, vol. 24, no. 7, p. 2261, Apr. 2024, doi: 10.3390/s24072261.

[57] V. L. Patil, "Historical perspectives and unbalanced growth of engineering education infrastructure in India," *Proceedings of IEEE International Conference on Teaching, Assessment, and Learning for Engineering, TALE 2012*, pp. 12–14, 2012, doi: 10.1109/TALE.2012.6360302.

[58] F. T. Zohora, M. R. R. Khan, M. F. R. Bhuiyan, and A. K. Das, "Enhancing the capabilities of IoT based fog and cloud infrastructures for time sensitive events," *ICECOS 2017 - Proceeding of 2017 International Conference on Electrical*

Engineering and Computer Science: Sustaining the Cultural Heritage Toward the Smart Environment for Better Future, pp. 224–230, 2017, doi: 10.1109/ICECOS.2017.8167139.

[59] J. Miranda *et al.*, "The core components of education 4.0 in higher education: Three case studies in engineering education," *Computers and Electrical Engineering*, vol. 93, no. September 2020, 2021, doi: 10.1016/j.compeleceng.2021.107278.

[60] M. Ciolacu, A. F. Tehrani, L. Binder, and P. M. Svasta, "Education 4.0 - Artificial Intelligence Assisted Higher Education: Early recognition System with Machine Learning to support Students' Success," *2018 IEEE 24th International Symposium for Design and Technology in Electronic Packaging, SIITME 2018 - Proceedings*, no. Ml, pp. 23–30, 2019, doi: 10.1109/SIITME.2018.8599203.

[61] R. L. C. Silva Filho, K. Brito, and P. J. L. Adeodato, "Leveraging Causal Reasoning in Educational Data Mining: An Analysis of Brazilian Secondary Education," *Applied Sciences*, vol. 13, no. 8, p. 5198, Apr. 2023, doi: 10.3390/app13085198.

[62] A. Verma, A. Singh, D. Anand, H. M. Aljahdali, K. Alsubhi, and B. Khan, "IoT Inspired Intelligent Monitoring and Reporting Framework for Education 4.0," *IEEE Access*, vol. 9, pp. 131286–131305, 2021, doi: 10.1109/ACCESS.2021.3114286.

[63] S. Shunmugaraj, "Social Loafing."

[64] K. K. Mihelič and B. Culiberg, "Reaping the Fruits of Another's Labor: The Role of Moral Meaningfulness, Mindfulness, and Motivation in Social Loafing," *Journal of Business Ethics*, vol. 160, no. 3, pp. 713–727, 2019, doi: 10.1007/s10551-018-3933-z.

[65] "Toyota's Core Principles: 'Total Participation' & 'Employee Engagement'Business Initiative Directions Blog | Business Initiative Directions Blog." Accessed: Mar. 31, 2020. [Online]. Available: http://blog.bid-org.com/toyotas-core-principles-total-participation-employee-engagement/

[66] P. J. Roig, S. Alcaraz, K. Gilly, C. Bernad, and C. Juiz, "Design and Assessment of an Active Learning-Based Seminar," *Educ. Sci. (Basel).*, vol. 14, no. 4, p. 371, Apr. 2024, doi: 10.3390/educsci14040371.

[67] S. Caeiro, U. M. Azeiteiro, W. L. Filho, and C. Jabbour, "Sustainability assessment tools in higher education institutions: Mapping trends and good practices around the world," *Sustainability Assessment Tools in Higher Education Institutions: Mapping Trends and Good Practices Around the World*, pp. 1–417, 2013, doi: 10.1007/978-3-319-02375-5.

[68] E. Jauk and J. C. Ehrenthal, "Self-Reported Levels of Personality Functioning from the Operationalized Psychodynamic Diagnosis (OPD) System and Emotional Intelligence Likely Assess the Same Latent Construct," *J. Pers. Assess.*, vol. 0, no. 0, pp. 1–15, 2020, doi: 10.1080/00223891.2020.1775089.

[69] U. Bagchi, "Delivering student satisfaction in higher education: A QFD approach," *2010 7th International Conference on Service Systems and Service Management, Proceedings of ICSSSM' 10*, pp. 1049–1052, 2010, doi: 10.1109/ICSSSM.2010.5530090.

[70] H. K. Virk, “Impact of Emotional Intelligence on Job Satisfaction, Organizational Commitment and Perceived Success,” *International Journal of Arts & Sciences*, vol. 4, no. 22, pp. 297–312, 2011, [Online]. Available: http://search.proquest.com.csuglobal.idm.oclc.org/docview/1318928076/120E20E975F54294PQ/70?accountid=38569

[71] I. Fronza and X. Wang, “Towards an Approach to Prevent Social Loafing in Software Development Teams,” *International Symposium on Empirical Software Engineering and Measurement*, vol. 2017-Novem, pp. 241–246, 2017, doi: 10.1109/ESEM.2017.37.

[72] R. O. Ajiboye, “Self-Efficacy , Collectivism and Social Loafing of University Workers in Southwest Nigeria : Implications for Staff- Students ’ Social Interactions,” vol. 4, no. 4, pp. 327–336, 2019.

[73] F. Salamone *et al.*, “Integrated method for personal thermal comfort assessment and optimization through users’ feedback, IoT and machine learning: A case study,” *Sensors (Switzerland)*, vol. 18, no. 5, 2018, doi: 10.3390/s18051602.

[74] K. J. Cunningham, “How language choices in feedback change with technology: Engagement in text and screencast feedback on ESL writing,” *Comput. Educ.*, vol. 135, no. March, pp. 91–99, 2019, doi: 10.1016/j.compedu.2019.03.002.

[75] L. Oliveira, A. Bento, V. J. S. Leite, and F. Gomide, “Evolving granular feedback linearization: Design, analysis, and applications,” *Applied Soft Computing Journal*, vol. 86, p. 105927, 2020, doi: 10.1016/j.asoc.2019.105927.

[76] C. Badii, P. Bellini, A. Difino, and P. Nesi, “Smart city IoT platform respecting GDPR privacy and security aspects,” *IEEE Access*, vol. 8, pp. 23601–23623, 2020, doi: 10.1109/ACCESS.2020.2968741.

[77] Y. Hassouneh, H. Turabieh, T. Thaher, I. Tumar, H. Chantar, and J. Too, “Boosted Whale Optimization Algorithm with Natural Selection Operators for Software Fault Prediction,” *IEEE Access*, vol. 9, pp. 14239–14258, 2021, doi: 10.1109/ACCESS.2021.3052149.

[78] X. Li and G. Zhao, “Democratic Involvement in Higher Education: A Study of Chinese Student E-participation in University Governance,” *Higher Education Policy*, vol. 33, no. 1, pp. 65–87, 2020, doi: 10.1057/s41307-018-0094-8.

[79] E. Baygin, Mehmet; Karakose Mehmet; Akin, “ITHET 2016 : 2016 15th International Conference on Information Technology Based Higher Education and Training (ITHET) : September 8-10, 2016, Istanbul, Turkey.,” *Institut of Electrical and Electronics Engineering*, 2016, [Online]. Available: 10.1109/ITHET.2016.7760744

[80] D. Mourtzis, E. Vlachou, G. Dimitrakopoulos, and V. Zogopoulos, “Cyber- Physical Systems and Education 4.0 -The Teaching Factory 4.0 Concept,” *Procedia Manuf.*, vol. 23, no. 2017, pp. 129–134, 2018, doi: 10.1016/j.promfg.2018.04.005.

[81] L.-I. González-Pérez et al., “Measuring digital transformation in education 4.0 with DT-smarty: Valid and reliable model,” *Technol. Knowl. Learn.*, pp. 1–34, 2025.

[82] E. C. K. Cheng and T. Wang, "Editorial for the Special Issue 'Information Technologies in Education, Research, and Innovation,'" *Information*, vol. 15, no. 1, p. 29, Jan. 2024, doi: 10.3390/info15010029.

[83] "Apex Education Bodies in India | AICTE | UGC | CBSE | UPSC | MHRD | IGNOU | MCI." Accessed: Mar. 31, 2020. [Online]. Available: https://www.indiaeducation.net/apexbodies/

[84] M. M. Iqbal, M. Farhan, S. Jabbar, Y. Saleem, and S. Khalid, "Multimedia based IoT-centric smart framework for eLearning paradigm," *Multimed. Tools Appl.*, vol. 78, no. 3, pp. 3087–3106, 2019, doi: 10.1007/s11042-018-5636-y.

[85] D. Wang, D. Chen, B. Song, N. Guizani, X. Yu, and X. Du, "From IoT to 5G I-IoT: The Next Generation IoT-Based Intelligent Algorithms and 5G Technologies," *IEEE Communications Magazine*, vol. 56, no. 10, pp. 114–120, 2018, doi: 10.1109/mcom.2018.1701310.

[86] "Apex Education Bodies in India | AICTE | UGC | CBSE | UPSC | MHRD | IGNOU | MCI." Accessed: May 01, 2020. [Online]. Available: https://www.indiaeducation.net/apexbodies/

[87] X. Baril, O. Coustié, J. Mothe, and O. Teste, "Application Performance Anomaly Detection with LSTM on Temporal Irregularities in Logs," *International Conference on Information and Knowledge Management, Proceedings*, pp. 1961–1964, 2020, doi: 10.1145/3340531.3412157.

[88] P. Glavič, "Identifying key issues of education for sustainable development," *Sustainability (Switzerland)*, vol. 12, no. 16, 2020, doi: 10.3390/su12166500.

[89] P. G. Altbach, "India's higher education challenges," *Asia Pacific Education Review*, vol. 15, no. 4, pp. 503–510, 2014, doi: 10.1007/s12564-014-9335-8.

[90] "World | Ranking Web of Universities: More than 28000 institutions ranked." Accessed: Jan. 16, 2020. [Online]. Available: https://www.webometrics.info/en/world

[91] K. Madhavi Devi, M. K. Gupta, and V. Muralidharan, "Empowering IT education in rural India," *2013 12th International Conference on Information Technology Based Higher Education and Training, ITHET 2013*, 2013, doi: 10.1109/ITHET.2013.6671049.

[92] Rajashree, "Indian Education System-A Historical Journey," *International Journal for Research in Education*, vol. 3, no. 3, pp. 46–49, 2014.

[93] D. K. C. Chakrabarty, "Indian education system – issues and challenges," *RBI Monthly Bulletin*, no. september, pp. 1–10, 2011.

[94] S. Shunmugaraj, "Social Loafing."

[95] I. Fronza and X. Wang, "Towards an Approach to Prevent Social Loafing in Software Development Teams," *International Symposium on Empirical Software Engineering and Measurement*, vol. 2017-Novem, pp. 241–246, 2017, doi: 10.1109/ESEM.2017.37.

[96] "AISHE Report 2018-19.pdf."

[97] "Countries arranged by Number of Universities in Top Ranks | Ranking Web of Universities: More than 28000 institutions ranked." Accessed: Jan. 16, 2020. [Online]. Available: https://www.webometrics.info/en/node/54

[98] "QS World University Rankings 2020: Top Global Universities | Top Universities." Accessed: Jan. 16, 2020. [Online]. Available: https://www.topuniversities.com/university-rankings/world-university-rankings/2020

[99] M. A. Varghese, "Development of collegiums of quality assessors for the Indian National Assessment & Accreditation Council (NAAC)," *2011 International Workshop on Institutional and Programme Accreditation: Connections and Opportunities - Proceedings, IWIPA 2011*, 2011, doi: 10.1109/IWIPA.2011.6221137.

[100] V. L. Patil, "Historical perspectives and unbalanced growth of engineering education infrastructure in India," *Proceedings of IEEE International Conference on Teaching, Assessment, and Learning for Engineering, TALE 2012*, pp. 12–14, 2012, doi: 10.1109/TALE.2012.6360302.

[101] V. Umashankar and K. Dutta, "Balanced scorecards in managing higher education institutions: An Indian perspective," *International Journal of Educational Management*, vol. 21, no. 1, pp. 54–67, 2007, doi: 10.1108/09513540710716821.

[102] K. C. H. Zhoc, R. B. King, T. S. H. Chung, and J. Chen, "Emotionally intelligent students are more engaged and successful: examining the role of emotional intelligence in higher education," *European Journal of Psychology of Education*, 2020, doi: 10.1007/s10212-019-00458-0.

[103] U. Bagchi, "Delivering student satisfaction in higher education: A QFD approach," *2010 7th International Conference on Service Systems and Service Management, Proceedings of ICSSSM' 10*, pp. 1049–1052, 2010, doi: 10.1109/ICSSSM.2010.5530090.

[104] A. Spokoiny and Y. Shahar, "An active database architecture for knowledge-based incremental abstraction of complex concepts from continuously arriving time-oriented raw data," *J. Intell. Inf. Syst.*, vol. 28, no. 3, pp. 199–231, 2007, doi: 10.1007/s10844-006-0008-x.

[105] S. M. Hassaan, M. Khajenejad, S. Jensen, Q. Shen, and S. Z. Yong, "Incremental Affine Abstraction of Nonlinear Systems," *IEEE Control Syst. Lett.*, vol. 5, no. 2, pp. 653–658, 2021, doi: 10.1109/LCSYS.2020.3004503.

[106] S. Assahli, M. Berrada, and D. Chenouni, "Data preprocessing from Internet of Things: Comparative study," *2017 International Conference on Wireless Technologies, Embedded and Intelligent Systems, WITS 2017*, no. Fig 1, 2017, doi: 10.1109/WITS.2017.7934676.

[107] M. Antunes, D. Gomes, and R. L. Aguiar, "Towards IoT data classification through semantic features," *Future Generation Computer Systems*, vol. 86, pp. 792–798, 2018, doi: 10.1016/j.future.2017.11.045.

[108] "NAAC - Home." Accessed: Mar. 31, 2020. [Online]. Available: http://www.naac.gov.in/

[109] V. V. Silaeva and V. P. Semenov, "Internal Education Quality Assurance through Standardization of Educational Organization Management System," *Proceedings of the 2018 International Conference "'Quality Management, Transport and Information Security, Information Technologies'", IT and QM and IS 2018*, pp. 70–73, 2018, doi: 10.1109/ITMQIS.2018.8525083.

[110] "More than half of South Asian youth are not on track to have the education and skills necessary for employment in 2030." Accessed: Mar. 31, 2020. [Online]. Available: https://www.unicef.org/press-releases/more-half-south-asian-youth-are-not-track-have-education-and-skills-necessary

[111] K. K. Mihelič and B. Culiberg, "Reaping the Fruits of Another's Labor: The Role of Moral Meaningfulness, Mindfulness, and Motivation in Social Loafing," *Journal of Business Ethics*, vol. 160, no. 3, pp. 713–727, 2019, doi: 10.1007/s10551-018-3933-z.

[112] R. O. Ajiboye, "Self-Efficacy , Collectivism and Social Loafing of University Workers in Southwest Nigeria : Implications for Staff- Students ' Social Interactions," vol. 4, no. 4, pp. 327–336, 2019.

[113] B. R. Palmer, C. Stough, R. Harmer, and G. Gignac, "Assessing Emotional Intelligence," pp. 103–117, 2009, doi: 10.1007/978-0-387-88370-0.

[114] K. C. H. Zhoc, R. B. King, T. S. H. Chung, and J. Chen, "Emotionally intelligent students are more engaged and successful: examining the role of emotional intelligence in higher education," *European Journal of Psychology of Education*, 2020, doi: 10.1007/s10212-019-00458-0.

[115] X. Li and G. Zhao, "Democratic Involvement in Higher Education: A Study of Chinese Student E-participation in University Governance," *Higher Education Policy*, vol. 33, no. 1, pp. 65–87, 2020, doi: 10.1057/s41307-018-0094-8.

[116] N. N. Aniskina and E. V. Lunina, "Integration of quality assurance models for education on the basis of comparative analysis," *Proceedings of the 2017 International Conference "Quality Management, Transport and Information Security, Information Technologies", IT and QM and IS 2017*, pp. 616–620, 2017, doi: 10.1109/ITMQIS.2017.8085900.

[117] W. Li, W. Meng, Z. Liu, and M. Au, "Towards Blockchain-Based Software-Defined Networking : Security," no. 2, pp. 196–203, 2020.

[118] W. Li, W. Meng, Z. Tan, and Y. Xiang, "Design of multi-view based email classification for IoT systems via semi-supervised learning," *Journal of Network and Computer Applications*, vol. 128, no. December 2018, pp. 56–63, 2019, doi: 10.1016/j.jnca.2018.12.002.

[119] S. Schönig, L. Ackermann, S. Jablonski, and A. Ermer, "IoT meets BPM: a bidirectional communication architecture for IoT-aware process execution," *Softw. Syst. Model.*, vol. 19, no. 6, pp. 1443–1459, 2020, doi: 10.1007/s10270-020-00785-7.

[120] E. Mezghani, E. Exposito, and K. Drira, "A Model-Driven Methodology for the Design of Autonomic and Cognitive IoT-Based Systems: Application to Healthcare," *IEEE Trans. Emerg. Top. Comput. Intell.*, vol. 1, no. 3, pp. 224–234, 2017, doi: 10.1109/TETCI.2017.2699218.

[121] N. Mishra, C. C. Lin, and H. T. Chang, "A cognitive oriented framework for IoT big-data management prospective," *2014 IEEE International Conference on Communication Problem-Solving, ICCP 2014*, pp. 124–127, 2014, doi: 10.1109/ICCPS.2014.7062233.

[122] M. Hernandez-de-Menendez, C. A. Escobar Díaz, and R. Morales-Menendez, "Engineering education for smart 4.0 technology: a review," *International Journal on Interactive Design and Manufacturing*, vol. 14, no. 3, pp. 789–803, 2020, doi: 10.1007/s12008-020-00672-x.

[123] H. Kuper, "Industry 4.0: changes in work organization and qualification requirements—challenges for academic and vocational education," *Entrepreneurship Education*, vol. 3, no. 2, pp. 119–131, 2020, doi: 10.1007/s41959-020-00029-1.

[124] J. ho Park, M. M. Salim, J. H. Jo, J. C. S. Sicato, S. Rathore, and J. H. Park, "CIoT-Net: a scalable cognitive IoT based smart city network architecture," *Human-centric Computing and Information Sciences*, vol. 9, no. 1, 2019, doi: 10.1186/s13673-019-0190-9.

[125] S. K. Gupta, T. S. Ashwin, and R. M. R. Guddeti, "Students' affective content analysis in smart classroom environment using deep learning techniques," *Multimed. Tools Appl.*, vol. 78, no. 18, pp. 25321–25348, 2019, doi: 10.1007/s11042-019-7651-z.

[126] P. Shanchen, Y. Jiamin, L. Ting, Z. Hua, and C. Hongqi, "A text similarity measurement based on semantic fingerprint of characteristic phrases," *Chinese Journal of Electronics*, vol. 29, no. 2, pp. 233–241, 2020, doi: 10.1049/cje.2019.12.011.

[127] W. Mazurczyk, S. Wendzel, M. Chourib, and J. Keller, "Countering adaptive network covert communication with dynamic wardens," *Future Generation Computer Systems*, vol. 94, pp. 712–725, 2019, doi: 10.1016/j.future.2018.12.047.

[128] A. C. Madeira, M. A. Carravilla, J. F. Oliveira, and C. A. V. Costa, "A methodology for sustainability evaluation and reporting in higher education institutions," *Higher Education Policy*, vol. 24, no. 4, pp. 459–479, 2011, doi: 10.1057/hep.2011.18.

[129] E. van Laar, A. J. A. M. van Deursen, J. A. G. M. van Dijk, and J. de Haan, "Determinants of 21st-Century Skills and 21st-Century Digital Skills for Workers: A Systematic Literature Review," *Sage Open*, vol. 10, no. 1, 2020, doi: 10.1177/2158244019900176.

[130] C. Hu, Y. Pu, F. Yang, R. Zhao, A. Alrawais, and T. Xiang, "Secure and Efficient Data Collection and Storage of IoT in Smart Ocean," *IEEE Internet Things J.*, vol. 7, no. 10, pp. 9980–9994, 2020, doi: 10.1109/JIOT.2020.2988733.

[131] A. Abeshu and N. Chilamkurti, "Deep Learning: The Frontier for Distributed Attack Detection in Fog-To-Things Computing," *IEEE Communications Magazine*, vol. 56, no. 2, pp. 169–175, 2018, doi: 10.1109/MCOM.2018.1700332.

[132] H. A. Alharbi and M. Aldossary, "Energy-Efficient Edge-Fog-Cloud Architecture for IoT-Based Smart Agriculture Environment," *IEEE Access*, vol. 9, pp. 110480–110492, 2021, doi: 10.1109/ACCESS.2021.3101397.

[133] X. Qi, C. Liu, and S. Schuckers, "IoT edge device based key frame extraction for face in video recognition," *Proceedings - 18th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing, CCGRID 2018*, vol. vid, pp. 641–644, 2018, doi: 10.1109/CCGRID.2018.00087.

[134] L. Greco, G. Percannella, P. Ritrovato, F. Tortorella, and M. Vento, "Trends in IoT based solutions for health care: Moving AI to the edge," *Pattern Recognit. Lett.*, vol. 135, pp. 346–353, 2020, doi: 10.1016/j.patrec.2020.05.016.

[135] S. Sarkar, R. Wankar, S. N. Srirama, and N. K. Suryadevara, "Serverless Management of Sensing Systems for Fog Computing Framework," *IEEE Sens. J.*, vol. 20, no. 3, pp. 1564–1572, 2020, doi: 10.1109/JSEN.2019.2939182.

[136] A. Tripathi, A. K. Singh, P. Choudhary, P. C. Vashist, and K. K. Mishra, "Significance of Wireless Technology in Internet of Things (IoT)," *Machine Learning and Cognitive Computing for Mobile Communications and Wireless Networks*, pp. 131–154, 2020, doi: 10.1002/9781119640554.ch6.

[137] A. Jaklič, "IoT as an Introduction to Computer Science and Engineering: A Case for NodeMCU in STEM-C Education," *IEEE Global Engineering Education Conference, EDUCON*, vol. 2020-April, pp. 91–95, 2020, doi: 10.1109/EDUCON45650.2020.9125356.

[138] B. Neji, N. Ferko, R. Ghandour, A. S. Karar, and H. Arbess, "Micro-fabricated RTD based sensor for breathing analysis and monitoring," *Sensors (Switzerland)*, vol. 21, no. 1, pp. 1–16, 2021, doi: 10.3390/s21010318.

[139] S. H. K. Yap, K. K. Chan, S. C. Tjin, and K. T. Yong, "Carbon allotrope-based optical fibers for environmental and biological sensing: A review," *Sensors (Switzerland)*, vol. 20, no. 7, 2020, doi: 10.3390/s20072046.

[140] J. Willner, A. Fornalczyk, M. Jablonska-Czapla, K. G. 2, and M. Rachwal, "(Germanium , Tellurium and Thallium) in Electronic Waste," *Materials*, vol. 14, p. 3722, 2021.

[141] E. Egorov, A. Shabalina, D. Zaitsev, S. Kurkov, and N. Gueorguiev, "Frequency response stabilization and comparative studies of MET hydrophone at marine seismic exploration systems," *Sensors (Switzerland)*, vol. 20, no. 7, 2020, doi: 10.3390/s20071944.

[142] U. Spaeth, H. Fechtner, M. Weisbach, and B. Schmuelling, "Potential of pressure sensor based mass estimation methods for electric buses," *Electronics (Switzerland)*, vol. 9, no. 5, 2020, doi: 10.3390/electronics9050711.

[143] D. Balageas, C. P. Fritzen, and A. Güemes, "Structural Health Monitoring," *Struct. Health Monit.*, pp. 1–495, 2010, doi: 10.1002/9780470612071.

[144] D. Shirole, A. Hedayat, E. Ghazanfari, and G. Walton, "Evaluation of an Ultrasonic Method for Damage Characterization of Brittle Rocks," *Rock Mech. Rock Eng.*, vol. 53, no. 5, pp. 2077–2094, 2020, doi: 10.1007/s00603-020-02045-y.

[145] E. J. Huang and J. P. Onnela, "Augmented movelet method for activity classification using smartphone gyroscope and accelerometer data," *Sensors (Switzerland)*, vol. 20, no. 13, pp. 1–18, 2020, doi: 10.3390/s20133706.

[146] M. A. Al Mamun and M. R. Yuce, "Recent Progress in Nanomaterial Enabled Chemical Sensors for Wearable Environmental Monitoring Applications," *Adv. Funct. Mater.*, vol. 2005703, pp. 1–43, 2020, doi: 10.1002/adfm.202005703.

[147] S. B. Sukhavasi, S. B. Sukhavasi, K. Elleithy, S. Abuzneid, and A. Elleithy, "Cmos image sensors in surveillance system applications," *Sensors (Switzerland)*, vol. 21, no. 2, pp. 1–52, 2021, doi: 10.3390/s21020488.

[148] A. O. Salazar, Y. Sugahara, D. Matsuura, and Y. Takeda, "Scalable output linear actuators, a novel design concept using shape memory alloy wires driven by fluid temperature," *Machines*, vol. 9, no. 1, pp. 1–22, 2021, doi: 10.3390/machines9010014.

[149] A. Tripathi, A. K. Singh, P. Choudhary, P. C. Vashist, and K. K. Mishra, "Significance of Wireless Technology in Internet of Things (IoT)," *Machine Learning and Cognitive Computing for Mobile Communications and Wireless Networks*, pp. 131–154, 2020, doi: 10.1002/9781119640554.ch6.

[150] L. Wang, "Metal-organic frameworks for QCM-based gas sensors: A review," *Sens. Actuators A Phys.*, vol. 307, p. 111984, 2020, doi: 10.1016/j.sna.2020.111984.

[151] S. Worrall, J. Ward, A. Bender, and E. M. Nebot, "GPS/GNSS Consistency in a Multi-path Environment and during Signal Outages," *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, vol. 2015-Octob, pp. 2505–2511, 2015, doi: 10.1109/ITSC.2015.408.

[152] Y. B. Arwansyah, N. Widyaningsih, and H. P. Daniswari, "The Use of Edmodo-Based E-Learning Media in Improved Reading Interest with Whole Language Approach," *J. Phys. Conf. Ser.*, vol. 1254, no. 1, 2019, doi: 10.1088/1742-6596/1254/1/012065.

[153] R. Chaudhary, N. Kumar, and S. Zeadally, "Network Service Chaining in Fog and Cloud Computing for the 5G Environment: Data Management and Security Challenges," *IEEE Communications Magazine*, vol. 55, no. 11, pp. 114–122, 2017, doi: 10.1109/MCOM.2017.1700102.

[154] A. Sugathan, G. G. Roy, G. J. Kirthyvijay, and J. Thomson, "Application of Arduino based platform for wearable health monitoring system," *2013 IEEE 1st International Conference on Condition Assessment Techniques in Electrical Systems, IEEE CATCON 2013 - Proceedings*, pp. 1–5, 2013, doi: 10.1109/CATCON.2013.6737464.

[155] C. Yan, L. Li, C. Zhang, B. Liu, Y. Zhang, and Q. Dai, "Cross-Modality Bridging and Knowledge Transferring for Image Understanding," *IEEE Trans. Multimedia*, vol. 21, no. 10, pp. 2675–2685, 2019, doi: 10.1109/TMM.2019.2903448.

[156] H. Park and J. Y. Jung, "SAX-ARM: Deviant event pattern discovery from multivariate time series using symbolic aggregate approximation and association rule mining," *Expert Syst. Appl.*, vol. 141, p. 112950, 2020, doi: 10.1016/j.eswa.2019.112950.

[157] H. Chao and Y. Liu, "Emotion Recognition from Multi-Channel EEG Signals by Exploiting the Deep Belief-Conditional Random Field Framework," *IEEE Access*, vol. 8, pp. 33002–33012, 2020, doi: 10.1109/ACCESS.2020.2974009.

[158] D. Jiang and Y. Cui, "ML estimation and MAP estimation for device activities in grant-free random access with interference," *ArXiv*, 2020.

[159] F. Zhou, W. Chen, and Y. Xiao, "Deep learning research with an expectation-maximization model for person re-identification," *IEEE Access*, vol. 8, pp. 157762–157772, 2020, doi: 10.1109/ACCESS.2020.3019100.

[160] "GRAPHEM : EM ALGORITHM FOR BLIND KALMAN FILTERING UNDER GRAPHICAL SPARSITY CONSTRAINTS Universit ´ School of Mathematics , University of Edinburgh , United Kingdom," pp. 5835–5839, 2020.

[161] K. G. Bath, "Synthesizing Views to Understand Sex Differences in Response to Early Life Adversity," *Trends Neurosci.*, vol. 43, no. 5, pp. 300–310, 2020, doi: 10.1016/j.tins.2020.02.004.

[162] Z. J. Sun, A. Duncan, Y. Kim, and K. Zeigler, "Seeking frequent episodes in baseline data of In-Situ Decommissioning (ISD) Sensor Network Test Bed with temporal data mining tools," *Progress in Nuclear Energy*, vol. 125, no. March, 2020, doi: 10.1016/j.pnucene.2020.103372.

[163] I. Chebbi, W. Boulila, N. Mellouli, M. Lamolle, and I. R. Farah, "A comparison of big remote sensing data processing with Hadoop MapReduce and Spark," *2018 4th International Conference on Advanced Technologies for Signal and Image Processing, ATSIP 2018*, pp. 1–4, 2018, doi: 10.1109/ATSIP.2018.8364497.

[164] M. Rao, Q. Li, D. Wei, and M. J. Zuo, "A deep bi-directional long short-term memory model for automatic rotating speed extraction from raw vibration signals," *Measurement (Lond).*, vol. 158, p. 107719, 2020, doi: 10.1016/j.measurement.2020.107719.

[165] R. Dey and F. M. Salemt, "Gate-variants of Gated Recurrent Unit (GRU) neural networks," *Midwest Symposium on Circuits and Systems*, vol. 2017-Augus, no. 2, pp. 1597–1600, 2017, doi: 10.1109/MWSCAS.2017.8053243.

[166] Y. Yu and Y. J. Kim, "Attention-LSTM-attention model for speech emotion recognition and analysis of IEMOCAP database," *Electronics (Switzerland)*, vol. 9, no. 5, 2020, doi: 10.3390/electronics9050713.

[167] S. Selvin, R. Vinayakumar, E. A. Gopalakrishnan, V. K. Menon, and K. P. Soman, "Stock price prediction using LSTM, RNN and CNN-sliding window model," *2017 International Conference on Advances in Computing, Communications and Informatics, ICACCI 2017*, vol. 2017-Janua, pp. 1643–1647, 2017, doi: 10.1109/ICACCI.2017.8126078.

[168] M. Bhatia, S. K. Sood, and A. Manocha, “Fog-inspired smart home environment for domestic animal healthcare,” *Comput. Commun.*, vol. 160, pp. 521–533, 2020, doi: 10.1016/j.comcom.2020.07.004.

[169] A. Verma, A. Singh, D. Anand, H. M. Aljahdali, K. Alsubhi, and B. Khan, “IoT Inspired Intelligent Monitoring and Reporting Framework for Education 4.0,” *IEEE Access*, vol. 9, pp. 131286–131305, 2021, doi: 10.1109/ACCESS.2021.3114286.

[170] G. Cai, Y. Fang, P. Chen, G. Han, G. Cai, and Y. Song, “Design of an MISO-SWIPT-Aided Code-Index Modulated Multi-Carrier M-DCSK System for e-Health IoT,” *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 2, pp. 311–324, 2021, doi: 10.1109/JSAC.2020.3020603.

[171] X. Baril, O. Coustié, J. Mothe, and O. Teste, “Application Performance Anomaly Detection with LSTM on Temporal Irregularities in Logs,” *International Conference on Information and Knowledge Management, Proceedings*, pp. 1961–1964, 2020, doi: 10.1145/3340531.3412157.

[172] T. Munchava, G. Basilaia, N. Vacheishvili, D. Kvavadze, D. Chkhaidze, and M. Elashvili, “IoT systems for the study of cultural heritage monuments - case of,” 2021.

[173] J. Miranda *et al.*, “The core components of education 4.0 in higher education: Three case studies in engineering education,” *Computers and Electrical Engineering*, vol. 93, no. September 2020, 2021, doi: 10.1016/j.compeleceng.2021.107278.

[174] M. Ciolacu, A. F. Tehrani, L. Binder, and P. M. Svasta, “Education 4.0 - Artificial Intelligence Assisted Higher Education: Early recognition System with Machine Learning to support Students’ Success,” *2018 IEEE 24th International Symposium for Design and Technology in Electronic Packaging, SIITME 2018 - Proceedings*, no. Ml, pp. 23–30, 2019, doi: 10.1109/SIITME.2018.8599203.

[175] J. Pan and J. McElhannon, “Future Edge Cloud and Edge Computing for Internet of Things Applications,” *IEEE Internet Things J.*, vol. 5, no. 1, pp. 439–449, 2018, doi: 10.1109/JIOT.2017.2767608.

[176] C. Slade and T. Downer, “Students’ conceptual understanding and attitudes towards technology and user experience before and after use of an ePortfolio,” *J. Comput. High. Educ.*, vol. 32, no. 3, pp. 529–552, 2020, doi: 10.1007/s12528-019-09245-8.

[177] R. Butt, H. Siddiqui, R. A. Soomro, and M. M. Asad, “Integration of Industrial Revolution 4.0 and IOTs in academia: a state-of-the-art review on the concept of Education 4.0 in Pakistan,” *Interactive Technology and Smart Education*, vol. 17, no. 4, pp. 337–354, 2020, doi: 10.1108/ITSE-02-2020-0022.

[178] T. Araujo, N. Helberger, S. Kruikemeier, and C. H. de Vreese, “In AI we trust? Perceptions about automated decision-making by artificial intelligence,” *AI Soc.*, vol. 35, no. 3, pp. 611–623, 2020, doi: 10.1007/s00146-019-00931-w.

[179] F. Corea, “Applied Artificial Intelligence: Where AI Can Be Used In Business,” no. Nakamoto 2008, p. 41, 2018, doi: 10.1007/978-3-319-77252-3.

[180] D. Balageas, C. P. Fritzen, and A. Güemes, "Structural Health Monitoring," *Struct. Health Monit.*, pp. 1–495, 2010, doi: 10.1002/9780470612071.

[181] M. Bhatia, S. K. Sood, and A. Manocha, "Fog-inspired smart home environment for domestic animal healthcare," *Comput. Commun.*, vol. 160, pp. 521–533, 2020, doi: 10.1016/j.comcom.2020.07.004.

[182] M. Kassab and M. Mazzara, *Towards Designing Smart Learning Environments with IoT*, vol. 12055 LNCS. 2020. doi: 10.1007/978-3-030-39306-9_11.

[183] M. A. Al Mamun and M. R. Yuce, "Recent Progress in Nanomaterial Enabled Chemical Sensors for Wearable Environmental Monitoring Applications," *Adv. Funct. Mater.*, vol. 2005703, pp. 1–43, 2020, doi: 10.1002/adfm.202005703.

[184] B. Neji, N. Ferko, R. Ghandour, A. S. Karar, and H. Arbess, "Micro-fabricated RTD based sensor for breathing analysis and monitoring," *Sensors (Switzerland)*, vol. 21, no. 1, pp. 1–16, 2021, doi: 10.3390/s21010318.

[185] E. Kormos and L. Julio, "Student attitudes toward instructor assessment in higher education: Does the delivery method matter?," *Educ. Inf. Technol. (Dordr).*, pp. 4287–4296, 2020, doi: 10.1007/s10639-020-10152-0.

[186] "NAAC ANNUAL Report 17-18.pdf."

[187] H. Huang, F. Liu, Z. Yang, and Z. Hao, "Automated Test Case Generation Based on Differential Evolution with Relationship Matrix for iFogSim Toolkit," *IEEE Trans. Industr. Inform.*, vol. 14, no. 11, pp. 5005–5016, 2018, doi: 10.1109/TII.2018.2856881.

[188] S. K. Gupta, T. S. Ashwin, and R. M. R. Guddeti, "Students' affective content analysis in smart classroom environment using deep learning techniques," *Multimed. Tools Appl.*, vol. 78, no. 18, pp. 25321–25348, 2019, doi: 10.1007/s11042-019-7651-z.

[189] T. Zhang, "The Internet of Things promoting higher education revolution," *Proceedings - 2012 4th International Conference on Multimedia and Security, MINES 2012*, pp. 790–793, 2012, doi: 10.1109/MINES.2012.231.

[190] "iFogSim References1".

[191] H. Gupta, A. V Dastjerdi, S. K. Ghosh, and R. Buyya, "Exploiting IoT and Big Data Analytics: Defining Smart Digital City Using Real-Time Urban Data," 2017.

[192] H. Gupta, A. Vahid Dastjerdi, S. K. Ghosh, and R. Buyya, "iFogSim: A toolkit for modeling and simulation of resource management techniques in the Internet of Things, Edge and Fog computing environments," *Softw. Pract. Exp.*, vol. 47, no. 9, pp. 1275–1296, Sep. 2017, doi: 10.1002/spe.2509.

[193] R. Mahmud and R. Buyya, "Modelling and Simulation of Fog and Edge Computing Environments using iFogSim Toolkit," Dec. 2018.

[194] E. Baccour, A. Erbad, A. Mohamed, M. Guizani, and M. Hamdi, "Collaborative hierarchical caching and transcoding in edge network with CE-D2D communication,"

Journal of Network and Computer Applications, vol. 172, p. 102801, Dec. 2020, doi: 10.1016/j.jnca.2020.102801.

[195] H. Meier, "Simulating energy efficient fog computing."

[196] W. Rivera, "Sustainable cloud and energy services: Principles and practice," *Sustainable Cloud and Energy Services: Principles and Practice*, pp. 1–268, 2017, doi: 10.1007/978-3-319-62238-5.

[197] M. A. Hernández-Mustieles *et al.*, "Wearable Biosensor Technology in Education: A Systematic Review," *Sensors*, vol. 24, no. 8, p. 2437, Apr. 2024, doi: 10.3390/s24082437.

[198] C. Novo, C. Zanchetta, E. Goldmann, and C. V. de Carvalho, "The Use of Gamification and Web-Based Apps for Sustainability Education," *Sustainability*, vol. 16, no. 8, p. 3197, Apr. 2024, doi: 10.3390/su16083197.

[199] W. Chia Chuan, S. Ul Arfeen Laghari, S. Manickam, E. Ashraf, and S. Karuppayah, "Challenges and Opportunities in Fog Computing Scheduling: A Literature Review," *IEEE Access*, vol. 13, pp. 14702–14726, 2025, doi: 10.1109/ACCESS.2024.3525261.

[200] F. Casino, P. Lopez-Iturri, and C. Patsakis, "Cloud continuum testbeds and next-generation ICTs: Trends, challenges, and perspectives," May 01, 2025, *Elsevier Ireland Ltd*. doi: 10.1016/j.cosrev.2024.100696.

[201] S. Duggal and P. Kaur, "Optimizing Healthcare Through Fog Computing: Simulating and Performance Evaluation of Real-Time Health Monitoring Systems," in *2024 3rd Edition of IEEE Delhi Section Flagship Conference (DELCON)*, IEEE, Nov. 2024, pp. 1–7. doi: 10.1109/DELCON64804.2024.10866954.

[202] S. H. K. Yap, K. K. Chan, S. C. Tjin, and K. T. Yong, "Carbon allotrope-based optical fibers for environmental and biological sensing: A review," *Sensors (Switzerland)*, vol. 20, no. 7, 2020, doi: 10.3390/s20072046.

[203] H. Liang, A. Xian, M. Mao, P. Ni, and H. Wu, "A research on remote fracturing monitoring and decision-making method supporting smart city," *Sustain. Cities Soc.*, vol. 62, no. March, 2020, doi: 10.1016/j.scs.2020.102414.

[204] K. de Fine Licht and J. de Fine Licht, "Artificial intelligence, transparency, and public decision-making: Why explanations are key when trying to produce perceived legitimacy," *AI Soc.*, no. 0123456789, 2020, doi: 10.1007/s00146-020-00960-w.

[205] E. Okai, X. Feng, and P. Sant, "Smart Cities Survey," *Proceedings - 20th International Conference on High Performance Computing and Communications, 16th International Conference on Smart City and 4th International Conference on Data Science and Systems, HPCC/SmartCity/DSS 2018*, pp. 1726–1730, 2019, doi: 10.1109/HPCC/SmartCity/DSS.2018.00282.

[206] W. Li, W. Meng, Z. Liu, and M. Au, "Towards Blockchain-Based Software-Defined Networking : Security," no. 2, pp. 196–203, 2020.

[207] S. K. Singh, S. Rathore, and J. H. Park, “BlockIoTIntelligence: A Blockchain-enabled Intelligent IoT Architecture with Artificial Intelligence,” *Future Generation Computer Systems*, no. xxxx, 2019, doi: 10.1016/j.future.2019.09.002.

[208] A. Baldominos and Y. Saez, “Coin.AI: A proof-of-useful-work scheme for blockchain-based distributed deep learning,” *Entropy*, vol. 21, no. 8, 2019, doi: 10.3390/e21080723.

LIST OF PUBLICATIONS

1. Verma, Anil, and Aman Singh. "New Era Of Technology Empowered Education: Education 4.0 A Systematic Review." In 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO), pp. 1-7. IEEE, 2021.
2. Verma, Anil, Aman Singh, Edwin Lughofer, Xiaochun Cheng, and Khalid Abualsaud. "Multilayered-quality education ecosystem (MQEE): an intelligent education modal for sustainable quality education." Journal of Computing in Higher Education 33, no. 3 (2021): 551-579.
3. Verma, Anil, Aman Singh, Divya Anand, Hani Moaiteq Aljahdali, Khalid Alsubhi, and Baseem Khan. "IoT Inspired Intelligent Monitoring and Reporting Framework for Education 4.0." IEEE Access 9 (2021): 131286-131305.
4. Verma, Anil, Divya Anand, Aman Singh, Rishika Vij, Abdullah Alharbi, Majid Alshammari, and Arturo Ortega Mansilla. "IoT-Inspired Reliable Irregularity-Detection Framework for Education 4.0 and Industry 4.0." Electronics 11, no. 9 (2022): 1436.
5. Verma, Anil, Divya Anand, Aman Singh, and Rishika Vij. "C-IoT Inspired Real-Time and Intervallic Accreditation Under Education 4.0." In 2022 8th International Conference on Advanced Computing and Communication Systems (ICACCS), vol. 1, pp. 1793-1798. IEEE, 2022.
6. Verma, Anil, Parampreet Kaur, and Aman Singh. 2024. "Assessment in the Age of Education 4.0: Unveiling Primitive and Hidden Parameters for Evaluation" *Information* 15, no. 8: 486. https://doi.org/10.3390/info15080486
7. Verma, Anil, Aman Singh, Divya Anand, and Rishika Vij. "Technology Inspired-Elaborative Education Model (TI-EEM): A futuristic need for a Sustainable Education Ecosystem." In *Deep Learning: Theory, Architectures and Applications in Speech, Image and Language Processing*, pp. 167-182. Bentham Science Publishers, 2023.
8. Verma, Anil, and Aman Singh. “Evaluation and Improvement of The Quality of Education in Rural India Through Integrated Quality Management System (IQMS).” Journal of The Gujrat Research Society, vol. 21, Issue 10s, pp. 217-226, November 2019.

LIST OF CONFERENCES

1. 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO), IEEE, 2021.
2. 8th International Conference on Advanced Computing and Communication Systems (ICACCS), IEEE, 2022