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Multilayered-quality education ecosystem (MQEE): an intelligent education modal for sustainable quality education

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Abstract
Sustainable quality education is a big challenge even for the developed countries. In response to this, education 4.0 is gradually expanding as a new era of education. This work intends to unfold some hidden parameters that are affecting the quality education ecosystem (QEE). Academic loafing, unawareness, non-participation, dissatisfaction, and incomprehensibility are the main parameters under this study. A set of hypothesis and surveys are exhibited to study the behavior of these parameters on quality education at the institution level. The bidirectional weighted sum method is deployed for precise and accurate results regarding boundary value analysis of the survey. The association between parameters understudy and quality education is illustrated with correlation and scatter diagrams. Academic loafing, the hidden and unintended rudiment that affects the QEE is also defined, intended and explored in this work. The study exhibits that the average percentage association between quality education and all the parameters under study is 93.32%, whereas awareness has the least association (82.63%) and academic loafing has the highest association (99.35%) with quality education. The paper proposes a cognitive-IoT (internet of things) based multilayered QEE as a remedial solution for sustainable quality education. The emerging demand of real-time data processing for the education 4.0 environment, makes MQEE suitable for education 4.0 environment. The IoT enabled heterogeneous-data preprocessing, integration, and analysis to foster the proposed model with robustness, scalability, and flexibility. The proposed abstraction mechanism, public/private reporting, and IoT-based data preprocessing system are rich enough to handle data management issues under education 4.0 environment.

Keywords Data preprocessing · Higher education · Intelligent modal · Education ecosystem · Academic loafing

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Introduction

Sustainable quality education ecosystem is the fundamental requirement of every nation. The global leaders in quality education such as United States (US), United Kingdom (UK), Germany, Canada, and China are also facing challenges in providing a sustainable quality education ecosystem (Glavič, 2020). 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 28,000 institutions ranked). It was observed that more than 51,649 educational institutions are presently imparting higher education in Indian. 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 enrollment. 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 citation per faculty which is at par with US and China (QS World University Rankings, 2020: Top Global Universities | Top Universities, n.d.). University Grants Commission (UGC), All India Council of Technical Education (AICTE), National Assessment and Accreditation Council (NAAC), Bar Council of India (BCI), Indian Council of Agricultural Research (ICAR), National Council of 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 sincerely 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 (Altbach, 2014). All India Survey on Higher Education (AISHE) is the largest national-level survey conducted and it's 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 the 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 commanded. 51,649 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 sill 98.8% education system fail to touch the global parameters of quality education (World | Ranking Web of

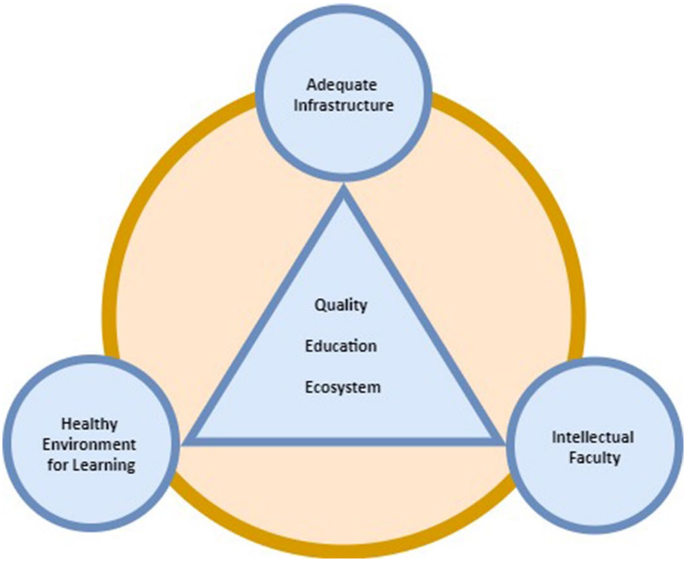


Fig. 1 Quality education ecosystem (QEE) with components

Universities: More than 28,000 institutions ranked n.d.). The present education system is not reachable to rural areas (Madhavi Devi et al., 2013), 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 of exploration in the Quality Education Ecosystem (QEE) (Rajashree, 2014). 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 Education 4.0 (Ciolacu et al., 2017) environment by empowering it with emerging technology is the main motivation behind this study. Improvised education ecosystem, use of emerging technology like IoT (Kassab et al., 2018), and AI (Rekh & Chandy, 2020) for monitoring, assessment, and accreditation at ground level are some of the key advantages of this study.

Requirement and contribution

Quality Education Ecosystem is an integral part of every educational institution, the components mentioned in Fig. 1 only reveal the outer shell of QEE that might be prerogative of the state or center 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) (Chakrabarty, 2011).

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 2 illustrates the broader view of the Multilayered-Quality

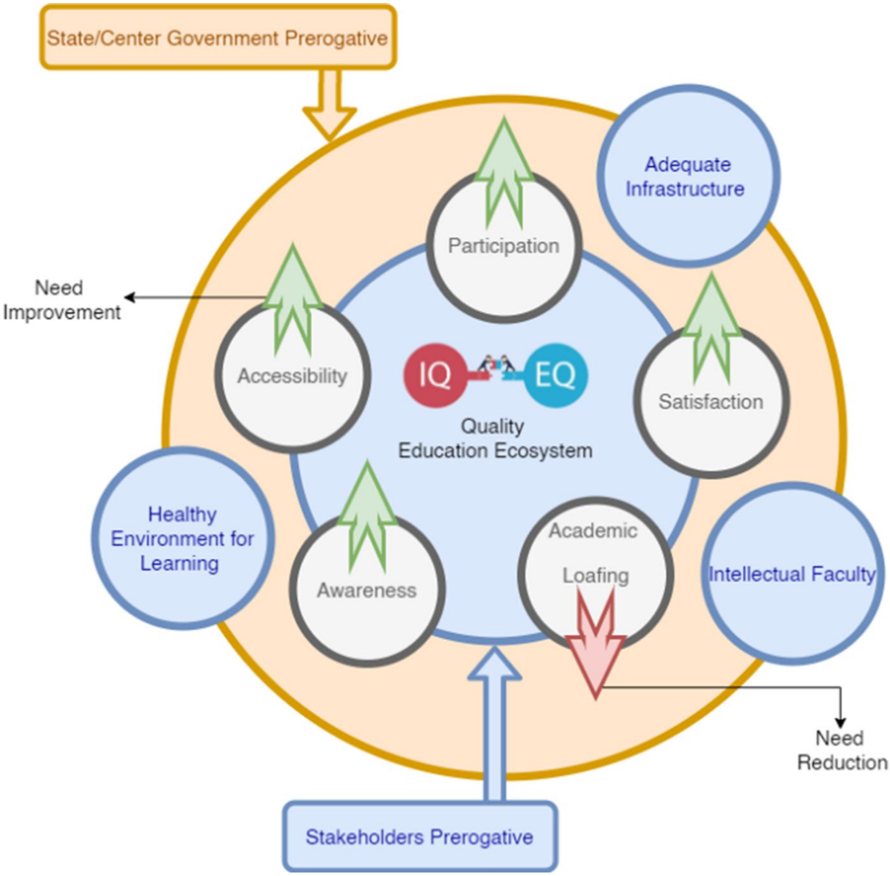


Fig. 2 Multilayered quality education ecosystem (MQEE)

Education Ecosystem. The outer layer is the prerogative of the state/central 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 dealt 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 quick and most effective remedial solution to diminishing quality education in India. This term academic loafing is driven by social loafing during this study. Social loafing means it is the tendency for individuals to expend less effort when working collectively than when working individually (Shunmugaraj n.d.). Social loafing is very common but very difficult to trace (Fronza & Wang, 2017). As academic is also a major and important part of society social loafing effect academicians that 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, 39,931 Colleges, and 10,725 Stand Alone Institutions by 2019 made India the top country in the world in terms of the number of universities and colleges (AISHE Report 2018–19.pdf n.d.). 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 (World | Ranking Web of Universities: More than 28,000 institutions ranked n.d.). China being the most populated country has 1736 fewer colleges and universities than India and 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 the nations across the world. In 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 necessity of time to stop mushrooming of institutions in India and focus on the quality of education in the existing infrastructure (Countries arranged by Number of Universities in Top Ranks | Ranking Web of Universities: More than 28,000 institutions ranked n.d.).

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, the global *'Academic Reputation'* of India is even below the average global academic reputation of world education (QS World University Rankings 2020: Top Global Universities | Top Universities n.d.) 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 (Varghese, 2011), AICTE (Patil, 2012) 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, best research-oriented faculty and domain-specific assessment agencies enabled the quality education ecosystem in India. The mushrooming of institutions is neither required nor it's improving the quality of education in India (Umashankar & Dutta, 2007). The proposed MQEE supports the 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 carrier growth and social appearances (Zhoc et al., 2020). The exploration of the quality education ecosystem and unbinding 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 irradiate IoT-Big Data problem in Education 4.0 environment.
- Feedback-Data preprocessing through Bidirectional Weighted Sum (BSW) 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.

The subsequent sections of this paper unveil these objectives. The rest of the paper is organized into sections. Section II discusses the recent work executed in this area. Section III presents the methodologies and a model is proposed with the elaborate working mechanism. Section IV illustrates the detailed discussion on various factors affecting education and their impact on the current education ecosystem. Section V concludes the paper and particularizes its future scope.

Related work

Christine Slade & Terri Downer conducted a survey on students' conceptual understanding and attitudes towards technology. They also studied the pre and post-experience of students' towards ePortfolio. In their work, they proposed an ePortfolio that records the students' performance and assessment. It also recommended various skill sets that the individual student is required for better employability. The authors found ePortfolio as a better place to record students' experience and assessment. (Slade & Downer, 2020) Fengfeng Ke, Meriya Pachman & Zhaihuan Dai in their study on virtual reality-based teaching–learning environment for teachers' training found it a suitable and effective method for the same. The VR-based assessment method for teachers' assessment also enhances the quality of teaching. Most of the teachers' during their study found enthused towards VR-based learning environments. They also found that the use of technology (Virtual Reality) in the teaching–learning environment also enhanced participation (Ke et al., 2020). Lucy Charity Sakala & Wallace Chigona proposed a technology that enables a learning management system for quality improvement. The authors elaborate the effects of teaching habits and capital in higher educational institutions. The authors recommended the integration of Information Communication Technology (ICT) tools such as LMSs i.e. Learning Management Systems within work practices of Higher Educational Institutions (HEIs) for improvement in teaching and learning practices (Sakala & Chigona, 2020). Wim Lambrechts and Kim Ceulemans evaluated the use of the[1] AISHE* tool i.e. Auditing Instrument for Sustainability in Higher Education. They found AISHE* 1.2 a reliable tool for sustainability assessment. AISHE* 1.2 uses the qualitative approach for sustainability assessment. AISHE* 1.2 is based on the European Foundation for Quality Management (EFQM) model. The authors recommend this tool for quality assessment (Caeiro et al., 2013). Erik Kormos & Liliana Julio conducted a study on students' attitudes towards instructors' assessment in the face to face and online classes. They found a significant difference in the impact on education between teachers' assessment in the face to face classes vs online classes. The authors found that the students enrolled in face-to-face classes improved a lot due to instructors' assessments. The study also claims that the instructor's assessments significantly helped the students of literature to organize speeches at a higher level (Kormos & Julio, 2020). Muhammad Farhan proposed an IoT-based student interaction framework for interaction analytics assessment in a real-time scenario. The authors found that student's information is very useful for instructors to track student progress and self-evaluation by using intelligent algorithms. The students' evaluation information is useful to distinguish their strengths, shortcoming, and also helpful in managing their learning objectives by collaboration using IoT-based Infrastructure and services (Farhan et al., 2018). Muhammad Munwar Iqbal suggested an IoT-enabled Multimedia and Agent-based Question Answering System (MAQAS) for analyzing the teacher-student interaction in real-time. The authors observed the crucial role of Question Answering to enhance student's learning capabilities. The authors claimed 92.6% accuracy over the other companion techniques like LIVE QA TRAK, QUORA, YODA QA LIVE, etc., and found MAQAS as the most suitable system for Question–Answer analysis (Iqbal et al., 2019).

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 subsections:

[1] AISHE under section *Related Work* refers to Auditing Instrument for Sustainability in Higher Education tool. AISHE is specifically marked as AISHE* under this section, in rest of the paper AISHE refers to All India Survey on Higher Education.

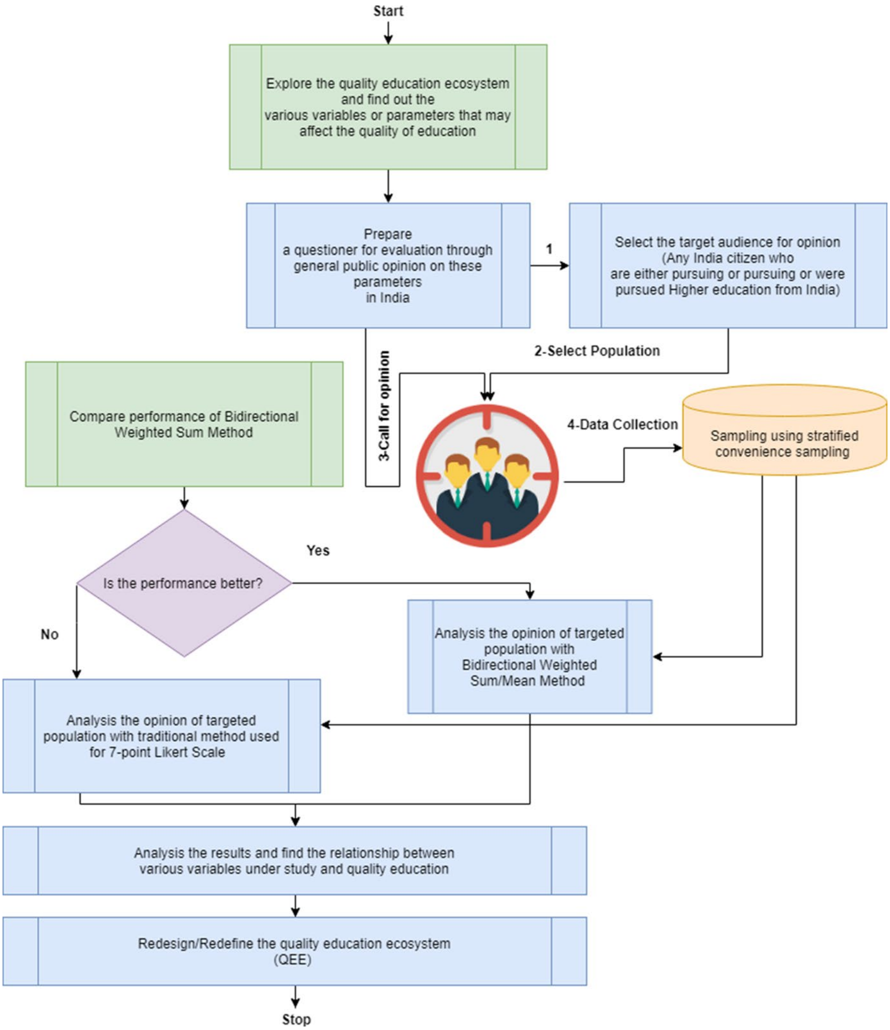


Fig. 3 Flow chart of the methodology used for restructuring of quality education ecosystem

Restructuring education ecosystem with five steps improvement model

Restructuring of education ecosystem is the need of time. Figure 3 illustrates the various steps involved in the restructuring quality education ecosystem. Subsequently, the conceptual and comprehensive models are proposed at various levels of its implementations. For the exploration of the quality education ecosystem case studies on the Indian education system is considered, 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. 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 various level courses like undergraduate (UG), Post Graduate (PG), Master of Philosophy (M.Phil.), Doctor of Philosophy (Ph.D.) or Postdoctoral (Postdoc). Himachal Pradesh, Punjab, Kerala, Haryana, Delhi, Gujrat, 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 a respective 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. BWS is a more efficient method in terms of efficiency and accuracy 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 paper. Evaluation of the correlation between y (quality education) and various other variables (x) like awareness, participation, satisfaction, and academic loafing, etc. was done using standard correlation techniques. The results were further used to analyze the different parameters (x) for 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, 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 the robust quality education ecosystem. The proposed 5-in-3 improvement model to strengthen the quality education ecosystem is illustrated in Fig. 4. Every stakeholder must be aware of the quality education ecosystem and the assessment process for quality education. Awareness will only be accomplished with the accessibility of their respective apex bodies like UGC, AICTE, NAAC, AISHE, NIRF, NBA, BCE, ICAR, NCTE, DCI, MCI, PCI, CCH, CCIM, etc. A ubiquitous technological model for every stakeholder at the ground level must establish this connection. The awareness and accessibility improve participation and reduces the reduction in academic loafing that leads to satisfaction. Bagchi defined student satisfaction as the difference between student perception and expectation (Bagchi, 2010). This model involves each stakeholder in quality management that reduces the gap between perception and expectation. Reduction in academic loafing and enhancement in satisfaction is the communicative results of the first three steps. The proper implementation of the first three steps enforces a behavioral change in every stakeholder, the positive impact of the first three steps automatically improves the concrete results of the last two steps. So, the policymakers only have to converge their focus on the first three steps and it will subsequently result in improving all five

Fig. 4 5-in-3 improvement model for robust quality education ecosystem

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 paper. The sequential implementation of this model enforces maximum results in comparatively lesser efforts.

Two-way handshaking algorithm (trust algorithm)

The use of IoT for data collection will achieve the three main primary goals of the conceptual model i.e. awareness, total participation and accessibility. The sensed data from IoT devices are collected, integrated and preprocessed through an intelligent gateway or control tire. The collected data are then further analyzed by an AI-based trust algorithm. The use of IoT, AI, or C-IoT as a whole makes this model robust for real-time implementation. The chances of human error and biasness in data collection, analysis, and preprocessing, which is present in the current model are also escaped in the proposed model by the use of IoT and AI. AI-based decision-making is evaluated on par or even better than the human for high-impact decision (Araujo et al., 2020).

The proposed AI-based trust algorithm for report generation improves transparency in the overall system. Now a day's trustworthiness is essential in all sort of services (Pang et al., 2019) due to the rapid use of technology in all domains of life trust, security and privacy has become a new challenge (EL-Latif et al., 2019). The proposed trust algorithm is a weighted handshaking method that improves trust in terms of transparency among various stakeholders. As student feedback for the

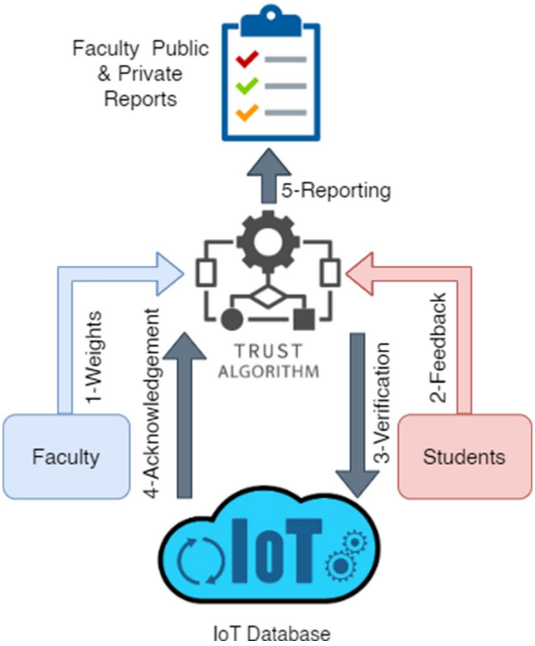


Fig. 5 Two way handshaking algorithm (trust algorithm) for report generation

teacher can make a significant improvement in teaching (Cohen, 1980), in this algorithm we are considering the *Teacher Feedback*-TF_i marked by an individual student (i) and the *Student Attendance*-w_i as weight marker by the respective teacher for the student (i).

Some other inputs like student academic records (as components of IQ) and their assessment (as components of EQ) may affect Algorithm 1. Every country has its evaluation system based on these two factors i.e. academic and assessment. A separate study is required to elaborate the exact effect of these components on proposed the algorithm and model. To make this model simpler, at an initial level only two components i.e. Teacher Feedback *TF* (Side-A) and Student Attendance as weight *w* (Side-B) are considered. As academic records and assessment are already a part of QEE and we have already many proven mechanisms to evaluate these factors, we are not considering these factors here in this study. Human Error Flag (HEF) indicates the input data errors. The larger value of HEF indicates more data manipulation. The dataset which indicates more HEF value may be rejected or recollected for final result calculation to make the result more accurate. HEF is the major factor, which indicates human data manipulation. HEF for a specific stakeholder also affects the trust factor in the concerned stakeholder. The public and private reports generated also indicated HEF as a trust factor for respective stakeholders. All the major steps of two way handshaking algorithm for report generation are illustrated in Fig. 5. This algorithm ensures trust among stakeholders in terms of transparency as the two-way handshaking method opened the 'Black Box' of AI algorithms (de Fine Licht and de Fine Licht, 2020) to improve transparency. In present practices, such reports are generated only based on the students' feedback which is a one-sided partial practice. The integration of weights

Table 1 Two-way handshaking algorithm (trust algorithm) for report generation

Algorithm 1	**Input: Teacher Feedback TF_{ij}(Side-A), Student Attendance- w_{ij} (Side-B) as weight, IoT dataset IOTDS and error $_{\text{(permissible)}}$**
1.	**Step 1:** For Student i=1 to n and Teacher j
2.	**Step 1.1:** Input Teacher Feedback TF_{ij} and Student Attendance- w_{ij}
3.	**Step 1.2:** Authenticate the value of weight w_{ij} from $IOTDS_{ij}$
4.	**Step 1.2.1:** If $w_{ij} \pm$ error $_{\text{(permissible)}} \approx IOTDS_{ij}$, goto Step 1.3
5.	**Step 1.2.2:** Else increment (Human Error Flag) $HEF_j += 1$ and $w_{ij} = IOTDS_{ij}$
6.	**Step 1.3:** $WTF_{ij} = TF_{ij} \times w_{ij}$ (Handshaking between Side-A and Side-B)
7.	**Step 2:** Calculate $WTF_j = \sum_{i=1}^{n} WTF_{ij} / n$
8.	**Step 3:** Use WTF_j and HEF_j for report generation.
9.	**Step 4:** Repeat Steps 1 to 3 for the next feedback parameter
10.	**Step 5:** Generate $Teacher_j$ public and private report
11.	**Step 6:** Exit

from the other side will improve the overall reliability of the report. Algorithm 1 is demonstrated in Table 1. Illustrated, only one reporting process, similarly, the other public/private reports for other stakeholders like students and administrative staff are also producing. All these reports collectively contribute to the Institutional level report. Correspondingly, other higher-level reports like university-level reports and apex-level reports are also produced with the requisite level of abstraction.

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-points 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 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 Fig. 10. The bidirectional weighted sum maintains the significance of the 7-point Likert Scale. If the researcher process the data further and calculate the sum of percentage for negative PS^{-ve} (Disagree) and positive PS^{+ve} (Agree) sides of this question then the result will be obtained as follows:

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

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

where $1 \geq i \leq 3$ for 7 - Point likert scale and $1 \geq i \leq 2$ for 5 - Point likert scale.

The values of $(PS)^{-ve}$ & $(PS)^{+ve}$ have been evaluated in Fig. 9 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.

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

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

where $1 \geq i \leq 3$ for 7 - Point likert scale and $1 \geq i \leq 2$ for 5 - Point likert scale.

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

$$if\ BWS > 0 \tag{6}$$

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

$$if\ \ BWS = 0 \tag{7}$$

$$\{then\ boundary\ value\ is\ not\ converged\ towards\ any\ side\ and\ the\ final\ result\ is\ Nither\ Agree\ nor\ Disagree\}$$

$$if\ \ BWS < 0 \tag{8}$$

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

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

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

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

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

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

Cognitive IoT based model for the quality education

The models illustrated in Figs. 2 and 4 are the conceptual designs of the proposed quality education ecosystem. Based on the survey conducted and various outcomes of the survey, the use of state-of-the-art technology at the grassroots level is of paramount importance for improvement in quality education. IoT is used by many organizations (Li et al., 2020), it is a network of physical objects used for real-time communication (Li et al., 2019). IoT environment (IoT devices, sensors, and mobile devices) is enabled to foster the quality of data communication and reduce the delay in communication (Schönig et al., 2020). 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 (Mezghani et al., 2017) is proposed in this model. IoT integration with Cognitive Computing is the new class of problem-solving (Zhang et al., 2018). Integration of IoT in the education sector may help in teaching and learning enhancements, classroom management, students and faculty healthcare, campus security, student assessment, attendance monitoring (Ali & Majeed, 2018), and many other activities for quality improvement. The proposed implementation model is a Cognitive-IoT based model to have a complete and robust quality education ecosystem. The use of Cognitive-IoT also manages the IoT-Big Data's lacunas which are caused by a huge amount of heterogeneous data in real-time (Mishra et al., 2014) by using an incremental abstraction model.

The proposed framework is suitable for Education 4.0 environment. Education 4.0 is the emerging necessity for the functioning of Industrial 4.0 manpower (Hernandez-de-Menendez et al., 2020). The education sector also needs to increase its potential to meet the requirement of quality needed for the functioning of Industry 4.0 (Kuper, 2020).

The ground-level implementation of this model will start repairing the current education model's drawbacks at the grassroots level and eventually affects every layer of the education ecosystem. C-IoT can also handle scalability and flexibility problems (Park et al., 2019). The integration of smartwatches, sensors, IoT devices, and the micro embedded system can collect distraction-free data in real-time during the teaching and learning environment (Ciolacu et al., 2019). 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 Fig. 6. All the stakeholders are sensed through IoT devices in a real-time environment for data collection.

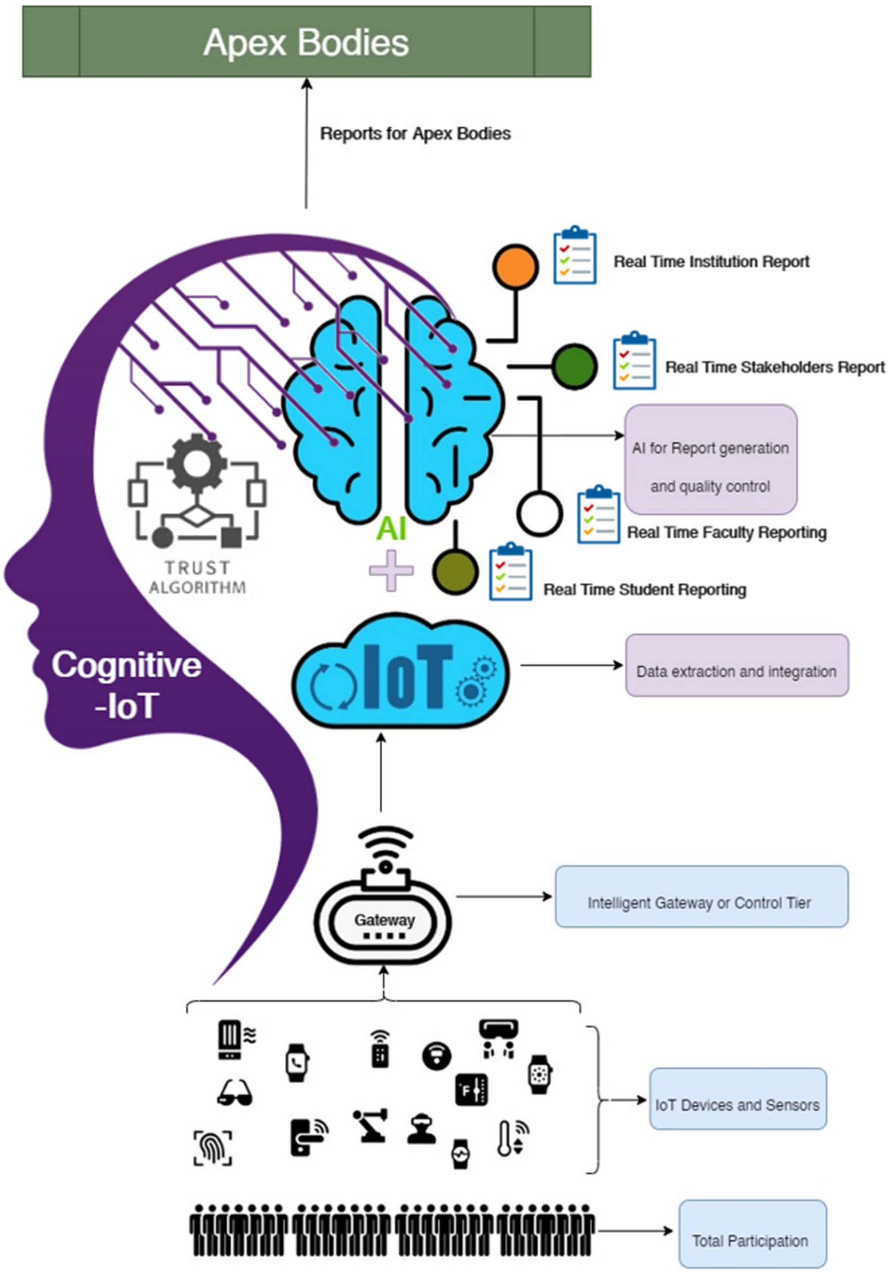


Fig. 6 Cognitive IoT based model for the quality education ecosystem

The outcomes of the above-mentioned trust algorithm are served as inputs for the report generation system. Effective data analysis is possible in a smart environment using AI and deep learning techniques (Gupta et al., 2019). The AI-based report

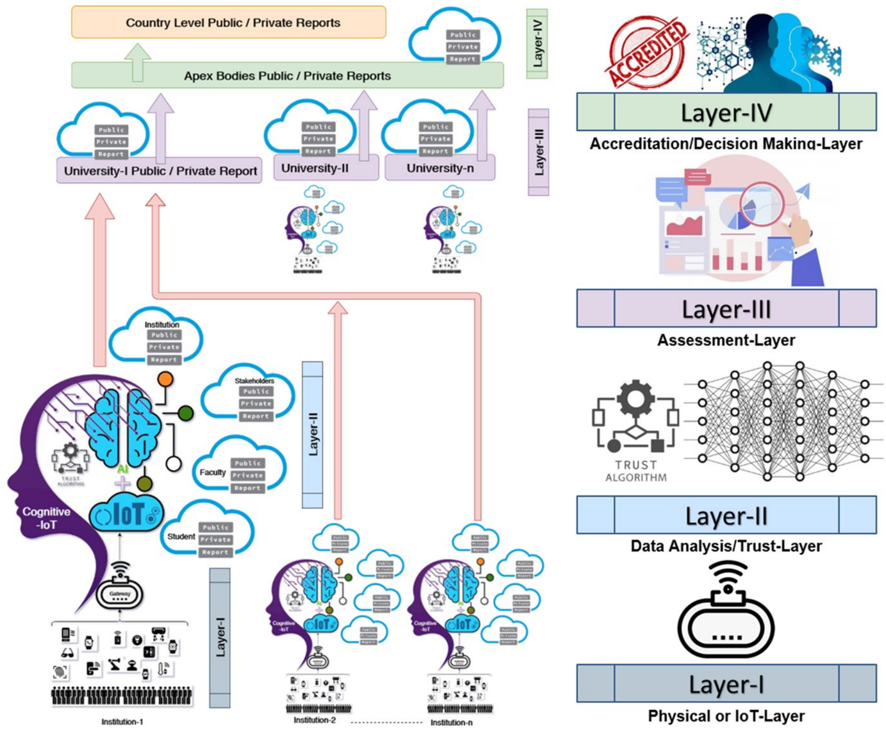


Fig. 7 C-IoT based multilayered quality education ecosystem

generation will generate a comprehensive report for each stakeholder i.e. student, teacher, and administrative staff. All the reports are text-based as mostly collected data by IoT devices are text-based (Shanchen et al., 2020). 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 although 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 (Mazurczyk et al., 2019) 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. Assessment-based diagnosis (based on the private report) will improve quality (Wang, 2019). Figure 7 illustrates the complete layered structure of the proposed multilayered quality education ecosystem. The Physical/IoT layer and Data analysis/Trust layer are implemented at the grassroots level. Figure 6 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. The online assessment tools or opinion mining feedback techniques are used for performance evaluation under higher educational institutions at the college/university level (Wook et al., 2020). The proposed ecosystem provides a Distributed Application Run-Time Environment (DARE) (Maddineni et al., 2012)

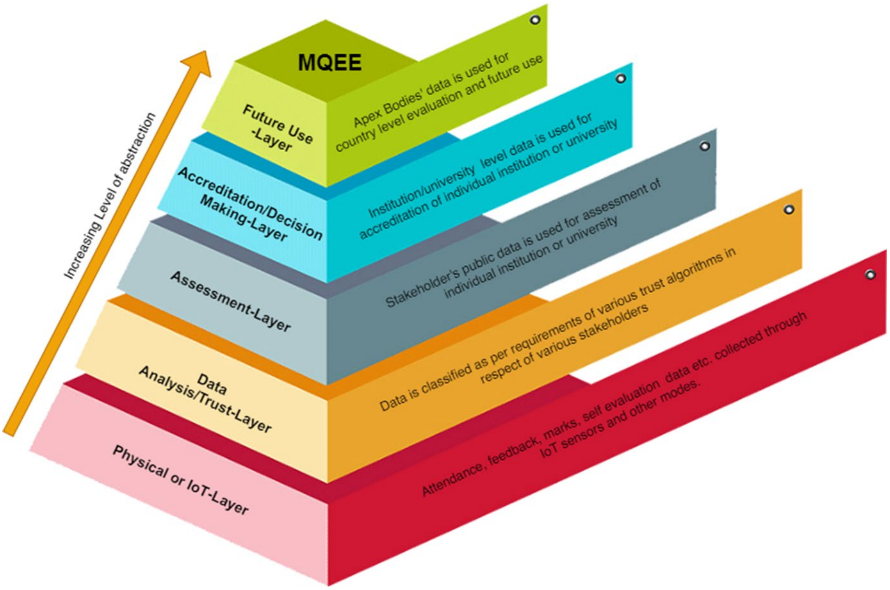
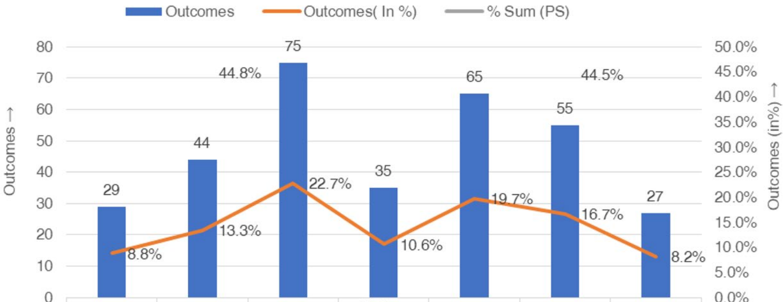


Fig. 8 Incremental abstraction model with various reports generated at different layers of the quality education ecosystem

with scalability and flexibility. 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 (Madeira et al., 2011).

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 real-time raw data (Spokoiny & Shahar, 2007), (Hassaan et al., 2021). 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 Fig. 8. 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 preprocessed



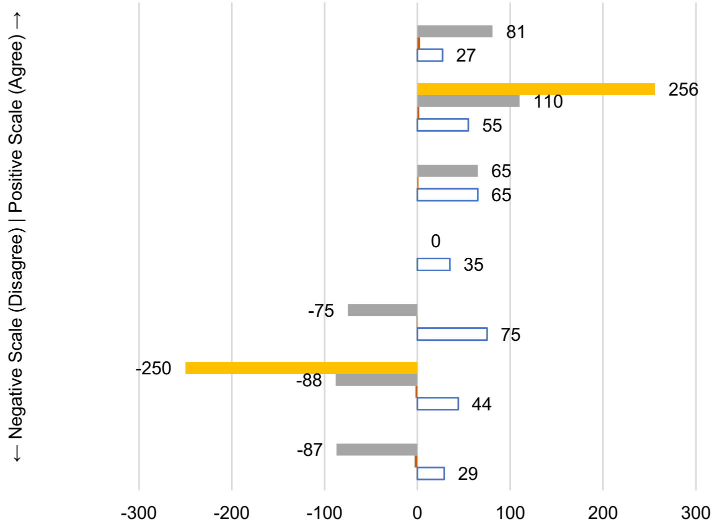
	Strongly Disagree (N3)	Disagree (N2)	Somewhat Disagree (N1)	Neither Agree nor Disagree (O)	Somewhat Agree (P1)	Agree (P2)	Strongly Agree (P3)
Outcomes	29	44	75	35	65	55	27
Outcomes(In %)	8.8%	13.3%	22.7%	10.6%	19.7%	16.7%	8.2%
% Sum (PS)		44.8%				44.5%	

Fig. 9 Statistical illustration of 7-point Likert scale with percentage outcomes

the heterogeneous data through BWS and BigDansing is deployed for data cleaning (Assahli et al., 2017). 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) (Antunes et al., 2018). 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 a 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 policymaking. 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 an abstraction method.

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



	Strongly Disagree (N3)	Disagree (N2)	Somewh at Disagree (N1)	Neither Agree nor Disagree (O)	Somewh at 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

← Negative Scale (Disagree) | Positive Scale (Agree) →

Bidirectional Weighted Sum (BWS) Weighted Mean (nw) Weight (w) Outcomes received (n)

Fig. 10 Statistical illustration of a 7-point likert scale with bidirectional weighted sum (BWS) method for boundary value analysis

330 outcomes of a survey question on the 7-points Likert Scale on some random values in Fig. 9 the respective chart and the percentage outcomes of all 7-points did not help the researcher for 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 10 examines the same data under the proposed *Bidirectional Weighted Sum method for boundary value analysis (BWS)* to obtain precise results.

The values of (BWS) + ve & (BWS)-ve have been evaluated in Fig. 10 are 256 and -250 respectively.

$$BSW = (256) + (-250) = 6 \tag{12}$$

The positive value of BSW indicates the overall boundary value is converged towards the positive side and the final result is positive i.e. Agree. Although in Fig. 9 the resultant percentage value of the positive side is lesser than that of the negative side the boundary value analysis through the bidirectional weighted sum Fig. 10

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 analyzing the questions in respect of various variables considered for this research. For more accuracy instead of a weighted sum, a 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 furthered 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.

$$\begin{aligned} &= 311 + 1234 + 567 = 2112 \\ &= (-1368) + (-738) + (-128) = -2234 \\ \mathrm{BWS} &= (2112) + (-2234) \\ &= -122 \end{aligned} \tag{13}$$

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 questioner. The Bidirectional Weighted Sum method for a survey question related to satisfaction is tabulated for illustration in Table 2.

Based on the above discussion and illustration the differences between the percentage outcome method and BWS method are tabulated as (Table 3).

Based on the survey conducted, formerly mentioned in the methodology section of this paper, the five parameters of the inner layer and the respective outcomes of the BWS method are mentioned in Table 4. The classification of data for five different variables i.e. Awareness, Participation, Satisfaction, Accessibility and Academic Loafing, and respective correlation coefficient for Quality Education is tabulated in Table 4. 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 quality education which means that all these variables are directly proportional to quality education with at most 7.93% average variation.

$$\textit{Quality Education} \propto \textit{Awarenes}, \ \textit{Participation}, \ \textit{Satisfaction and Accessibility} \tag{14}$$

The scatter diagram in Fig. 11 indicates the positive correlation between variables (Awareness, Participation, Satisfaction, and Accessibility) and Quality education.

The average correlation between quality education and all these four variables is 91.82%. So, the government can enrich the higher education policies by enriching awareness, participation, satisfaction, and accessibility among all stakeholders. As all these rudiments are directly proportional to quality so, in turn, it will improve

Table 2 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					

Table 3 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

Table 4 Correlation table between quality education (y) and variables under study i.e. awareness, participation, satisfaction, accessibility and academic loafing (x)

Variable	$BWS(x)$			$BWS(y)$			Coefficient corelation (ρ^{xy})	Corelation
	$(BWS)^{-ve}$	$(BWS)^{+ve}$	BWS^x	$(BWS)^{-ve}$	$(BWS)^{+ve}$	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 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 touch 37.3 million students out of 37.4 million students across India during 2019 (AISHE Report 2018–19.pdf n.d.), which is above 99% but on the

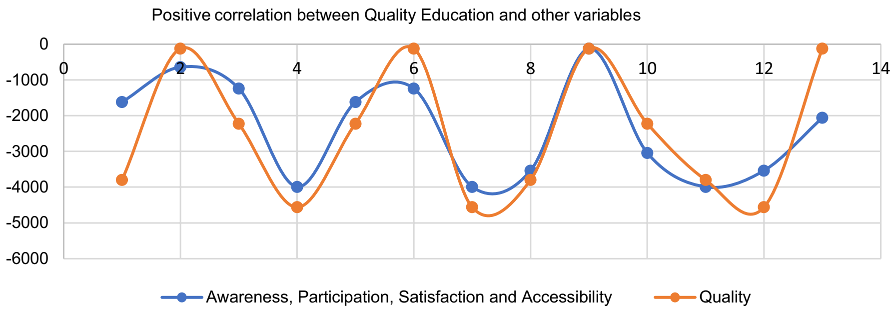


Fig. 11 Scatter diagram between different variables under study (awareness, participation, satisfaction, and accessibility) and quality education shows a positive correlation between quality education and various other variables under study

ground level, the situation is completely contradictory. 68.8% of participants who participated in this survey did not even hear about 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) (NAAC—Home n.d.). 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 has to put some steps forward to bring awareness to all stakeholders about the quality assessment and to also improve the participation of all stakeholders in the same. For accessibility (Silaeva & Semenov, 2018) 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. that they must be in direct contact with their respective apex bodies. Only 36.6% of students are satisfied with the quality of education of their respective institutions. More than 70% of students are not satisfied with the employable skill 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 the intelligence i.e. IQ-Intelligence Quotient and is willing to introduce another important factor of intelligence i.e. EQ (Emotional Intelligence) 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' (More than half of South Asian youth are not on track to have the education and skills necessary for employment in 2030 n.d.), and 87.7% of students agrees with UNICEF's report about Indian Education System. So, improving accessibility by establishing direct contact between every stakeholder and their respective apex education bodies' government may improve the accessibility. The introduction of the EQ evaluation

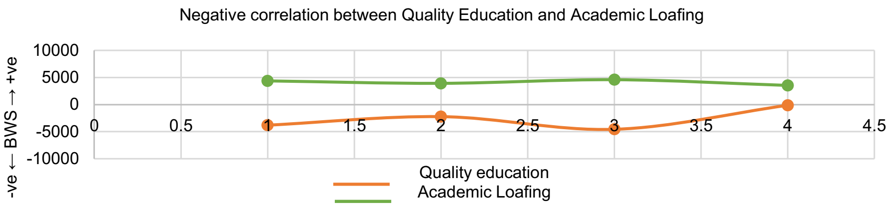


Fig. 12 Scatter diagram between academic loafing and quality education showing a negative correlation between quality education and academic loafing

system in higher education is one more important factor for quality improvement (Zhoc et al., 2020). 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 Academic is an untouched term that has a very high significance (Mihelič & Culiberg, 2019) 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 Fig. 12 indicates the negative correlation between quality education and academic loafing.

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

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 (Ajiboye, 2019) 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, unemployable skill set, 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 citation 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 (QS World University Rankings, 2020: Top Global Universities | Top Universities n.d.). Academic loafing is one of the major factors behind the perseverance of low quality-education by the world's best faculty members in India.

From Table 2 the value of (ρ^{xy}) i.e. correlation coefficient for all five variables is not equal to zero.

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

(ρ^{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 analyses 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, Accessibility all four variables 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. So, again for improvement in quality education, the government must reduce this factor. Total participation (i.e. all stakeholders including students, teachers, and 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). 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 the lack of state-of-the-art technology and easily accessible methods at the 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 (Li & Zhao, 2020). So, E-participation can also be considered as an effective tool to achieve total participation. The integration of quality assurance systems in every institution is the mandate (Aniskina & Lunina, 2017) and implementation of this quality assurance system on state-of-the-art technology enhances all the parameters of quality assurance.

Conclusion and future perspective

Multilayered-Quality Education Ecosystem (MQEE) proposed in this study is a suitable model for Education 4.0. The recommended, Bidirectional Weighted Sum (BWS) method for the 5-piont/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 ground level is recommended. 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 the accessibility and satisfaction among stakeholders so that there is lessening in 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 Healthy Environment for learning). The overall improvisation 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%. Awareness, Satisfaction, Participation and Accessibility are the factors that need improvement for sustainable quality education, whereas academic loafing is the only factor that shows the reversal effect on sustainable quality education. 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' preview. Such limitations need further improvement in the near future. Policy maker's 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, total quality management.

Declarations

Conflict of interest The authors declare no conflict of interest.

References

"AISHE Report 2018–19.Pdf."

Ajiboye, R. O. (2019). Self-efficacy, collectivism and social loafing of university workers in Southwest Nigeria: Implications for staff-students. *Social Interactions, 4*(4), 327–336.

Ali, M., & Asim, M. (2018). How internet-of-things (IoT) making the university campuses smart? 646–648.

Altbach, P. G. (2014). India's higher education challenges. *Asia Pacific Education Review, 15*(4), 503–510.

Aniskina, N. N., & Lunina, E.V. (2017). Integration of quality assurance models for education on the basis of comparative analysis. In *Proceedings of the 2017 international conference "quality management, transport and information security, information technologies, IT and QM and IS 2017* (pp. 616–620).

Antunes, M., Gomes, D., & Aguiar, R. L. (2018). Towards IoT data classification through semantic features. *Future Generation Computer Systems, 86*, 792–798. https://doi.org/10.1016/j.future.2017.11.045

Araujo, T., Helberger, N., Kruikemeier, S., & de Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. *AI and Society, 35*(3), 611–623. https://doi.org/10.1007/s00146-019-00931-w

Assahli, S., Berrada, M., & Chenouni, D. (2017). Data preprocessing from internet of things: Comparative study. In *2017 International conference on wireless technologies, embedded and intelligent systems, WITS 2017* (Fig. 1).

Bagchi, U. (2010). Delivering student satisfaction in higher education: A QFD approach. In *2010 7th International conference on service systems and service management, proceedings of ICSSSM'* (Vol. 10, pp. 1049–1052).

Caeiro, S., Azeiteiro, U. M., Filho, W. L., & Jabbour, C. (2013). Sustainability assessment tools in higher education institutions: mapping trends and good practices around the world. In *Sustainability assessment tools in higher education institutions: Mapping trends and good practices around the world* (pp. 1–417).

Chakrabarty, K. C. (2011). Indian education system—Issues and challenges. *RBI Monthly Bulletin* 1–10.

Ciolacu, M. I., et al. (2019). Education 4.0-jump to innovation with IoT in higher education. In *SIITME 2019—2019 IEEE 25th international symposium for design and technology in electronic packaging, proceedings* (pp. 135–141).

Ciolacu, M., Tehrani, A. F., Beer, R., & Popp, H. (2017). Education 4.0-fostering student's performance with machine learning methods. In *2017 IEEE 23rd international symposium for design and technology in electronic packaging, SIITME 2017-proceedings* 2018-Janua (pp. 438–443).

Cohen, P. A. (1980). Effectiveness of student-rating feedback for improving college instruction: A meta-analysis of findings. *Research in Higher Education, 13*(4), 321–341.

Countries Arranged by Number of Universities in Top Ranks | Ranking Web of Universities: More than 28000 Institutions Ranked. https://www.webometrics.info/en/node/54 (2020).

de Fine Licht, K., & de Fine Licht, J. (2020). Artificial intelligence, transparency, and public decision-making: Why explanations are key when trying to produce perceived legitimacy. *AI and Society*. https://doi.org/10.1007/s00146-020-00960-w

El-Latif, A. A. A., Abd-El-Atty, B., Venegas-Andraca, S. E., & Mazurczyk, W. (2019). Efficient quantum-based security protocols for information sharing and data protection in 5G networks. *Future Generation Computer Systems, 100*, 893–906. https://doi.org/10.1016/j.future.2019.05.053

Farhan, M., et al. (2018). A real-time data mining approach for interaction analytics assessment: IoT based student interaction framework. *International Journal of Parallel Programming, 46*(5), 886–903. https://doi.org/10.1007/s10766-017-0553-7

Fronza, I., & Wang, X. (2017). Towards an approach to prevent social loafing in software development teams. In *International symposium on empirical software engineering and measurement* (pp. 241–46).

Glavič, P. (2020). Identifying key issues of education for sustainable development. *Sustainability (switzerland), 12*(16), 6500.

Gupta, S. K., Ashwin, T. S., & Guddeti, R. M. R. (2019). Students' affective content analysis in smart classroom environment using deep learning techniques. *Multimedia Tools and Applications, 78*(18), 25321–25348.

Hassaan, S. M., et al. (2021). Incremental affine abstraction of nonlinear systems. *IEEE Control Systems Letters, 5*(2), 653–658.

Hernandez-de-Menendez, M., Escobar Díaz, C. A., & Morales-Menendez, R. (2020). Engineering education for smart 4.0 technology: A review. *International Journal on Interactive Design and Manufacturing, 14*(3), 789–803. https://doi.org/10.1007/s12008-020-00672-x

Iqbal, M. M., et al. (2019). Multimedia based IoT-centric smart framework for elearning paradigm. *Multimedia Tools and Applications, 78*(3), 3087–3106.

Kassab, M., Defranco, J. F., & Voas, J. (2018). Smarter education. *IT Professional, 20*(5), 20–24.

Ke, F., Pachman, M., & Dai, Z. (2020). Investigating educational affordances of virtual reality for simulation-based teaching training with graduate teaching assistants. *Journal of Computing in Higher Education, 32*(3), 607–627. https://doi.org/10.1007/s12528-020-09249-9

Kormos, E., & Julio, L. (2020). Student attitudes toward instructor assessment in higher education: Does the delivery method matter? *Education and Information Technologies, 25*, 4287–4296.

Kuper, H. (2020). Industry 4.0: Changes in work organization and qualification requirements—Challenges for academic and vocational education. *Entrepreneurship Education, 3*(2), 119–131. https://doi.org/10.1007/s41959-020-00029-1

Li, W., Meng, W., Liu, Z., & Au, M. H. (2020). Towards blockchain-based software-defined networking. *Security, 2*, 196–203.

Li, W., Meng, W., Tan, Z., & Xiang, Y. (2019). Design of multi-view based email classification for IoT systems via semi-supervised learning. *Journal of Network and Computer Applications, 128*(2018), 56–63. https://doi.org/10.1016/j.jnca.2018.12.002

Li, X., & Zhao, G. (2020). Democratic involvement in higher education: A study of chinese student E-participation in university governance. *Higher Education Policy, 33*(1), 65–87. https://doi.org/10.1057/s41307-018-0094-8

Maddineni, S., Kim, J., El-Khamra, Y., & Jha, S. (2012). Distributed application runtime environment (DARE): A standards-based middleware framework for science-gateways. *Journal of Grid Computing, 10*(4), 647–664.

Madeira, A. C., Carravilla, M. A., Oliveira, J. F., & Costa, C. A. V. (2011). A methodology for sustainability evaluation and reporting in higher education institutions. *Higher Education Policy, 24*(4), 459–479.

Madhavi Devi, K., Krishna Gupta, M., & Muralidharan, V. (2013). Empowering IT education in rural India. In *2013 12th International conference on information technology based higher education and training, ITHET 2013*.

Mazurczyk, W., Wendzel, S., Chourib, M., & Keller, J. (2019). Countering adaptive network covert communication with dynamic wardens. *Future Generation Computer Systems, 94*, 712–725. https://doi.org/10.1016/j.future.2018.12.047

Mezghani, E., Exposito, E., & Drira, K. (2017). A model-driven methodology for the design of autonomic and cognitive IoT-based systems: Application to healthcare. *IEEE Transactions on Emerging Topics in Computational Intelligence, 1*(3), 224–234.

Mihelič, K. K., & Culiberg, B. (2019). Reaping the fruits of another's labor: The role of moral meaningfulness, mindfulness, and motivation in social loafing. *Journal of Business Ethics, 160*(3), 713–727. https://doi.org/10.1007/s10551-018-3933-z

Mishra, N., Lin, C. C., & Chang, H. T. (2014). A cognitive oriented framework for IoT big-data management prospective. In *2014 IEEE international conference on communication problem-solving, ICCP 2014* (pp. 124–127).

More than Half of South Asian Youth Are Not on Track to Have the Education and Skills Necessary for Employment in 2030. https://www.unicef.org/press-releases/more-half-south-asian-youth-are-not-track-have-education-and-skills-necessary. March 31, 2020.

NAAC-Home. http://www.naac.gov.in/. March 31, 2020.

Pang, S., et al. (2019). A behavior based trustworthy service composition discovery approach in cloud environment. *IEEE Access, 7*, 56492–56503.

Park, J. H., et al. (2019). CIoT-Net: A scalable cognitive IoT based smart city network architecture. *Human-Centric Computing and Information Sciences*. https://doi.org/10.1186/s13673-019-0190-9

Patil, V. L. (2012). 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*, 12–14.

QS World University Rankings 2020: Top Global Universities | Top Universities." https://www.topuniversities.com/university-rankings/world-university-rankings/2020. January 16, 2020.

Rajashree. (2014). Indian education system—A historical journey. *International Journal for Research in Education 3*(3): 46–49.

Rekh, S., & Chandy, A. (2020). Implementation of academia 4.0 for engineering college education. *Procedia Computer Science, 172*(2019), 673–678. https://doi.org/10.1016/j.procs.2020.05.088

Sakala, L. C., & Chigona, W. (2020). How lecturers neutralize resistance to the implementation of learning management systems in higher education. *Journal of Computing in Higher Education, 32*(2), 365–388. https://doi.org/10.1007/s12528-019-09238-7

Schönig, S., Ackermann, L., Jablonski, S., & Ermer, A. (2020). IoT meets BPM: A bidirectional communication architecture for IoT-aware process execution. *Software and Systems Modeling, 19*(6), 1443–1459. https://doi.org/10.1007/s10270-020-00785-7

Shanchen, P., et al. (2020). A text similarity measurement based on semantic fingerprint of characteristic phrases. *Chinese Journal of Electronics, 29*(2), 233–241.

Shunmugaraj, S. Social Loafing.

Silaeva, V. V., & Semenov, V. P. (2018). Internal education quality assurance through standardization of educational organization management system. In *Proceedings of the 2018 international conference "'quality management, transport and information security, information technologies'", IT and QM and IS 2018* (pp. 70–73).
Slade, C., & Downer, T. (2020). Students' conceptual understanding and attitudes towards technology and user experience before and after use of an EPortfolio. *Journal of Computing in Higher Education, 32*(3), 529–552. https://doi.org/10.1007/s12528-019-09245-8
Spokoiny, A., & Shahar, Y. (2007). An Active database architecture for knowledge-based incremental abstraction of complex concepts from continuously arriving time-oriented raw data. *Journal of Intelligent Information Systems, 28*(3), 199–231.
Umashankar, V., & Dutta, K. (2007). Balanced scorecards in managing higher education institutions: An Indian perspective. *International Journal of Educational Management, 21*(1), 54–67.
Varghese, M. A. (2011). Development of collegiums of quality assessors for the Indian National Assessment & Accreditation Council (NAAC). In *2011 international workshop on institutional and programme accreditation: Connections and opportunities-proceedings, IWIPA 2011*.
Wang, M. (2019). Research on construction of the internal quality assurance system of assessment-based diagnosis and reformation in higher vocational colleges. In *2019 IEEE Eurasia conference on IOT, communication and engineering, ECICE 2019* (Vol. 9, pp. 518–521).
Wook, M., et al. (2020). Opinion mining technique for developing student feedback analysis system using lexicon-based approach (OMFeedback). *Education and Information Technologies, 25*(4), 2549–2560.
World | Ranking Web of Universities: More than 28000 Institutions Ranked. https://www.webometrics.info/en/world. January 16, 2020.
Zhang, Y., Peng, L., Sun, Yi., & Huimin, Lu. (2018). Editorial: intelligent industrial IoT integration with cognitive computing. *Mobile Networks and Applications, 23*(2), 185–187.
Zhoc, K. C. H., King, R. B., Chung, T. S. H., & Chen, J. (2020). Emotionally intelligent students are more engaged and successful: Examining the role of emotional intelligence in higher education. *European Journal of Psychology of Education*.

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