Received: 29 March 2017 | Accepted: 18 May 2017
DOI: 10.1002/cae.21849

RESEARCH ARTICLE

WILEY

Smart computing based student performance evaluation framework for engineering education

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Abstract

Internet of Things (IoT) technology has changed the educational landscape by allowing educators and administrators to turn data into actionable insight. Education organization begin to leverage solutions like cloud computing and radio frequency identification (RFID) across an IoT platform. Relative to this context, this paper proposes a five layer framework to facilitate automated student performance evaluation in engineering institutions based on smart computing concept. Student daily activity datasets are formed based on sensing capabilities of IoT nodes. Smart computing integrates hardware, software, and network technologies that provides systems with real-time situation awareness and automated analysis. The engineering student performance per session is calculated by combining the results from sensory nodes based education data mining algorithms and student academic datasets. Moreover, based on student sessional performance score, decisions are taken by management authority to increase the reputation score of the engineering institution. The experiment comprises two sections. In first section, RFID based experimental setup is defined with objects interaction patterns. In second section, student performance score generated using proposed system is compared with manual system. The results depict that by introducing IoT in engineering education, more effective decisions can be taken to improve student learning experiences and over-all growth of the institution.

KEYWORDS

educational data mining, game-theory, Internet of Things (IoT), performance evaluation, radio frequency identification (RFID)

1 | INTRODUCTION

The exponential IoT technological advances have attracted the attention of researchers from various education disciplines. IoT has the potential to cause major disruption in variety of fields. As education institutions also become part of this evolution, the IoT is likely to bring significant changes to the education sector as well. IoT technology in education can move engagements beyond the classroom for more authentic and relevant learning. Using IoT technology in education we can connect learners worldwide, improve campus safety, and most importantly increase the efficiency related to streamlining the day-to-day operations of students and staff using connected devices and RFID technology.

Smart devices and intelligent technologies are required in education domain to explore smart learning environment. Smart devices refer to artefacts, exhibit some properties of ubiquitous learning (u-learning) that helps student to gain information on demand, accessible anytime and anywhere [17,18]. IoT based wearable technology in the form of accessories such as glasses, RFID tags on clothing's and other sensor devices in learning environment forms a u-learning space. On the other hand, intelligent technologies, such as cloud computing, learning analytics, focused on how learning data can be captured, analyzed to improve learning as well as decision making capabilities of an education institution. Despite of the distinction between smart devices and intelligent technologies, they are in fact interrelated, because data from smart devices are analyzed using intelligent technologies. For instance, the Internet of Things (IoT) and most of the wearable technologies require big data analytics to generate meaningful information and provide the user with real-time feedback [25].

Smart computing plays a significant role in education sector for generating smart learning environments. It incorporates elements of hardware, software, and network together with the digital sensors, smart devices, big data analytics, and computational intelligence to realize various applications in education domain [37]. In addition to that, the advancements of computing technologies can lead smart computing to a new dimension and improves the way in which learning can be made more effective in education sector.

Based on the above mentioned points, an IoT based student performance evaluation framework for engineering education is systematically developed. Student performance in education institution like engineering colleges and business schools can be automated through our proposed IoT based student performance evaluation framework. To effectively compute the student performance in IoT based ubiquitous environment, sensor readings are analyzed at cloud layer as explained ahead in section 3. Machine learning algorithms are used to extract results based on activity based context. Student activity based performance is added with student sessional score to compute final student performance score.

Furthermore, this paper proposes a system that allow students to interact with each other and objects using smart devices. An IoT based layered cloud framework is proposed for the engineering students on the basis of interaction among objects and the real-world environment. The objectives of the paper is described as (i) IoT technology based smart devices for student activity performance calculation in engineering education; (ii) Educational data mining based on student, teacher and object interactions; (iii) To evaluate the performance of each student by integrating results from sensory activity set and student academic dataset; (iv) To make continuous decisions using game-theory from the information retrieved from student performance database; and (v) Comparing the results of automated IoT based student performance system with manual student performance evaluation system.

The remainder of this paper is organized as follows. Section 2 discusses the work related to IoT based ubiquitous learning, data mining in education domain, and Game-theory for IoT. In section 3, IoT based student performance evaluation framework is defined. In section 4, we define RFID interaction environment followed by experiment evaluation of the system. Finally, section 5 summarizes the paper with conclusive remarks.

2 | RELATED WORK

This section focuses on the literature review in the domains of u-learning in education, data mining concepts and game theory for IoT. Various education based data mining algorithms, IoT based ubiquitous learning in education and game theory based decision making algorithms are discussed in three sub sections ahead.

2.1 | IoT based ubiquitous learning

The ubiquitous based learning in higher institutions are gaining impetus day by day. This subsection covers the latest innovations that are incorporated in the smart institutions. In 2005, Davies and Graff [9] have examined the frequency of online interactions of 122 undergraduate students and the effect of online interactions with their grades at the end of the year. The findings reveal that the quality and dynamics of interaction plays a significant role in student learning and performance. In 2010, Liu and Hawang [23] have defined a theoretical framework for paradigm shift in e-learning. Three components namely conventional e-learning, mobile learning and context-aware u-learning are used to explain the changes involved in the student learning environment. To effectively demonstrate the arrangement required for context-aware u-learning, an example of butterfly garden is taken into consideration as learning area. In 2013, Chin and Chen [8] have proposed a mobile learning support system which enables students to interact with learning materials using 2D barcodes and GPS technology. This paper also provides an opportunity to create ubiquitous learning environment that combine real-world and digital world resources. In 2016, Pimmer et al. [27] have systematically analyzed 36 empirical papers which emphasize on mobile and ubiquitous learning in higher education settings. They came to a conclusion that by including ubiquitous learning system using mobile media, a number of unprecedented educational affordances can be operationalized to enrich and extent more traditional form of higher education. In 2016, Gros [13] has discussed the key characteristics of smart learning. A new pedagogical approach is used to integrate smart learning environment into the learning ecosystem and educational contexts. In

2016, Zhu et al. [37] have emphasized on new technologies in education domain. They discussed the definition of smart education by presenting a novel conceptual framework. A four-tier framework of smart pedagogies with ten key features of smart learning environments are proposed for foster smart learners who need master knowledge and skills of the 21st century learning. In 2013, Gomez et al. [12] have proposed a system in which real objects are associated as a learning resource through IoT to facilitate meaningful learning. The approach is experimentally validated, yielding evidence of improvement in student's learning outcomes. In 2010, Cattuto et al. [7] have proposed a scalable experimental framework for gathering real-time data and resolving face-to-face social interaction using RFID devices. An experimental framework is defined for RFID tag based social interactions, by defining the similarities in the way individuals interact in different contexts, and identifying patterns of super-connector behavior in the community. In 2011, Atzori et al. [2] have introduced a novel paradigm of "social network of intelligent objects," namely the Social Internet of Things (SIoT). They statistically analyzed the structure of the SIoT network through simulations by incorporating the mobility of objects and their relationships. In 2013, Guo et al. [14] have presented an opportunistic IoT, which is formed based on the adhoc, opportunistic networking of devices. In 2014, Borgia [5] has presented the key features and the driven technologies of IoT. By involving intelligence into everyday objects, they are turned into smart objects. In addition, he discussed the major challenges that need to be faced for supporting the IoT vision. In 2014, Wu et al. [36] proposed an operational framework for creation of intelligent IoT environment named as Cognitive Internet of Things (CIoT). They emphases on empowering the current IoT with a "brain" for high-level intelligence. Intelligence task can be fulfilled if cognitive tasks include decision making component.

2.2 | Data mining in education domain

Data mining operations in IoT environment plays a critical role in making smart system capable enough to provide convenient and efficient services. Massive data generated or captured by IoT is converted into useful and valuable information by data mining operations. In 2004, Huang et al. [16] have developed a new approach to mine colocation patterns by using the concept of proximity neighborhood. An interesting term participation index, is proposed for spatial colocation patterns. This participation index measure is quite similar to *cross-K* function, used often as a statistical measure of interaction among pairs of spatial features. Moreover, authors have designed a colocation miner algorithm used as a measure to discover colocation patterns from spatial datasets. In 2005, Borodin et al. [6] have introduced a theoretical framework for the study of Link analysis algorithms. They have defined the specific properties of link analysis algorithms with a self-evident characterization of the INDEGREE heuristic, forming a ranking mechanism according to the number of incoming links. Moreover, they have performed an extensive experimental study on multiple queries, using user feedback for studying the behavior of ranking algorithms. In 2012, Schall [29] has introduced a link intensity based ranking model for recommending relevant users in human collaborations. He has presented DSA Rank for estimating the relative importance of persons based on reputation mechanism in collaborative networks. He tested the applicability of ranking model by using datasets obtained from real human interaction networks including smart devices and email communications. In 2015, Rafiei and Kardan [28] have developed a hybrid method for expert finding in online communities. Content analysis based on the concept map and the social network analysis based on PageRank are used to determine expertise level of users in online communities.

2.3 | Game-theory for Internet of Things

Game-based decision models are gaining impetus in IoT environment. Game theory is a systematic study of strategic interaction among rational individuals. In 2014, Hamdi and Abie [15] have proposed a Markov game-based adaptive security model in IoT environment. They have designed a two-player game theory between security-effectiveness and energy- efficiency to evaluate adaptive security strategies. In 2008, Machado and Tekinay [24] have discussed the suitability of using game-theory to optimize node-level as well as network-wide performance by exploiting the distributed decision-making capabilities of wireless sensor networks. Moreover, potential applicability of WSN's to intruder detection environment also advances itself to game-theoretic formulation of these environments. In 2015, Kaur and Sood [20] have presented a game theoretic approach for an IoT-based employee performance evaluation in industry. The information mined from sensory nodes are used to draw automated decisions using game theory. In 2017, Bhatia and Sood [3] have proposed a framework for monitoring defense personnel social activities using IoT devices. Suspicious index is calculated for every personnel on the basis of their social interactions. A game-theoretic decision making model is presented to aid the monitoring officials in reducing the probability of secret information outflow. Recently, authors have found helpfulness of decision-making methodologies in forming cognitive IoT system. They use cognitive decision-models in IoT environment, like consensus model [22], agent-based model [31], neural networks [32], Bayesian decision model [30], and many more [4,19].

3 | PROPOSED WORK

Figure 1 presents the modeling of proposed system which consists of five layers (i) data acquisition and synchronization layer; (ii) cloud storage repository and activity classification layer; (iii) daily activity recognition and visualization layer; (iv) data mining and student performance calculation; and (v) game-theoretic decision making. Layer 1 is responsible for automated data collection from personal body sensor network and other IoT devices implanted in the school environment. The students and teachers physiological parameters are collected by coordinator known as Gateway, this is a portable device or smart-phone. In layer 2, the interaction and location measurements are transferred to third party platform known as cloud storage repository. Cloud storage infrastructure is responsible for data pre-processing and classifying activities into different datasets. In layer 3, student IoT based datasets are temporally analyzed during activity recognition phase. Based on IoT based activity datasets, student interactions are visualized, followed by temporal graph creation. Layer 4 computes the student performance score by integrating results of IoT based data mining algorithms for IoT based activities with engineering student academic dataset for the sessional performance. Based on the student sessional performance score, management authority further computes reputation score of the institution. In layer 5, game-based decision component takes automated decisions based on student performance score and institution reputation score for a particular session.

3.1 | Data acquisition and synchronization

The students are first registered with the system by entering his/her academic details through mobile application installed on the student's mobile phone. Each registered student is provided with a unique student ID, known as beacon. The attributes associated with student are shown in Table 1. The students IoT based daily interaction metadata is indexed with beacon to draw important information related to student learning environment.

Student daily interaction and location data is acquired by data acquisition system, which allows seamlessly integration of intelligent, miniature low-power sensors and other monitoring devices. Sensors like radio frequency identifiers (RFID), GPS sensors and other sensor devices constitute a student body network. This system aims in acquiring information related to student or staff with respect to their location and other routine activities. Moreover, gateway collects data from student data network in structured and unstructured form which is further transferred to cloud storage repository for further analysis. The transfer mechanism is implemented using wireless communication system such as

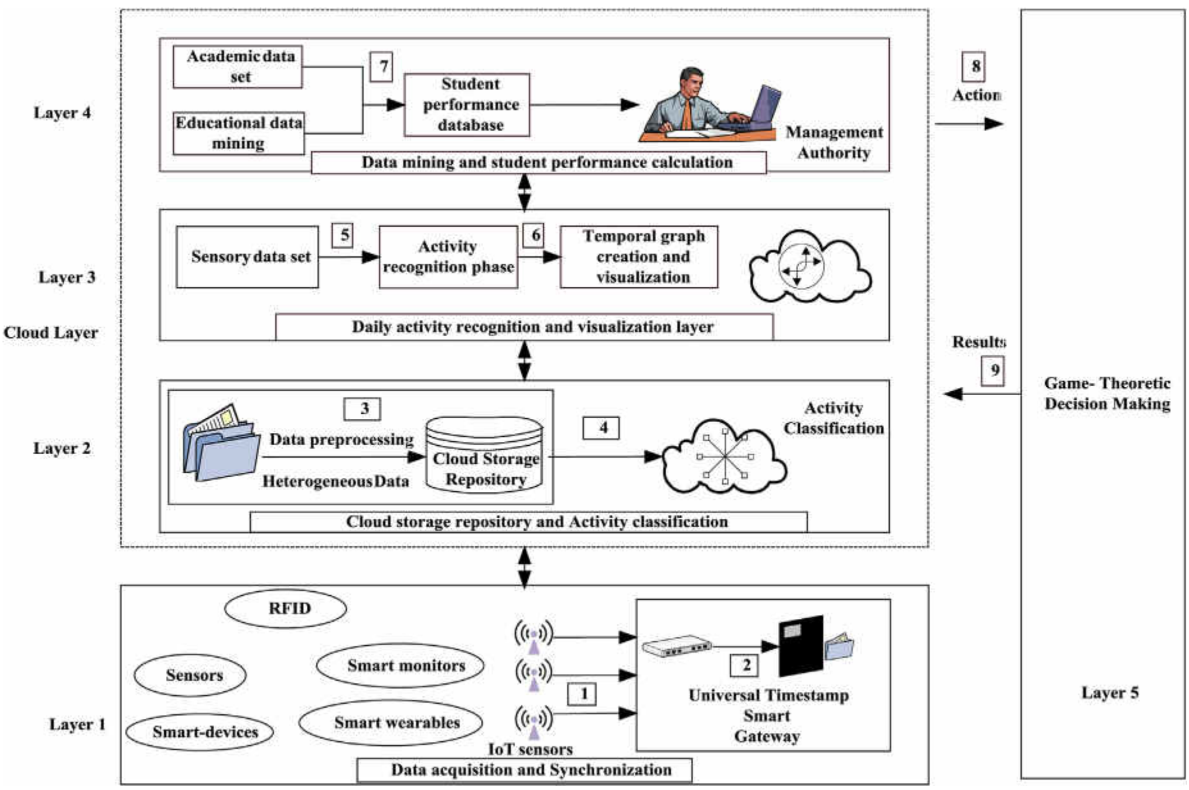

FIGURE 1 Flow diagram of the proposed system

mobile networks 3G/CDMA/GPRS as shown in Figure 1. However, the transmission channel is secured with secure socket layer (SSL) for providing security at cloud storage.

3.2 | Cloud storage repository and activity classification

The student daily activity related dataset is stored at cloud layer, which can be described as infrastructure as a service (IaaS) provider. The data is ubiquitously sensed and regularly retrieved during different time units. Therefore, a cloud based storage repository is required to learn sensory nodes interaction pattern during different time-intervals. The student activities are properly classified based on some presumptions explained ahead. Moreover, student personal information is already stored at cloud side repository. The security mechanism is applied for providing access to two types of user's category. First category consists of institution management authority, having access to both isolated and shared data. On the other hand, only shared data is provided to the students or government agencies for survey purposes.

3.2.1 | Data pre-processing

The goal of this component is to acquire data from various IoT enabled sensor devices and impart analytical processes on that data to improve performance and efficiency. As the real-world data tends to be incomplete, noisy and inconsistent, data pre-processing is required. In data pre-processing missing values are filled up, noisy data is smoothed, data inconsistency is removed, and data is reduced while minimizing the loss of information content. Moreover, data transformation routines segregate data into appropriate form for mining purpose as shown in Figure 2. In addition to that, different data preprocessing techniques for mining heterogeneous data can be used to classify an activity on a particular day [11,34].

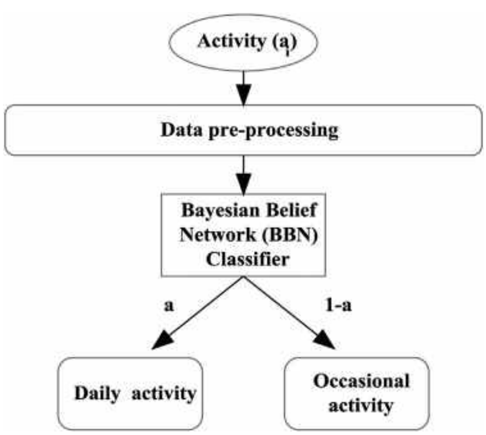

FIGURE 2 Activity classification

3.2.2 | Activity classification

Activities in our proposed methodology is classified into two different classes, namely daily activity and occasional activity. Daily activities consists of those activities for which student performance is calculated on daily basis. On the other hand, occasional activities are performed randomly during a session of a semester. The classification procedure is based on Bayesian Belief Network (BBN) classifier [21]. It is a directed acyclic graph that assigns an activity to certain class based on probabilistic parameters with prefixed assumptions as shown in Figure 2. The data collected from IoT devices and student body network are used to depict the student activities in engineering institutions. BBN activity models are used to define various student activities. The activity set used for calculating engineering student performance is explained ahead:

(1) *Locational activity*: Location activities are concerned with student presence at a particular location in the institution premises. The IoT devices like GPS, RFID's are used to depict location based student information. Activities like attending a seminar, classes and study-group comes under location based activities.
(2) *Interactive activity*: These activities mainly emphasizes on student interaction with other students and faculty members. These activities can be smoothly monitored using sensors, RFID tags and other IoT devices. Activities like student participation in a study-group, participation of student in sports activity, student teacher interaction related to subject, and participation in group discussion are the main interactive activities.
(3) *Academic activity*: The student performance in each subject concerned can be computed by using results of exam in particular semester.
(4) *Behavioral activity*: This include activities like effective utilization of institution facilities and attentiveness in class. These activities related data is smoothly retrieved using behavioral sensors and health sensors placed at different locations in institution premises. The detail regarding activity classification is shown in Table 2.

3.3 | Activity recognition and visualization

3.3.1 | Activity dataset

In our proposed methodology, 10 activities are taken into consideration for calculating student performance using IoT based activity set and student academic activity set. Datasets which comprise of heterogeneous data are defined for all the activities conducted during a day. However, to effectively demonstrate our proposed system, two datasets are used (i) sensory related dataset and (ii) student academic datasets.

TABLE 1 Personal attributes of student

S. No.	Attributes	Description
1	SID	Student identification number
2	Name	Student name
3	Age	Age of the student
4	Semester	Semester of engineering
5	Branch	Branch of engineering
6	Sex	Male or female
7	Address	Permanent address of the student
8	Family member name	Name of the family member
9	Family member mobile number	Family member mobile number
10	Student information	Student previous performance information

(i) Sensory related datasets

In this domain, biometric readings, GPS, and smart-wearable's readings are utilized to predict student performance for the activities like student attentiveness in class, presence at particular location, attending a study group etc.

The RFID tags best describe the interaction based activity datasets. RFID system constitute interactive datasets based on spatial-temporal patterns formed during a day. Using, spatial and time oriented information, various spatial data sets are created for each activity. The activity instances like team-work participation, sports contribution, and student spending time in labs and library are some important activities whose results can be drawn from interactive datasets.

(ii) Student academic datasets

Student academic datasets are composed of student academic performance in each subject on sessional basis in engineering institutions. The student performance score consists of both academic and sensory datasets, explained in section 3.4.

3.3.2 | Activity recognition phase

Definition 1*: Student Activity Description (SAD)***:** *Given an activity j in the time-interval* $[t_i, t_{i+1}, \ldots\ldots, t_{i+k-1}]$ *where k is the number of time-instances, the activity j can be best recognized based on the working set of sensor sequence during a particular time interval.*

Moreover, parameters like time-dependency and sensory dependency [34] can be utilized for activity recognition phase. However, to smoothly conduct the activity recognition mechanism, additional features like appending the context information of the previous activity in the current temporal sliding window is quite feasible. After recognizing each activity, student performance score is stored at performance database for decision making in future.

3.3.3 | Temporal graph creation and visualization

The interaction between IoT devices and nodes can be best viewed using temporal spatial pattern graphs. The cloud based repository stores the time stamped information of radio packets generated from objects which is further relayed to real-time system for analysis purpose. Real-time system aggregates received radio packets to generate real-time temporal interaction graphs. The real-time interaction graphs are formed based on the phenomenon of spatial proximity relation, elaborated in experimental section. In this

TABLE 2 Activity classification

S. No.	Activity	Few instances	Information sources
1	Locational	Attending a class, study-group, or seminars.	Biometric attendance, GPS, and RFIDs
2	Interactive	Student participation in study group, team-work participation of student in sports, student-teacher interaction based on subject, group-discussion, student preferred company, etc.	Sensors and RFIDs
3	Academic	Academic performance.	Semester results
4	Behavioral	Attentiveness in class, interaction with other students and staff.	Bio-sensors, Q-sensors, and smart wearables

phenomenon, RFID reader, installed at experimental area fed the received packets to a real-time system. Figure 3 shows the formation of temporal proximity graph based on RFID tag interactions.

Spatial-temporal patterns can be visualized in the form of interactive web of sensory data composed of nodes (students) called as beacon. It consists of various sensory events and RFID interactions which can be mined based on spatial and activity knowledge. Using daily spatial information, various *spatial data sets* are created for each activity. The spatial data sets, with different time instances during a particular day can be visualized to draw important results based on spatial-temporal mining technique. Moreover, proximity sensing graph provides instance network system in which each edge thickness reflects the priority given by one node to another node (i.e., strength in different activity concern). The instance network system for each activity concern play a significant role in generating mining results.

3.4 | Data mining and student performance calculation

3.4.1 | Data mining

Activity based datasets are used to construct proximity matrix for each student. Proximity matrix can be further updated based on the temporal formation of social patterns explained in experimental section. Graph-based clustering technique is used to view the data, in which data objects (student and IoT devices) is represented by nodes and the proximity between two objects is represented by the strength of the edge between the corresponding nodes. To include key properties of student data in the form of graph, sparsification technique is used to cluster the graph based on activity set. The key steps followed during clustering is shown in Figure 4.

In Figure 4, the final output of sparsification is the partition graph sets based on each activity concern. Moreover, each activity is based on some predefined context, therefore required different data mining algorithms to yield student performance. The data mining algorithms used in different context are explained ahead.

(i) Co-location pattern mining from spatial datasets

To retrieve the requisite information from spatial patterns of IoT devices we can apply spatial-colocation mining technique. Spatial datasets are created for each activity concern. Moreover, spatial temporal mining concept can be best described by generating temporal activity set based graphs during a definite time interval. Spatial temporal mining analyses data based on spatial location and time bound sensor sequence. Based on the spatial patterns, participation index of each student is calculated using co-location mining concept [20].

(ii) Page-Rank based mining

Page Rank algorithm retrieves student participation index in sports activity and his/her contribution in study group. Page Rank algorithm computes the importance of each node (student) by computing its interaction score (IR) with other nodes in the spatial dataset. Based on the IR (u) score of uth node, student participation index is calculated as follows:

$$\mathrm{PR}\,(u) = \alpha\rho + (1-\alpha)\sum\nolimits_{(v,u)\epsilon E}\frac{\mathrm{PR}(v)}{\text{out degree}(v)} \tag{1}$$

Here, ρ is personalized vector used to assign preferences toward certain nodes. Moreover, without any preferences, a

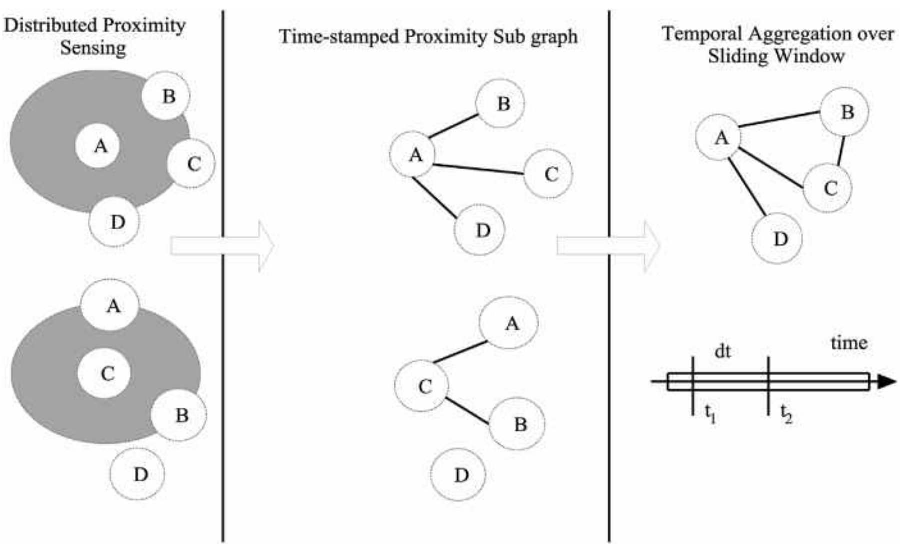

FIGURE 3 Proximity sensing during time-interval [$t - \Delta t$, t], forming interaction graph using sliding window concept

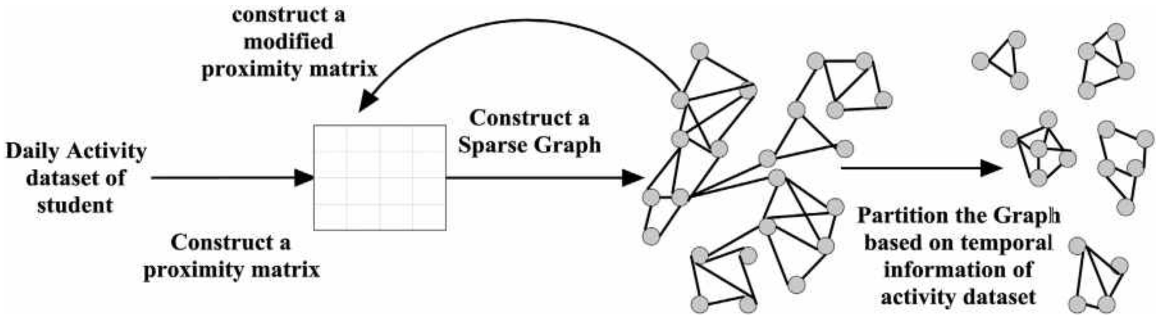

FIGURE 4 Ideal process of clustering using sparsification

personalization vector with $\rho = [1/[\mathrm{N}]]_{\mathrm{N}\times 1}$ is assumed, N is the number of nodes in use. For example, we assume $\alpha = 0.16$, called as "teleportation factor," which typically follow for six student links (i.e., $1/6 = 0.16$).

(iii) HITS based mining

HITS model computes the student teacher interaction related to each subject. Based on the student-teacher interaction features bipartite graph is formed. This model is used for expertise ranking mainly in question and answer communities. In our proposed system, hubs H comprises student asking questions by attracting answers from knowledge teachers representing authorities A.

$$H(u) \sum_{(u,v)\epsilon E} A(v) \quad A(v) \sum_{(u,v)\epsilon E} H(u) \tag{2}$$

This concept is beneficial in task-based online help and support in IoT based e-learning environments. Each nodes composed of two ranking score (hub and authority) based on which student teacher interaction score is computed. Moreover, details regarding each activity with data mining technique is shown in Table 3.

3.4.2 | Student performance score

Student must participate in each activity (A_j), where j is the number of activities from 1 to n. V_j^k is a probabilistic value of activity A_j at day k, where $1 \le k \le p$, here p is the number of times an activity result is computed during a session. The score of student related to each activity $S(A_j)$ can be computed as following:

$$S(A_j) = \frac{\sum_{k=1}^{p} V_j^k}{p} \tag{3}$$

The value of $S(A_j)$ is a probabilistic value and is computed by calculating the mean of the cumulative V_j^k score for each activity j. The performance score PS (S_i) for each sessional is evaluated using Eq. 4, which depicts that 70% of the student score is taken from student performance in daily activities and 30% of the score is taken from occasional activity set. The daily activities are those activities which are of great importance and their V_j^k scores is evaluation on daily basis. On the other hand, rest of the activity set are those activities which are performed occasionally. To effectively compute the student performance score, academic record of the

TABLE 3 Activities with mining information

Activity ID	Activity instance	Mining methodology
	Monotonous activity	
A03	Attending a study group or class	Co-location mining
A05	Student academic performance	Sessional marks
A06	Teacher-student interaction for subject related doubts	Hyperlink Induced Topic Research model
A09	Attentiveness in class	RFID and other bio-sensor readings (diagnosis schemes)
	Occasional activities	
A15	Student performance in group-discussions	Page Rank
A17	Student performance in technical activities	Online teacher feedback forms
A21	Team-work performance in sports	Page Rank
A24	Attending computer labs	Co-location mining
A29	Utilization of institution facilities	Co-location mining
A32	Student behavior in class	Online teacher feedback forms

engineering students during that session is also added with activity results, as shown in formula ahead.

$$\mathrm{PS}(S_i) = \frac{1}{4}\left(70\% \text{ of } \frac{\sum_{j=1}^{r} S(A_j)}{r} + 30\% \text{ of } \frac{\sum_{j=1}^{s} S(A_j)}{s}\right) + \frac{3}{4}\left(\sum_{k=1}^{n} \mathrm{MS}(Su_k)\backslash k\right) \tag{4}$$

Where r is the number of activities taken on daily basis and S is remaining activities taken as occasional. A threshold value (α) is set by the management committee for each activity concern. In addition, PS (S_i) score of each student is used to compute the reputation score of the organization. The reputation score is the main probabilistic value considered by the management to access over-all development of the institution. The mathematical calculation of reputation score of the institution for the session is defined as P (RS), and mathematically computed as follows:

$$\mathrm{RPS}\ (S_i) = \gamma \times \mathrm{PS}(S_i) \tag{5}$$

$$P(\mathrm{RS}) = \frac{\sum_{i=1}^{n} \mathrm{RPS}(S_i)}{n} \tag{6}$$

Here, n is the total number of students in an engineering institution. Moreover, RPS (S_i) is the reputation score of the each student, calculated by multiplying PS (S_i) score with a scaling factor γ. These parameters importance are best utilized in the section ahead. However, description regarding each notation used to compute student performance score is shown in Table 4.

3.5 | Game based decision making

3.5.1 | Game theory

Game theory can be regarded as a multi-agent decision problem, that emphasis on the phenomenon of many people contending for limited reward/payoffs. Payoff is the numerical profit or loss which each player has to bear based upon their strategies. Player's moves decide how payoff will be effected. Moves are based on certain rules and each player is supposed to behave rationally [26]. Students involved in maintaining standard score strategy must be encouraged so that they remain positive, enthusiastic and ambitious. On the other hand, student involved in obstructive activities must be dealt with reduction in performance score. The decision making process is carried out using game theory. The decisions in student perspective is taken in the form of providing development measures or reduction in performance score based on the student performance. We adopted non-cooperative game model, which is concerned with management and student players, as shown in Figure 5.

TABLE 4 List of notation used in calculating student performance score

Notation	Description
A_j	Activity j taken into consideration.
V_j^k	Probabilistic score of activity j during day k.
$S\ (A_j)$	Student monthly score for activity j.
$P\ (A_j)$	Activity j performance score.
PS (S_i)	Performance score of ith student.
RPS (S_i)	Reputation performance score of ith student.
P (RS)	Reputation value of the institution.
MS (S_k)	Marks of student in k subjects of the semester.

i) *Game Players and their Strategies*: The game model is based on two player system. The goal of player 1 (management) is not only to maximize its reputation score but also to build intellectual, positive, and healthy competition among students for their overall development. The role of player 1 is to encourage the ambitious students by providing development measures in the form of extra academic classes, specialized faculty in each activity concern and taking retribution measures against unambitious ones. Management player 1 can provide development measures to the students by adopting development strategy denoted by S_D and can deduce student score by adopting non-development strategy denoted by S_{ND}, respectively. Hence, the model identifies the strategy set $S_{\mathrm{mag}} = (S_D, S_{ND})$.

Player 2 (student) can work toward increase in standard score for its over-all growth. The student working on maintaining standard score strategy S_S, while student not-maintaining standard score strategy is denoted by S_{NS}. Hence, the model identifies the strategy set as $S_{STD} = (S_S, S_{NS})$ for player 2.

ii) *Game Parameters*: Table 5 lists the game parameters recognized by the game-theoretic model. RS is the reputation score computed by management authority for each session. PS (S_i) is the monthly score of each student computed from proposed methodology. DM is the development measures taken to encourage the student to maintaining standard score strategy S_S. DM is computed as (PS (S_i) × DF). Here, DF is the

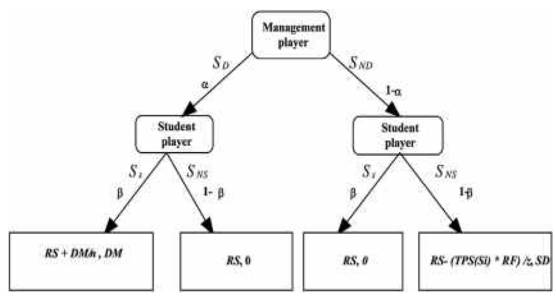

FIGURE 5 Payoff calculation

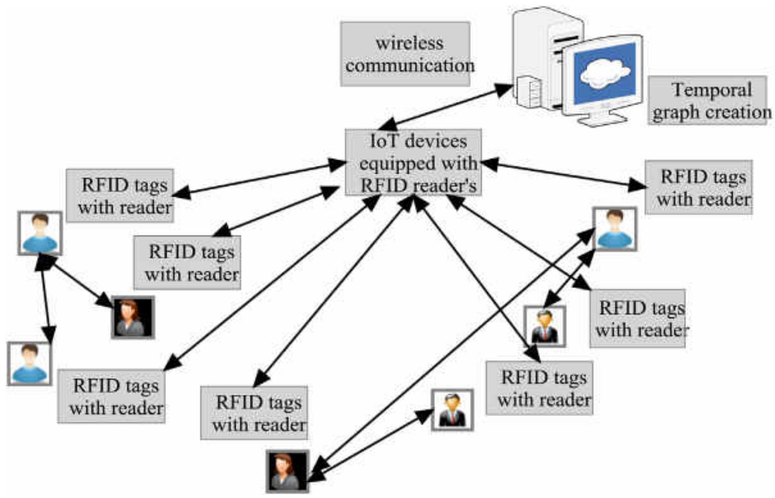

FIGURE 6 RFID based student interaction basic experiment setup

development factor used to compute the new reputation score when student maintains standard score S_S strategy. SD is the reduction score calculated from the student current performance score for adopting non-maintaining standard score strategy S_{NS}. The reduction score SD is computed using formula PS (S_i) (1-RF). Here, RF is the reduction factor used to compute new reputation score when student adopts non-maintaining standard score strategy S_{NS}. The parameters n and z are the scaling factor used to balance the new reputation value when DF and RF values are computed from student session based performance.

iii) *Payoff Calculation*: The model computes the payoff matrix for game by calculating the payoff for each strategy as described in this section. Let $U_{\text{mag}}(S_x, S_Y)$ and $U_{\text{std}}(S_x, S_Y)$ denotes the payoff of the management and student respectively when "Mag" plays strategy S_x, "Std" plays strategy S_Y. The calculation of payoff by game plan software is as follows:

1. $U_{\text{std}}(S_D, S_S) = \text{DM}$, development measure taken into consideration, associated with each student when there is increase in student performance score.
2. $U_{\text{mag}}(S_D, S_S) = \text{RS} + DM/n$, since student improves its total performance score which leads to increase in reputation value by DM/n, where n is the scaling factor used to compute new reputation status.
3. $U_{\text{mag}}(S_D, S_{NS}) = \text{RS}$, there is not any change in reputation value because management opts for development strategy S_D, even if student follow not-maintaining standard score strategy S_{NS}.
4. $U_{\text{std}}(S_D, S_{NS}) = 0$, there is not any deduction in performance score of student because management opts S_D strategy.
5. $U_{\text{mag}}(S_{ND}, S_S) = \text{RS}$, even if student adopting S_S strategy, there is not any consideration of increasing reputation status of the institution.
6. $U_{\text{std}}(S_{ND}, S_S) = 0$. Since no development measures are taken into consideration for student following S_S strategy due to management opting S_{ND} strategy.
7. $U_{\text{mag}}(S_{ND}, S_{NS}) = \text{RS} - (\text{PS}(S_i) \times \text{RF})/z$, this is so because student opts for S_{NS} strategy which leads to decrease in reputation status by $(\text{PS}(S_i) \times \text{RF})/z$, where z is the scaling factor used to compute new reputation status in this scenario.

TABLE 5 Game parameters

Parameter	Description
RS	Reputation score of the institution.
PS (S_i)	Total performance score of ith student for the current session.
DM	Development measure taken to encourage the student to maintain standard score S_S strategy.
SD	Reduction score computed from student current performance for adopting S_{NS} strategy.
DF	Development factor used to compute the new reputation score when student maintain standard score S_S strategy.
RF	Reduction factor used to compute the new reputation score when student adopting S_{NS} strategy.
n	Scaling factor used to balance RS value when management adopting S_D followed by S_S strategy.
z	Scaling factor used to balance RS value when management adopting S_{ND} followed by S_{NS} strategy.

8. $U_{\text{std}}(S_{ND}, S_{NS}) = \text{SD}$, since student opts for S_{NS} strategy which leads to decrease in student score and new score is computed as SD. Figure 5 shows the strategically implementation of game-theory in our proposed methodology.

3.5.2 | Probability calculation

After calculating the payoff matrix, game-based decision making must calculate the values of "α" and "β," that is, the probabilities with which "Management Authority" and "Student" chooses their respective strategies. To calculate "α" and "β," game decision module uses PS (S_i) values retrieved by student performance database. To specify how game decision module calculates "α" and "β" from PS (S_i) values, we take following example. Let the values of PS (S_i) calculated by student performance database is as shown in Table 6. It may be noted that the values considered for calculating PS (S_i) are arbitrary values taken to illustrate the concept. Game decision module simply equates the value of "α" equal to respective PS (S_i) value of student. However, the PS (S_i) is always positive and lies between 0 and 1. For calculating "β," the student PS (S_i) must be stored in sorted form. The first "n" students are taken from the TPS (S_i) list to be considered as students to get benefit from development measures considered by management. For example management chooses "n" = 7, so that top 7 students are taken for providing development measures. The value of "β" is taken as the PS (S_i) score of seventh student in the sorted list. Furthermore, the data generation and processing for student evaluation is automated by the proposed model. The management have to provide only the value of "n" to the Game Plan software to evaluate the value of "α" and "β" Lastly, the learning capabilities of Game Plan tool and dynamic nature of the proposed system helps in taking cognitive decisions in smart engineering education environment.

TABLE 6 TPS (S_i) calculated by game-theory component

Student ID	TPS (S_i)
Student selected for developmental measures	
S11	0.878
S08	0.873
S13	0.855
S22	0.839
S21	1.804
S32	0.764
S11	0.755[a]
S43	0.546

[a]Value of β.

4 | EXPERIMENTAL EVALUATION

4.1 | Experimental setup

In order to evaluate the performance of our proposed system experimentally, we monitored daily activities of 24 students of 6th semester in computer science and engineering using IoT devices. In this methodology, student body sensor network features are extracted for calculating student performance score in each activity concern. Activities are recognized based on spatial patterns and time stamped radio packets generated using RFID based proximity sensing concept.

4.1.1 | RFID working in student environment

RFID tags plays a vital role in calculating student performance in IoT environment. In RFID environment, radio packets are exchanged between two persons in close proximity. The experimental setup is created by defining the RFID based experimental procedure in Figure 6.

1. In our experiment, personal body sensor network composed of both wearable and implanted sensor devices. Moreover, active RFID tags are clipped at the chest level so that other devices can be detected in its close proximity.
2. A set of 10 activities as shown in Table 3 are considered for calculating student sessional performance in six semester. The daily activity set for each student is generated using Figure 7. Student's activities are monitored using sensor network which composed of both wearable and implanted sensor devices. At the end of the each sessional, student performance score is calculated using performance evaluation system as shown in Eq. 4.
3. Experiments are conducted by comparing the performance score of the proposed system with the manual evaluation system. The results depict that by introducing IoT based learning in engineering education, the student performance score is increased. The increase in student performance score reflects the effectiveness of our proposed methodology. Moreover, increase in student performance score also leads to increase in reputation score by taking more informed decisions for the institution development.

Figure 6 also shows the RFID environment in education institutions. RFID tags on students can act as radio packet generator as well as RFID reader. The other devices in institution learning environment can also act as RFID reader for further relaying the signals to the experimental area using wireless communication network.

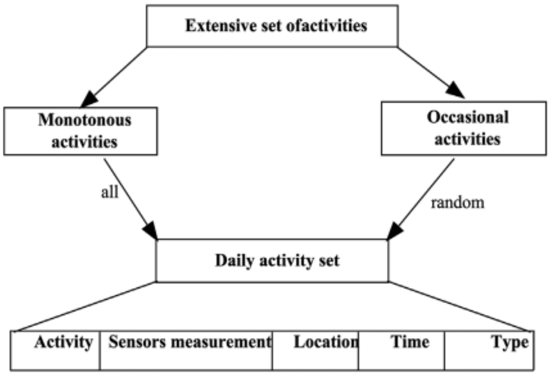

FIGURE 7 Daily activity dataset

4.1.2 | RFID interaction visualization

RFID tags plays a significant role in determining the proximity relationship between students and faculty members. Two types of visualization are carried out during the whole day. The first defines the instantaneous network of proximity. The second represents the strength between nodes by forming cumulative network of contacts, which summaries the amount of time each pair of students spent together as measured from the activity time setup during the experiment.

A snapshot of the real-time visualization [33] (socio.pattern.org) is shown in Figure 8. An interaction oriented graph is used to display the current student network. The data collection system at cloud storage repository computes the proximity graph in real-time, and visualization is updated according to the requirement.

4.1.3 | Data-mining in IoT environment

The IoT data is generated using Pentaho platform, tools to extract, prepare and blend the data. Pentaho data mining (Weka) [35] consists of machine learning algorithms for a broad set of data mining tasks. Functions for data processing, classification methods, cluster analysis, and visualization are implemented using Pentaho tools. The mining criteria can be fulfilled by establishing a third party cloud namely Amazon EC2 [1]. It is an Infrastructure as a service (IaaS) provider that helps in generating various type of machine instances. In our system, different Amazon Machine Image (AMI) with default instance "m1.small" is chosen to run on Cent OS 6.7 with a Linux 2.6.32Xen Kernel. For calculating student performance score for each activity concern, range of AMI instances are described. Moreover, each activity related minimum and maximum AMI instances are set by the managerial authorities for generating correct results.

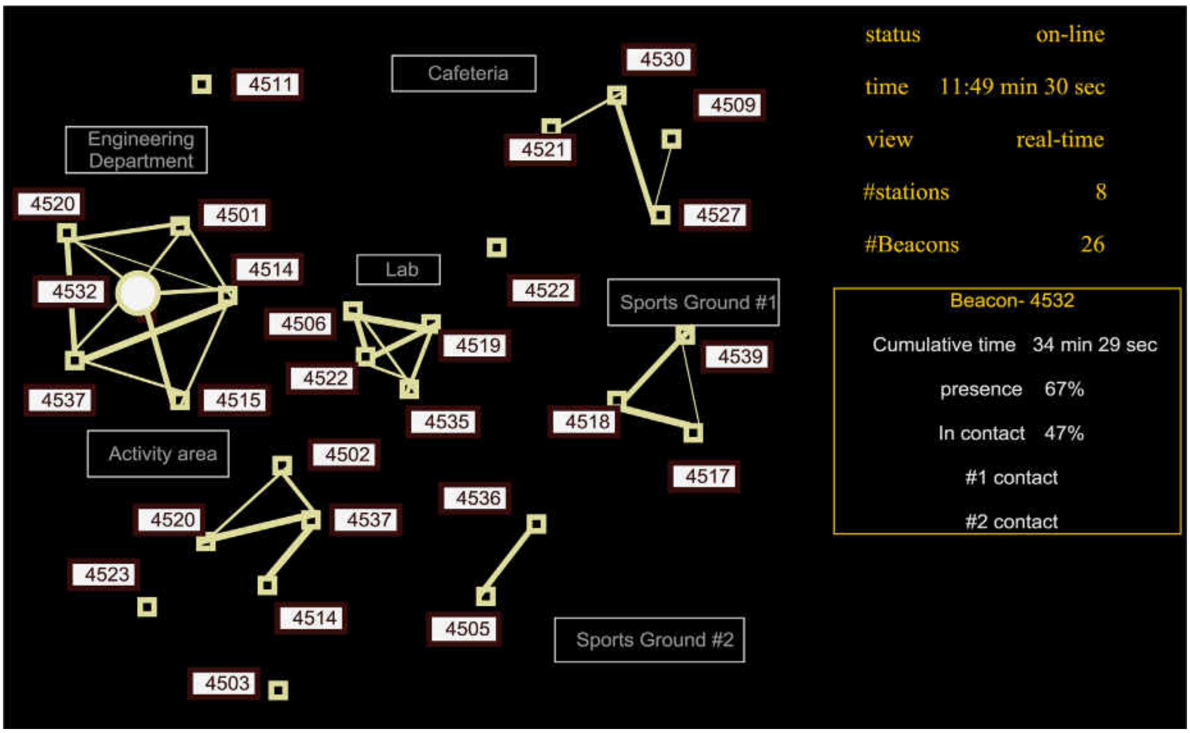

FIGURE 8 A snapshot of the visualization, displaying RFID tags are labeled with Student IDs, known as beacon, which can also be labeled with available metadata (such as, e.g., the actual registration ID of the student). Moreover, the figure displays the student position information and instantaneous network of proximity sensing. Edges between the nodes represent face-to-face proximity relation, and their thickness represents the strength of the proximity relation

4.2 | Results and discussion

4.2.1 | Student performance score calculation

Each student activity dataset for the whole session is used to compute activity based performance score for the student. On the other hand, session based academic dataset is used for academic score calculation. The activity based performance score is based on the context of the activity and data mining based algorithms are used to compute necessary results, as shown in section 3.4. Moreover, each student sessional based performance score is utilized to generate reputation score of the institution as shown in Eq. 6.

4.2.2 | Decision making

The proposed system decisions are derived from game-theoretic approach. Game plan software (V4.6) generates strategies defined by the proposed system to calculate the probabilistic value of "α" and "β," respectively. Moreover, applying game based decisions using Game Plan reduces the execution time of the proposed system [10].

4.2.3 | Overall system performance

To test the scalability of the proposed system, the IoT based activity dataset of 24 students for the whole session is bootstrapped in order to create dataset for up to 150 students. A java script is developed for random selection of students from the created dataset. The system is initially fed with the data of 24 students selected by java script and execution time is noted. The process is repeated for 6 iteration by increasing data for 24 students for each iteration. Figure 9a depicts the comparison between student performance score computed using manual student performance system and the proposed system for the next two consecutive sessions. Results shows that, students are following development strategy which leads to increase in performance score as well as institution reputation score. Figure 9b depicts execution time of different components used for computing student daily activity based score. From Figure 9b, it is clear that data mining phase execution time is more as compared to activity classification phase and activity set formation phase. This is due to the fact that data mining stage has to consider activities in different context and different data mining algorithms are used to analyze student interactions. Moreover, as the number of students increases with time, retrieving information from new datasets leads to increase in overall execution time.

In addition, combination of different datasets make the results more accurate and classification can be done accurately. Furthermore, the execution time for session based performance evaluation with decision making is

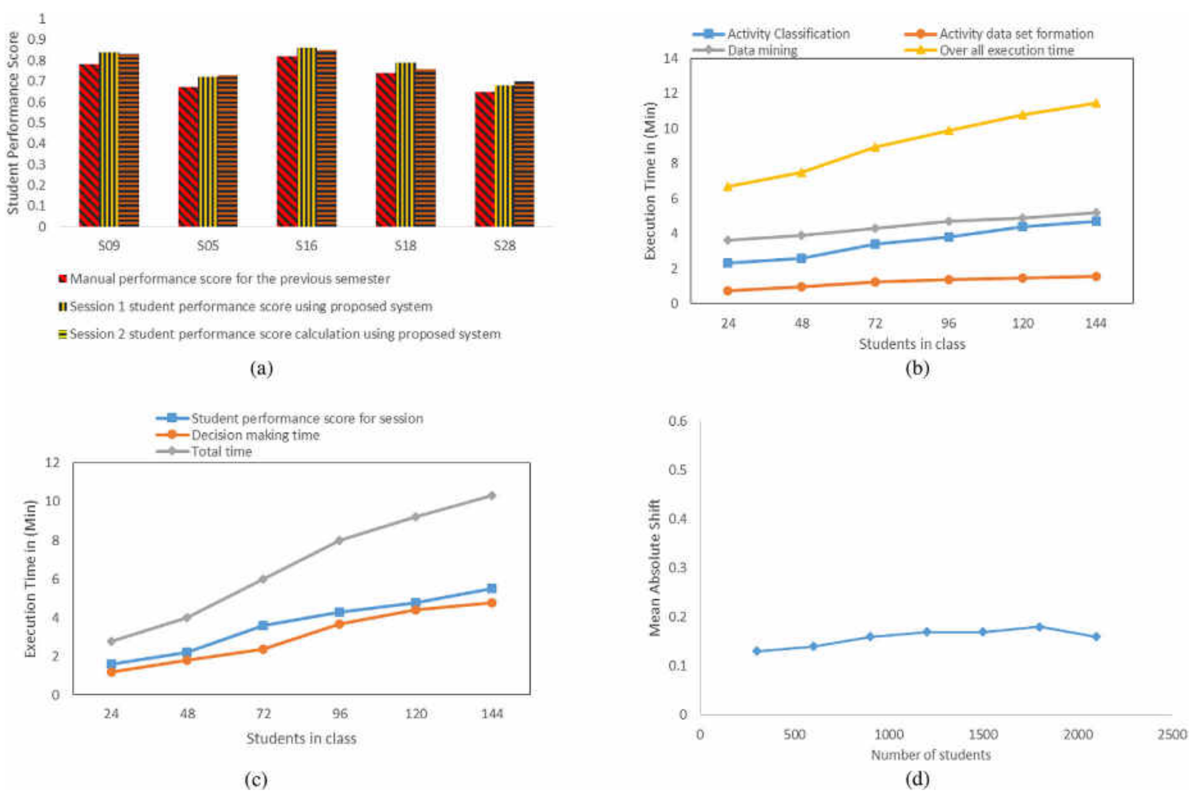

FIGURE 9 (a) Performance score computation using proposed system. (b) Component based execution time (in min) for students of same engineering stream on a random day. (c) Performance calculation at the end of session with decision making. (d) Proposed system stability

calculated in Figure 9c. This figure depicts that, increase in number of student's will increase the execution time for the session based student performance score calculation because of the fact that results from data mining component and student academic dataset are combined during this phase. Moreover, decision making based on game plan software takes more time to compute the probabilistic value of "α" and "β" when number of students increases with time.

Lastly, the overall performance of the proposed system can be observed on the foundation of stability. A stability concept in this domain reflects that the system can maintain its stability if its results does not change much when there is increasing in number of datasets. Stability of a system is calculated in accordance with mean absolute shift. The less change to this value as we increase number of students indicates that the system maintains its stability. Figure 9d demonstrates that there is very less shift (0.13–0.18) in mean absolute value when number of data sets are increased with respect to increase in number of students.

5 | CONCLUSION

This study had described a system that facilitate significant student activity based learning by introducing IoT in engineering education. A system was designed and implemented that allow students to interact with each other and surrounding objects which are virtually associated with an activity in an engineering education. The study have used IoT devices like GPS and RFID technology to increase the effectiveness of the proposed system. With the inclusion of IoT technology in education, authority can effectively combine student IoT based activity performance with the academic results to generate student sessional performance score. In other words, taking students as a real object and associate them as a learning resource through Internet of Objects facilitates meaningful learning. Using this, one can link specific knowledge to a real context.

In experimental section, RFID based student interaction system is defined, which comprises student activity interaction patterns at a particular time-instance. Education data mining algorithms are applied on student daily interaction patterns based on activity information to compute final activity performance score of the engineering student during a particular session. Furthermore, results show that, student performance score based on proposed system, followed by authority decision making further improves the student performance score for the next session. Lastly, game based decision making using parameters like institution reputation score and student sessional performance score enhance the utility of the proposed system.

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How to cite this article: Verma P, Sood SK, Kalra S. *Smart computing based student performance evaluation framework for engineering education*. *Comput Appl Eng Educ*. 2017;1–15. https://doi.org/10.1002/cae.21849