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Internet of Things-based student performance evaluation framework

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ABSTRACT

In recent years, solutions based on Internet of Things (IoT) are gaining impetus in educational institutions. It is observed that student performance evaluation system in education institutions is still manual. The performance score of student in traditional evaluation system is confined to its academic achievements while activity-based performance attributes are overlooked. Moreover, the traditional system fails to capitalise information of each student related to different activities in learning environment. In relation to this context, we propose to facilitate automated student performance evaluation system by exploring ubiquitous sensing capabilities of IoT. The system deduces important results about the performance of the students by discovering daily spatial–temporal patterns. These patterns are based on the data collected by the sensory nodes (objects) in the institution learning environment. The information is generated by applying data mining algorithms for each concerned activity. The automated decisions are taken by management authority for each student using game theory. In addition, to effectively manage IoT-based activity data, tensor-based storage mechanism is proposed. The experimental evaluation compares the student performance score generated by the proposed system with the manual student performance evaluation system. The results depict that the proposed system evaluates the performance of the student efficiently.

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Internet of Things (IoT); game theory; radio frequency identification (RFID); cloud computing; performance evaluation

1. Introduction

Educational institutions are the nation builders. They provide a large variety of learning environments and learning spaces. The advancement in information and communication technology has affected educational institutions' functionality significantly. The potential of ubiquitous learning is reflected in increasing access to learning content and other objects in the interaction environment supported by computers anytime and anywhere (Gubbi et al. 2013). The purpose of ubiquitous computing technology in our domain is to improve student-activity-related learning environment. It tries to adopt data from various objects in different activity context, which plays a significant role in generating student-related daily-activity performance score in education perspective.

Despite various technological developments in educational institutions, performance evaluation of student is still manual. Moreover, many important parameters are usually overlooked while calculating student performance score. Personal (evaluator) views may be unfair to reflect the actual performance of each student. Therefore, the decisions taken by management authorities cannot be acceptable in the current scenario. In addition, generating student performance score based on objects (students, teachers and other objects) interactions for various activities is the need of the hour.

To eliminate human biasness and aforementioned flaws in accessing student capabilities in educational institutions, the best alternative is to shift towards automated student performance evaluation system by observing the student behaviour using IoT devices. The student performance calculation in an educational institute is a continuous process and can be effectively handled by exploring the ubiquitous features of IoT devices. Hence, student performance must be evaluated by considering scores from various fields such as academics, sports, behaviour and interaction activities. Students must maintain consistency between academic and other development activities so that they remain positive, encouraged, enthusiastic and ambitious. Therefore, there is a need to evaluate student performance on regular basis considering important student performance attributes. These results are useful in deciding the field, in which a student can excel.

IoT (Internet of Objects) is emerging as a network of interconnected uniquely identifiable objects. Its basic objective is to create smart environment/spaces and self-aware things. Smart environment encompasses a low-power, low-cost, high capacity and miniaturised

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sensors, wired and wireless communication network (Miorandi et al. 2012). Smartness is achieved from the interaction of a ubiquitous network of interconnected objects through sensors, actuators, RFID, GPS devices and other wireless and mobile devices (Gubbi et al. 2013). Moreover, the 'smart' objects from pervasive computing environment are paving the way to continuous monitoring of students and staff by heterogeneous IoT devices. Based on aforementioned facts, this paper proposes a system that allows students to interact with each other and objects in the form of Internet of Objects. The student-behaviour-based activity is recognised by a student body network which is composed of behaviour sensors (IoT devices, medical sensors and RFID tags and RFID readers). Each of these objects has associated devices which provides information in the form of interactive spatial datasets. The objectives of this paper are: (i) to collect data related to student activities using IoT technologies, (ii) to record the IoT-based student activity using tensor, (iii) to evaluate the performance of each student from the web of data using different mining techniques, (iv) to take continuous decisions using game theory from the information generated using IoT devices' interaction.

The paper is organised as follows. Section 2 discusses the work related to data mining, IoT interactions and game-based decision making. In Section 3, IoT-based student performance evaluation framework is defined. In Section 4, technical flow of the proposed system is defined. In Section 5, we calculated student performance score followed by experimental evaluation of the system. Finally, Section 6 concludes this paper with conclusive remarks.

2. Related work

To realise and analyse the proposed methodology in IoT environment, this section focuses on student performance evaluation systems, data mining concepts in education domain and decision-making techniques.

2.1. Student performance evaluation

Jayasinghe, Dharmaratne, and Atukorale (2015) reviewed the literature concerned with evaluating the performance of the students engaged in online education systems. It highlights the ideas to measure the emotional level and behaviour of students followed by a response in accordance to their behaviour through the online education systems. Sheldon, Malone, and Mc Bride (2003) designed a component which helps diagnose the student's performance in a tutoring system. Various physiological measures (skin conductance level, muscle tension and heart rate) were recorded to provide an objective evaluation of changes in student's behaviour based on physiological feedbacks. They build a model of student performance as a function of the feedback, physiological measures of affect and personality. McQuiggan, Mott, and Lester (2008) investigated an induction approach in which self-efficacy-based constructing models are automatically generated. Self-efficacy defines the individual belief about his/her ability to perform well in a given situation. These models of self-efficacy can be used at runtime to inform pedagogical decisions. The experiment was conducted based on survey results. The students are allowed to complete a survey after going through online tutorial to indicate the problem-solving self-efficacy scale. Jabbarifar (2009) gave importance to classroom assessment and evaluation criteria. He stressed on qualitative judgments in class room assessment and evaluation. These judgments are used to improve students' knowledge and learning. He also provided some useful assessment and evaluation techniques which could assist language teachers in creating a dynamic classroom situation for evaluation. Liu and Hwang (2010) defined a context-aware u-learning system in butterfly garden. In this context, students have RFID readers on their mobile devices, and host plants are labelled with RFID tags. A wireless interaction environment is created by noticing the student movements around learning areas. Moreover, some researchers (Cobo, Rocha, and Rodríguez-Hoyos 2014; Islam 2015) have also used interactive learning environment for teacher–student and student–student interaction based on different modelling approaches and data mining techniques. Research related to student performance evaluation is restricted to online education system or tutoring systems but none of them utilises the ubiquitous capabilities of IoT devices in evaluating the student performance score in different situations.

2.2. Data mining concepts

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. Huang et al. (2004) developed a new approach to mine co-location patterns by using the concept of proximity neighbourhood. An interesting term participation index is proposed for spatial co-location patterns. This measure is closely related to cross-K function, which is used often as a statistical measure of interaction among pairs of spatial features. Moreover, participation index also possesses an anti-monotone property which could be exploited for computational efficiency. Borodin, Roberts, and Rosenthal (2005) introduced a theoretical framework for the study of Link analysis algorithms. They defined the specific properties of link analysis algorithms with a self-evident characterisation of the INDEGREE heuristic, forming a ranking mechanism with reference to the number of incoming links. Moreover, they performed an extensive experimental study on multiple queries, using user feedback for studying the behaviour of ranking algorithms. Compieta et al. (2007) proposed a system to deal with very large spatio-temporal datasets. The system includes a mining engine based on an adopted version of the well-known Apriori algorithm. Moreover, two complementary 3D visualisation environments have been implemented. Google Earth is used to display mining outcomes, while Java 3D-based tool is provided for advanced interactions with datasets in non-geo-referenced space. Schall (2012) introduced a link intensity-based ranking model for recommending relevant users in human collaborations. He 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. Tsai et al. (2014) discussed the features of 'data from IoT' and 'mining for IoT'. They have defined an architecture for IoT with knowledge discovery in databases. They reviewed studies on applying data mining techniques to the IoT, which concentrates on clustering, classification and frequent pattern mining technologies, from the perspective of infrastructure and from the perspective of services. Rafiei and Kardan (2015) evaluated the accuracy of posted comments in online communities. Content analysis based on the concept map and the social network analysis based on PageRank is used to determine expertise level of users in online communities.

2.3. IoT interactions and decision-making techniques

IoT environment is mingled with sensors, computational elements, RFID and display devices which are connected by a continuous network. Cattuto et al. (2010) proposed a scalable experimental framework for gathering real-time data resolving face-to-face social interactions with tunable spatial and temporal granularities. They have used RFID devices that access mutual proximity in a distributed fashion by exchanging low-power radio packets. Atzori et al. (2011) introduced a novel paradigm of 'social network of intelligent objects', namely the Social Internet of Things (SIoT). They statistically analysed the structure of the SIoT network through simulations that model the mobility of objects and their relationships. Guo et al. (2013) presented an opportunistic IoT which is formed, based on the ad hoc opportunistic networking of devices. The opportunistic IoT demonstrates inherently the close relationship between human and opportunistic connection of smart objects. Jorge et al. (2013) proposed a system that allows students to interact with physical surrounding objects which are virtually associated with a subject of learning. Experiment results show that student learning process has been improved, which was evidenced from the results of measuring academic outcomes compared to the control group. Borgia (2014) 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. Wu et al. (2014) proposed an operational framework for creation of intelligent IoT environment named as Cognitive Internet of Things (CIoT). They emphasise on empowering the current IoT with a 'brain' for high-level intelligence. Intelligence task can be fulfilled if cognitive tasks include a decision-making component. Recently, authors have found helpfulness of decision-making methodologies in forming cognitive IoT system. They used cognitive decision models in IoT environment, such as consensus model (Li et al. 2014), agent-based model (Schlesinger and Parisi 2001), neural networks (Shultz 2014), Bayesian decision model (Schlesinger and Mcmurray 2014), Game theory (Hamdi and Abie 2014) and many more (Bonawitz et al. 2014; Joseph 2006).

3. Proposed work

Figure 1 presents the modelling of proposed system which consists of four layers: (i) data acquisition and synchronisation layer, (ii) cloud storage repository and activity classification, (iii) activity recording and data mining and (iv) decision-making layer. 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, which is a portable device or smartphone. In layer 2, the interaction and location measurements are transferred to a third-party platform known as cloud storage repository. Cloud storage infrastructure is responsible for data preprocessing and classifying activities into different datasets. In layer 3, student environment dataset is bifurcated into two datasets: one forms sensory datasets and another forms interactive datasets. Based on these activity datasets, activities are recognised

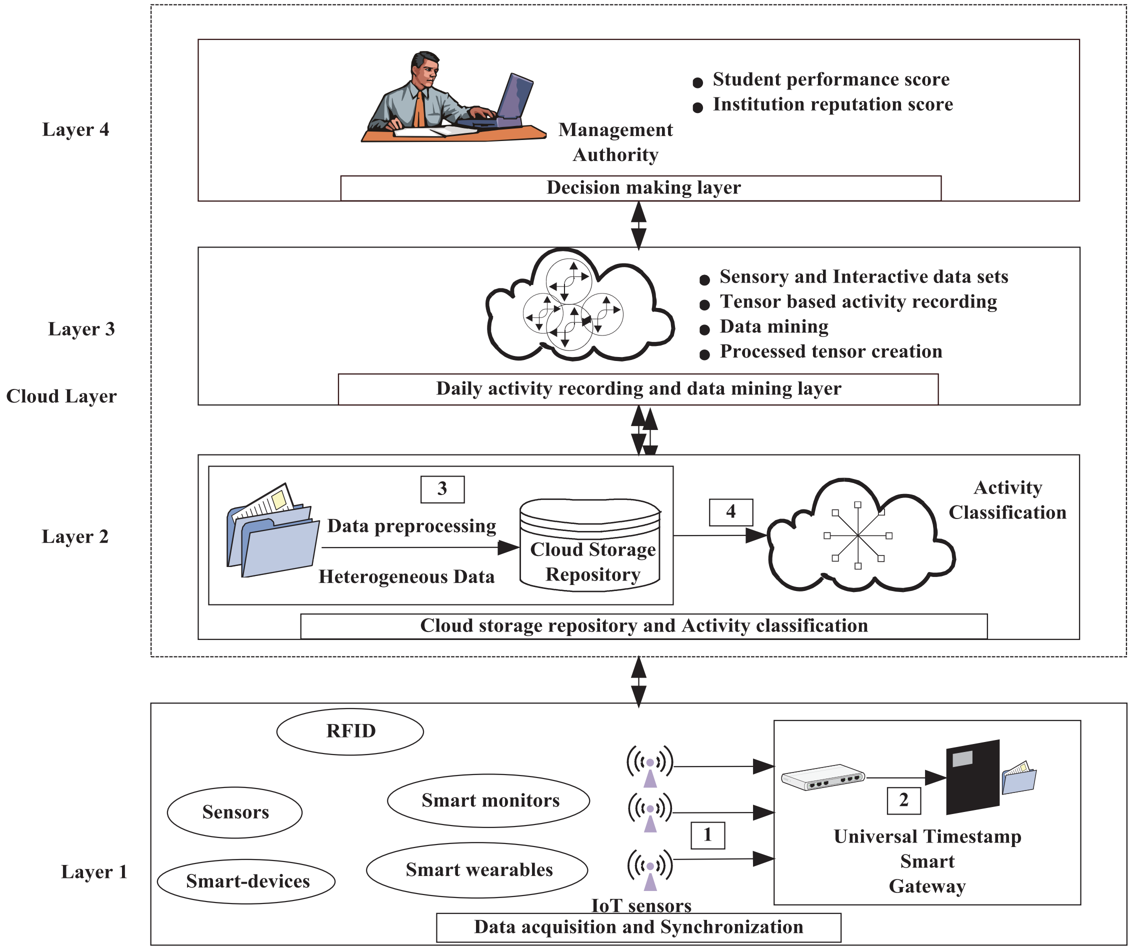


Figure 1. Flow diagram of the proposed system.

followed by recording various activities in the form of tensor. In this layer, tensor-based activity record is transferred to meaningful information by creating a processed tensor using educational data mining algorithms. Layer 4 computes the student performance score and institution reputation score by exploring the results from IoT-based student activity performance and student mid-term academic performance. Lastly, game-based decision component takes automated decisions based on student performance information and reputation score.

3.1. Data acquisition and synchronisation

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 such as radio frequency identifiers (RFID), GPS sensors and other IoT devices constitute a personal sensor network. This system aims at acquiring information related to student and staff with respect to their location and other routine activities. Moreover, gateway collects data from personal sensor network in structured and unstructured forms, which are further transferred to cloud storage repository for analysis. The transfer mechanism is implemented using a wireless communication system such as 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 which can be described as Infrastructure as a service (IaaS) provider. The data is ubiquitously sensed and regularly retrieved during different time intervals. Therefore, time-stamped data are stored at cloud storage repository for further analysis. The student activities are properly classified based on some presumptions defined in activity classification section. Moreover, student personal information is already stored at cloud side repository. A unique identification number is assigned to each student associated with its daily IoT-based interaction in school premises. The security mechanism is applied for providing access to two types of user's category. First category

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.	Sex	Male or Female
5.	Address	Permanent address of the student
6.	Family member name	Name of the family member
7.	Family member mobile number	Family member mobile number
8.	Student information	Student previous performance information

consists of institution management authority, having access to both isolated and shared data. On the other hand, only shared data are provided to the students, staff and government agencies for survey purposes.

3.2.1. Data preprocessing

This component receives two types of information: (i) sensory data and (ii) student basic information. At the time of recording various activity readings from sensors and RFID tags, noise level must be reduced and missing samples must be accurately determined for better results. The task of this component is to reduce the dimensionality of sensor attributes. Moreover, student basic information can be utilised for further necessary action. Table 1 shows the list of attributes considered for student basic information.

3.2.2. Activity classification

Activities in our proposed methodology are classified into two different classes, namely monotonous activity and occasional activity. Monotonous activities consist of those activities for which student performance is calculated on a daily basis. On the other hand, occasional activities are performed randomly during a month. Table 2 shows various activities and mining algorithms applied to generate student interaction results. The classification procedure is based on Bayesian Belief Network (BBN) classifier (Kumar, Chilamkurti, and Misra 2015). It is a mathematical modelling technique that assigns an activity to certain class based on probabilistic parameters with prefixed threshold as shown in Figure 2 (a). The data collected from IoT hardware devices and sensors are used to depict the student activities in institutions. Activity models are used to define various student activities. Table 3 defines the activity instances coming under various activity sets. Details regarding each activity are explained ahead.

Locational Activity: Location activities are concerned with student presence at a particular location in the school premises. The IoT devices such as GPS, RFIDs are used to depict location-based student information.

Table 2. Activities in school premises.

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	Sensor readings (diagnosis schemes)
	Occasional activities	
A15	Student performance in group discussions	Page Rank
A17	Student performance in management activities	RFID interaction-based computation in learning area
A21	Team-work performance in sports	Page Rank
A24	Attending labs	Co-location mining
A29	Proper utilisation of institutional facilities	Co-location mining
A32	Student behaviour in class	Dynamic Bayesian Network for stress calculation (Liao et al. 2005)

Activities such as attending a seminar, classes and study group come under location-based activities.

Interactive Activity: These activities mainly emphasise on student interaction with other students and faculty members. These activities can be smoothly monitored using sensors, RFID system and other IoT devices. Activities such as student participation in a study group, participation of student in sports activity, student–teacher interaction related to subject, participation in group discussion and student preferred company are the main interactive activities.

Academic Activity: The student performance in each subject concerned is retrieved from academic database of student for each session.

Behavioural Activity: This include activities such as effective utilisation of school facilities and attentiveness in class. These activities-related data are smoothly retrieved using smart wearables and medical sensors worn on body, as shown in Table 3.

3.3. Daily-activity recording and data mining layer

In this layer, activity-based datasets are bifurcated into two sets, namely sensory datasets and interaction-related datasets. The detail regarding each set is provided in Section 4. Moreover, activities are recognised based on time dependency and sensory dependency (Chen et al. 2012) sequences.

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

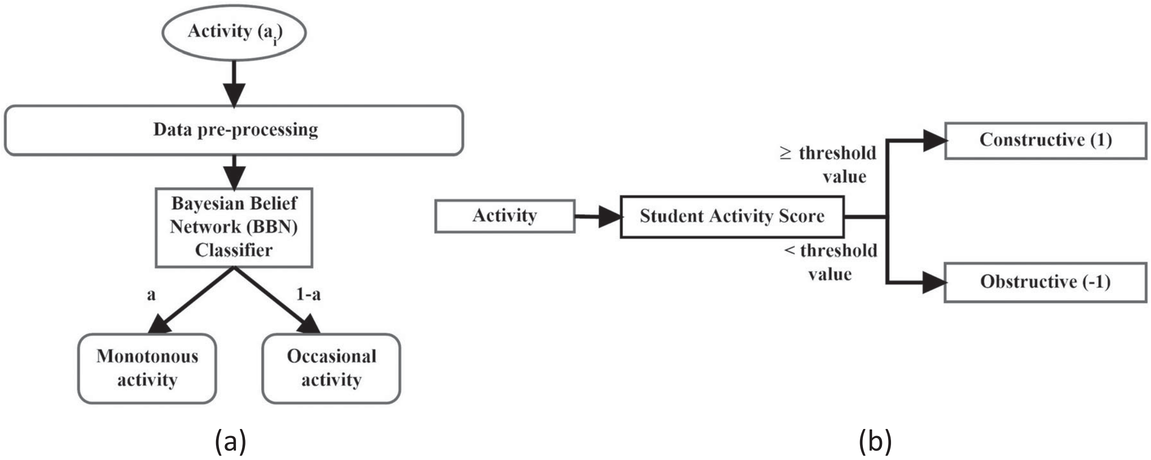


Figure 2. (a) Activity classification and (b) student score classification.

Moreover, additional features can also be appended during activity recognition phase by adding context information of the previous activity in the current time instance.

After recognising each activity, student performance score is calculated by recording the student-activity data in tensor followed by implementing data mining algorithms for different activity concern. The performance score for each activity is classified as constructive, and obstructive based on the threshold value set by the school management committee for each activity, as shown in Figure 2(b).

3.4. Decision making

The decision-making layer is responsible for generating student performance score followed by game-theoretic decision-making process. In decision making, a two-player game theory is used in which moves are based on student performance score and institution reputation score. The details regarding technical flow of the proposed system are completely explained in Section 4 (Figure 3).

4. Technical aspects of the proposed system

4.1. Activity datasets

In our proposed methodology, 10 activities are taken into consideration for calculating student performance using IoT devices and online procedures. Datasets which comprise heterogeneous data are defined for all the activities performed during the day. However, to effectively demonstrate our proposed system, datasets can be bifurcated as (i) sensory-related dataset and (ii) interaction-related dataset.

4.1.1. Sensory-related datasets

In this domain, RFID, Q-sensors, biometric readings, GPS, biosensors and smart-wearable readings are utilised to predict student performance for attributes such as student attentiveness in class, presence at particular location and attending a study group.

4.1.2. Interaction-related datasets

The RFID technology best describes the interaction-based activity datasets. To generate interaction pattern

Table 3. Activity classification.

S. no.	Activity	Few instances	Information sources	Actual measurements
1.	Locational activity	Attending a class, study group or seminars	GPS and RFIDs	RFID readers with teachers and RFID tags on student, GPS-based student location in school premises
2.	Interactive activity	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 RFID	Temporal graph creation based on RFID reader and tag interaction using Gephi tool
3.	Academic activity	Academic performance	Sessional exam results	Student performance in subjects
4.	Behavioural activity	Attentiveness in class, ineffective utilisation of equipments and other objects in school premises	Biosensors, Q-sensors and smart wearables (behavioural sensor), RFIDs	Sensors placed on the hand: galvanic skin response (GSR), blood volume pulse (BVP), skin temperature (ST), and eye gaze tracking instrument: pupil diameter (PD). RFID reader at different locations in school is used to access student interaction with objects in the school premises

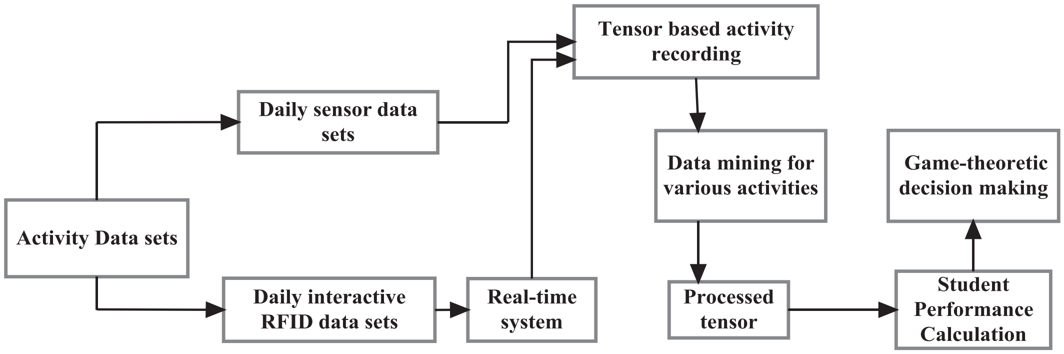


Figure 3. Technical flow of the proposed system.

among students and staff, RFID tags and RFID reader play a significant role. RFID exchange radio waves when they are in close proximity to each other (Read et al. 2012). It is one of the promising technologies in the area of automatic identification of an object. Recent advances in RFID devices such as small, lightweight and long battery life make it ideal for social network studies. In our proposed system, RFID tags are attached to the chest of the students and teachers in school premises for calculating the result of interaction-based activity. A smartphone with RFID reader is used to sense the RFID tag carried by another object (student and staff). Moreover, RFID readers are implanted in student learning spaces to get knowledge about student interaction with other objects during a particular time interval. Figure 4 shows the basic proximity interaction between students or student and staff.

The temporal proximity sensing (TPS) concept is utilised to generate results from RFID-based interactions in the school premises. Temporal analysis graph is used in our model representing the node and edges formed between objects (student and staff) having close proximity interaction between them. Gephi 0.9.1 (Fu et al. 2016) is used to generate temporal analysis graph. It is an open-source software for visualising and analysing temporal network graphs. Gephi uses a 3D render engine to display graphs in real time and speed up the exploration. The edge thickness between nodes in temporal graph represents the strength of proximity relation for a particular activity. Lastly, based on the activity-based temporal analysis graph, educational data mining algorithms are applied, which are discussed in Section 4.4 (Figure 5).

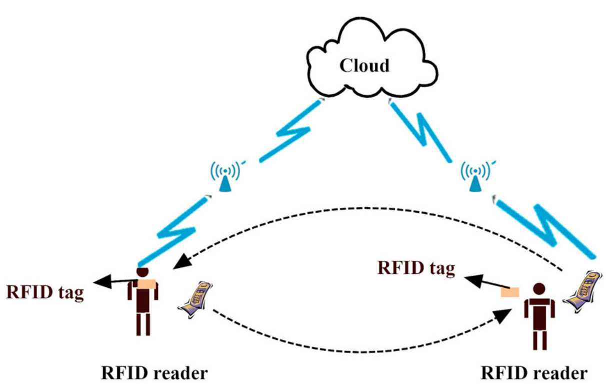


Figure 4. Proximity interaction between student–student and student–staff.

4.2. Real-time system

Student-interaction-based activities are stored in the form of datasets at cloud storage repository. The interaction between nodes (RFID tag and RFID reader) can be best viewed using a real-time system. Cloud stores the time-stamped information of radio packets generated from objects, which is further relayed to real-time system for analysis purposes (Gephi 0.9.1). Real-time system aggregates received radio packets to generate real-time interaction graphs. The real-time interaction graphs are formed based on the phenomenon of spatial proximity relation described in experimental section. In this phenomenon, RFID reader, installed at experimental area and within smartphones of student and teachers, fed the received packets to a real-time system.

4.3. Tensor-based activity recording

4.3.1. Tensor metrics formation (S_dT_r)

The activities-related data come from IoT devices, text data and scan images. The main challenge in this phase is how to store such heterogeneous data in a manageable format so that effective results can be drawn later. To achieve this goal, a tensor, called student-activity data tensor (S_dT_r), has been proposed to store such data on a daily basis (Kolda and Bader 2009).

Definition 2: (Student Activities Tensor). *Given an unequal spaced temporal activities data of 'n' students consists of 'm' activities metrics, a student activities' data*

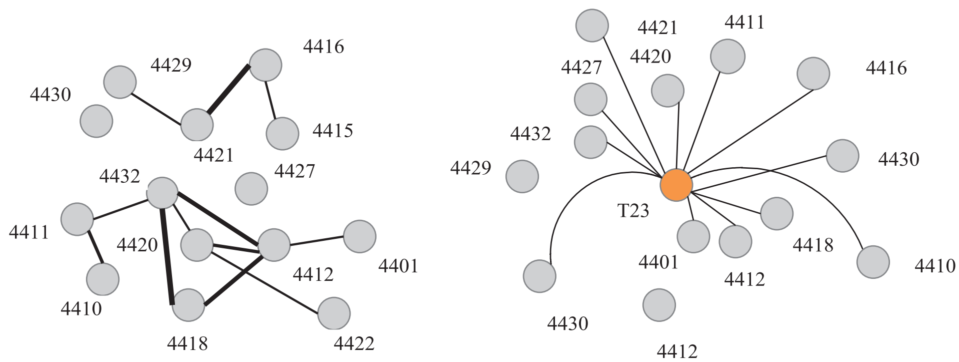


Figure 5. Real-time visualisation of temporal network graph in Gephi 0.9.1. (a) Student interaction in a study group during a definite time interval and (b) student attending a class (T23 is teacher with RFID reader and others are students with RFID tags).

tensor can be defined by a 3D tensor $S_dT_r \; \varepsilon \; \mathbf{R}I_S{*}I_T{*}I_A$, *where the orders* I_S, I_T *and* I_A *correspond to the dimensions 'students', 'time' and 'activities metrics' respectively such that* $I_S{=}n, I_A{=}m, I_T{=}\max(\{t_i\}_{i=1}^{n})$, *where* t_i *denotes the number of distinct timestamps for ith student.*

In the above definition,

- The student activities' data are coined as temporal data, since each instance of student activity is associated with a timestamp. At different timestamps, different-activities-related sensory data are represented in the form of activities metrics.
- Various activities-related metrics are attending a study group or class, teacher–student interaction in class, student performance in group discussions, team-work performance in sports, etc.
- The timestamp differs from one student to another, because they belongs to different classes, hence timestamp axis does not have absolute values.

Mathematically, daily S_dTr of a student can be expressed as

$$S_dT_{r=}[S_1, S_2, S_3, \ldots, S_m].$$

Here, each S_i is a frontal slice corresponding to 'm' activities of student in whole day. Further, each activity metric consists of various attributes. For example, student personal data include attributes such as S_{ID}, age, class, and Reg. No. Therefore, each cell of the frontal slice itself forms a matrix. Hence, S_dT_r can be further expressed as

Figure 6 shows the IoT-based sensor data creation (S_dT_r) representation of student activities in school premises. Here, student personal data slice represents sessional performance of student in each activity concern. It serves the purpose of storing multiple activity conditions in one tensor slice effectively. With respect to multiple activities, different threshold levels, activity information, attending activity assigned to each student are stored in the corresponding cells of the other tensor slice. Table 4 shows the general activity metrics with information.

When a new student is registered to the system, he/she is added with the operation called 'data addition'. Here, S_dT_r remains same but the dimension 'student' expands as $I_S = I_S{+}1$, $I_A = I_A$ and $I_T = I_T$. On the other hand, adding new data about existing student in S_dT_r is termed as 'data inclusion'. Here, S_dT_r remains the same but the dimension 'time' expands by one if $I_t = t_j$, where t_j denotes the number of distinct timestamps for student 'j', i.e. $I_S = I_S$, $I_A = I_A$ and $I_T = \begin{cases} I_T + 1, & I_T = t_j \\ I_T, & \text{otherwise} \end{cases}$.

4.4. Data mining

The sensory-based activity information can be retrieved by applying spatial co-location mining and spatial–temporal mining techniques on sensory patterns during the day at different locations. However, to analyse the RFID interaction graph based each activity context, Page Rank (Rafiei and Kardan 2015) and HITS model (Schall 2012) are used.

$$S_dT_r = [[S_{11}\ S_{12}\ \ldots\ S_{1_{I_T}}],\ [S_{21}\ S_{22}\ \ldots\ S_{2_{I_T}}],\ \ldots,\ [S_{I_{A_1}}\ S_{I_{A_2}}\ \ldots\ S_{I_A I_T}]]$$

$$= \begin{bmatrix} [[a_{111}\ a_{112}\ \ldots\ a_{11n_1}], & [a_{121}\ a_{122}\ \ldots\ a_{12n_1}], \ldots, & [a_{1I_T1}\ a_{1I_T2}\ \ldots\ a_{1I_Tn_1}]], \\ [[a_{211}\ a_{212}\ \ldots\ a_{21n_2}], & [a_{221}\ a_{222}\ \ldots\ a_{22n_2}], \ldots, & [a_{2I_T1}\ a_{2I_T2}\ \ldots\ a_{1I_Tn_2}]], \ldots, \\ \vdots & \vdots & \vdots \\ [[a_{I_A11}\ a_{I_B12}\ \ldots\ a_{I_A1n_{I_A}}], & [a_{I_A21}\ a_{I_A22}\ \ldots\ a_{I_A2n_{I_A}}], \ldots, & [a_{I_AI_T1}\ a_{I_AI_T2}\ \ldots\ a_{I_AI_Tn_{I_A}}]] \end{bmatrix}$$

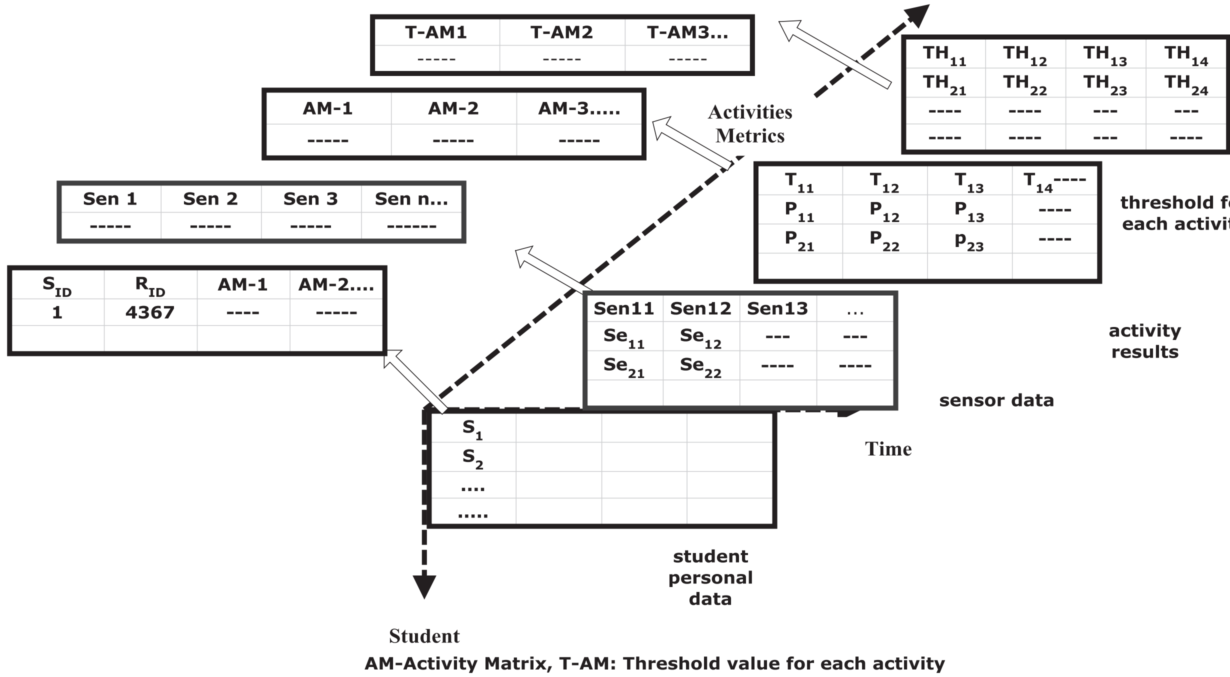


Figure 6. Student activity tensor formation.

4.4.1. Co-location pattern mining from spatial datasets

To retrieve the requisite information from spatial patterns of IoT devices, we can apply spatial-co-location mining technique. Spatial datasets are created for each activity concern. Moreover, spatial temporal mining concept can be best utilised to draw spatial patterns using datasets upon time-series sequence. Spatial dataset is used to compute participation of student in particular activity (example, behavioural activity). Participation index of each student based on the activity is calculated using conditional probability concept (Huang et al. 2004).

Table 4. Identification of activity metrics of S_dT_r.

Activity metrics	Attribute	Remarks
Student personal data (L_1)	Student Identification number (S_{ID}), Registration number (R_{ID}), Name, Gender, Class, Address, Contact number, Age, Activity matrix (AM-1), Activity matrix (AM-2), … , Timestamp (T)	• SID is a unique number assigned by the proposed system to each distant student in the institution premises • Activity matrices consist of sensor values and interaction record generated during a day for each student
Sensor readings (L_2)	Sensor Id, sensor type, sensor location, sensor readings	Objects interaction with each other and IoT sensors in the campus
Activity results (L_3)	Result of activity (AM-1), result of activity (AM-2), …	Activity set for the student daily performance evaluation
Threshold for each activity (L_4)	Threshold for activity AM-1 (TAM-1), threshold for activity (TAM-2), …	For each activity concern, threshold value is set by the managing authority for student performance evaluation
Attending activities (L_5)	–	Sensor readings at different locations in the institution

4.4.2. Temporal mining

Student-behavioural-related activity is mined based on a time-series sequence retrieved from various health attributes during a definite time interval using IoT devices and medical sensors worn on the body.

4.4.3. 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:

$$\mathrm{PR}\,(u) = \alpha\rho + (1-\alpha)\sum\nolimits_{(v,u)\epsilon E} \frac{\mathrm{PR}(v)}{\mathrm{outdegree}(v)}. \quad (1)$$

Here, ρ is personalised vector used to assign preferences towards certain nodes. Moreover, without any preferences, a personalisation vector with $\rho = [1/[N]]_{N*1}$ is assumed, where N is the number of nodes in use. For example, we assume α=0.16, called as 'teleportation factor', which typically follow for six student links (i.e. 1/6 = 0.15).

4.4.4. HITS-based mining

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

$$H(u) = \sum\nolimits_{(u,v)\epsilon E} A(v) \quad A(v) = \sum\nolimits_{(u,v)\epsilon E} H(u). \quad (2)$$

This concept is beneficial in task-based online help and support in IoT-based e-learning environments. Each nodes composed of two ranking scores (hub and authority), based on which student–teacher interaction score is computed.

4.5. Processed S_dT_r formation (PS_dT_r)

In S_dT_r, all information is collected in structured and unstructured forms from sensors such as RFID, GPS sensors and other sensor devices forming the student body network. These information are stored in their respective database and indexed with the tensor slices. Although S_dT_r provides an efficient way to store student-IoT-based data, but it is not effective to analyse data in a heterogeneous format. To make tensor efficient for generating student performance score, S_dT_r is converted to processed S_dT_r with the help of predictive-technology-based data mining tools. These tools analyse different activities data, extract information and store that in the tensor slice, as shown in Figure 7. Data mining algorithms used for different activities are elaborated in Section 4.4. The processed tensor, hence formed, is coined as processed S_dT_r (PS_dT_r).

4.6. Student performance calculation

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

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

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. Total development score TDS (S_i) is evaluated using equation 4, which depicts that

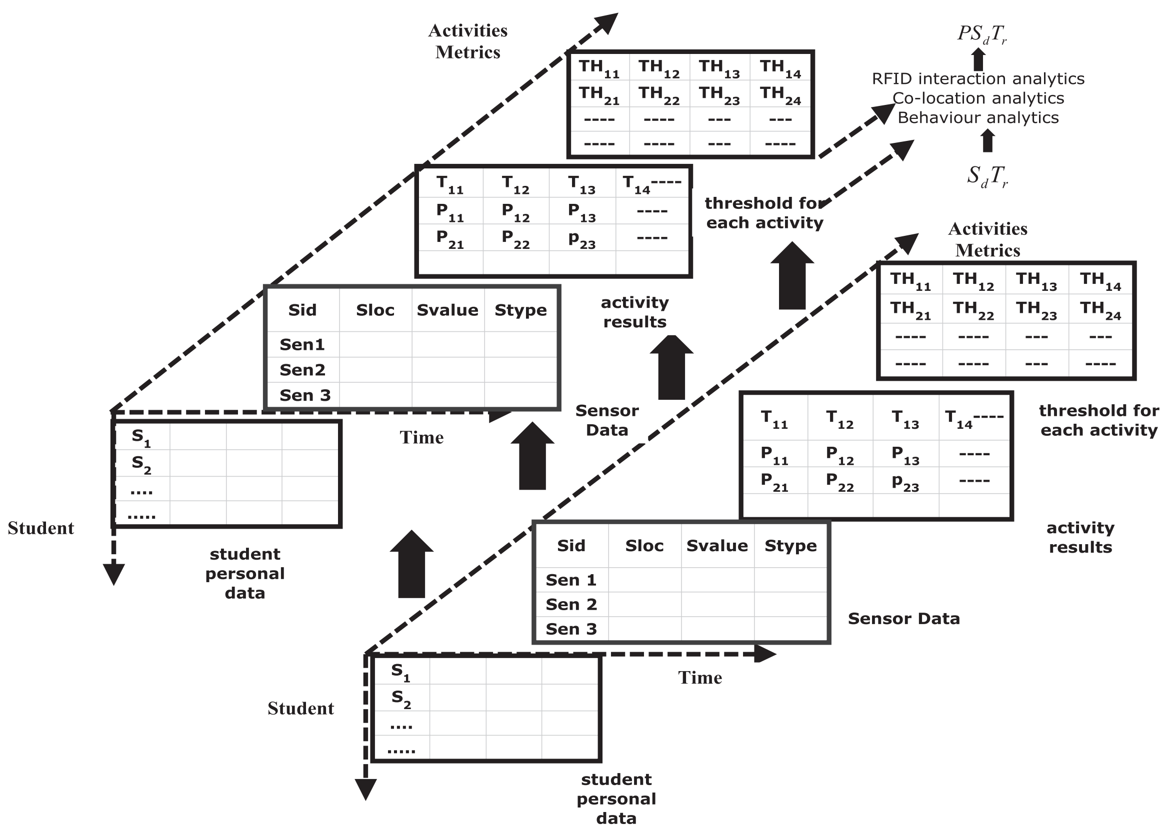


Figure 7. Final processed S_dT_r generation during the sessional.

70% of the student score is taken from student performance in monotonous activities and 30% is taken from rest of the activity set. The monotonous activities are those activities which are of great importance and their V_j^k score is evaluated on a 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 students during that session is also added with activity results, as shown in formula ahead:

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

where r is the number of activities taken as monotonous and s is remaining activities taken as occasional. A threshold value (α) is set by the management committee for each activity concern. Academic performance is of high concern in student domain. Therefore, TDS(S_i) is mainly concerned with academic score and only one-fourth is taken as activity base score. In addition, TDS (S_i) score of each student is used to indirectly compute the reputation score of the organisation. The reputation score is the main probabilistic value considered by the management to access overall 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:

$$\mathrm{TPS}(S_i) = \gamma * \mathrm{TDS}(S_i) \quad (5)$$

$$P(RS) = \frac{\sum_{i=1}^{n} TPS(s_i)}{n} \quad (6)$$

Here, n is the total number of students in school premises. $TPS(S_i)$ score of each student is calculated by multiplying $TDS(S_i)$ score with a scaling factor γ. These parameters' importance are best utilised in the section ahead. However, description regarding each notation used to compute student performance score is shown in Table 5.

Table 5. List of notations used in calculating student performance score.

Notations	Description
A_j	Activity j taken into consideration
$\boldsymbol{V_j^k}$	Probabilistic score of activity j during day k
$S(A_j)$	Student monthly score for activity j
P()	Activity j performance score
TDS($\boldsymbol{S_i}$)	Total development score of ith student
TPS($\boldsymbol{S_i}$)	Total performance score of ith student
P (RS)	Reputation value of the institution
MS(S_k)	Marks of student in k subjects for the current month

4.7. Game-based decision making

4.7.1. Game theory

Game theory can be regarded as a multi-agent decision problem, that emphasise upon 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 (Osborne 2011). 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 are 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 8.

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 maximise 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, specialised 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 $S_{mag} = (S_D, S_{ND})$.

   Player 2 (student) can work towards increase in standard score for its overall 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 6 lists the game parameters recognised by the game-theoretic model. RS is the reputation score computed by school management for each month. TPS(S_i) is the monthly score of each student computed from proposed methodology. DM is the development

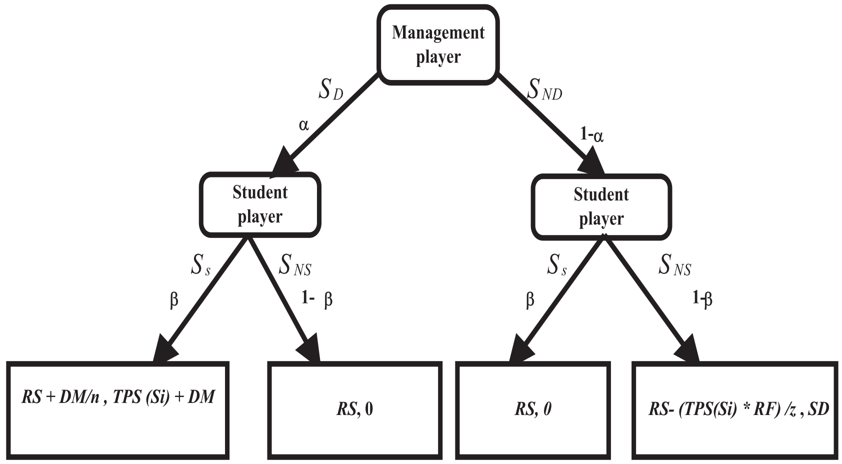


Figure 8. Payoff calculation.

measures taken to encourage the student to maintaining standard score strategy S_S. DM is computed as **(*TPS(S*$_i$*)**DF)**. Here, DF is the 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 ***TPS (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 factors used to balance the new reputation value when DF and RF values are computed from student monthly 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 $U_{\mathrm{mag}}(S_x, S_Y)$ and $U_{\mathrm{std}}(S_x, S_Y)$ 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. $U_{\mathrm{std}}(S_D, S_S) = \mathrm{TPS}(S_i) + DM$, development measure taken into consideration, associated with each student when there is increase in student performance score.
2. $U_{\mathrm{mag}}(S_D, S_S) = RS + DM/n$, since each student improves his/her 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. $U_{\mathrm{mag}}(S_D, S_{NS}) = \mathrm{RS}$, there is not any change in reputation value because management opts for development strategy S_D, even if students follow not-maintaining standard score strategy S_{NS}.
4. $U_{\mathrm{std}}(S_D, S_{NS}) = 0$, there is not any deduction in performance score of student because management opts S_D strategy.
5. $U_{\mathrm{mag}}(S_{ND}, S_S) = RS$, even if students adopt S_S strategy, there is not any consideration of increasing reputation status of the institution.
6. $U_{\mathrm{std}}(S_{ND}, S_S) = 0$. Since no development measures are taken into consideration for student following S_S strategy due to management opting S_{ND} strategy.
7. $U_{\mathrm{mag}}(S_{ND}, S_{NS}) = RS-(\mathrm{TPS}(S_i)*RF)/z$, this is so because student opts for S_{NS} strategy, which leads to decrease in reputation status by $(\mathrm{TPS}(S_i)*RF)/z$, where z is the scaling factor used to compute new reputation status in this scenario.
8. $U_{\mathrm{std}}(S_{ND}, S_{NS}) = SD$, since student opts for S_{NS} strategy, which leads to a decrease in student score and new score is computed as SD. Figure 8 shows the strategically implementation of game theory in our proposed methodology.

Therefore, the decisions taken by management authority using game-theoretic decision system are (i) encouraging students to maintain standard score strategy by giving extra points on overall performance score. (ii) If a student not follows standard score strategy then authority should warn him/her in the form of reduction in performance score by relatively comparing its current sessional performance score with previous sessional performance score. (iii) Reputation score of institution will increase or decreases based on student current sessional performance score.

4.7.2. Probability calculation

After calculating the payoff matrix, game theory decision making must calculate the values of 'α' and 'β', i.e. the probabilities with which 'Management' and 'Student' chooses their respective strategies. To calculate 'α' and

Table 6. Game parameters.

Parameters	Description
RS	Reputation score of the institution
TPS(S_i)	Total performance score of ith student for the current month
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

'β', the game decision module uses TPS(S_i) values retrieved by student performance database. To specify how the game decision module calculates 'α' and 'β' from TPS(S_i) values, we take following example. Let the values of TPS(S_i) calculated by student performance database is as shown in Table 6. It may be noted that the values considered for calculating TPS(S_i) are arbitrary values taken to illustrate the concept. The game decision module simply equates the value of 'α' equal to respective TPS(S_i) value of student. However, the TPS(S_i) is always positive and lies between 0 and 1. For calculating 'β', the student TPS(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. The value of 'n' is computed by counting the number of students having TPS(S_i) greater than or equal to 0.750 in each class. For example, in Table 7 management chooses 'n'=7, so that top 7 students are taken for providing development measures. The value of 'β' is taken as the TPS(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 school environment.

5. Experimental evaluation

5.1. Experimental setup

In order to evaluate the performance of our proposed system experimentally, we monitored daily activities of 34 students in a class using IoT devices. In this methodology, student body sensor network and its interaction with other objects-based features are extracted for calculating student performance score in each activity

Table 7. TPS(S_i) calculated by Game Theory component.

Student ID	TPS(S_i)
S11	0.878
S08	0.873
S13	0.855
S22	0.839
S21	0.804
S32	0.764
S15 (student up to S15 is selected for development measure)	0.755 → (value of β)
…	…
S43	0.546

concern. Activities are recognised based on spatial–temporal patterns (Compieta et al. 2007) and time-stamped radio packets generated using RFID tags and RFID reader based proximity sensing concept.

5.1.1 RFID working in student environment

RFID tags plays a vital role in calculating student performance in IoT environment. In RFID environment, each student and teacher are equipped with RFID tag and RFID reader, as shown in Figure 4. The basic experimental setup for an RFID-based interaction is shown in Figure 9. The interaction is based on RFID reader reading from one student related to proximity of other student RFID tag within the range of 1–2 m. The readings are relayed to the experiment area in the school premises through wireless communication mechanism such as Wi-Fi/GPRS/CDMA. Moreover, in learning areas of school premises, objects are equipped with RFID readers and they can communicate with students by interacting with their RFID tags, as shown in Figure 9. The basic steps employed to evaluate the student performance is as follows:

1. In our experiment, student body sensor network are equipped with behaviour sensors and RFID-based interactions with environment and other objects as shown in Table 3. Moreover, active RFID tags are clipped at the chest level so that other devices can be detected in its close proximity using RFID reader such as smartphones and routers.
2. A set of 10 activities are considered for calculating student monthly performance as shown in Table 2. Daily-activity set for each student for calculating its daily performance is shown in Figure 10(b). Moreover, four student interactions for specific activity A24 are shown in Figure 10(a). At the end of each session, student performance score is calculated using performance evaluation system as shown in Equation (4).
3. Results shows that the performance score of each student was assessed using proposed methodology and manual evaluation system. The increase in student performance score reflects the effectiveness of our

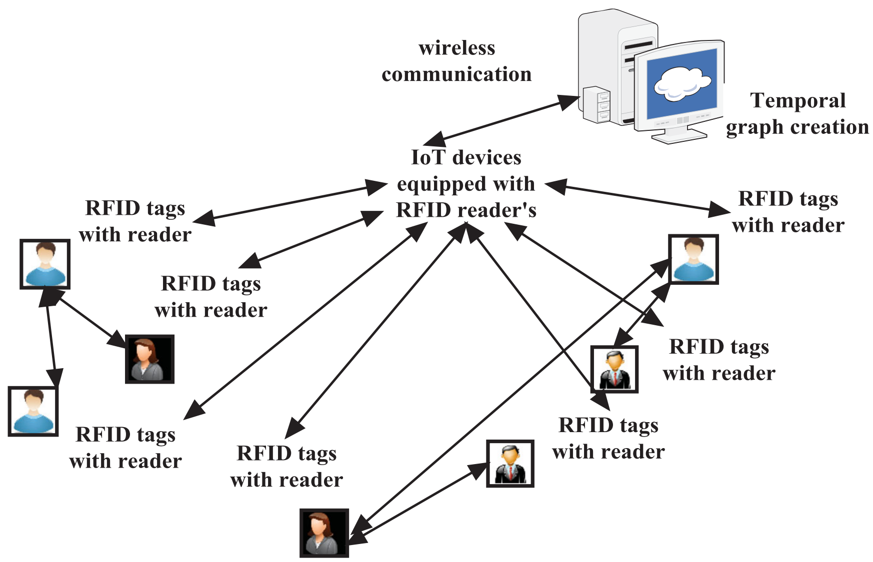


Figure 9. RFID tag and RFID reader interaction set up.

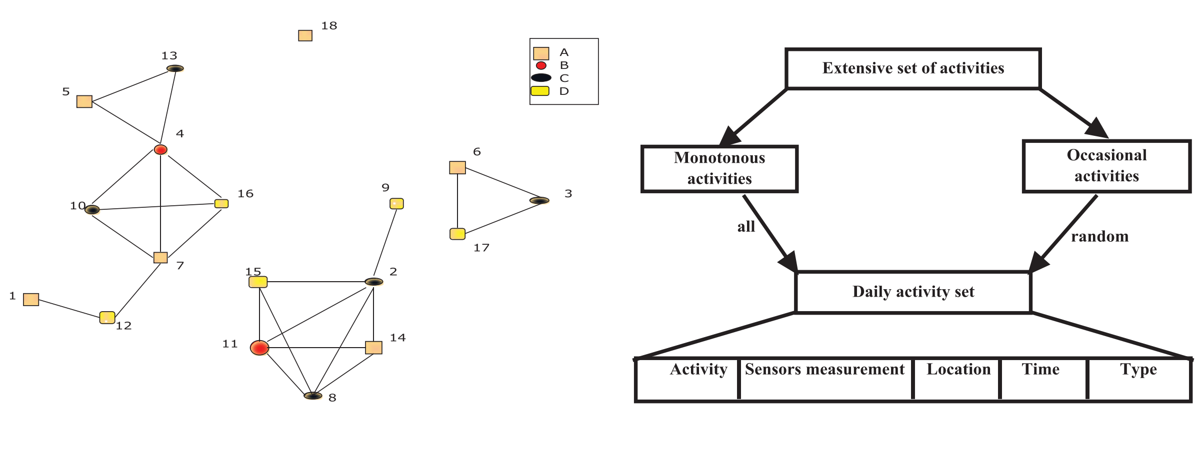
proposed methodology. Moreover, increase in student performance score also leads to increase in reputation score of the institution. Lastly, decisions are taken by game-theoretic system based on the parameters described in Table 5.

5.1.2. Data mining in IoT environment

The real-time and synthesised data are generated using Pentaho platform, tools to extract, prepare and blend the data. Pentaho data mining (Weka 3.6 2017) consists of machine learning algorithms for a broad set of data mining tasks. Functions for data processing, classification methods, cluster analysis, and visualisation are implemented using Pentaho tools. The mining criteria can be fulfilled by establishing a third-party cloud namely Amazon EC2 2017. 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, a range of AMI instances are described. Moreover, each activity concerning minimum and maximum AMI instances is set by the school authorities for generating correct results.

5.2. Results and Discussion

Table 2 shows the details regarding calculating student performance score based on 10 activity scores. Activity A03, A06, A09, A15, A21, A24, A32, A17 and A29 score are computed based on Internet of Objects analysis. Table 7 shows the probabilistic score for each activity



(a) (b)

Figure 10. (a) Spatial dataset {A, B, C, D} for an activity A24 and (b) daily-activity dataset.

during a session for the student with IDS22. Figure 11(a) depicts the monthly performance score of ten students from a class for the three consecutive months. The first month score is based on manual score system and the next two month performance score is according to the proposed methodology. Moreover, the execution time of the proposed model when number of students are increased is depicted by Figure 11(b). The detailed explanation of the experimental results is described in the subsection ahead.

5.2.1. Student Performance Score Consist of ID S22

The V_j^k score of each activity j during day k for student with ID S22 is depicted in Table 8. The activities with ID as A03, A06 and A09 are monotonous activities, whose contribution in standard score calculations is 70% of the total weightage, as described in equation 3. Moreover, rest of the activities are occasional and V_j^k score is explained ahead. Student score in each activity j i.e. $S(A_j)$ is changed to 1 or −1, based on the classification shown in Figure 2(b). Table 9 clearly shows that $S(A_j)$ score for monotonous activities is the cumulative mean of the V_j^k scores retrieved during the entire month. Instead of directly using probabilistic value of $S(A_j)$ for $P(A_j)$ calculation, the following method has been used for monotonous activities' score calculation:

$$\begin{aligned} P(A_j) &= 1, \text{ if probabilistic value of } S(A_j) \geq \alpha \\ &= -1, \text{ otherwise} \end{aligned}$$

Whereas when occasional activities are considered, then $P(A_j)$ is calculated by classifying each day V_j^k score of student as constructive and obstructive category. $P(A_j)$ calculation for occasional activity A15 and A32 is shown in Table 10. The activity A15 was held on Day 1, Day 2, Day 18, and Day n with probabilistic score of 0.7865, 0.6785, 0.7894, and 0.7885, respectively. The threshold value α for activity A15 (student performance in study group) is taken as 0.750. The threshold value for each activity is calculated on the basis of different mining techniques, which leads to setting of a different threshold value for each activity. Each day probabilistic score was converted into 1, 0 or −1 based on classification threshold α. Therefore, the value of $S(A_j)$ for activity A15 is computed as (1 + 1+1−1)/4. Similarly, activity A26 was held on Day 6 and Day 18 with probabilistic score of 0.8540 and 0.6785 respectively. Therefore, $S(A_{26})$ is computed as (1−1)/4. The occasional activities may be conducted on even days or odd days of the month based on the schedule prepared by the school

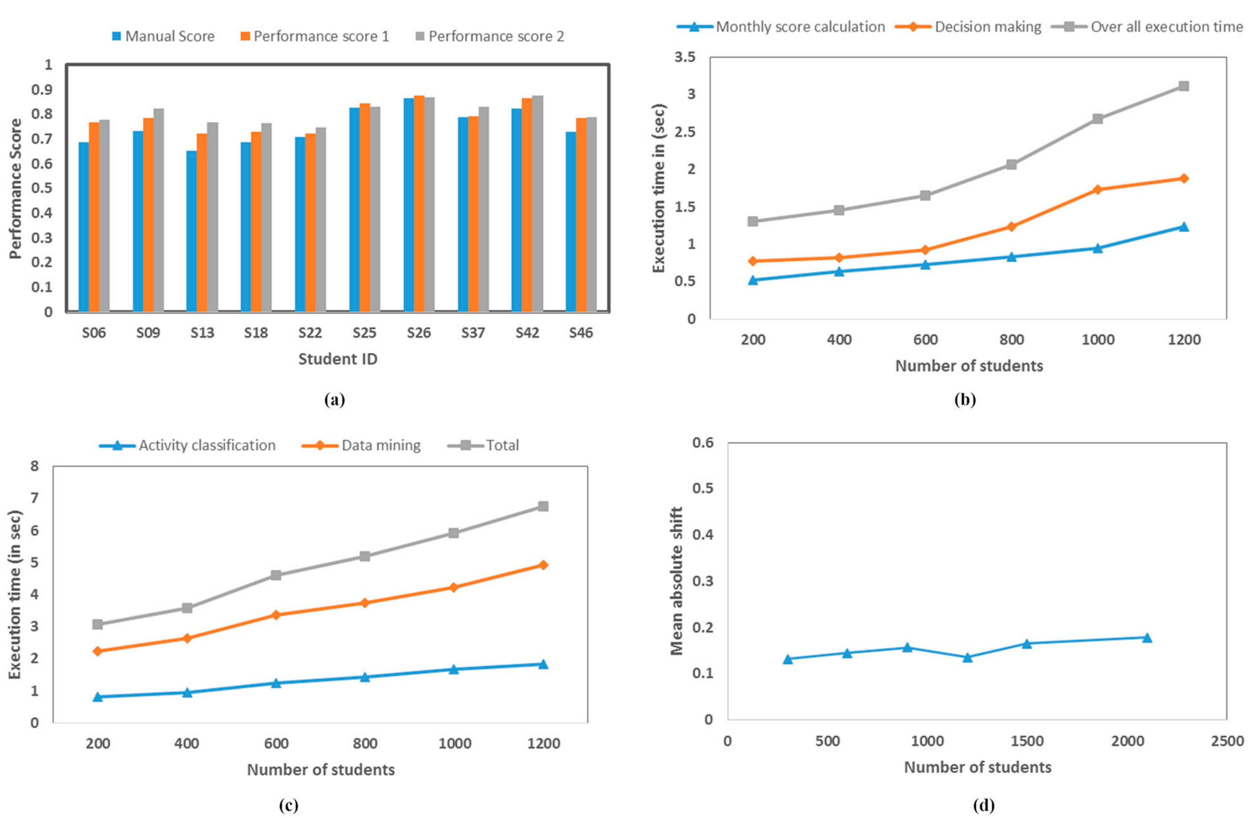


Figure 11. (a) Performance score computation using proposed methodology, (b) proposed system component based execution time (in seconds) for each day, (c) final score calculation with execution time, (d) proposed system stability.

Table 8. Experimental result of student with ID S22.

Activity ID	Day 1 (V_j^k)	Day 2	Day 3	…	Day 15	… Day n	$P(A_j)$
Monotonous activities							
A03	0.8942	0.7864	0.6573		0.8453	0.6854	1
A05	–	–	–		–	–	Sessional score
A06	0.8967	0.9060	0.7400		0.8945	0.8765	1
A09	0.8343	0.8443	0.7330		0.4647	0.8677	1
Occasional activities							
A15	0.7865	0.6785	0.7689		0.8456	0.7885	1
A17	0.8978	0.7868	0.6895		0.8210	0.8765	1
A21	0.7894	0.6844	0.7905		0.7864	0.8323	1
A24	–	–	0.8900		–	0.7892	1
A26	–	0.7868	–		–	–	0
A29	–	0.6540	–		0.786	0.5648	−1
							TDS (S_i) = 0.7688

Table 9. $P(A_J)$ calculation for monotonous activity A03 and A06.

Activity ID	Day 1	Day 2	…	Day 6	Day 14	…	Day 23	…	Day n	$S(A_j)$	$P(A_J)$
A03	0.8942	0.7864		0.6885	0.7346		0.7547		0.6990	0.7854	1
A06	0.8967	0.9060		0.8756	0.8950		0.8540		0.8765	0.8768	1

management. Moreover, if $S(A_j) \geq ¾$, then $P(A_j)$ is taken as 1 otherwise 0.

5.2.2. Decision Making

The proposed system decisions are derived from game-theoretic approach. Nash equilibrium is calculated using Game Plan Software (Version 3.6) from the data provided by decision-making component. Game plan generates strategies define 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 (Game plan 2017).

5.2.3. Overall System Performance

To test the scalability of the proposed system, the IoT-based activity dataset of 34 students for the whole session is bootstrapped in order to create dataset of 1200 students. A java script is developed for random selection of students from the created dataset. The system is initially fed with the data of 200 students selected by java script and execution time is noted. The process is repeated for 6 iterations by increasing data for 200 students for each iteration. Figure 11(b) depicts execution time of different components used for computing student daily performance score. From Figure 11(b), it is clear that data mining phase execution time is more when compared to activity recognition phase. This is due to the fact that mining procedure capitalise the importance of various mining algorithms, as shown in Table 2. 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 monthly decision making is calculated in Figure 11(c). This figure depicts that, increase in number of students increases the execution time for the monthly score calculation, which leads to a increase in execution time of the decision-making process.

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 do not change much when there is increasing in number of datasets. Stability of a system is calculated in accordance with mean absolute shift. The value changes remotely as we increase the number of students, which indicates that the system maintains its stability. Figure 11(d) demonstrates that there is very less shift (0.13–0.18) in mean absolute value when number of datasets are increased with respect to an increase in number of students.

6. Conclusion

IoT can be used to create more significant learning spaces in education institutes. Based on this concept, we have proposed a system that focuses on student's interaction with each other and surrounding objects which are

Table 10. P (A_J) calculation for occasional activity A15 and A26.

Activity ID	Day 1	Day 2	…	Day 6	Day 15	…	Day 18	Day n	$S(A_j)$	$P(A_j)$
A15	0.7865	0.6785		–	–		0.7894	0.7885	3/4	1
A26	–	–		0.854	–		0.6785	–	0/4	0

virtually associated with an activity. Tensor is defined to store activity recording of each student for a particular day. Processed tensor is generated to compute student-activity-based performance based on the educational data mining results. In the experiment section, results show evidence that IoT, applied as a tool to support the evaluation process, improves the student overall performance score. Moreover, 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. Lastly, game-based decision making using parameters namely institution reputation score and student performance score enhances the utility of the proposed methodology.

The road in front of Internet of Objects and their application in education is just a beginning. In future we can utilise IoT concept for student academic learning process.

Disclosure statement

No potential conflict of interest was reported by the authors.

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