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Ego Network Analysis for Predicting Students Performance

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ABSTRACT

Students and teachers use more detailed information about their strengths, weaknesses, and individual academic performance to understand why students face a learning gap and try to understand the patterns to overcome the risk in future. So the data are collected from students with greater privacy by making them answer questions that indirectly helps us to determine the character, behavior and performance of the student, And helps the college to provide great promise of quality education for all.

Keywords: *Feedback, Students Trajectories, Data mining, Betweeness Centrality, Ego Network*

1. INTRODUCTION

Thoughtful use of education data has tremendous potential to improve and address inequities in education system. Scientists better understand how the brain incorporates new information and skills. Educators have a more accurate sense of student progress and potential risk for dropping out.

Districts and schools can use data to allocate resources and create institutional reform to better meet student needs in a world where students take increasingly personalized or non-traditional paths to graduation.

With this data, we can finally observe patterns during instruction, across classrooms, between schools, and over time to create a more complete understanding of which students succeed and why. The ability to compare administrative, academic, demographic, and social information from various sources at last provides a means to examine the full multiplicity of factors that contribute to student success. Examining student trajectories over time shows how well students are prepared for the next steps in the learning process.

They can identify ways to facilitate application and transition between school levels and into the workforce. To provide useful insights, research about long term education and career success often requires sharing information—sometimes including sensitive data—across schools, between states, and over time. The student data used in this research must be collected, used, and deleted with sufficient privacy protections.

Appropriate policies, well-tailored laws, best practices, and genuine enforcement mechanism minimize the privacy risks, and ensure the best outcomes for students.

The cases here illustrate how students, educators, researchers, and advocates apply data analysis to encourage student success and retention, facilitate more effective instruction, advising, and administration, and ameliorate inequalities.

2. LITERATURE REVIEW

2.1 EXISTING SYSTEM

In present teachers classify students based on marks and behavior based on the visualization .The main drawback is that we can't say a student who gets less mark is not good at discipline; maybe he will shine in some other skills, and may also be perfect at discipline similarly a person getting more marks cannot also be said as a obedient student with good characters

2.2 PROPOSED SYSTEM

Our proposed system gets feedback from the students directly either pre/post enrollment and based on the some indirect questions in which

We can try to identify the behavior or skills of person/students. So it gives us the exact accuracy of a student's performance, behavior, skills and it also helps the teachers to make improvements and make students shine better in future.

2.2.1. Methodology:

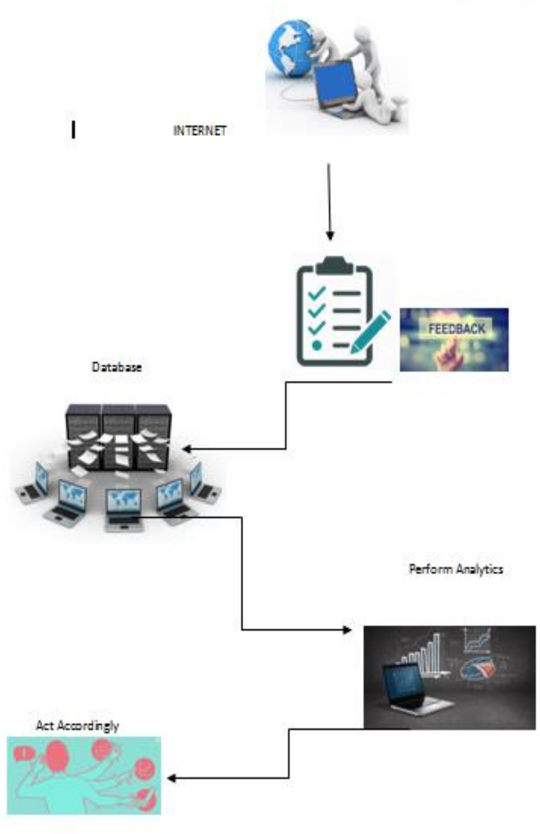

Fig. 1: Flow Diagram of Method Used

2.2.2. NETWORK DIAGRAM

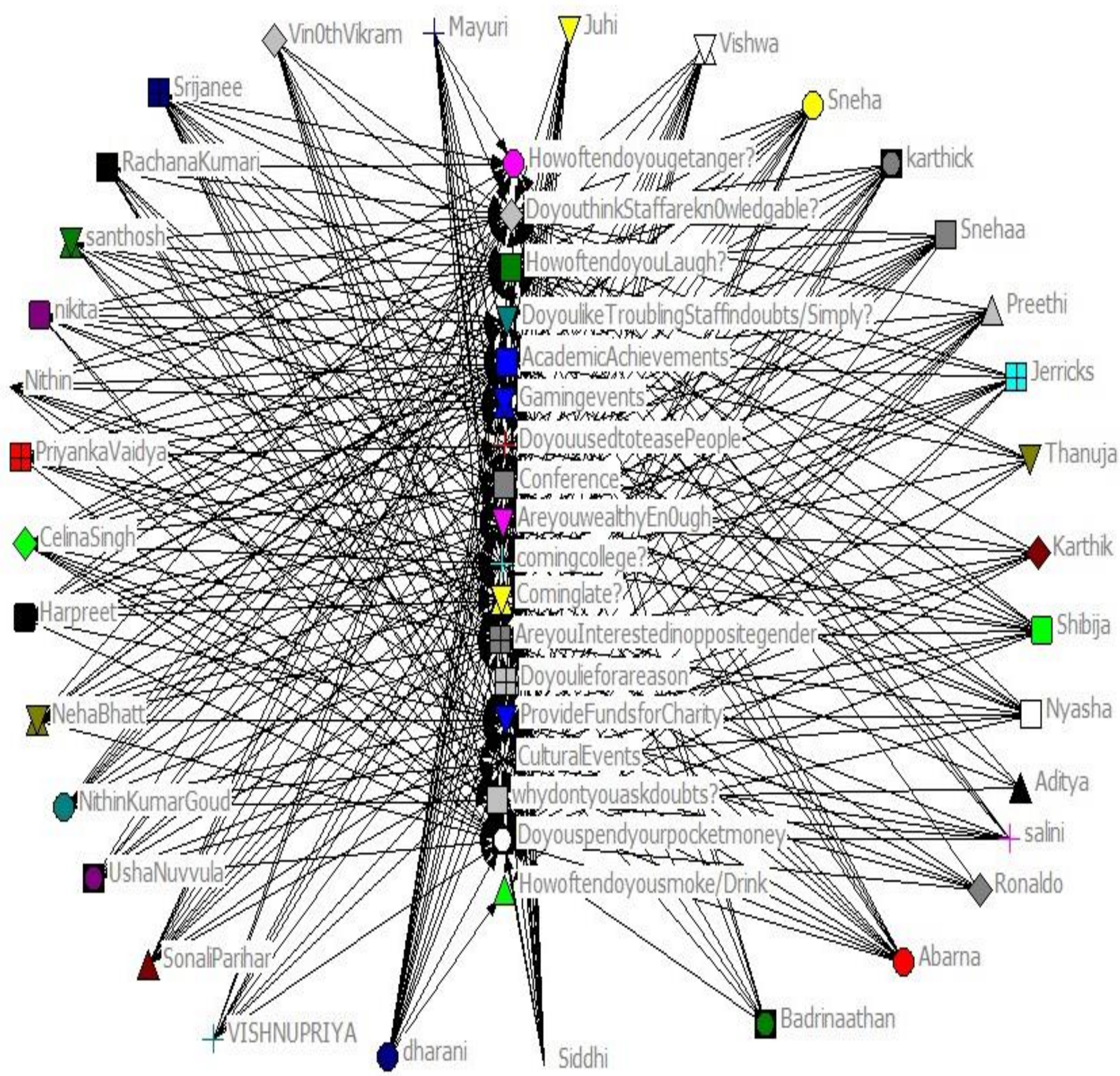

Fig. 2 : Network Diagram using Ucinet

2.2.2.1 Ego Network

Ego networks consist of a focal node ("**ego**") and the nodes to whom **ego** is directly connected to (these are called "alters") plus the ties, if any, among the alters. Of course, each alter in an **ego network** has his/her own **ego network**, and all **ego networks** interlock to form the human social **network**.

EGO Based on Single Userid:

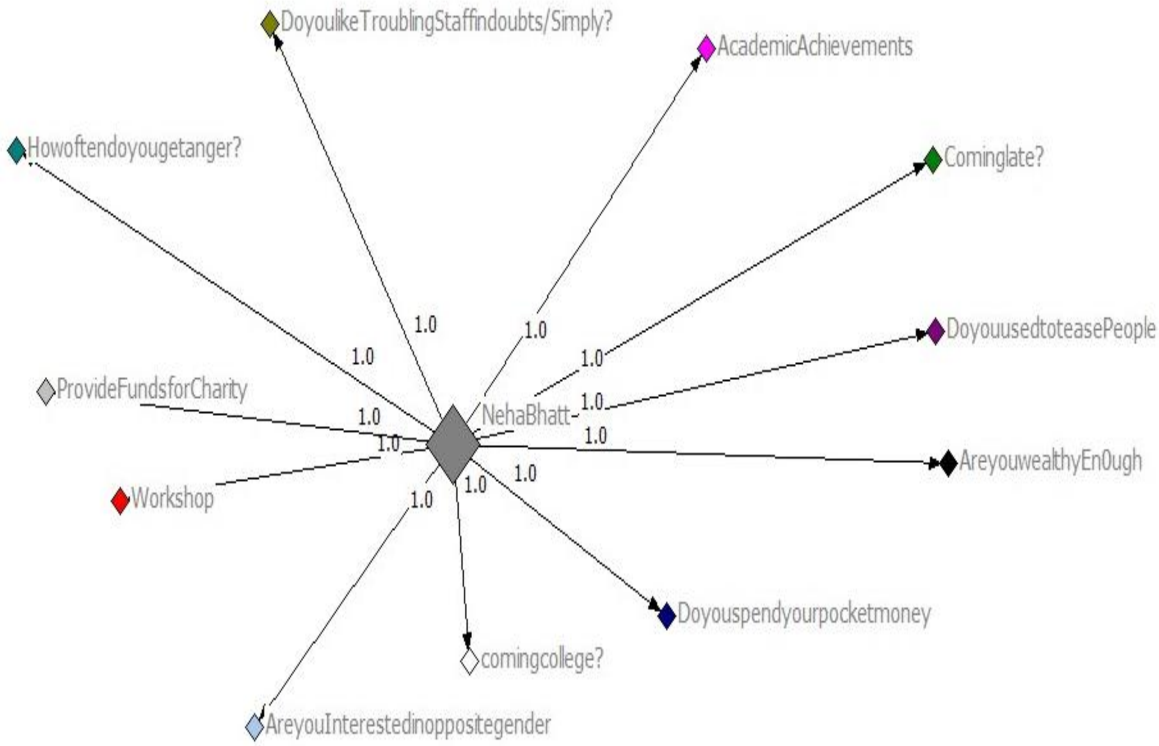

Fig. 3: Ego Network using Ucinet

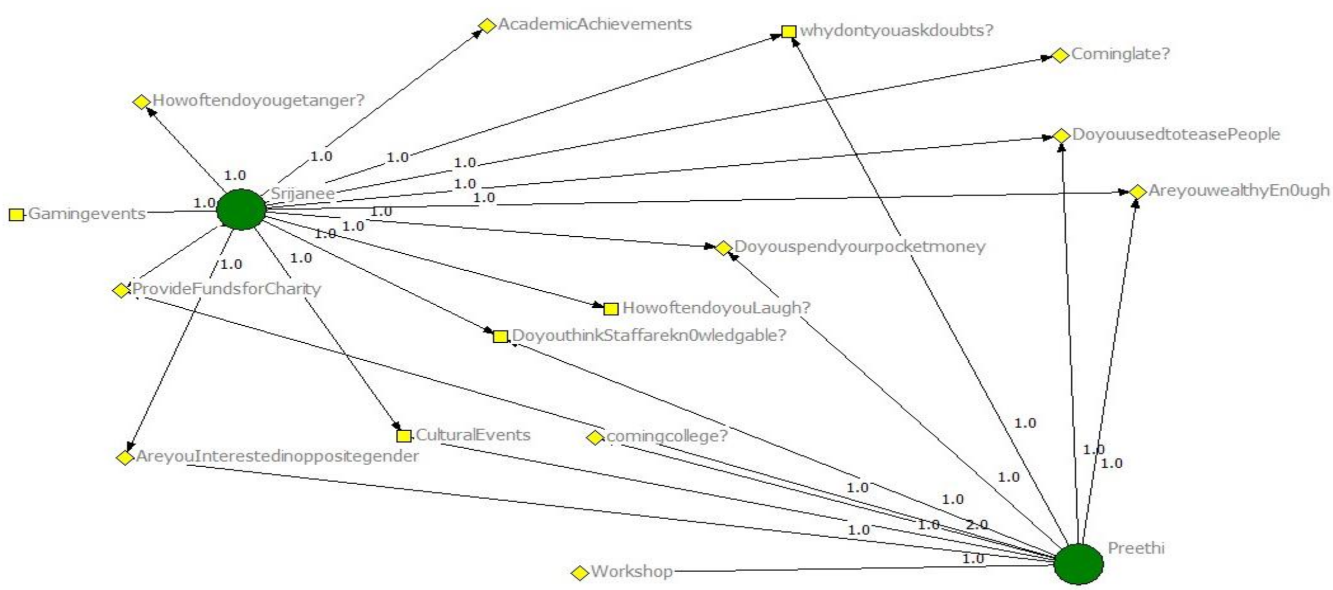

Fig. 4: EGO Based on Multiple Userid

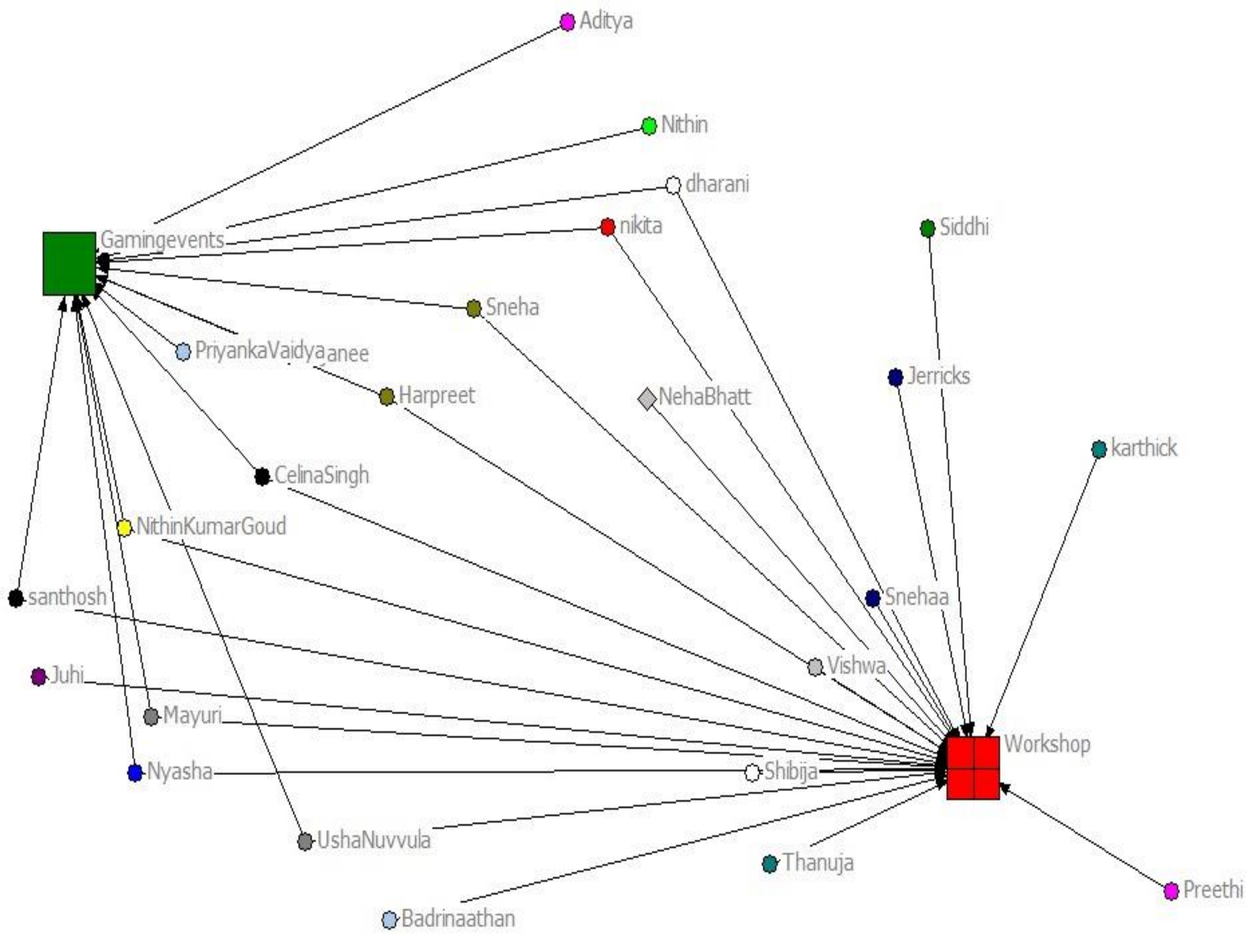

Fig. 5: EGO Based on The Classified Attributes

Betweeness Centrality

In graph theory, betweenness centrality is a measure of centrality in a graph based on shortest path.

Betweeness centrality for attribute Coming College

```
> g <- sample_pa(`comingcollege?`)
> betweenness(g)
  [1]  0 65  2  6  0 14 15  2 40  0  6  0 16 21 10  3  2  0  0 14  1  0 16  0  0  0
 [27]  4  0 15 21 16  0  0  4  0  0  0  0  4  0 10  0 12 10  0  0  6  4 12  5  0  3
 [53]  2  1  0  0  0  0  0  9  3  0  0  0  3  0  0  0  0  0  0  0  0  0  0  0  0  0
 [79]  0  0  0  0  0  0  0  0  0  0  0  3  0  0  0  0  6  0  0  0  0  0
> g
IGRAPH D--- 100 99 -- Barabasi graph
+ attr: name (g/c), power (g/n), m (g/n), zero.appeal (g/n), algorithm
| (g/c)
+ edges:
 [1]  2-> 1  3-> 1  4-> 2  5-> 2  6-> 2  7-> 6  8-> 2  9-> 2 10-> 1 11-> 2 12-> 6
[12] 13-> 2 14-> 9 15-> 1 16-> 1 17->16 18-> 1 19-> 1 20->15 21-> 1 22-> 9 23->14
[23] 24-> 2 25-> 8 26-> 1 27-> 1 28->23 29->13 30-> 9 31-> 7 32->23 33->29 34-> 2
[34] 35->14 36-> 4 37->17 38-> 1 39-> 2 40-> 2 41->31 42->30 43->30 44->43 45->30
[45] 46-> 2 47->41 48-> 2 49->29 50->23 51->20 52->48 53->15 54-> 1 55->20 56->13
[56] 57-> 3 58->13 59->16 60->20 61->34 62->60 63->49 64->52 65->39 66->53 67->50
[67] 68-> 1 69-> 9 70-> 2 71-> 2 72->65 73->49 74->54 75->49 76-> 9 77-> 2 78->27
+ ... omitted several edges
> plot(g)
```

This is a simple stochastic algorithm to generate a graph. It is a discrete time step model and in each time step a single vertex is added. We start with a single vertex and no edges in the first time step. Then we add one vertex in each time step and the new vertex initiates some edges to old vertices. The probability that an old vertex is chosen is given by

$$P[i] \sim k \alpha i + a$$

sample_pa generates a directed graph by default, set directed to FALSE to generate an undirected graph. Note that even if an undirected graph is generated ki denotes the number of adjacent edges not initiated by the vertex itself and not the total (in- + out-) degree of the vertex, unless the out.pref argument is set to TRUE.

Output for Centrality Measure

In our proposed model, we hypothesized that demographic information and the classroom context combined with centrality measures would predict persistence. Knowing the correlation between centralities and persistence leads to a natural question about the likelihood those students with indices within a certain range will actually continue their education.

3. EXPECTED OUTPUT

Sample Questions

1) Do you like coming to college?

Ans: It helps to determine whether the student is interested in studies.

2) Have you attended conference, events, and workshop?

Ans: helps to determine how actively students participates.

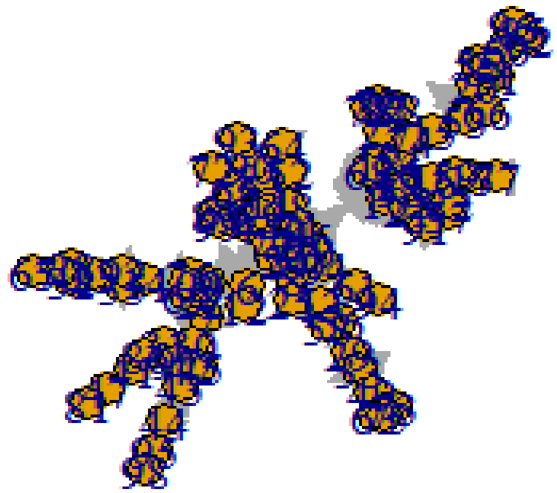

Fig 6: centrality Measure

3) Do you like coming to school late?

Ans: helps to determine Punctuality

4) Academic Achievements?

Ans: helps to determine whether he is a knowledgeable person or not

5) Do you like troubling Staff in doubts?

Ans: helps to determine how much the student is interactive in class

6) Use of free time?

Ans: helps to determine whether he is utilizing the time properly

7) How often do you get anger?

Ans: helps to determine whether the student is tempered person or not

8) How often do you laugh?

Ans: helps to determine whether the person is jovial or not

9) How often do you smoke / Drink?

Ans: helps to determine whether the person is health conscious or not

10) Provides funds for charity?

Ans: determines whether the student has helping tendency or not

Similarly some more questions can be asked to students indirectly to determine the students character, skills, performance etc.

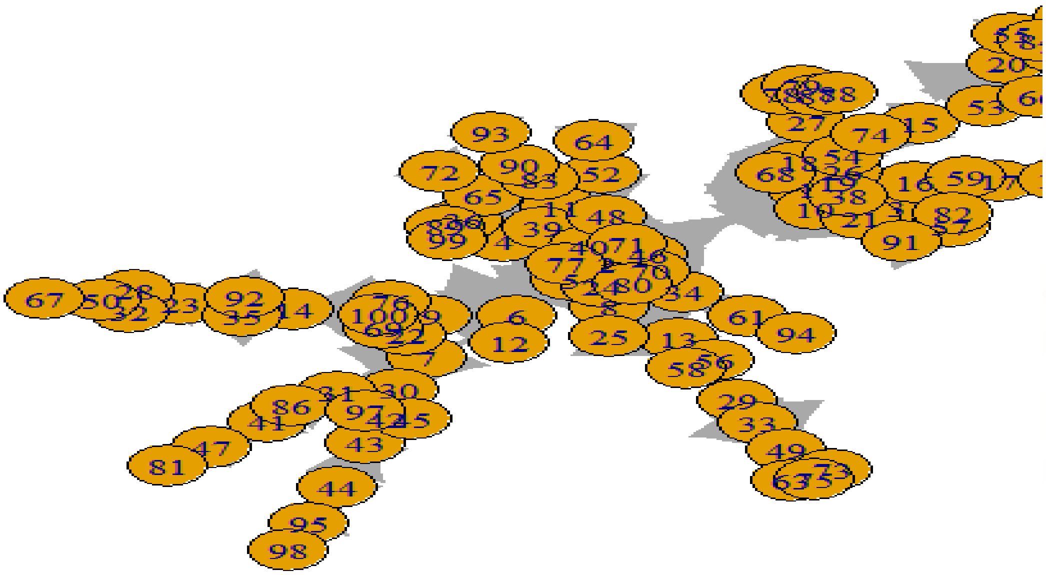

Fig 7: Betweeness Centrality Values

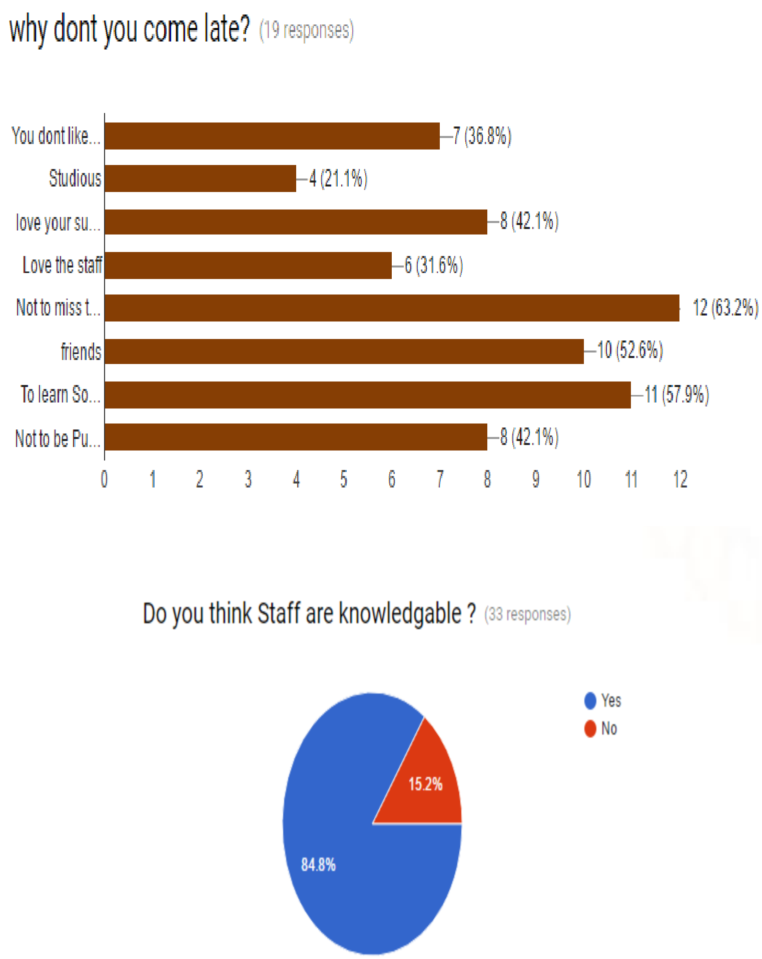

Fig 8: visualization of lecture knowledge

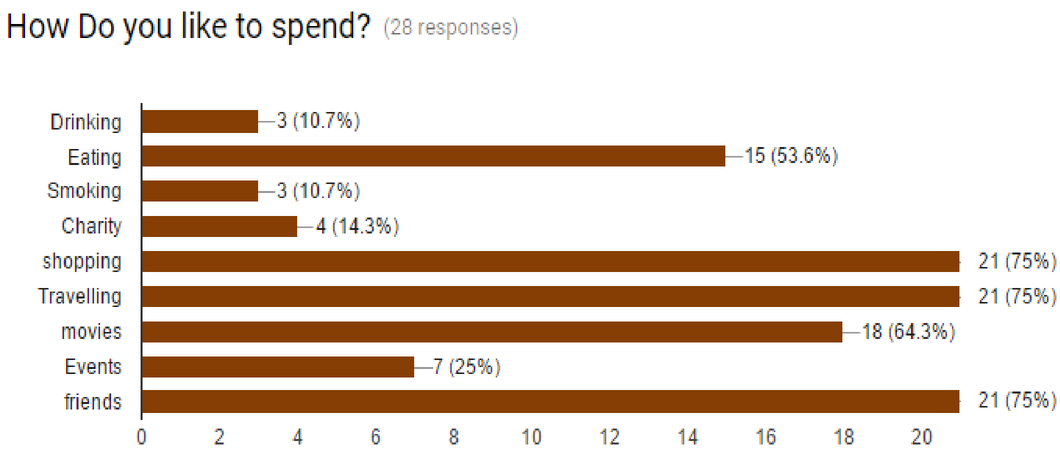

Fig 9: Visualisation of Expenditure

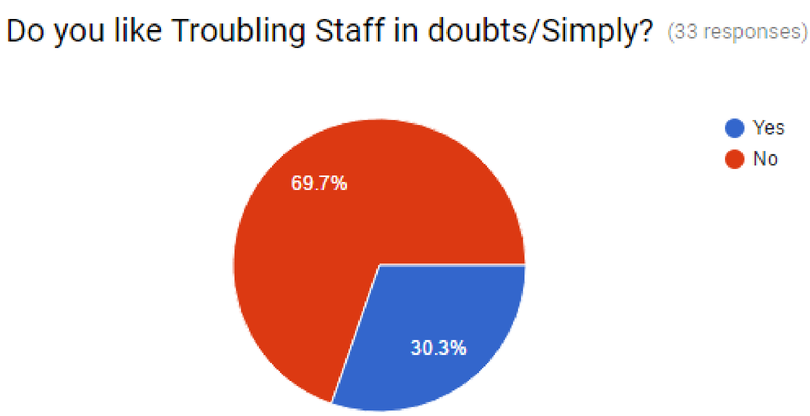

Fig 10: Visualisation of troubling staff

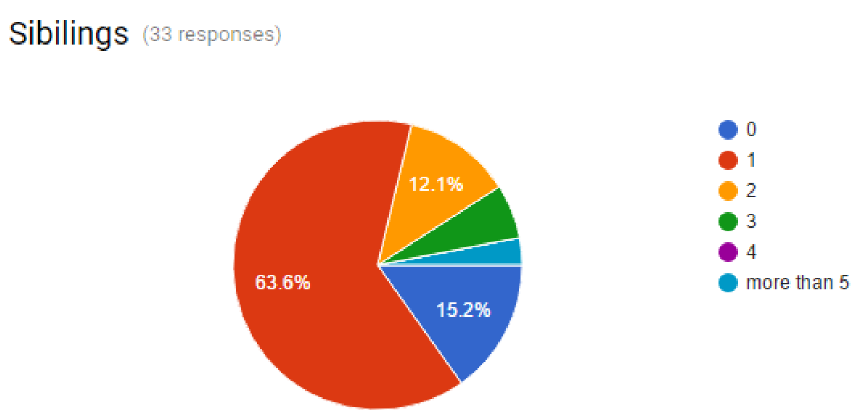

Fig 11: Visualisation of siblings

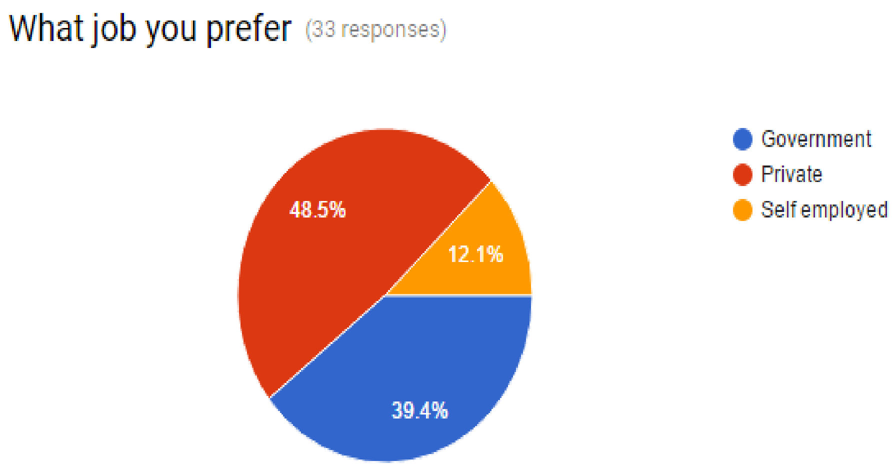

Fig 12: Visualisation of job preferences

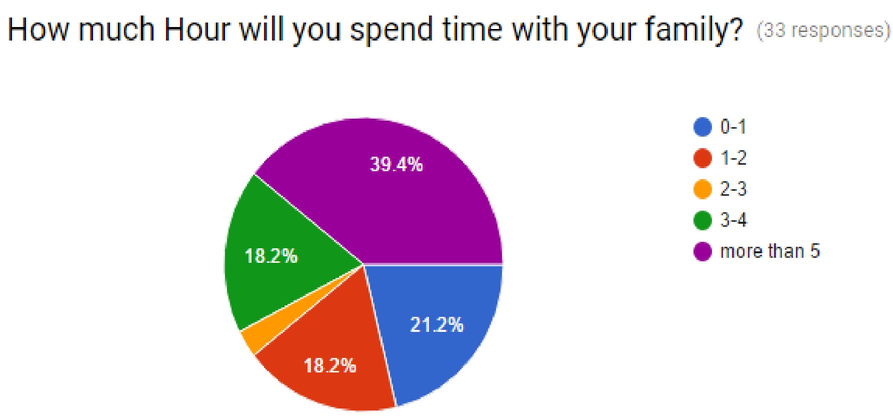

Fig 13: Visualisation of time spent with family

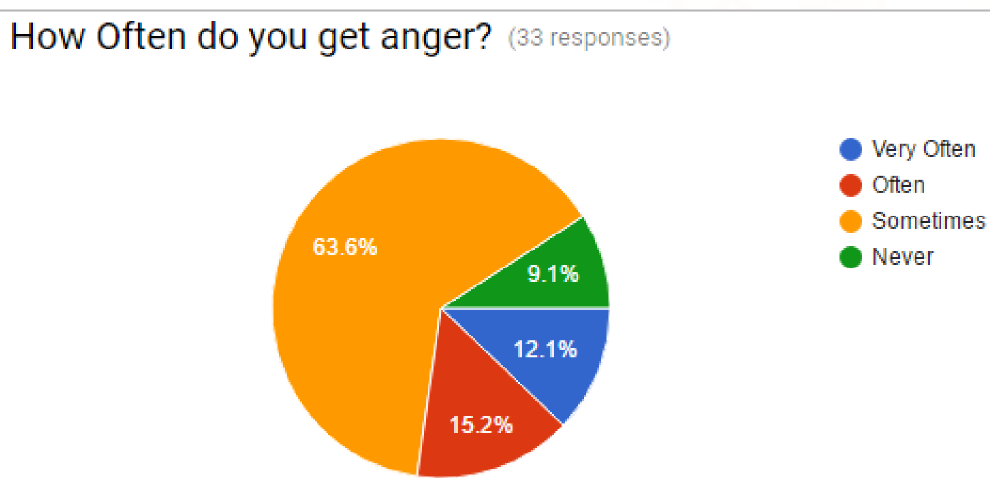

Fig 14: Visualisation of getting anger

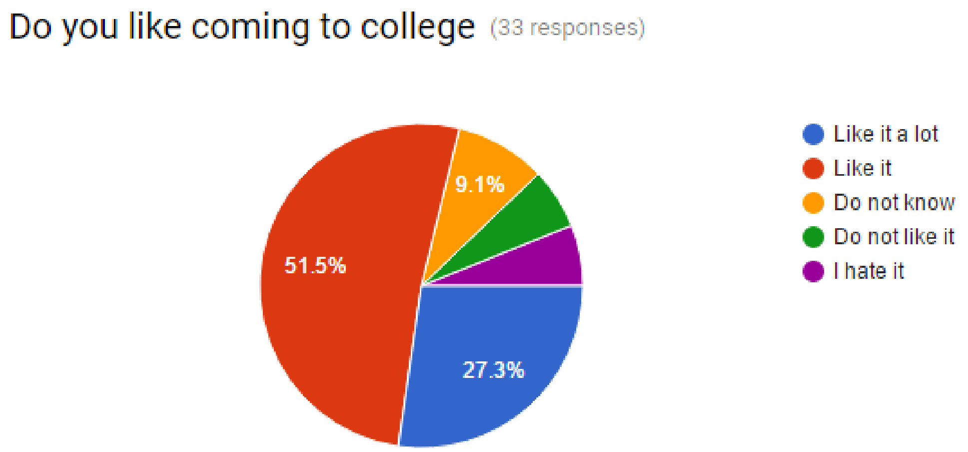

Fig 15: Visualisation of coming to college

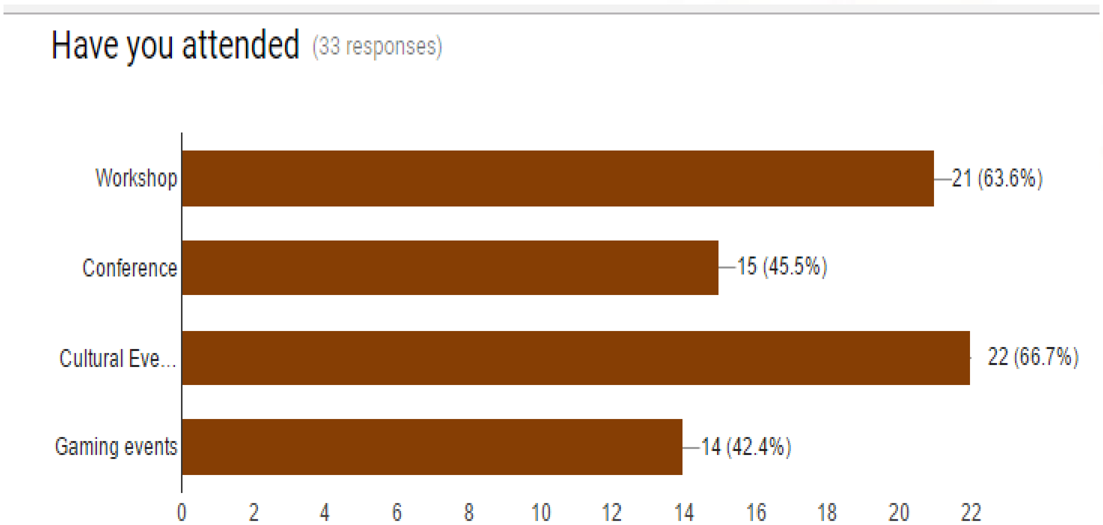

Fig 16: Visualisation of events Attendend

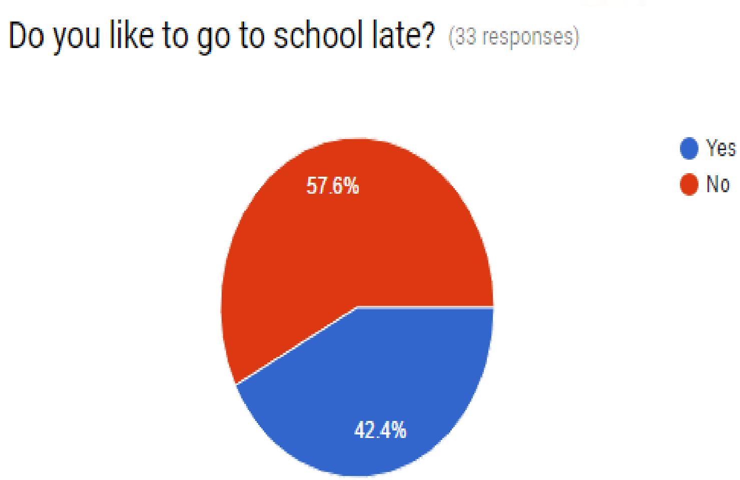

Fig 17: Visualisation of coming late

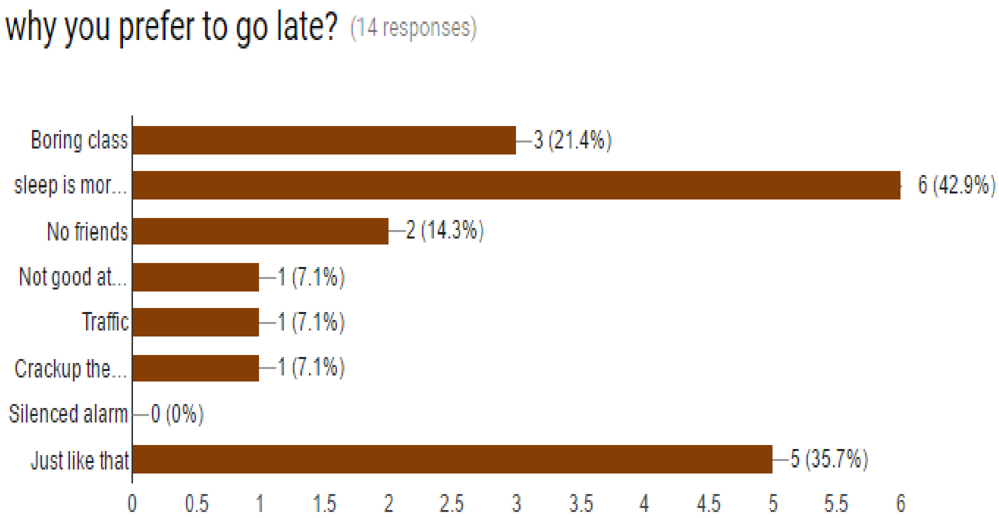

Fig 18: Visualisation of preference of going late

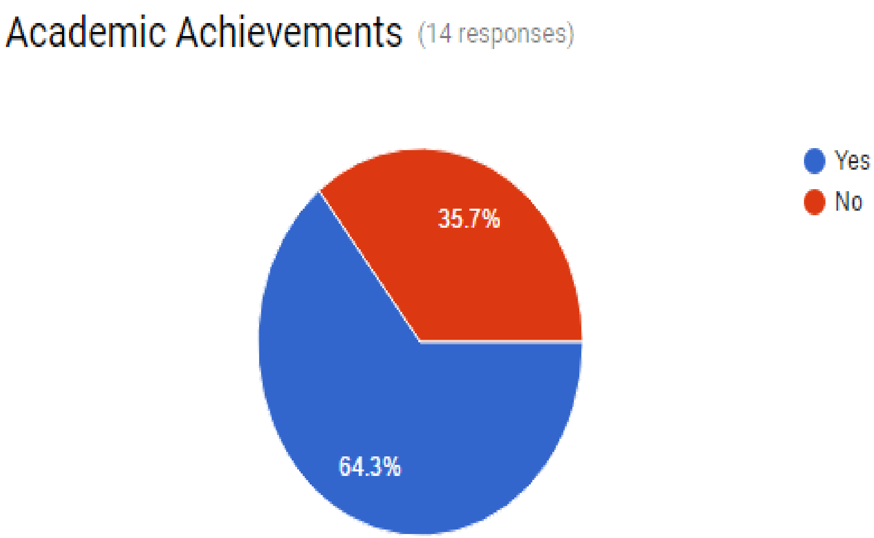

Fig 19: Visualisation of achievements

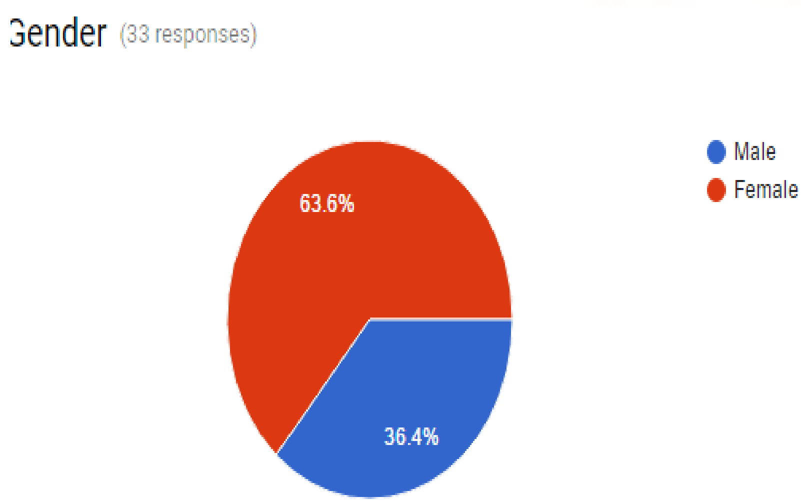

Fig 20: Visualisation of gender

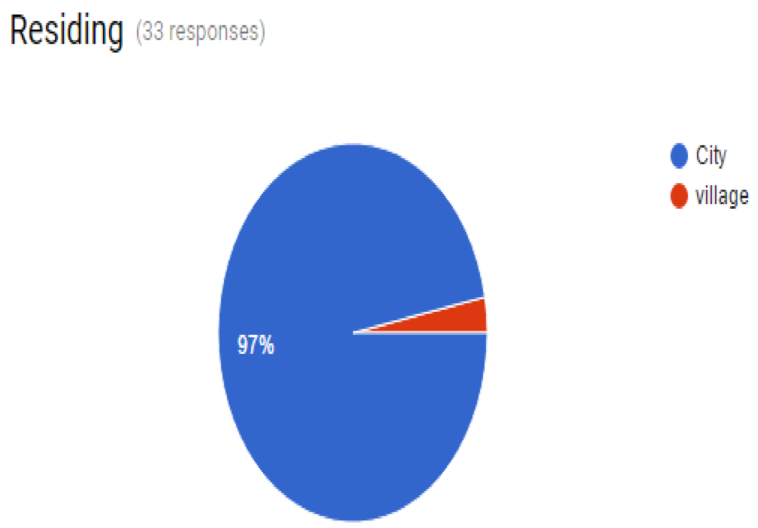

Fig 21: Visualisation of residing location

Fig 22: Visualisation of getting laugh

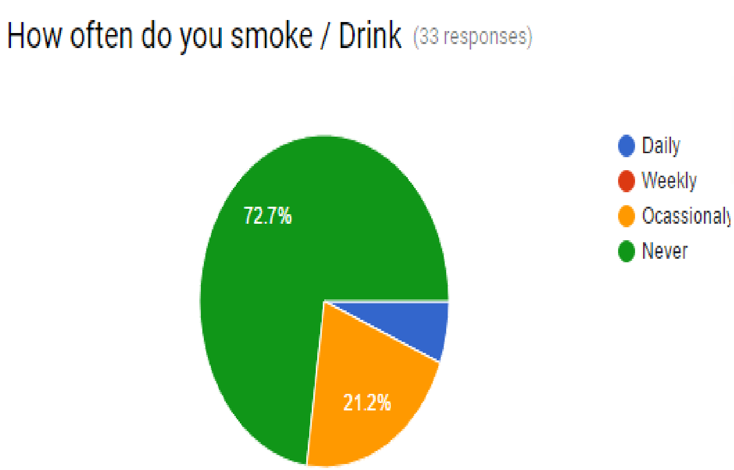

Fig 23: Visualisation of how often smoke/drink

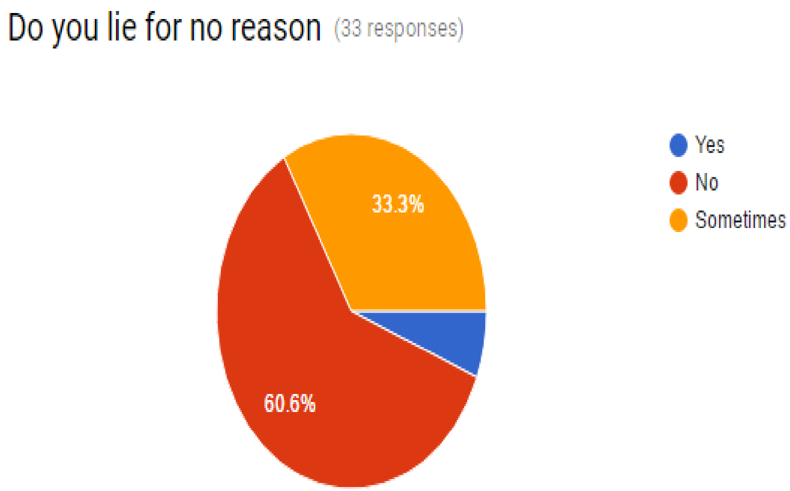

Fig 24: Visualisation of how often do you lie

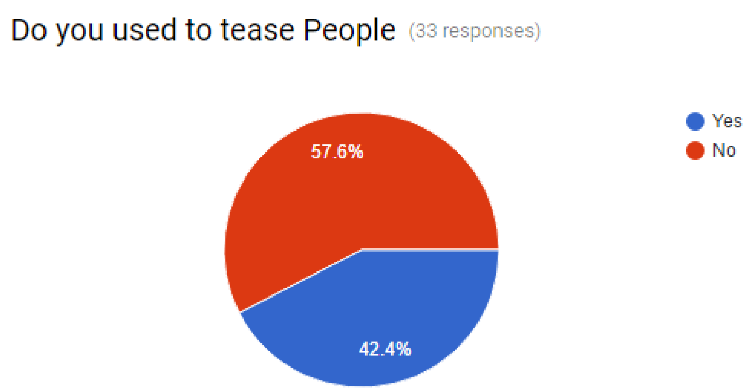

Fig 25: Visualisation of how often you tease

4. CONCLUSION

Finally, access to real-time information about student progress empowers students and educators to make timely adjustments to their studying and instructional practices. Properly used, mindfully implemented, and with appropriate privacy protections, student data is a tremendous resource to help schools fulfill the great promise of providing quality education for all.

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