

Analytics Dashboard on Talent search Examination Data using Structure of Intellect Model

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The potential of Analytics and Data mining methodologies, that extract useful and actionable information from large data-sets, has transformed one field of scientific inquiry after another. Analytics has been widely applied in Business Organizations as Business Analytics and when applied to education, these methodologies are referred to as Learning Analytics and Educational Data mining. Learning Analytics proposes to collect, measure and analyze data in learning environments to improve teaching and learning process. Educational Data mining (EDM) thrives on existing data collected by learning management systems. The applicability of Learning Analytics and Educational Data mining can be extended to traditional learning processes by suitably combining data collected from technology enabled processes such as Admission and Assessment with data generated from analysis of learning interactions. The intellectual performance of the students can be analyzed using some well known Learning Frameworks. This paper demonstrates the Complete Analytics process from data collection, measurement to Analysis using Guilford's structure of intellect model. An analytic dashboard provides the necessary information in concise and visual form and in an interactive mode. The analytic process presented on talent examination data can be generalized to similar examinations in traditional educational setup.

Keywords: Dashboard, Educational Data Mining, Learning Analytics, Structure of Intellect model.

1. INTRODUCTION

Learning Analytics(LA) tends to focus on understanding and optimizing learning by discovering patterns in data that tells what is learnt and applying techniques for predicting what should be learnt next, to take appropriate actions (Patwa, Seetharaman, Sreekumar, and Phani, 2018) (Leitner, Ebner, and Ebner, 2019). Educational Data Mining(EDM) is primarily applied to on-line learning systems, where the data collection, about the learner's behavior as also the presented content, can be automated (Hung, Rice, and Saba, 2012) (Mining, 2012). It is essential to expand the applicability of LA and EDM to a wider set of learning processes occurring in traditional setup. An assessment is also a type of learning interaction in which the learners showcase their learning abilities and the examiners assess them. The teaching and learning as well as the examination process can be improved by using the knowledge extracted from the analysis of examination data (Liñán and Pérez, 2015) (Khalil and Elkhider, 2016).

Talent search examination aims at identifying students with intellectual abilities so that they can be nurtured further by providing academic and financial support. One cannot measure intelligence but can measure intellectual performance that is, how one uses his/her intelligence to

adapt to the environment. The mental and scholastic abilities can be assessed using well-designed examination process. Usually such tests are objective and cover a wide range of topics followed by interview process.

Talented students are not challenged enough by the existing school curriculum. Considering the inadequacy of current examination system, the Centre for Talent Search and Excellence, N. Wadia College, Pune has taken the challenge of identifying and motivating Talented Students through "Maharashtra Talent Search Examination" since 1992.

The aim of this Talent search exam is

- (1) To identify the students with learning potential,
- (2) To prepare the students for NTS or other competitive examinations and to inspire them to excel in each examination from an early age,
- (3) To motivate students by awarding scholarships.

Intellectual performance can be measured as a multidimensional construct to assess different types of intellectual abilities. Guilford designed his Structure of Intellect (SOI) model (Guilford, 1982), where various intellectual abilities are organised along three dimensions of content, process and product. Along each dimension there are subcategories which present different abilities required for intellectual functioning. In this study, Talent search test is considered as a learning interaction allowing the candidate to demonstrate his/her intellectual abilities and the examiner to pose each question so that these abilities can be measured. The questionnaire content is then classified based on SOI model so that student performance can be analysed along various dimensions. An Analytics dashboard provides analysis in an interactive mode and can be effectively used by decision maker.

The study taken up in this paper

- Presents a complete Analytic process for a traditional teaching and learning setup,
- Demonstrates the use of a Learning model such as Structure of intellectual Model (SOI) in measuring and comparing scholastic abilities,
- Explores the varied ways in which analytics can be used by decision makers to improve the teaching and learning as well as assessment process.

The paper is organized as follows. Next section presents Background and related work. Section 3 describes the complete Analytics process for traditional teaching and learning environment including structure of Intellect model as chosen Learning framework. Section 4 provides the experimental analysis, including the design of Analytics dash board, followed by conclusion.

2. BACKGROUND AND RELATED WORK

2.1 Learning Analytics and Educational Data Mining

The objective of Learning Analytics(LA) is to design effective and efficient educational model to support all the needs of the educational stakeholders by collecting and analyzing educational data and providing actionable reports. The inferences of LA are used in many ways. It is used by recommendatory systems for prediction, learning pattern identification, relationship mining (Avella, Kebritchi, Nunn, and Kanai, 2016). It is used for reporting student's learning curve, student's learning pattern. Teachers use it to support decision making on their teaching learning process (Iandoli, Quinto, De Liddo, and Shum, 2014). Learning analytics focuses on tracking learning activities and the context in which these activities occur (Verbert, Govaerts, Duval, Santos, Van Assche, Parra, and Klerkx, 2014). The learning traces can be used by intelligent tutoring systems, recommenders or adaptive systems. Alternatively, the reporting of learning traces to

stakeholders is through Learning dashboards (LD) (Bodily and Verbert, 2017). Educational Data Mining (EDM) provides technological support to LA by designing new computational methods of analysing big data that is generated by technology-mediated educational processes (Siemens and Baker, 2012) (Brouns, Zorrilla Pantaleón, Álvarez Saiz, Solana-González, Cobo Ortega, Rocha Blanco, Collantes Viaña, Rodríguez Hoyos, De Lima Silva, Marta-Lazo, et al., 2015). Data generated through on-line learning systems and student social-media interactions are big in the sense of volume, velocity and variety requiring non-traditional ways of analysis (Daniel, 2015).

2.2 Learning Dashboards

Learning dashboards aggregate in a single page multiple visual representations of several indicators about the learners, learning processes and the environment in which learning takes place (Schwendimann, Rodriguez-Triana, Vozniuk, Prieto, Boroujeni, Holzer, Gillet, and Dillenbourg, 2016). They mainly thrive on continuous data collection in the form of logs by technology-driven learning processes such as Learning Management Systems(LMS) and Massive Open On-line Courses (MOOCs). Student performance and demographic data can be used by a learning dashboard to facilitate a student-Adviser dialogue as demonstrated by LISSA (Charleer, Moere, Klerkx, Verbert, and De Laet, 2017). Analytics helps students control their learning by giving them a quick insight into their present performance and thus make better study-related choices. Learning dashboards have emerged as an excellent instrument that teachers can use to assess their pedagogical actions (Molenaar and Knoop-van Campen, 2018). The learning process is strongly connected to learning science which contemplates on how knowledge is acquired and applied, therefore learning frameworks or models based on learning science concepts need to be considered in designing of LD (Jivet, Scheffel, Specht, and Drachsler, 2018).

3. ANALYTIC PROCESS FOR TRADITIONAL SETUP

Learning Analytics(LA) need to be extended to the teaching and learning processes in traditional setup. In a traditional teaching and learning environment, teaching is through direct teacher-learner interaction and thus no data related to such interaction gets collected (Khalil and Elkhider, 2016). Analytics can be applied on data collected by technology enabled processes such as Admission and Assessment (Vaidya, Munde, and Shirwaikar, 2020).

3.1 Multi-step Analytics process

In an examination, learners demonstrate their intellectual abilities which reflect in their performance and the examiners design assessment tool so that each of these qualities can be identified and measured. Learning Models or taxonomies support instructional as well as assessment design. The Analysis of student performance along with that of assessment tool can be used to understand and measure the learning outcomes (Mangaroska and Giannakos, 2018). In this study, we propose a complete Analytic process that can be applied to the examination as a learning interaction (Talib, Alomary, and Alwadi, 2018).

The process is divided into 5 steps as described in Table 1 each of which will be demonstrated.

3.1.1 Data Selection. Learning Analytics requires data about the learners and the learning interaction. Examination is a learning interaction where the performance data indicate the learning state of the student. In an objective test , the performance data is available at lower level of granularity that is at each question level. In this study, available Talent search test data is used as shown in Table 2. Talent search examination is held to assess scholastic abilities of students so that they can be further nurtured by providing financial and training support. The tests are held for three different levels of students that is standard VIII, IX and X. The personal

1. **Data Selection** - Choosing appropriate Admission and examination data that can support Analytics
2. **Choosing Learning Frameworks** - Selecting one or more Learning Frameworks/model that is well established and understanding its applicability
3. **Data Preparation** - Generate data by applying learning framework to the learning instrument such as Question paper
4. **Design Analytics** - Find different ways of analysing data that can help improve the learning process
5. **Design and Implementation of an Analytics Dashboard** - Make available an Analytics dashboard that can be used by the stakeholders

Table I: Multi-step Analytics Process

information about the learner such as name, class, gender as well as his locality information such as school, district etc.. is collected as part of the registration process. The performance data in each of the 200 questions by each student is available.

Sr No	Year	Number of Students	Size of csv file
1	2011	118712	40.4 MB
2	2012	107453	36.6 MB
3	2013	96100	32.8MB
4	2014	105423	36.1MB
5	2015	106795	36.5 MB

Table II: Data-set used for Analysis

3.2 Choosing Learning Frameworks

It is challenging to understand how the learning happens and many researchers have presented varied learning models, defined various taxonomies for instructional design and designed different frameworks that explain intellectual processing (Khalil and Elkhider, 2016) (Bakharia, Corrin, De Barba, Kennedy, Gašević, Mulder, Williams, Dawson, and Lockyer, 2016) (Greller, Santally, Boojhawon, Rajabalee, and Kevin, 2017). The structure of Intellect model was proposed by J. P. Guilford, as multiple Intelligence theory can be used for assessing learning disabilities as also scholastic abilities (Guilford, Hoepfner, et al., 1971). Meeker's studies has demonstrated the potential of SOI in the field of education and that intellectual abilities can be both identified and improved (Meeker, 1969). Structure of intellect model has several limitations and is heavily criticized but still remains a well established tool for analysing intelligence or intellectual abilities (Sternberg and Grigorenko, 2001). Once the learning model is finalised, it need to be applied to the assessment tool that is Question papers and appropriate data need to be prepared. This requires a complete understanding of the chosen model.

3.3 Structure of Intellect Model

Guilford's structure of intellect model (Guilford, 1982) evolved out of his efforts at developing tests for selecting pilots. Guilford isolated different factors of thinking and organized intellectual abilities along the three dimensions. of Content, Process and Product (Guilford, 1980).

3.3.1 Content. Content relates to ability to process different types of information. The information is categorized into five types but only three types will be applicable to written test while the other two may be applicable to oral assessment.

Visual/Figural - indicate the content that can be perceived through seeing . This include ability to recognize colors, different shapes such as circles, rectangles, polygons, textures such as filled unfilled regions.

Symbolic - content can be recognized by the ability to associate the defined meaning with the

symbol. This include numbers from 0 to 9 , letters of the alphabet, special symbols with attached meaning such as \$, π , ? etc. and designs such as arrows indicating direction.

Semantic / Word - content can be recognized by knowing the literary meaning of words and also the concepts, ideas presented using words or word phrases.

Auditory - content need to be perceived through hearing that is by understanding the variations in the sound.

Behavioural - content need to be recognized by actions and expressions of people.

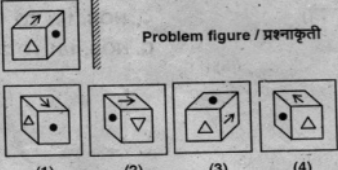
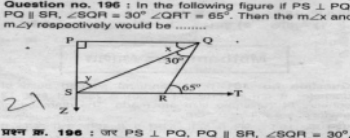
<p>Question no. 119 : Which of the following equation is balanced ? प्रश्न क्र. 119 : पुढीलपैकी कोणते समीकरण संतुलित आहे ?</p> <p>1) $\text{Na}_2\text{CO}_3 + \text{HCl} \rightarrow \text{NaCl} + \text{H}_2\text{CO}_3$ 2) $\text{Na}_2\text{CO}_3 + 2\text{HCl} \rightarrow 2\text{NaCl} + \text{H}_2\text{O} + \text{CO}_2 \uparrow$ 3) $\text{Na}_2\text{CO}_3 + 2\text{HCl} \rightarrow \text{NaCl} + \text{H}_2\text{O} + \text{CO}_2 \uparrow$ 4) $2\text{Na}_2\text{CO}_3 + 2\text{HCl} \rightarrow 2\text{NaCl} + \text{H}_2\text{O} + \text{CO}_2 \uparrow$</p> <p>a) Semantic & Symbolic</p>	<p>5. </p> <p>Problem figure / प्रश्नाकृती</p> <p>b) Symbolic & Visual</p>
<p>Question no. 196 : In the following figure if PS ⊥ PQ, PQ ∥ SR, ∠SQR = 30°, ∠QRT = 65°. Then the m∠x and m∠y respectively would be</p>  <p>प्रश्न क्र. 196 : जर PS ⊥ PQ, PQ ∥ SR, ∠SQR = 30°, ∠QRT = 65° तर m∠x आणि m∠y अनुक्रमे असेल.</p> <p>1) 65°, 35° 2) 45°, 45° 3) 35°, 55° 4) 60°, 30°</p> <p>c) Visual Symbolic & word</p>	<p>Question nos. 23 to 26 : It is decided that Hindi, Gujarati, Marathi, Tamil, English and Punjabi films will be screened daily one show from Monday in a week.</p> <p>i) There will be a holiday in the middle of the week and English film will be shown on the next day. ii) There will be Punjabi show on Saturday and Gujarati show will be immediately after Hindi film. iii) There will be no Tamil show on the first day or on the last day of the week. iv) On the fourth day after Tamil film, there will be Marathi film.</p> <p>23. On which day will there be Hindi film? 1) Sunday 2) Monday 3) Wednesday 4) Saturday</p> <p>d) word</p>
<p>1. ZWU, TQO, NKI, ? 1) GDA 2) HEC 3) HDB 4) GEC</p> <p>e) Symbolic</p>	

Figure 1. Marking questions based on content type.

In a subjective test, types of information (content types) of question could be different from that of the answer for example student may have to write a note describing a scene, in which case question content type is Visual while that of the answer is semantic. In an objective test, answer is provided as part of question and thus the content type the student has to deal with can be easily specified. The following figure shows how the different questions in talent search examination can be tagged to having visual, symbolic or semantic content. In Figure 1, different questions are tagged according to their content type, in most cases partly the content is of one type and partly that of other.

3.3.2 Product. The product dimension relates to kind of content processed and Operations/ processes dimension relates to different processes applied to kind of content. The product can be both an input as also the output of a mental process. Product dimension is further categorized into six types.

Units – represents single unit of information. The units are of specific content type. Visual unit could be shapes, symbolic units could be numbers, semantic units could be words, behavioral units could be facial expressions. The mental processes can be applied at unit level.

Classes – represent a set of items that share an attribute. The ability to form groups from units, or select the right group.

Relation – represents relationships, connection between pair of items which could be ordering between items, opposites, analogies etc..

Systems – relates to relationships or interconnectedness of more than two items with interacting parts.

Transformations -is the ability to grasp modifications in information, such as rotation of visual

figures, changes in the semantics when words are used in particular context.

Implications- refers to relation between two sets of informations. One can expect certain information to be true once the validity of other information is known.

3.3.3 *Process.* Process or operations is further categorised into six types out of which only four are applicable to objective tests.

Cognition - relates to recognising or discovering the kind and type of information. Shapes, Symbols can be recognised. Cognition is assimilating and integrating knowledge. Cognition process uses existing knowledge to generate new knowledge. Cognition can be improved by training and repeatedly doing the activity so that you do it with ease when required. You can recognise commonly used symbols with ease without straining your memory. (Schunk, 2012) (Fueller, Loescher, and Indefrey, 2013) .

Memory retention – Storing the information (content) in memory so that it can be processed in memory specifically during a oral test. This is not required in case of written test.

Memory Recall – Recalling higher order concepts formulas which are retained in memory over a period.

Divergent production – Divergent thinking is the ability to solve a problem in multiple ways, which can be very well demonstrated in an open ended test but not applicable to close ended(objective) test. Fluency, Flexibility, creativity are some of the outcomes of divergent thinking.

Convergent production – Convergent thinking gives the ability to find the best answer to the given problem. The ability to use variety of facts and arrive at a correct answer. The facts act like constraints reducing number of possibilities leading to one right answer. In mathematical problems convergent production may include operations such as addition, subtraction that help in arriving at the correct answer.

Evaluation - is the ability to make judgements about the various kinds of information. It helps in identifying identical or similar items, comparing items , finding better items, selecting qualities that are shared by various items. In objective tests since options are available they can be evaluated.

Considering that all the dimensions in the structure of intellect are not mutually exclusive the three main components combine to give in all $3 \times 4 \times 6 = 72$ possible dimensions as shown in Figure 2.

After understanding the SOI model it is applied so that each question can be appropriately tagged as requiring a particular intellectual ability (Guilford et al., 1971). Each question can be marked to have one or more among the thirteen qualities as shown in Figure 2.

4. EXPERIMENTAL ANALYSIS

The experimental analysis can be carried out with the help of a tool that supports both statistical analysis, data mining and with good visual capabilities. R is open source environment that is extendable with lots of packages supporting various analytical tasks (Crawley, 2012) (Matloff, 2011). R shiny package can be used to quickly design an analytical dashboard. The experiment Analysis can be both Student performance analysis as also Question paper analysis. Student performance can be analyzed at individual level as also along the different demographic groups (Hasan, Palaniappan, Mahmood, Abbas, Sarker, and Sattar, 2020) (Ryan, 2014).

4.1 Student Performance Analysis using SOI

The available datasets contains for every student the demographic information as well ticks for 200 questions. The question paper is analyzed and tagged using the Meeker [1969] SOI dimensions. Using the Question paper key the performance score in each dimension can be computed and presented as in Figure 3. The ability scores of a student can be presented alongwith average

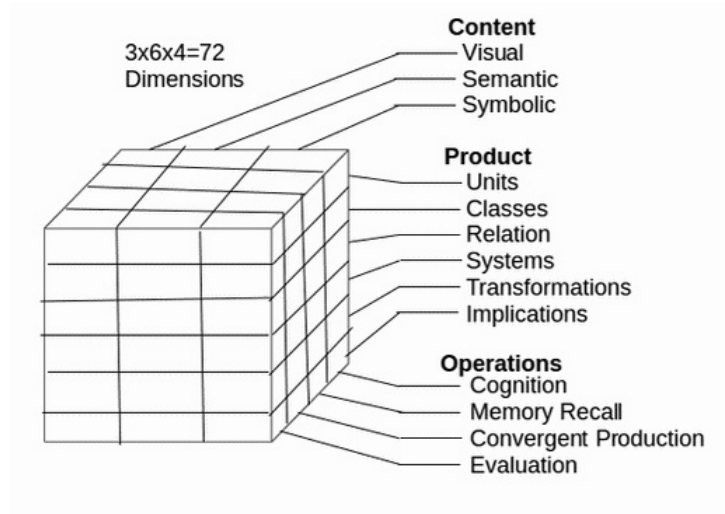
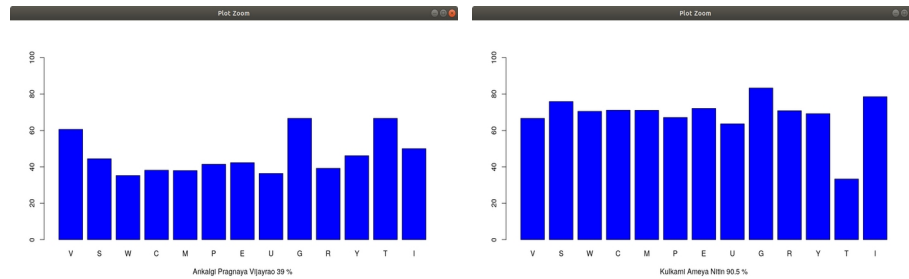


Figure 2. Structure of Intellect Model



(a) The performance of below average student (b) The performance of high scoring student

Figure 3 : Performance along 13 SOI dimensions

performance of the school and also the district to which the student belongs as in Figure 4.

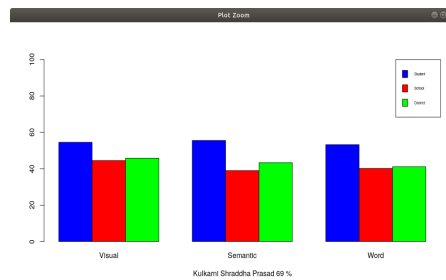
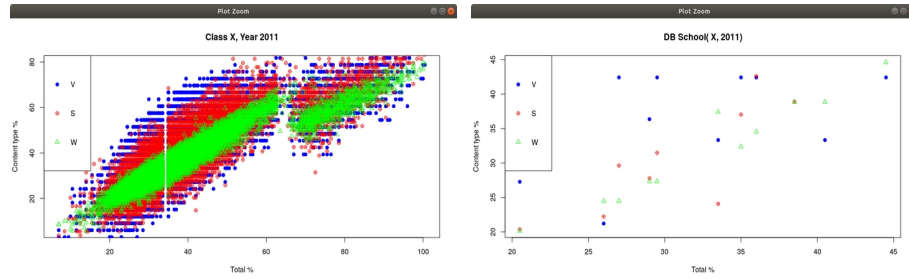


Figure 4. Comparative plot for content types

4.2 Schoolwise, Genderwise Performance Analysis

The performance in terms of total marks obtained can be plotted against the performance scores in each content type. The semantic(word) ability has an almost linear relationship with the total.

The Genderwise performance in the year 2011 for three content types is shown in Figure 6.



(a) Three content types against Final total for whole class (b) Three content types against Final total for a school

Figure 5: Relation of content types to Total score

Similar analysis can be carried out for the different abilities in Process and Product dimension .

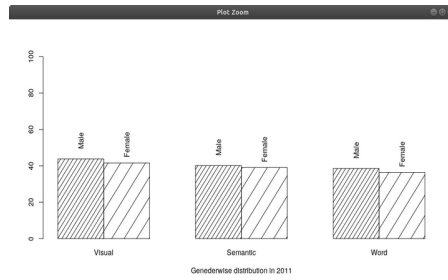
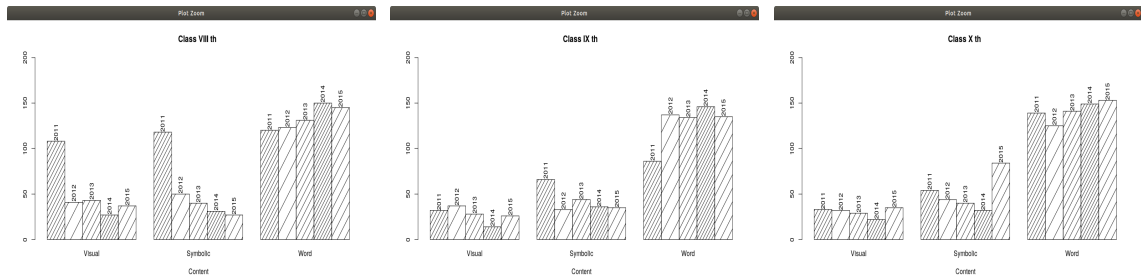


Figure 6. Genderwise performance of different Content types

4.3 Question Paper Analysis

The dataset contained Question papers for three levels of students of VIII, IX and X, for five years that is 2011 to 2015. For all the 15 question papers, each of the 200 questions were tagged according to the SOI model. For the content dimension the distribution along the three sub dimensions year wise is presented for each batch in Figure 7.



(a) Content distribution for class VIII (b) Content distribution for class IX (c) Content distribution for class X

Figure 7: Content distribution yearwise for each batch

4.4 Analytics Dashboard

A dashboard helps in reporting of analytics directly to stakeholders usually in a visual form thus supporting learners, teachers and authorities in taking right actions. A learning Analytics dashboard presents different indicators about learners, learning instrument and learning outcomes in the form of visual reports that can help in improving learning instrument as well as the learning process depending on learners and the context.

Shiny R package helps in quickly implementing a dashboard as shown in figure 8. A student can be selected after selecting an year and a batch, and whole lot of information about student performance is presented at a detailed level by using different learning frame works.

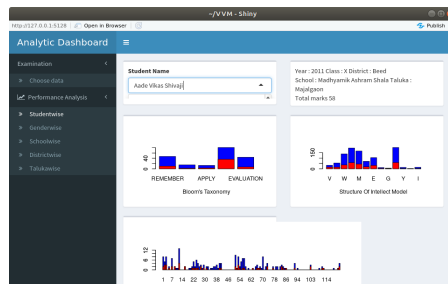


Figure 8. A Learning Analytics Dashboard

5. CONCLUSION AND FUTURE WORK

The paper presents the complete Analytics process that can be applied to an available examination dataset. Guilford's Structure of Intellect Model is used as a Learning framework and it has its own set of critics and followers. Alternatively the most popular Bloom's taxonomy can be used. The multistep process defines clearly the steps to bring in learning Analytics in traditional teaching and learning setup by using student performance and demographic data that is collected by technology enabled Assessment and Admission process. There are well designed Learning frameworks in literature and this study demonstrates use of one such Learning framework. The learning dashboard can include indicators from multiple learning frameworks depending on the requirements of stackholders.

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