

## Assessment Analytic Theoretical Framework Based on Learners' Continuous Learning Improvement

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### ABSTRACT

Currently, university students are required to follow stringent curriculum structure regardless of their performance. Personalized learning is not being offered resulting the whole cohort must comply to a customized fixed curriculum design. This is because the designed curriculum does not take into account different students' attainment. Furthermore, there is a mismatched between supply and demand of graduates' skill sets to fulfil the requirement of industry. Due to these issues, employers face difficulties in finding suitable high-skilled worker which contributes to large number of unemployed graduates. Thus, a systematic intervention of students' learning process is essential to construct informed and strategic responses in order to manage challenges and minimize skill mismatch, at the same time providing adequate fundamental knowledge. In this paper, an assessment analytics framework is proposed based on automated extracted skill sets from curriculum documents and individual performance to recommend adaptive learners' learning system (ALLS). By preparing the graduates with the required industry skill sets, the graduates' unemployment rate is envisaged to reduce.

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## 1. INTRODUCTION

Fourth Industrial Revolution (IR 4.0) is about the discovery of new technologies, including automation, analytics and big data, simulations, system integration, robotic usage, clouds, and Internet of Things (IoT). Such evolution utilizes ICT as a key enabling technology to accelerate and improve productivity including in lifelong learning. Lifelong learning is essential in handling inevitable constant changes to equip learners with voluntary and self-motivated knowledge acquisition. The European Commission stated that lifelong learning offers individual development, active citizenship, social inclusion and intensify employability opportunities [16]. It can also increase individual competitiveness and improve conflicts negotiation. The European Commission also reported that lifelong learning emphasizes the centrality of the learner, the importance of equal opportunities and the quality and relevance of learning opportunities.

However, the common practice in many universities world-wide is that the students are required to follow stringent curriculum structure based on his/her selected program. The students have limited options in charting their own preference and need to follow the same curriculum cohort regardless of their performance on the pre-requisite subjects. Personalized learning that allows student to choose subjects that they want to

take at their own preferred time is not being currently offered to the student. This is because the university management tries to simplify and standardizing learning for operational purposes. Typically, a cohort curriculum is designed by the curriculum developer without taking into account different learners' competencies of the same pace [1]. Such scenario, makes the slower pace learners struggle to cope with the contents delivered by the instructors/lecturers. Hence, by being able to identify areas for targeted intervention at each level of achievement, it has the potential to benefit the students [2].

To complicate matters, a mismatched between supply and demand of graduates' skill sets to fulfil the requirement of industry is observed [3]. This mismatch is only expected to get tougher to be resolved as technological disruptions reshape industries and alter the types of jobs available. According to [4], 39% of employers experienced difficulties to find labour for high-skilled vacancies. Such statistic is supported with [5] report that currently there is about 22.7% of 2016 graduates in Malaysia who are still unemployed even after 6 months of graduation. This is due to the graduates' skills sets that are not in accordance to the industrial requirements. Thus, the systematic anticipation of skills needs is essential to construct informed and strategic responses in order to manage challenges and prevent skill mismatch [6].

Martin and Ndoye [7] propose a learner-centered assessments that shift the move from grades, marks and credits to learning, outcomes, and graduating with the skills needed as a professional. Such approach is very much in line with other researchers' findings that assessment is fundamentally important to students and it is widely recognised to motivate learning [8]. Boud [8] mentioned that assessment gives indicator to learners about the amount of content the learners should learn and verify the learning technique suitability. For instance, if the result of the assessment is good, it can be hypothesized that the learners understood the content with relevant learning technique. Hence, assessment results offer the potential for students to measure attainment across time, in comparison to their starting point to their peers, and/or against benchmarks or standards.

In this paper, assessment analytics framework is proposed to provide the input to the continuous learner improvement in lifelong learning. The relevant concepts are discussed in Section 2. The research methodology consist in this work is outlined in Section 3. The development of assessment analytics theoretical framework is also provided. Subsequently, this paper concludes with summary and discussion of future work.

## 2. LITERATURE REVIEW

Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, in which learning takes place [9], [10]. Usually the implementation will use analytic tools to improve learning and education [11]. In HE institution, there are 3 major roles that will be benefited by implementing the learning analytics. The administrative will gain competitive advantage, improve quality assurance, and value of learning experience. For educators, it can help them to further plan their teaching activities. For learners, receiving information about their performance will help them to reflect and optimize their learning experiences. Learning analytics cannot stand alone as it is an emergence from various fields such as business intelligence, web analytics, educational data mining, action analytics, academic analytics and latest, assessment analytics [12].

Figure 1 illustrates the correlation between Learning Analytics, Big Data Analytics and IR 4.0. The disruptive technology empowers the IR components to be utilized and such changes affect the way the learners' accessibility to learning content. The high volume of information that can be propagated in high velocity spoil the learners' choice for a choice of learning contents. These vast amounts of information from various sources and composition makes up "big data" in education industry [13]. Big data analytics, specifically through learning analytics in education context take advantage of the explosion in data to extract insights for making better informed decisions.

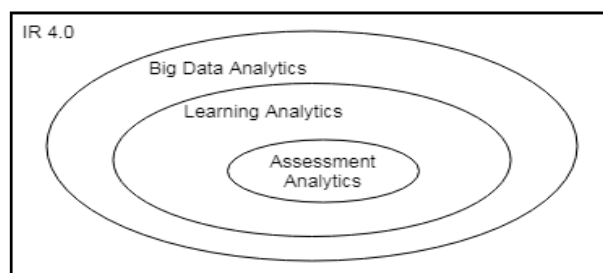


Figure 1. Assessment Analytics Overview

Part of learning analytics that is focusing on the real time assessment analysis is known as assessment analytics. The field is currently underdeveloped and underexplored [2]. The assessment data include, but are not limited to: completed degree attainment, progression results, module results, individual assessment results, achievement mapped against explicit learning outcomes and specific strengths and weaknesses within an individual student's work. The traditional assessment procedure precisely measures the usefulness of the curriculum. However, these assessments only occurred at the end of the course or program to the extent that the students may not receive any feedback on their performance during the course [14]. Analysis at the end of the course might be too late for the institution to improve students' learning [15]. Evaluating the learning process by using assessment analytics might help the HE institutions to make immediate changes or provide intervention procedures when needed. Assessment is fundamentally important to students because it able to motivate them to learn [16]–[18]. Higher Education (HE) institutions are continuously seeking improvement of assessment practices as it is a fundamental student learning support tool to know on what, how and when students study and learn [19]. Achievements of students in given assessments reflect the level of skills and knowledge that they manage to capture [20].

Set of skills and knowledge that are offered by each course can be identified from the course information and description. However, doing the process manually may be cumbersome and time consuming due to huge number of documents that need to be analyzed. Knowledge extraction technique might help to ease the process by automatically analyze the documents. Extracting knowledge from text document has been a long-standing goal of Natural Language Processing and Artificial Intelligence. It is mainly used in medical fields in analyzing clinical narrative [21]–[25], This technique is based on traditional natural language techniques, statistical analysis, and machine learning [26]. The resulting knowledge is in machine-interpretable format that facilitates inferencing and querying [27] which can be used for identifying skills gap between industry required skills set and students obtained skill sets.

### 3. METHODOLOGY AND THEORETICAL FRAMEWORK

There are 6 phases in the assessment analytics model which are Research Planning, Literature Review and Analysis, Develop Theretical Model, Case Study Implementation, Evaluate Relevance of Model and Report Writing and Documentation as shown in Figure 2.

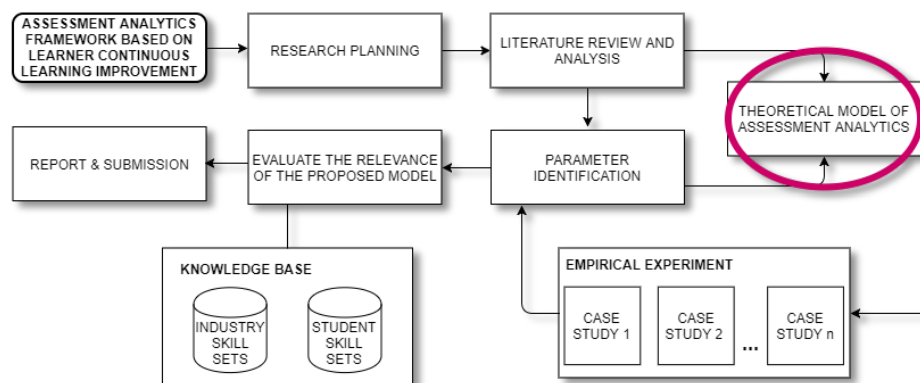


Figure 2. Phases in Research Methodology

For research planning, the activities to perform are fine tuning the research background, planning the timeline of the research, research budget and others basic groundwork. At the end of this phase, a clear problem and objectives are outlined. Then, in the second phase, literature reviews on learning analytics, assessment analytics and related concepts were identified. Furthermore, university's curriculum structure documents are also analyzed to get the idea on how the higher education specifically in Malaysia is strategized to engage the learning process of students. In Malaysia, Ministry of Higher Education (MOHE) through Malaysian Education Development Plan (2015-2025) implementing new integrating mechanism for assessing and reporting students' development and performance as well as learning gains of their ethics, knowledge and abilities through integrated Cumulative Grade Point Average (iCGPA).

iCGPA is an integrated mechanism for assessing and reporting of students' development and performance as well as learning gains of their ethics, knowledge and abilities. These qualities are reflected by six primary attributes: ethics and spirituality, leadership skills, national identity, language proficiency,

thinking skills, and knowledge together with eight domains of learning outcomes listed in the Malaysian Qualifications Framework. The purpose of iCGPA reporting is to assist in identifying the strength of students through the subjects taken and their result. The result will be shown in spider web representation which will clearly see the areas in which the students is lacking and has excelled in. Hence, curriculum structured documents that may be used later in this research can be iCGPA documents that had been analysed to extract required skill sets by the curriculum of the institution.

Once the first part of phase 2 is done, the theoretical framework is drafted as in Figure 3.

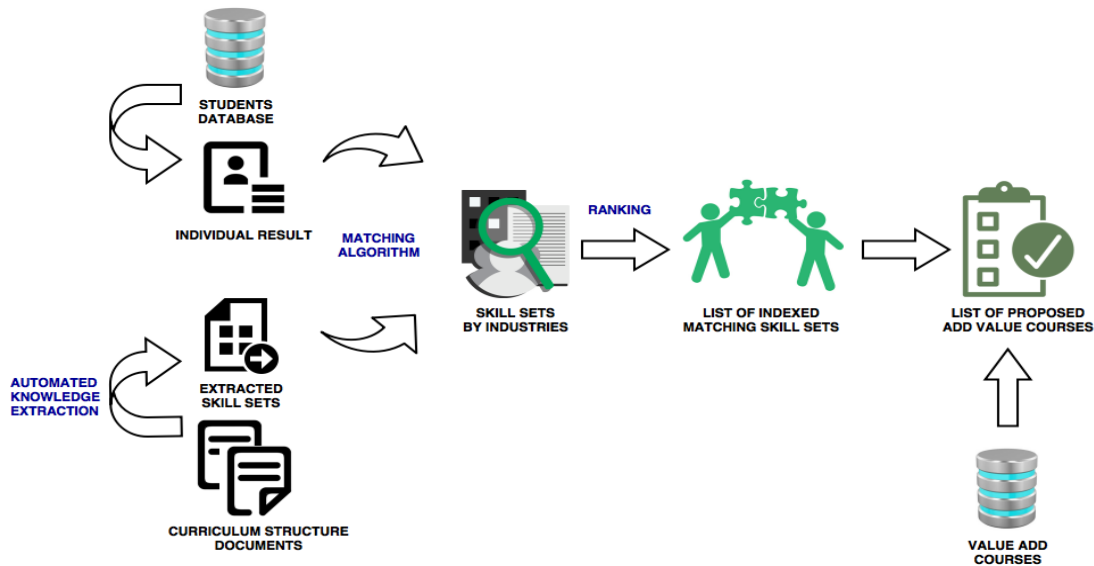


Figure 3. Proposed Theoretical Framework for Assessment Analytics Based on Learners’ Continuous Improvement

The theoretical framework will get individual student results from database. Then, from the collected curriculum structure document, an automated knowledge extraction will be done to get the extracted skill sets. Next, a matching algorithm will process the individual results and extracted skill sets in form of knowledge feature to infer with the skill sets that are coming from related industries. Once the skill sets from student and industries is matched, a ranking to list the insufficient skill sets will be shown. The recommendation of value add courses will be suggested to improve student’s skill which are extracted from value add course database.

In this paper, we present work in progress. We are currently involved in designing parts of the system which is the theoretical model. As for now, the theoretical framework is drafted, hence, literature on the suitable knowledge extraction and matching algorithm will be studied in the next phase of the whole research. Next, once the knowledge extraction and matching algorithm is studied, related works of assessment analytics will be done to complete the literature review phase. In phase 3, theoretical model will be constructed after parameters for the model is identified. Data analytics approach that is suitable for this model will be developed for general assesment analytics model. In next phase, case study implementation will be done. Curriculum structure documents will be analyzed to choose the right curriculum and value add course offered in higher education institutions. This phase also will produce an algorithm design for automatic skill sets extraction. Once this phase is done, next phase of the research will evaluate the relevance of the proposed model before documentation of the research is done in phase 6.

#### 4. CONCLUSION

This research will contribute into the development of adaptive learners’ learning systems (ALLS) that can reflect, optimize time, cost and effort to complete the relevant skill sets needed by the industry. Value add program can be added based on the system recommendation of their performance. This will strengthen their skills that they have obtained from university’s curriculum. Currently, Malaysia Education Blueprint 2015-2025 (Higher Education) planned for preparing for new challenges which will guide Malaysia through 2025 and beyond. Ministry of Higher Education (MOHE) recognises the need to keep

evolving to stay abreast with, if not ahead of global trends. The blueprint outlines 10 shifts to address key performance issues in the system, particularly with regard to quality and efficiency, as well as global trends that are disrupting the higher education landscape. The first shift is holistic, entrepreneurial and balanced graduates. The report states that there is a mismatch in the supply and demand of graduates, with employers reporting that graduates lack the requisite knowledge, skills and attitudes. This research will help in achieving this first shift by identifying the key skills and knowledge gap that need to be fulfilled by students during their study. Hence, ALLS is needed as to support the ministry's agenda in promoting digitization and computerization culture among students.

By having this analytics, most of the students will be more informed and strategic in planning their learning experiences that will help them in building their skill sets to match the industrial requirements. By having the skill set required by the industry, the unemployment rate of graduates is envisaged to be reduced. This is because the mismatch between supply and demand of students and industry's skill sets is less. This model also will lead to automation of choosing the correct value add program after the analytics part is done as per suggested in IR 4.0.

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