Insights for Academic Analytics

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Abstract

Education plays a vital role in any civilisation; improving education thus comes priority. With tons of interest shown in analytics, it has become natural for the education world to dive into academic analytics (AA), which two primary methods are educational data mining (EDM) and learning analytics (LA). EDM and LA are used to predict students in academic difficulty, allow faculty and advisers to customise their learning path, or provide guidance tailored to unique learning needs. EDM is a method for extracting useful information that could potentially affect an organisation. LA is a method of collecting, understanding data to optimise the learning experience. This project aims to identify the business requirement specification (BRS) for the Razak Faculty of Technology and Informatics (RFTI). The BRS insight will create a foundation for academic analytics implementation at RFTI. The methodology used in the project is qualitative, with the data collected from the semi-structured interview. This project's end product is the BRS insight that can be used to apply AA at RFTI.

Keywords: *Academic analytics, education data mining, learning analytics, education, business requirement specification*

1. Introduction

The ever-increasing complexity of the system causes expansion of BRS for those systems. Identifying possible mistakes at the requirement level is critical to avoiding expensive redesign at a later stage. Writing these requirements and making sure they are satisfactory is a very time-consuming procedure. Stakeholders are likely not to have the correct expertise in deciding if their demands are adequately written down.

Today, every organisation keeps showing its capabilities in handling data and using all the technology to improve market share, customer service, and business decisions. Organisations incredibly involved in commercial business have led the way in developing strategies to gather insights from the data to identify opportunities that will generally expand their businesses. On the other hand, critics worry about problems such as student privacy, the consequences of learners profiling, and test-driven teaching pedagogies [1].

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The use of data for decision-making is not new. BI methods may differentiate past patterns and trends from data and construct models that forecast future trends and patterns [1]. These techniques identify patterns within the data and afterwards create predictive models that predict what will happen. EDM and LA are two fields that are unique to the use of big data in education. EDM focuses on creating and applying techniques to facilitate data discoveries in education settings [2]. LA's goal is to customise access to education based on the needs and abilities of individual learners through behaviour such as intervention with learners at risk or providing response and educational material. Contrary, EDM aims to produce systematic and automated reactions to learners without teachers' intervention [3].

Realising the importance of Academic AA, the project attempts to identify the BRS used in applying analytics within the RFTI domain. At the current date, the implementation of EDM or LA is at the project stage; thus, this project proves it can provide clear BRS insight based on the understanding of the business requirement.

1.1 Inadequate Knowledge of Business Understanding

Data analytics will primarily focus on modelling the business, analysing the needs, and developing the solution that meets the overall top management business needs. This neglects the importance of understanding the end-user and other stakeholder requirements. In another view, if the focus is more on user requirements, it captures more "bottom-up" requirement specifications[4]. Understanding the business goals from a user and management viewpoint should be prioritised. This approach will allow a symbiotic understanding between parties in which it recognises the individual needs and the organisation's needs in general. All these needs will shape the analytics to be more precise in answering the condition of the whole business.

1.2 Business Requirement Specification

The business process is a series of related procedures or activities that collectively accomplish a business objective or goals. The business process gives us an ability to efficiently handle projects by planning, simulating, and executing precise scheduled procedures. In another view, the specification will benefit from using the business understanding process to define the specification [4]. The objective of the business requirement specification is to provide a common language for stakeholders in understanding the projects.

BRS explains the purpose of starting the project, what business solutions it offers, its motivation, its specification and implementation, and the timetable for completing the project [5]. BRS describes the nature of the project and allows everyone involved to agree on what will be accomplished and what they should anticipate from completing the project [6]. Most of the time, BRS try to answer set challenges such as:

(a) How business stakeholders can ask the right question to solve and set a proper requirement for an analytics project

(b) How stakeholder and data analytics teams can work together in solving the business problems

(c) How to choose the correct project for answering the right set of problems and prioritise based on the needs of the business.

(d) How to communicate the value of analytics to the user without burdening them

1.3 Educational Data Analytics (EDA).

The purpose of the EDA is to enable those responsible for business decisions in the academic environment to evaluate, capture, decode, report, and exchange data efficiently so that organisational, programmed, and student success and failures can be defined [7]. There are three specific analytics-domain related to educational data analytics: Educational Data Mining (EDM) and Learning Analytics (LA). A new concept of Academic Analytics (AA) has arisen in this decade, a subset of EDM and LA. The summary of these three fields has been summarised as in the Venn Diagram of Figure 1 below.

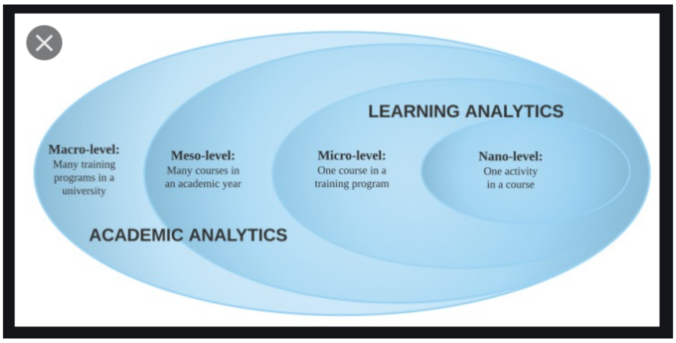

Figure 1. Venn Diagram

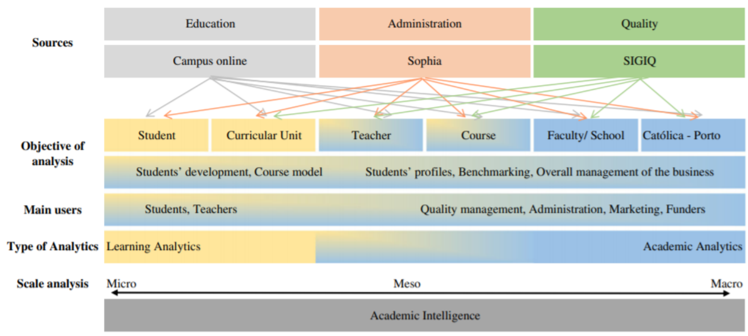

Figure 2 Architecture of the Aa with data sources of teaching activity

1.4 Academic Analytics (AA)

AA is the interrelationship of technologies, data, management culture, and information to manage the academic organisation [8]. It refers to all facets of managing an organisation of an education institution, from enrolment management to finance and human resource to student development. AA has the potential to generate actionable information to improve teaching, learning, and students' achievement [9]. Traditionally, educational systems such as course management and student response systems have provided a broad range of data to contribute to students' effort and performance. AA such as EDM and LA are used to predict students in academic difficulty, allow faculty and advisers to customise their learning path, or provide guidance tailored to unique learning needs.

1.5 Educational Data Mining (EDM)

EDM is a multidisciplinary field that enables vast quantities of data to be processed into helpful knowledge correlated to artificial intelligence, statistics, and information science. EDM's main advantage is that the service can perform all the analysis and knowledge discovery by specifying where the data file is. EDM can analyse the data produced by any system used in education and concentrate on different aspects of a person or group by taking demographic and motivational data based on hierarchy or historical data [10]. EDM can involve analysing social networks, educational psychology, cognitive psychology, and other psychometrics in education. EDM is mainly used to diagnose or visualise students' performance, outlier analysis, group students based on the specific context, and construct learning plans and predictions on academic results.

1.6 Learning Analytics (LA)

The most acknowledged definition of LA is "the use of intelligent data, learner produced data, and analysis models to discover information and social connections and predict and advise on learning" [11]. LA was first used in a formal educational setting which its main application includes tracking and predicting students' performance, including identifying potential problems or risks. LA can improve student retention by providing information concerning students to educators in real-time [12]. This real-time information helps educators to tailor their approach accordingly.

LA also helps the teacher develop they are own precise based on their knowledge[13]. In which LA will provide input to educators on the consistency of the pedagogical content, the effect of the lesson they use, or their evaluation process to ensure continuous improvement. LA also opens up an opportunity for the students to take charge of their learning, as it teaches them regarding their current success and lets them make educated decisions about what to learn [14]. Meanwhile, for the educational institution, LA helps the institution to recognise at-risk learners early.

Adejo and Connoly state that three main stakeholders have significant accountabilities in applying and utilising LA: administrators, teachers, and students[15]. The administrator plays a vital role in LA, where they are a critical pillar in implementation strategy and accountable for deciding the utilisation of LA in an educational institution. Meanwhile, teachers are the user of the LA tools, which will offer feedback and knowledge on enhancing the performance.

1.7 Benefits of EDM and LA

According to the UNESCO Institute For Information Technologies in Education, LA's benefits can be separated into three categories; macro, meso, micro [16]. Macro seeks the impact across the institution by improving data usage, which transforms the institution in terms of academic models and pedagogical approaches. While at the meso level, it enhances the decision-making process through the optimisation of resources. It also allowed the improvement of organisation productivity by providing real-time information and quick response. While at the micro-level, it quickly identifies at-risk students and provides feedback and insight on students' academic habits.

Introducing this technology also helps create a visual representation of students' knowledge and skills that are important for the educator in moulding their teaching approach. The benefits of the technology also allowed the implementation of automated interventions which are not accessible before.

2 The method

A BRS is primarily a communication method between the developer and system user and system implementors. BRS allows the user, stakeholder, and implementors to express their view on the needs according to the business goals to enable the developer to understand and create a well-balanced system. The first step is to evoke the specification from the user [5]. This can be done using interview techniques where more details can be extracted from the user. It is essential to ask the right question using layman language instead of a question full of jargon because this impacts the answer given by the user. According to Balbay, sociotechnical approaches may help improve communication by providing a more active role to the user and participating in the specification and design stage [17]. This statement also was supported by Johnson & Christenen. They believe that only interview techniques or placing the expert in the user and design team could understand the needs properly [18].

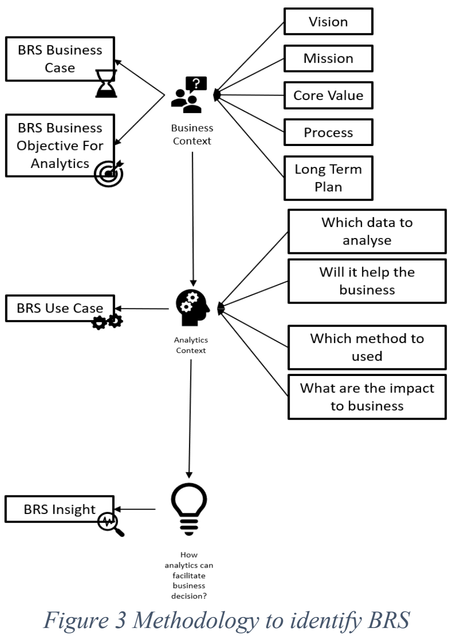

Figure 3 Methodology to identify BRS

2.1 Data Collection For Business Requirement Elicitation

Referred to Jilka Sileyew (2020), it is imperative to use a precise technique for collecting data [19]. The process of collecting data can be either primary or secondary. The preliminary data can be defined as any data collected by the researcher, such as a questionnaire, interview, and experiment. Meanwhile, secondary data could be described as data taken from literature, articles, or other materials collected by other parties. For this study, the data collection used will be primary and secondary data. The preliminary data will be focused on the semi-structured interview (SSI). The secondary data come from the literature that has been evaluated and studied to give more insight and support the theoretical and methodological part of the project.

One type of instrument will be used in the project, which is the interview. For the interview, a semi-structured interview was chosen. The best way to have a semi-structured interview is to have a set of questions that will guide the conversation into areas that need to be highlighted [20]. There is 3 type of people who may be appropriate for semi-structured interview: (1) program recipient – students, clients, customers, members (2) interested parties – contributors, suppliers, the stakeholder who are neither direct recipients nor program administrators (3) administration – staff, top managers, program board members [21]. In conducting the SSI, selecting the correct response is essential as the project's focus is BRS insight; the main stakeholder is the students, separated into two groups: top-performing and at-risk students. Each interview will be proceeding within a limit of 30minutes to 1 hour based on the agenda set.

For this project, purposive sampling for interviewers has been identified from students' perspectives. This qualitative study is based on interviews of 4 students, of which two people are at-risk students and another two people for top-performing students. All students voluntarily participated in the study. All the participants are a student of Universiti Teknologi Malaysia Kuala Lumpur and under RFTI. Each participant experienced at least two years of the study period at RFTI.

The first group, which consists of at-risk students, The students selected are part-time students who have enrolled and at least on the 5th semester of the Master of Science Business Intelligence and Analytics program. The second group of participants are top-performing students. The criteria to cluster the participant under top performing are they have at least finished the study after the 4th semester; they have obtained CGPA of 3.75 out of 4.00, students under the Master of Science Business Intelligence and Analytics program

Table 1 Sampling

Participant ID	**Category**	**Background**
PID01	At-risk Student	Student of MSc Business Intelligence and Analytics Enrolled for 5th semester under the master program
PID02	At-risk student	Student of MSc Business Intelligence and Analytics

Participant ID	Category	Background
		Enrolled for 5th semester under the master program
PID03	Top-performing student	Student of MSc Business Intelligence and Analytics Completed the master program (4th semester) CGPA is more than 3.75/4.00
PID04	Top-performing student	Student of MSc Business Intelligence and Analytics Completed the master program (4th semester) CGPA is more than 3.75/4.00

According to Braun and Clarke, thematic investigation is beneficial to identifying, analysing, and reporting themes for the data collected[22]. The data can be analysed with the thematic approach to producing an insightful analysis that answers the research question by facilitating the interview analysis. Two perspectives can be gained from the data: (1) data-driven data perspective typically used for inductive study. (2) research question perspective meanwhile function to check if the data were consistent with the research question and provide the necessary information to achieve the objective.

3 Analysis dan Findings

Based on the interview, it can be concluded that student performance is the core factor needed to focus on the faculty.

Table 2 BRS insight

Application Level	Academic Analytics Element	Criteria	Interview Observation	Insight
Learning level	Personalise learning experience	Assessment	At-risk students believe it is essential, where top-performing students thought general assessment analysis is enough	Past exam questions trend and performance (exam topic trend, course performance)
		Study resources	Analysis of resources, which highlight journals or books that related to the course and topics, will	Resource Indexing (indexing books, journal, thesis)

Application Level	Academic Analytics Element	Criteria	Interview Observation	Insight
			extend the focus of study	
		Course information	Allowed the students to choose their vital area of interest which will enhance their studies in general and their job opportunity	Student academic performance and correlation between industry needs (analysis of student performance, analysis of course need and student expectation)
	Reaction and attitude	Learning feedback	Detail's feedback is essential to allow the students to focus on their weaknesses, whereby automate is focused on notifying and giving prompt feedback	Student engagement performance (analysis of engagement level) Course performance (analysis of course performance gap)
		Student behaviour	Behaviour is not a vital analysis; instead, understanding the personality profile will be beneficial to the teaching approach	Enrolment demographic (analysis of the impact of demographic) Student personality test (analysis of student personality)

From the table above, it can be concluded that the foundation of the insight is the students' performance. This supported the study by Nguyen. At a course level, he stated that the fundamental factor impacting the course is the students' performance, which then moves into course performance and program performance [23]. Additionally, a specific type of analysis such as feedback, assessment, personality, and industry need will support the main foundation. From the figure above, it can be shown that the study only focuses on one branch of academic analytics that is student analysis. The study also focuses on the primary insight of a student's view. It neglects the lecturer's views, where their understanding might have given a beneficial thought in teaching methods, class management, and students support program, which directly impacts the students' performance.

4 Conclusion

This project report proposes and completes BRS insight for RFTI according to the business needs. The offered BRS insight will create a foundation for AA implementation at RFTI. It will also support the corporate mission and vision as per the needs of the stakeholders. Let us hope that the outcome of this project will be used for future studies in other fields. As the practical impact is concerned, the BRS insight could be used as a basis for AA development. This will direct the decision-making phase by critically setting out the goals for the project. This will also help minimise communication breakdown between the IT specialist and stakeholder and concentrate on the shared interest. It would also improve the analytical process, contributing to better strategy and more intelligent decisions in applying AA.

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