Personalised Learning Analytics: Promoting Student's Achievement and Enhancing Instructor's Intervention in Self-regulated Meaningful Learning

Muhammad Izzat Izzuddin bin Zainuddin and Hairulliza Mohamad Judi

***Abstract*—Academic monitoring is implemented at higher learning institutions to allow students and instructors to communicate academically, especially learning progress. However, the system cannot monitor student performance on an ongoing basis, such as class attendance, continuous assessment records and assignment submissions. Personalised learning analytics use student-generated data and analytical models to gather learning patterns so that instructors may advise on students' learning. Although various studies provide insight into the analytical framework of learning, attention to self-regulated meaningful learning is still insufficient. This study aims to propose a personalised learning analytics system designed by a student that unifies the self-regulated learning components: plan, monitor, and evaluate the learning commitment, and activates alert of student's achievement for close monitoring and further intervention by the instructor. For this reason, the procedure for analysing the learning pattern for experiment subjects such as Internet of Things, Data Analysis and System Management. Personalised learning analytics has been designed to deliver an interactive learning analytics environment that stimulates students to focus on the achievement of problem-solving skills and enhance the instructor's decision to support students' concern.**

***Index Terms*—Learning analytics, personalised learning, self-regulated meaningful learning.**

I. Introduction

A learning analytics system is a system that displays an analysis of the learning followed by students at various levels. In Malaysia, the learning analytics system has begun to be practised in many public and private universities. Undoubtedly, this system helps educators carry out their duties in educating students who will be the backbone of the future of this country that we love. However, in the already available facilities, a few shortcomings can also be improved.

Self-regulated learning emphasises the role of students to manage learning by setting goals, monitoring progress and implementing learning strategies to achieve the expected skills and knowledge [1]. This approach is in line with self -directed learning or student-centered learning that ensures the main functions of students in the learning process include finding and accessing learning materials, doing exercises and revision and asking questions to instructors [2]. Self-regulated learning features are also needed in an online learning environment that is widely implemented following concerns of pandemic pandemics [3].

Many learning analytics application aim for students to share their data directly with them in real-time, using visualisation methods that motivate and personalise their learning experience [4]. Personalised learning analytics aims at increasing engagement, making the facilities more active spaces for learning and teaching and bridging the gap between physical and digital spaces. The synergies between learning analytics and learning theories may contribute to the broader perspectives of learning design to encourage a future where learning is personalised and adaptive educational field [2], [5]. Among the examples involve a framework that connects learning analytics and learning design to consider how to apprehend better and systematise learning analytics data.

Integration between learning analytics and meaningful learning strategies and designs may allow instructors and learning organisations to measure the extent to which their learning instructions are comprehended via actual learning engagements and manners of students [6]. Learning analytics capture students' interactions within online learning, particularly the gap between designed and experienced learning, as there is no guarantee that students will experience learning as designed by instructors. Learning analytics deliver some insight into the whole process within the learning activities instructed for them.

More studies are required to connect learning design and learning analytics, which bridge the gap between theory and practice and offer guidance in the understanding, interpretation, and reflection on learning analytics for refinement and redesign of learning activities. Many current learning analytics systems are primarily designed to cater to academics as the target audience; and very scarce focus on students, with almost no system being established with student participation and undertaking a comprehensive evaluation [4].

This study aims to address this issue by highlighting a single student continuous involvement in the design, development and evaluation of a personalised learning analytics system. The objective of this study is to propose a personalised learning analytics application that unifies self-regulated learning. The system highlights self-regulated learning components to help students plan, monitor, and evaluate their learning commitment, and activates alert of student's achievement for close monitoring and further intervention by instructor.

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Muhammad Izzat Izzuddin bin Zainuddin and Hairulliza Mohamad Judi are with the Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor Darul Ehsan, Malaysia (e-mail: hmj.ftsm@gmail.com).

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Among the scope of the study used to meet the needs of users are:

1) Analytical learning through statistical analysis.
2) Visual learning analytics.
3) Analysis of learning through social network analysis

II. Learning Analytics in Self-regulated Learning

This section discusses the design of learning analytics in the context of self-regulated learning.

A. *Learning Analytics Design*

Today, higher education institutions use a large number of software systems to automate their activities for different user groups including students. Learning analytics is driven by the collection and analysis of footprints left by students [2]. It can help understand and optimise the learning process and the environment in which it takes place. To date, learning analysis has mostly provided feedback to users in the display of web-based learning interfaces. Such interfaces can support increased awareness and reflection of individual and peer performance, suggest additional learning activities or content, and impact learning behaviour. For example, monitoring the situation in learning activities can motivate students to achieve learning goals. This cognitive process has been defined as "self-monitoring" and "understanding how to learn".

Learning analytics is the measurement, collection, analysis, and reporting of data about students and their context to understand and optimise learning [7], [8]. Learning analytics is a fast-growing research discipline that uses insights generated from data analysis to support students and optimise learning processes and the learning environment. The use of learning analytics may enhance teaching and learning in higher learning institutions [9]. The results inform users regarding students' profile, learning activities, and learning behaviour; to help educators identify students' proficiencies, including strengths and weaknesses and decide properly to optimise students learning achievement.

Learning analytics is driven, among others, by the accessibility of huge data archives on students, the growth of the big data revolution, and economic and high-speed computing [10]. With the successful employment of analytics and the growth of online learning, the advancement of Learning Analytics to make use of student data becomes more prominent in higher learning institutions [11].

Learning analytics support self-regulated learning in many ways. The collection and analysis of footprints left by students help instructors understand and optimise the learning process and the environment in which it occurs [6]. To date, learning analytics mainly provide feedback to users on the web-based learning interface. The advance can support increased awareness and reflection and peer individual performance, suggest activities or additional learning content, and impact learning behaviour. From the perspective of Learning and Educational Technology, academic advisor has become one aspect of the academic support system that is relatively neglected, although important for students' learning process and final success [12]. A large number of higher education institutions provide moderate technical support to academic advisors with basic descriptive statistics.

B. *Self-regulated Learning Analytics*

Self-regulated learning consists of student motivational orientations. Besides instructors role, students play more important responsibility in self-regulated learning, to focus on students' ability to control their own learning journey, making them better able to cope changing needs of their roles [13]. Learning analytics enable students to track their activities and success rates during learning and be able to evaluate them from there [14]. The goal should be clear and should be achieved within a set period of time even in the context of online learning. Each goal for such learning has been crafted by the course educators to ensure that these online learning objectives are achieved.

The new structure of self-regulated learning is discussed in the New Normal Education to show the transition of learning centres to students and no longer shouldered by instructors [15]. Self-regulated learning comprises of personalised learning that aim to implement learning on the go, and suits to individual students. Planning plays an integral part in self-regulated learning that enable students to categorise learning profile through clear learning goals to accomplish their learning commitment and task [13].

The learning environment encourages freedom and flexibility that gives options to students in determining how they learn. Flexible learning utilises augmented reality, visualisation, and virtual reality to support the virtual learning environment to enhance the learning experience by manipulating students' imagination of concept using illustration and images [16], [17]. By giving students freedom to monitor their own progress in online learning, students are empowered to knowledge construction and decide if they comprehend the concept correctly and move forward with their learning tasks [18].

Learning tasks involve hands-on learning to allow students to participate in project-based learning while strengthening authentic learning that encourages students to develop learning experiences through visits and collaboration. As part of the knowledge construction process, students apply and modify suitable learning strategies such as checking current learning progress based on certain goals, organising learning resources in an intelligent learning environment, boosting their enthusiasm, and selecting the right time to pursue assistance [3].

Self-regulated learning emphasises constructive development of concepts by exposing students to data interpretation and cultivating reasoning skills. Constructive development emphasises relating meaning to the new concepts and connecting them in mental structure [19]. Meaningful learning encourages authentic learning and the application of learned concepts to the real world by providing context and application of concepts right at the beginning [20]–[22].

With proper attention to each individual student and their background, individual valuation takes place by conducting students assessment differently based on their skills. Such environment requires progress data from learning analytics to create a conducive environment for emotional construction and social interaction [23], propose learning strategies appropriate to student preferences [24] and be able to monitor learning pattern for individual students [7].

The goal achievement theory conceptualises two types of student motivation orientation in self-directed learning [25]. First, mastery focuses on developing personal competence and aims to obtain an immediate individual learning goal. Second, performance, which focuses on demonstrating competence over others, works externally among peers. Learning interventions usually consist of early warning systems that track students' progress to identify whether they are at risk [3]. The traditional approach suggests course instructors look at the information provided by the early warning system and act accordingly. Self-regulated learning uses performance benchmarks to help students keep track of their progress compared to their peers [23], such as to answer whether they are participating actively in the course, their potential to succeed in the course, and adherence to the learning schedule.

III. Method

Agile Methodology has been chosen due to its flexibility and adaptability as a guide for the design and development of the system. This methodology has six phases. The planning phase identifies the pertinent features of the system. Needs analysis phase gathers user and learning information to identify system requirements. The design phase details the system strategy based on identified needs. Fig. 1 outlines the system architecture. The development phase produces a prototype of the system. The test phase executes assessment to the completed system to ensure the product achieves its objectives. The utilisation phase adopts the system and fixes any problems.

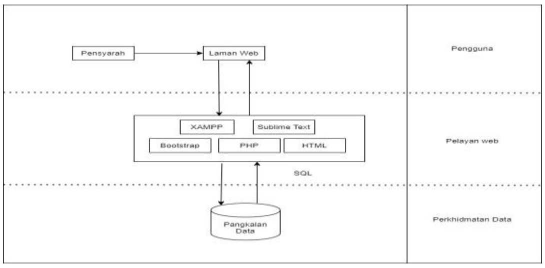

Fig. 1. Module architecture.

IV. Personalized Learning Analytics

In the intended self-regulated learning environment, learning analytics facilitate students' adoption of self-directed learning. The proposed platform presents a set of visualised metrics that students and educators could filter to monitor their progress compared to their cohort. Fig. 2 shows the user entry implementation of the proposed system. The orientation of student records is based on the course offered by the faculty.

The system intends to inform users regarding students' profile, learning activities, and learning behaviour. Such interfaces can support increased awareness and reflection of individual and peer performance, suggest additional learning activities or content, and impact learning behaviour. For example, monitoring the situation in learning activities can motivate students to achieve learning goals. This cognitive process has been defined as "self-monitoring" and "understanding how to learn. Fig. 3 displays student profiles, while Fig. 4-5 monitor and plan class assessments.

Fig. 2. Login activities.

The instructor or course advisor monitoring module aims to help educators identify students' proficiencies, including strengths and weaknesses and decide properly to optimise students learning achievement. Fig. 6 displays academic monitoring to assist students. Alarm indication alerts instructors to pay more attention to problematic issues. Commitment to class attendance, submission of assignments, and continuous assessment scores give more insight into students' progress. The system activates alerts of students' achievements for close monitoring and further intervention by instructor.

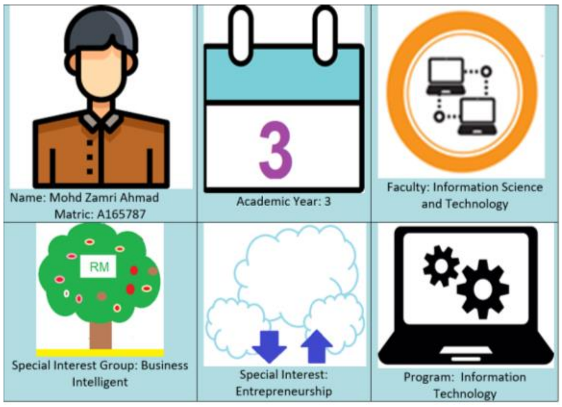

Fig. 3. Student profile.

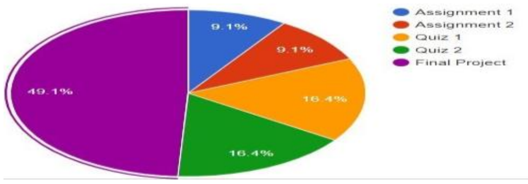

Fig. 4. Individual assessment scores.

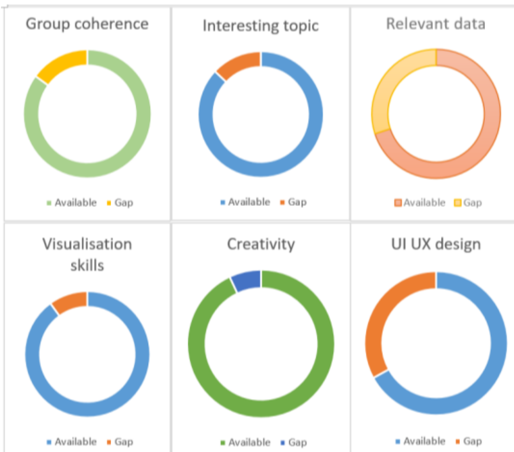

Fig. 5. Project plan based on a rubric.

Fig. 6. Academic monitoring.

Testing on the system verifies that every part and function of the system operates appropriately without errors and is presented on instructors' actions. Test on the overall functional requirements aims to meet all user requirements, while test on non-functional requirements assesses the usability component.

Each function is tested by entering the appropriate inputs, validating the output, and comparing the expected results. This test is made to test the level of efficiency and effectiveness of the system in checking and providing feedback to users if the information or input entered by users is incomplete or does not match the type of information that has been set in this system.

V. Discussion and Conclusions

Instructors and academic advisors have become one aspect of the educational support system that is relatively neglected, especially in online learning of the New Normal Era, although important for the learning process and the final success of students [12]. A large number of higher education institutions provide moderate technical support to academic advisors with basic descriptive statistics. Still, learning analytics can do more to enhance action and initiate learning intervention to support problematic students. Learning analytics support better quality decisions and provide evidence to understand current situations better and address individual students' learning problems [23], [26].

Learning intervention as part of learning analytics suggestion works better if students voices and perspectives are included in the design process to address the real situation [2]. Learning analytics can be an effective enabler for targeted interventions for students, but more understanding is required about the success factors, including how students' perceive the intervention. Students' perspective in personalised learning analytics needs to be fully addressed by emphasising students' voices and overview, including embracing their design and development of the application. The proposed personalised learning analytics systems are primarily designed to focus on students issues and provide an example of a learning analytics system established with student participation and total commitment [4].

Personalised learning analytics integrate data from various sources, including learning activities and assessment scores, focusing on individual learning or current competencies than on performance [27], [28]. Such application uses self and peer assessment in online learning for comparison in promoting student's achievement. Students themselves use the visualised data and identify what they need to do to improve their learning, as part of the learning process. This study addresses the issue and proposes a personalised learning analytics application that unifies the self-regulated learning components: plan, monitor, and evaluate the learning commitment, and activates alert of student's achievement for close monitoring and further intervention by instructor.

Personalised learning analytics could further support the higher learning institution to initiate a learning analytics unit by using a data-friendly learning management system, such as Moodle, to assist data-savvy and data-hungry executive leadership [10]. The development of personalised learning analytics to support academics in the classroom and manage student problems encounters various perplexing processes related to the main requirements of usefulness and scalability and the constraints of a university ecosystem.

Due to current and drastic changes in education in the New Normal, online learning occurs in almost all learning activities in higher education institutions. The combination of learning analytics in online learning seems to contribute to a diverse group of students [29]. Such a plan aims to recognise students' learning patterns and behaviour while addressing learning management, assuming a high demand of instructors' workload [30].

The proposed personalised learning analytics application highlight student full involvement in the design and development of a system, which unifies the role of students and instructors in self-regulated learning. The system helps students to plan, monitor, and evaluate their learning commitment. Thus students themselves utilise the visualised data and recognise the right strategy to improve the learning process, which promotes student achievement. The system also activates alerts of student achievement for close monitoring and further intervention by instructor.

Personalised learning analytics has been designed to deliver an interactive learning analytics environment that stimulates students to focus on the achievement of problem-solving skills and enhance the instructor's decision to support students' concern. Many improvements can be made in the future system, especially algorithms and programming further to simplify the plan, monitoring and evaluation process. Among them is automating the handling of data from the database to the system. In addition, the interface design may also be streamlined to be more user-friendly.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Muhammad Izzat Izzuddin bin Zainuddin develops and evaluates the functionality of the learning analytics. Hairulliza Mohamad Judi provides the theoretical backbone of the study.

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Muhammad Izzat Izzuddin bin Zainuddin is persuing his degree in information technology from Universiti Kebangsaan Malaysia. His research interests include learning application development and analytic strategy. His recent training aims to apply fundamental mathematical, scientific and theoretical computing in analysing, modelling, designing, developing and evaluating computing solutions.

Hairulliza Mohamad Judi has been an academic member with the Department of Industrial Computing, Faculty of Information Sciences and Technology, Universiti Kebangsaan Malaysiasince 1997. Her research interests include learning application with sustainable product development, serious game design, usability of software products and learning analytics.