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APPLYING LEARNING ANALYTICS IN ACHIEVING ADAPTIVE BLENDED LEARNING

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ABSTRACT : Today's technology challenges education with various opportunities to disrupt traditional teacher-centered learning environments. Learning analytics provides learning patterns based on learner interactions through a metacognitive adaptive blended learning environment. Literature describes several techniques to generate learning analytics but introduces numerous academic disciplines leading to varied and diverse practices, theories, and methodologies. Through a customized open source learning management system, learners' log files, activity accomplishment status, progress indicators, scores, and visibility indicators were recorded and analyzed to generate rule-based algorithms to control, regulate and guide learners' progression in the blended learning environment. The paper identifies the critical topics that require immediate research attention. The study aims to present educational technologists with mechanisms and indicators needed to generate learning analytics and to make a sustainable influence on the practice of learning and teaching. The study further expects to dramatically improve student-centered learning as well as teacher efficiency.

KEYWORDS: Learning Analytics, Metacognitive Instruction, Adaptive Learning, Blended Learning

I. INTRODUCTION

For the past several years, the education landscape received numerous disruptions through technological innovations and pedagogical practices. There is a growing trend for improvements in the delivery of instruction and the rapid advancements in technology, particularly educational technology (EdTech), afforded the essential infrastructure [1] for the recognition of blended learning. The widespread availability of EdTech tools and support provided higher education institutions (HEIs) [2] the capability to offer diversified learning environments that complement classroom experience to uphold learner-centered education. Currently, with a diverse composition of learners in a classroom, where each learner possesses unique capabilities, skills, and interests, teachers are challenged to provide necessary intervention to provide support and sustain a learner's learning experience. The study aimed to address the following research questions: (1) What adaptive blended learning features correlate significantly with learning analytics to design learning patterns for students? (2) What motivating factors contribute to influence the adoption of learning analytics?

Blended learning adoption has been increasing and is more personalized. Blended learning is the synthesis of various approaches to pedagogy and a variety of technology integrated with traditional classroom learning [3] to achieve an encouraging impact on student motivation and performance [4]. Blended learning, also referred to as "mixed-mode learning" or "hybrid learning", is increasingly important and is being adopted by institutions. Numerous bodies of literature are supporting the increase in blended learning use by higher education [5]. Blended learning provides opportunities to achieve learning outcomes and demands of a connected and technology-driven learning environment [6]. Higher education institutions (HEIs), nevertheless, have different interpretations and contrasting implementation of blended learning [7]. According to [8], blended learning systems "combine face-to-face instruction with computer-mediated instruction". Additionally, [9] suggests that "blended learning involves the combination of two fields of concern: education and educational technology". In blended learning environments, teachers take on multiple roles[10], [11] and each role requires specific tasks and responsibilities that add burden to teachers [12]. Eventually, teachers' focus is on the mode of instruction [13] rather than the formation of a blended learning environment. Teachers begin to provide a linear progression of learning which initiates information overload for learners and reverts instruction to a teacher-centered approach. If adopted fittingly, blended learning can transform HEIs into a more accommodating, open, and responsive institution [14] to swiftly address challenges and respond to opportunities in improving educational outcomes, extending accessibility, and reducing costs [15]. While there is much conceivable opportunity for blended learning, the use of web-based educational systems become less valuable when learners' individual and unique needs are left unnoticed [16]. Providing adaptivity offers learners a tailored learning experience and maximizes learners' efficiency in achieving objectives [17], [18].

The initiative of infusing interactive technology to instruction to help learners acquire knowledge and deepen understanding has been the basis of adaptive learning. According to [19], "adaptive learning is a method of

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education that seeks to personalize learning by using sophisticated algorithmic technology to continually assess students' knowledge, skill, and confidence levels, and design targeted study paths based on the resulting data". Adaptive learning technology is the result of continuous years of research. Experimental research with technology-assisted instruction and rule-based systems paved the way for the development of intelligent learning systems such as intelligent tutoring systems (ITS), educational games, gamification, and Adaptive hypermedia systems. According to [20] an adaptive learning system "should be efficient in carrying out decisions and recommendations and can scale to support a multitude of simultaneous users". With automation, teachers can readily generate in-depth information on content consumption and more importantly learner performance and subsequently allocate time to provide intervention and support to learners needing remediation. As stated by[21] "the ultimate goal of an adaptive learning system is to personalize teaching and learning to accelerate the student's learning outcome".

Today's learners are of varying backgrounds, having heterogeneous needs, different levels of knowledge and abilities [16], [22], thus it is no longer appropriate to assume that all the learners follow the same instruction model. The diversity and multiplicity of learners challenge the one-size-fits-all tradition of classrooms. Despite the spread of learner differences, all learners must reach the same academic goals and standards [23]. The ubiquitous use of Internet technologies in education transformed teaching and learning through web-based educational systems that are employed to offer dynamic adaptation and provide guidance and regulation in a learners' progression. With the abundance of adaptive EdTech tools, learning management systems (LMS) are configured to provide adaptivity and adaptive educational applications, the collection of learners' data becomes spontaneous and involuntary [18] while a high volume of data from every learner's interaction becomes easier to retrieve and process [24].

Educators, however, can no longer manually analyze and interpret the accumulated data to produce individual learning paths for learners [25]. [1] defined learning analytics as "the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs". Additionally, [26], [27] state that learning analytics deals with processing, analysis, and visualization of knowledge about the learning process. According to [24], learning analytics is the analysis of electronic learning data which allows educators, course designers, and administrators of web-based educational systems to observe patterns and underlying information in the learning process to improve learning outcomes and the overall learning process. Learning analytics provides data-driven patterns for endorsement to enhance learners' learning paths [28]. Studies in learning analytics [25], [29] indicate that data generated through an LMS significantly influence academic performance. However, there is insufficient research in the learning analytics community on which specific learner behavior and interaction data are appropriate to measure academic performance.

II. METHOD

An open source LMS was customized to continuously monitor and automatically record learners' access through logs. Additionally, the LMS was designed to show the learners' activity accomplishment status and progress indicators through visibility indicators (Figure 1).

Figure 1 : Different visibility indicators

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Tokens were strategically positioned in certain areas within activities as markers that learners accomplished a significant task (Figure 2). Learners were rewarded with badges for the accomplishment of milestones (Figure 3). Classes were conducted in rotation for a total of 157 learners and 2 tutors.

Figure 2 : Tokens were strategically positioned within activities

Figure 3 : Badges were awarded to students for accomplishing milestones

For several days of the week, classes were conducted in a classroom and on several days in a computer laboratory room equipped with an Internet connection. Recorded data of learners were analyzed by the tutors to generate learning paths through rule-based algorithms from a learner's completion status, grade, tokens accumulated, badges earned, and additional learner profile. Learners were able to progress linearly or in an adaptive approach. At any point in the experiment, a learner had full control of learning progression such as attempting new concepts and could review previous concepts. At the end of the experiment, learners' reflections and feedback were obtained through a facilitated focus group discussion.

III. RESULTS

With data on hand, tutors generated different reports and were able to design individual learning paths. Results revealed that 87 learners (55%) accomplished much of the activities (91% - 100%) as prescribed by learning paths (Figure 4).

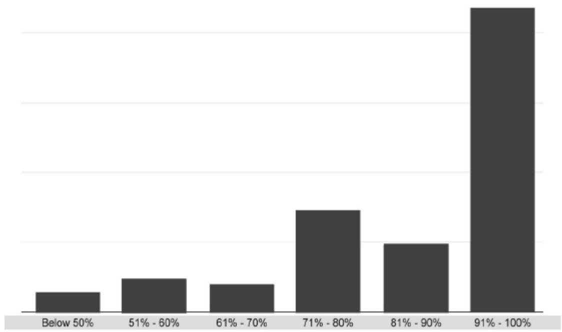

Figure 4 : Accomplishment of learners for online activities

Collected data, however, exposed different results in assessment activities where 60 learners (38%) obtained below 50% of the total number of points, 15 learners (10%) obtained more than 80%, 61 learners (38%) obtained points ranging from 51% to 70% (Figure 5). Time to completion, the duration and frequency of use revealed 64 learners (41%) spent less than 3 hours, 59 learners (38%) spent more 3 hours but less than 5 hours, 24 learners spent more than 5 hours but less than 7 hours, 10 learners spent more than 7 hours in using the LMS for the entire semester (Figure 6).

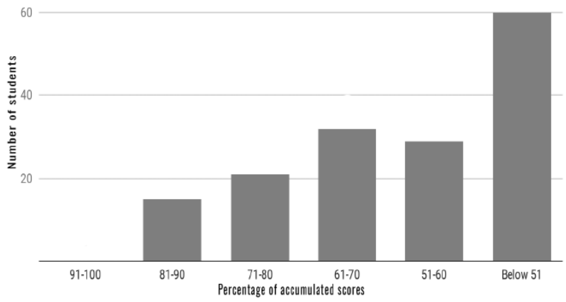

Figure 5 : Accumulated points of learners for assessments

For this study, 4 milestone badges (MB1 to MB4) were created, results indicated 24 learners (15%) earned MB1, 116 learners (74%) earned MB2, 94 learners (60%) earned MB3 and 125 learners (80%) earned MB4. Additional results indicated that 125 learners (80%) found 5 of the 7 tokens.

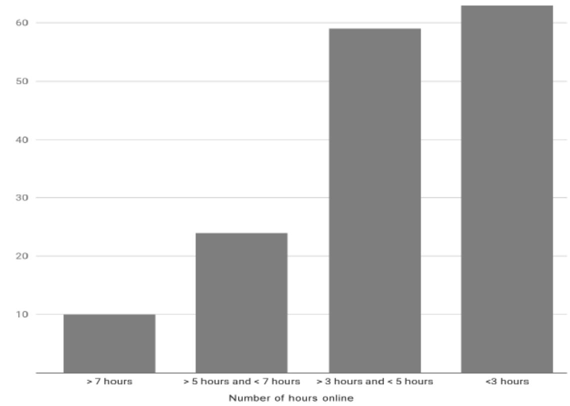

Figure 6 : Hours spent in using the LMS

IV. DISCUSSION

Findings revealed that to obtain significant success and impact of learning analytics on blended learning, learner interaction must be recorded and every activity should instinctively possess a means for tracking individual learner progress [30]. This, in turn, recommends learners to perform self-monitoring for guidance in obtaining the corresponding credits and incentives. The availability of indicators that influence the data-driven decisions in designing learning paths is essential for educators. Results taken from these indicators help educators plan and create rule based algorithms to automate student assessment and progression. Likewise, such indicators become markers for learners' guidance in accomplishing tasks and achieving required course objectives towards course completion with minimal tutor supervision but student progression is controlled and regulated by rule based algorithms. Findings, however, exposed a concern where learners accomplished tasks but failed in cognitive assessments. Learners hurriedly accomplished tasks without grasping essential concepts from the learning materials. Further investigations revealed learners who received higher assessment marks are the same learners who spent more than 7 hours with the LMS. According to learners, course content was immense. This feedback encourages closer collaboration between educators and technologists to ensure that classroom content complements online activities. Moreover, findings encourage additional research for the development of better data-driven decisions in generating rule-based algorithms for adaptive learning as well as the development of enriched data collection for a more balanced outcome.

Findings revealed tutors were able to generate on-demand reports and perform needed interventions on learners. Educators need to recognize the shift towards a learner-centered education as well as the remarkable surge in the quantity of data about learner activity and digital footprints [31], [32]. Current LMSs possess common features to deliver and administer learning objects [33], [34] while being able to minimally track and assess learner interaction [35], however, teachers are not fully prepared for how to extract the right information and use these to generate rule-based algorithms for the class [36]. For educators to embrace learning analytics, the blended learning environment should possess adaptive learning capabilities and the capability to use the data gathered from learners' interactivity and digital footprints to make interventions towards improved learning. Additionally, teachers need overwhelming and necessary support from technologists for the blended learning environment to flourish.

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