Using Learning Analytics and Adaptive Formative Assessment to Support At-risk Students in Self-paced Online Learning

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***Abstract*—Online education is growing but facing a problem of high academic failure rates. In self-paced online learning (SPOL), the lack of academic support – social interaction, formative feedback, learning awareness, and academic intervention – is recognized as a critical factor causing the academic failure problem. To facilitate such academic support, this study has identified three relevant technical and pedagogical strategies (formative assessment, adaptive assessment and learning analytics) that could work together as a possible solution. Design-based research is considered for this study to investigate the effectiveness of this solution in the context of STEM disciplines of formal higher online education. A computing course is selected for a case study. The design principles of the adaptive assessment model and the intervention learning analytics model are explained. Also, the expected contributions are summarized at the end.**

Keywords – formative assessment; adaptive assessment; learning analytics; academic failure; social interaction; formative feedback; learning awareness; academic intervention

I. MOTIVATION FOR THE RESEARCH

Online education creates enormous and equal learning opportunities because of its flexibility in terms of time, location, and ways of learning. Students can learn anywhere, anytime, with different devices. The use of multimedia, web and computing technologies in online education brings further potentials to this education model, such as personalized and adaptive learning. The enrollments in distance education have been growing year over year in the worldwide (Qayyum & Zawacki-Richter, 2019).

One important online education model is self-paced online learning (SPOL), where the asynchronous and individualized study is the primary approach. In this model, not only can students learn anywhere and anytime, but also can they learn at any pace and pathway. Thus, it offers even more flexibility comparing to other online education models. Students, especially adult learners who usually have work and family commitments, are benefiting from such flexibility. This flexibility, however, could impose some challenges for learning success. Currently, many SPOL courses experience high academic failure rates, usually higher than traditional face-to-face education (Stone, 2017).

A variety of factors are causing the academic failure in online education, including the academic factors (e.g., student, instructor, course design, support) and the non-academic factors (e.g., family, work, financial). Of them, the lack of academic support is a critical factor leading to unsuccessful learning in SPOL (Protopsaltis & Baum, 2019). This study has recognized that four aspects of academic support are often missing in many courses: meaningful social interaction, formative feedback, learning awareness, and academic intervention.

Social interaction between instructors and students is important for learning dialogue and learning motivation. In online self-paced learning, as the synchronous teaching is not achievable and students can learn at any pace, it is usually difficult for instructors to know where individual students are in a course. In some disciplines (e.g., STEM – Science, Technology, Engineer, and Math), students mostly interact with learning content rather than with instructors and peer students. Thus, meaningful social interaction is often lacking in SPOL.

Formative feedback is among the most critical influences on student achievement (Carless & Boud, 2018). In SPOL, many courses are designed in the way of learning materials plus summative assessment only (assignments and exams). Also, students can choose to work on learning materials offline and submit all the assignments at the very end of the course contract. As a result, students may rarely get formative feedback during their learning process.

Learning awareness is also essential for learning success as it helps an instructor as well as students themselves to realize how they are doing in a course. For example, whether a student has adequate prior-knowledge, what mastery level of the knowledge the student has reached, why a solution is wrong, where are the learning gaps, and what materials the student should work on to fill the gaps. Without social interaction with instructors and formative feedback, students often lack self-awareness of learning; without social interaction with students and not knowing where students are at, instructors often find they are not aware of students' knowledge state and learning status.

Finally, academic intervention is critical for students who get stuck in learning. In the context of SPOL, academic intervention may include actionable insights, recommendations, and tutoring, which can be provided by the instructors or the learning systems. It is usually difficult to offer such intervention to students in a proactive way due to the lack of awareness of students' learning in SPOL. Rather, instructors only respond to student's questions reactively. However, not every student has the skill of seeking help, especially those with weaker academic backgrounds (Kinshuk, 2016). Also, the lack of self-awareness of learning makes it difficult for students to discern what help they need. So, if students at the risk of academic failure do not ask for help, they probably never get it.

As a result, students could be at high risk of academic failure due to those challenges in SPOL. Thus, it is imperative to find a solution that can improve meaningful social interaction, enhance formative feedback, increase learning awareness, and facilitate academic intervention. As different disciplines usually have different pedagogical needs, the solution could be distinctive from one discipline to another. This study will focus on the STEM disciplines, which share certain common pedagogical needs such as STEM-related conceptual development, inquiry-based, problem-solving, real-world connection, using current tools and technologies (Kennedy & Odell, 2014).

II. BACKGROUND KNOWLEDGE

To address those challenges, three relevant technical and pedagogical strategies have been explored in this study for a possible solution: formative assessment, adaptive assessment, and learning analytics. In this study, these three technologies and pedagogical strategies are termed as techno-pedagogies.

A. *Formative Assessment*

Unlike summative assessment for credit purposes, formative assessment can provide students with the practice opportunities and, therefore, the formative feedback. Students can attempt formative assessment multiple times and discuss assessment questions with their instructors or peer students without grading concerns. As Elmahdi et al. (2018) pointed out, formative assessment should be an integral and vital part of learning systems to enhance learning. In STEM courses, as students interact with learning content predominately, automatic feedback from the learning system becomes essential. Computerized formative assessment can automatically inform feedback, and it is also a systematic process of continuously gathering learning evidence for instructors. Thus, this study considers the computerized formative assessment as a part of the solution addressing those challenges in SPOL.

B. *Adaptive Assessment*

Due to its capability of accurately estimating a student's knowledge and skill state, adaptive assessment is considered as another part of the solution in this study. Adaptive assessment or computer adaptive testing (CAT) adapts to the ability level of individual students where each subsequent question item is selected based on the response to the previous items (Rezaie & Golshan, 2015). The adaptive assessment has certain benefits over traditional fixed-form assessment, such as accurate and reliable estimation of proficiency, flexible, individualized, efficient and fast, promotion of motivation by avoiding too easy or too difficult items (Rezaie & Golshan, 2015). As adaptive assessment can better evaluate students' mastery level of a skill or concept and the learning gaps, it can help students as well as instructors to increase learning awareness.

C. *Learning analytics*

Learning analytics is an appropriate tool for reflecting students' learning behaviour and providing suitable assistance for students in higher education (Leitner et al., 2017). Learning analytics (LA) has been actively researched for various educational purposes, such as monitoring, analysis, prediction, intervention, tutoring/mentoring, assessment, feedback, adaptation, personalization, recommendation, and reflection. With an abundance of learning data possibly generated in SPOL, learning analytics holds great potential for academic intervention in providing actionable insights, recommendations and tutoring to students. As Brown et al. (2020) stated, the use of analytics as a tool for early alerts and proactive outreach is becoming essential. Therefore, learning analytics is considered as the third part of the solution addressing those challenges in SPOL.

D. *Integrate the three techno-pedagogies*

Formative assessment and adaptive learning can help to improve formative feedback and increase learning awareness. But students might still need further intervention, for example, when they get stuck on a learning topic – a student keeps failing a formative assessment even after she/he spends a great deal of time on the learning materials. This situation is similar to the wheel-spinning problem (Kai et al., 2019) in intelligent tutoring systems. In such cases, learning analytics can help with the intervention by detecting who gets stuck, at what point and why. To do this, learning analytics needs to track and analyze students' learning data. A crucial part of such data can be gathered from adaptive formative assessment, such as the correctness of answers, attempt times, test date/duration/interval, learning materials accessed during the test, etc.

Therefore, with the three techno-pedagogies working together, it is possible to address those challenges in SPOL and create an inclusive academic support solution for students who are at the risk of academic failure.

E. *Previous work*

1) *Regarding the adaptive formative assessment*

Adaptive assessment/CATs have been extensively studied over the past years, and they have been put into practice (Vie et al., 2017). Many adaptive models are developed, such as Item Response Theory, GenMA, knowledge space, BKT, DKT, multi-armed bandit. Some of them can provide formative feedback, but most of them assume that the knowledge of a student does not increase within a test (multi-armed bandit is one exception). Models used for adaptive assessment have been mostly summative, and only recently are they advancing to formative assessment (Vie et al., 2017). In formative assessment, the knowledge level can be changed if students can check the course material during the test. Also, other parameters such as guessing, slipping, forgetting also need to be factored in the adaptive formative assessment model for this study.

2) *Regarding the learning analytics for intervention*

From the very early stage, research in the field of learning analytics predominantly focused on establishing predictive models to predict students at risk of dropout or course failure. It is now starting to move to a more sophisticated analysis of learning processes (Tateo, 2019), for example, providing academic intervention at the topic level.

The intervention has been claimed to be the biggest challenge in learning analytics, and few studies have addressed the intervention strategies (Wong & Li, 2020). To our knowledge, LA intervention models have not widely used the data generated from formative assessment, not to mention adaptive formative assessment.

III. Research Question

Due to the potentials of adaptive formative assessment and learning analytics as well as the research gaps in this field, this study will investigate whether and how these three techno-pedagogies can work together to facilitate academic support in SPOL. Such academic support includes facilitating meaningful social interaction, enhancing formative feedback, improving learning awareness, and offering academic intervention. This study will focus on STEM disciplines in formal higher education. So, the research question of this study is formulated as:

How can adaptive formative assessment and learning analytics be designed and used to facilitate academic support for students at the risk of academic failure in self-paced online STEM courses?

IV. Research Methodology

Based on the educational needs and the research context, the design-based research (DBR) is selected as the method for this study. DBR is widely used in the area of TELEs (Technology Enhanced Learning Environments). It is theory-driven research, where a solution is proposed based on the theories in the field and for solving a real-world problem, such as the one identified in this study. According to McKenney and Reeves' model (2012), the study will go through three stages and possibly in an iterative process: analysis & exploration, design & construction, evaluation & reflection.

Currently, this study is in the design & construction stage. An online computer science course offered at Athabasca University – Computing Data Structure and Algorithm – is chosen for a case study. It is a challenging course in the field, with a relatively higher academic failure rate comparing to other courses. The course professor is interested in trying the three techno-pedagogies to increase the course success rates.

Some design principles for the adaptive formative assessment are considered: a) pedagogical sound; b) enhancing feedback; c) focusing on learning awareness; d) easy to implement; e) keeping learning analytics in the loop of design.

For learning analytics, some design considerations include a) what intervention model should be; b) what data from the adaptive formative assessment can be used; c) what other data sources need to be included; d) what triggers learning analytics to run in SPOL.

Also, an evaluation plan is being developed. This study will use multiple data sources to analyze the effectiveness of the proposed solution, such as the log data on the learning system, the survey with students, and the interview with the instructor of the course.

V. Expected Contributions

For STEM disciplines, this study is expected to: 1) prove the combining use of the three techno-pedagogies can identify academically struggling students (who, where, and why) in SPOL; 2) discover an effective adaptive assessment model that considers formative feedback and knowledge change during the test; 3) contribute certain research findings and theories to the field of learning analytics that focuses on the intervention model for SPOL;

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