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Learning Analytics for support and enhancement of self-regulated learning: Systematic review

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Abstract: Learning analytics is a field that brings with it new possibilities on how to understand the learning process. In this review we explore the current research on use of learning analytics to support and enhance self-regulated learning (SRL).We draw useful insights on how to future research can borrow from already existing work while embracing new technologies. The search for relevant literature was done using identified search terms on internationally recognized scientific databases. Initial filter resulted in 43 papers but after doing further investigation of the abstracts and objectives, 27 papers fit the search criteria. A notable finding in this nascent field is that despite the significant increase in use of learning management systems in higher education to collect learners' data, the study of self-regulated learning requires data that is not intentionally collected by such systems. Accordingly, researchers have explored other systems as better SRL data collection vehicles which have produced promising results. These new enriched data sets together with advanced analytics techniques give us better ways to understand the learning process and how we can best improve it.
Keywords: Learning Analytics; Self-regulated learning; self-directed learning; technology enhanced learning

I. INTRODUCTION

The twenty first century is marked by great strides in technological advancements which has in turn affected almost all sectors of the economy. There is increased automation of tasks leading to an even greater demand for a smarter workforce. Individuals with the capacity to solve complex problems on demand are those equipped with skills such as critical thinking, creativity, collaboration, cognitive and metacognition, motivation, among others; which have come to be referred to as 21st century competencies[*1*]. These skills have to be nurtured in young people towards becoming lifelong learners. In pursuance of these, self-regulation in learning is an important attribute that any individual must possess in a world where change is constant. Self-regulated learning (SRL) has been defined as a process that creates self-generated thoughts, feelings and behaviors targeted towards achievement of goals [*2*]. This concept is applicable both to students who are working towards improving their academic achievement as well as individuals who want to hone their skills in a work environment.

Learning analytics (LA) is an area that is increasingly receiving a great deal of research focus due to the promise it holds of improving our understanding of how learning occurs and consequently ways in which to enhance the same. The principle behind learning analytics is that every learner will leave behind a digital footprint while interacting with an educational system. These traces, which were not possible to collect in traditional learning contexts, can now be studied to better our knowledge on learning behaviors. Learning is a complex process that is achieved as a result of interplay between factors that are extrinsic and intrinsic to the learner. One of the aspects of learning that has been studied using learning analytics is self-regulated learning. Our focus on SRL is derived from the fact that it is an essential skill for realization of lifelong learning capability [*3*].

This paper reviews the current research on how learning analytics has been used to enhance self-regulated learning. The goal of this review is to bring together the ideas of how so far researchers have had a go at using learning analytics to understand and enhance self-regulated learning as well as identify which methods have seen better positive effects and what we can learn from past research to improve future studies. We build upon the work of[*4*] who identify the current research in self-regulated learning enabled by learning analytics. Our work, however, differs from theirs in that we seek to scrutinize at a deeper level comparing the methods and SRL constructs, from a broader set of studies, employed in research of SRL using learning analytics.

II. THEORETICAL BACKGROUND

As[*5*] correctly puts it, learning analytics is really about learning and we should not forget it is the central focus and therefore all efforts in this field must be based on sound learning theoretical underpinnings. Self-regulated learning is a fundamental concept that was designed to aid in understanding the cognitive, motivational and emotional aspects of learning [*6*]. A lot of research has been conducted and various theories emerged thereof. A recent comprehensive review by [*6*] highlights that these models share some similarities although each has a different point of emphasis. In general, we see that four phases are characteristic of the SRL process although some authors may use different terms to describe them. Derived from Pintrich's model, the phases include: planning and activation, monitoring, control or what others refer to as evaluation and finally reaction and reflection [*7*]. For learning analytics to have meaningful impact, it has to be based on theory. In this review we pay attention to how researchers are interpreting the SRL models and translating them in to observable constructs that are measurable using learning systems.

III. RESEARCH QUESTIONS

This review was guided by the following research questions.

RQ 1. Which are the general approaches that researchers are using to study self-regulated learning using learning analytics?

RQ 2. What type of data from a digital learner's footprint has the existing research used to study self-regulated learning?

RQ 3. Which learning analytics methods have achieved better results in understanding and enhancing self-regulated learning?

RQ 4. What lessons can we learn from existing research on how to exploit the power of learning analytics to promote self-regulated learning?

IV. METHODS

First, we began with selecting the key search terminology guided by the objective of the review. The search was conducted on internationally recognized academic databases including: ACM, IEEE, Springer, Science Direct, Computers and applied sciences, ERIC and Elsevier. We also scanned through EDM and LAK conference proceedings as well as google scholar. The search terms included learning analytics, self-regulated learning, self-directed learning, technology enhanced learning. Since the focus of our review was to find literature that used learning analytics to study self-regulated learning, we combined the search terms such as 'LA and SRL'.

The first round of search did not yield as many directly relevant results. This we attribute to the fact that learning analytics has only started gaining momentum in the last few years. We support this claim with the fact that the first Learning analytics conference took place in 2011. To expand our search we included 'technology and SRL' to find the studies that looked at how technology can be used to support self-regulated learning. The search period was not explicitly defined as the limitation of the results led us to include the publications that matched our criteria and this fell between the years 2010 to date. Only peer reviewed journal articles were included. After filtering in the first round, we ended up with 43 papers. We further explored the set and found that some papers despite having both concepts of learning analytics and self-regulated learning implied, did not address our research objective. In the end, the papers that met our criteria were 27. These are what we discuss in the following section

V. RESULTS

In this section, we analyze and present our findings using non statistical methods.

RQ. 1: Which are the general approaches that researchers are using to study self-regulated learning using learning analytics?

To answer our first research question, there are a variety of ways that researchers are using to study self-regulated learning using learning analytics. Earlier discussions include[*8*] who proposed that autonomy in student's learning process can be promoted if they were allowed to choose the learning tools as well as content so long as scaffolding is provided. This point is also comes out in [*9*] who posits that recommendation is important during personalization of learning which should be based on a learner's profile. The same author also highlighted how giving feedback in form of visualization would be an effective way of promoting self-reflection.

A Learning management system (LMS) is one of most common tools that makes possible the unobtrusive collection of learners' data. In this review, however, we noticed that self-regulation was studied mostly using other specialized tools and only a few cases used LMSs. This may be due to the fact that LMSs tend to be very structured limiting how learners can enforce their own learning pathways[*10*]. In table1 below, we give a brief snapshot of the type of technologies that researchers are employing to collect data that enables them to study self-regulated learning. Besides the use of technologies to study SRL, we also found some work [*11*],[*12*][*10*] where researchers proposed conceptual frameworks that can be used to form the theoretical background needed in this relatively new field. In addition, [*3*]also enriched the research in this area by

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designing a protocol for measuring the effects of scaffolding in self-regulated processes.

Table 1. Summary of tools used to collect data for SRL studies

Tool	Objective	References
LMS	relationship between SRL and performance	[13],[14],[15]
Compod Service	SRL support based on competence	[10]
SoftLearn, Hypermedia LE	Study learner behavior using process mining	[16],[17]
Video annotation	Improve learner SDL skills through visualisation of lecture annotation	[18]
LearnB	Integrated tool that support SRL process for users in a workplace environment	[19]
MOOCs	Study behavior of learners with self-set goals	[20],[21]
LET^{J}S(Programming)	Improve student's achievement and SRL skills	[22]
Wearable technology	Find relationship between heartrate variability and self-regulatory abilities	[23]
Social media	Role of social media in SRL	([12], [24], [19]
E-portfolio	Study how e-portfolios promote SRL	([25], [26]
Intelligent tutor (Betty's brain)	Study learner behavior as student train a virtual agent	[27]

RQ. 2: What type of data from a digital learner's footprint has the existing research used to study self-regulated learning?

The second objective of this study was to identify the type of data from the aforementioned tools that was collected to represent the SRL constructs. The reason behind this objective is that the age of big data has meant that we are faced with a deluge of data and most times it is hard to determine which data is relevant and which is not. Studying self-regulated learning using learners' digital footprint is no different. For any useful inference to be drawn, the data has to be representative of the construct under study. In this study, we highlight that researchers have, based on theory, identified several measurable factors that can give insight on learners' SRL behaviours.

There were multiple cases[*26*],[*3*], [*10*],[*17*]where tools allowed learners to explicitly set goals, plan their learning based on the competence they aimed to achieve, monitor and evaluate how they performed in various tasks, as well as reflect on their progress based on the target competencies. The analysis stage would therefore involve looking at how learners executed these events. Time spent/access on a learning resource was another measured variable[*13*],[*21*],[*27*],[*28*],[*29*]; [*15*].

In some cases, researchers did not directly measure the time but focus on the type of resource accessed e.g. viewing or a dashboard or time line on how they were progressing on their goals. This was considered an indication of self-evaluation and reflection. Highlighting, clicking, bookmarking, annotation, edit frequency seen in [*18*]; [*19*]; [*27*]; [*3*]; [*20*] were another set of common variables that were used as a proxy to when new knowledge was being acquired or revision of the already existing one. An interesting use of feedback to understand self-regulated learning was when [*30*]gave learners the freedom to choose between positive and negative feedback. Those who requested for negative feedback showed more evidence of learning as they used it to improve on their skills. The actions undertaken by learners after receiving the feedback were used accordingly to evaluate the difference in learning outcomes.

Using social media to study self-regulated learning was another approach. This is based on the connectivist and constructivist theories that argue that knowledge and learning is spread out across social environments[*31*]. Thus, [*12*],[*19*]proposed integration of social media as part of the integrated tools to form a personalized learning environment. A more focused study, however, is found in the work by [*24*]who explored how learners form connections with peers and instructors. They used number of connections as an indicator of learners' initiative to acquire new knowledge. The thinking behind this being that those who formed connections were using the network to seek information hence regulating their learning.

Researchers are also expanding their boundaries as they begin to explore how physiological factors come in to play during self-regulated learning. In this category, most notably, we observed the use of eye [*11*] and wearable technology [*23*]. The movement of the eyes while interacting with say a learning portal would indicate the areas of focus or stress points that induce heavy cognitive load. Wearable wristbands were used to measure heartrate variability during an exercise that demanded attention and self-regulation [*23*]. This is an illustration that there are incredible opportunities for research beyond the traditional somewhat narrow focus. [*32*] in their paper argue for embracing of multimodal data; log-files, eye gaze behaviours, transpiration, facial expressions of emotions, heart rate and electro-dermal activity, in learning analytics studies as these have the potential to give insight not only on the cognitive but also metacognitive, affective and motivation processes in learners.

A noteworthy observation we made is that despite the use of diverse variables to study SRL, in several of the articles we reviewed, self-report questionnaires were deployed as an additional source of data to act as a triangulation measure. There was also an instance where in addition to tracking the learners' data in a learning system, the researcher used the think aloud protocol whose results were later to be compared with the event log data [*17*]. The Motivated Strategies for Learning Questionnaire (MSLQ), a tool developed to assess college student orientations and what learning strategies they deploy [*33*], was the most common as seen in [*24*],[*14*]; [*23*],[*28*]; [*29*] with some administering them pre-test and post-test or post-test only. [*28*], however used the Online Self-regulated Learning Questionnaire (OSLQ) that was designed for use with distance education learners [*34*]. [*23*]designed their own questionnaire whereas [*13*]explicitly posed questions to learners during a meta learning task. As such, we see that the approach of using additional data collection methods in an effort to test the validity of the electronically collected data is not uncommon despite the great advances we have seen in technology.

RQ. 3: Which learning analytics methods have achieved better results in understanding and enhancing self-regulated learning?
To answer our third research question, we looked at the results reported by the various studies. To begin with, it is important to underscore the fact that self-regulated learning is not an end in itself but rather a means to achieving a certain state. An individual who is a self-regulated learner is one that is able to control their cognitive, metacognitive, affect and motivation processes in order to transition from a state of lack of to one where they acquire and continually advance in a certain competence. Thus, in the cases we reviewed, some sought to establish if in the presence of self-regulated learning skills, a learner is able to perform better in certain tasks while others aimed to enhance SRL skills given the role they play in academic achievement (Zimmerman, 2002). Our finding was that researchers were able to observe increased learning ([*13*],[*30*],[*21*],[*10*]and distinguish between good and poor performers[*14*],[*27*]; [*15*]by observing their SRL skills through analysis of their engagement data from learning tools. Moreover, the patterns followed in execution of cognitive tasks, interact with learning resources also helped to understand and enhance the process of self-regulated learning [*18*], [*25*],[*16*],[*22*]; [*17*]; [*35*]which is an important factor that needs to be considered in design of learning systems.

RQ. 4: What lessons can we learn from existing research on how to exploit the power of learning analytics to promote self-regulated learning?
Finally, our last research question was to identify key lessons that we can learn from the existing research. One, we learn that there is enormous potential in using learning analytics to understand and enhance self-regulated learning. This is based on the fact that there better ways to collect data on learners than was possible before. Two, learning behaviors can be easily studied by extracting interaction data from the tools used for example by applying process mining techniques. Three, to enhance the SRL process, system designers should aim to incorporate functions that give flexibility to learners such that they are able to define their goals and desired competencies, monitor their learning progress as well as evaluate the whole process. Visualization of the entire learning process as the learners work towards their target competencies through a timeline can be a useful way

to encourage self-reflection. Four, given the technological advances in the world today, it behooves learning analytics researchers to embrace multimodal analytics so as to gain an even broader understanding of the learning process. Most notably in this line of research, is the development of the experience API (Tin can/xAPI) that provides a standard of collecting a wide range of learning behaviors and improves how this data is collected and shared [*36*]. We can therefore collect data from a wide range of resources such as learning management systems, social media sites, wikis, websites, wearable devices and centrally collect the data through writing xAPI statements that can then send data to the Learning Record Stores. The rich data set stored in the LRS can then be mined to extract useful patterns that give us better understanding of how the learning process occurs, how to optimize learning paths based on learners' preference of modes of learning, and which materials or media to put more emphasis on so as to achieve maximum learning outputs.This provides an incredible opportunity for researchers to broaden their thinking to explore multiple behaviors and attributes exhibited by learners during the learning process that were not possible to define in the past. Five, the study of self-regulated learning is made rich by not only studying the learner's digital footprint, but complementing it with qualitative studies that help to give fuller picture of this complex process.

VI. CONCLUSION

Learning analytics is a relatively new field that is giving researchers great affordances in understanding and improving the learning process. Self-regulated learning is a key process in the development of lifelong learners. In this paper we reviewed the existing research to establish how this complex process can be understood and improved. We observed that researchers are exploring not only the data emerging from learning management systems, but also building specialized tools that provide better ways to study the SRL process. Experiments conducted so far are promising in the outcomes reported and therefore, there is room to explore even more critically, the process of self-regulation e.g. through multimodal analytics, studying the effect of context, among other unexplored variables that were not possible to study but now are with the experience API. There are now more than ever more ways to collect data on learners but we have to be careful that the data we collect correctly represents the subject under study. The SRL theories give us a good foundation on what data can help understand the SRL process. Learning analytics provides an incredible tool that can help us understand and interpret the final outcomes we observe in learners.

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