Learning Analytics Intervention Using Prompts and Feedback for Measurement of e-Learners' Socially-Shared Regulated Learning

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Abstract: The future of university learning in Sub-Saharan Africa has become increasingly digitally transformed by both e-Learning, and learning analytics, post-COVID-19 pandemic. Learning analytics intervention is critical for effective support of socially-shared regulated learning skills, which are crucial for twenty-first-century e-Learners. Socially-shared regulation is the major determinant of successful collaborative e-learning. However, most e-learners lack such skills thereby facing socio-cognitive challenges, due to the unavailability of intelligent support during learning. This research aims to investigate and understand the effect of Learning Analytics instructional support using feedback and prompts, on e-learners' SSRL indicators. A theoretical model was derived from these factors and built from selected features. Both survey data and behavioral trace data were employed in the Learning analytics-based intervention. In this paper, only a segment of the data is discussed. The e-learners' perceptions and feedback confirmed that Learning Analytics-based interventions using prompts and feedback are effective in promoting SSRL in collaborative e-learning contexts. The findings indicated that the success of SSRLA-based intervention be tied to support from instructors and academic counselors, particularly feedback on previous problems and quizzes. This will improve e-learners' SSRL skills for quality educational experience, hence motivate e-learners, and help lecturers to identify at-risk learners in web programming problem-based courses. In conclusion, without adequate utilization of the Learning Analytics interventional trace data, critical information about learners' behavior patterns in terms of their online interactivity with the course activities and their SSRL profiles and strategies cannot be disclosed leading to little improvement of e-Learning interventions.

Keywords: Socially-shared regulated learning, Learning analytics intervention, Feedback and prompts, Collaborative e-Learning, Quality educational experience

1. Introduction

The future of university learning in Sub-Saharan Africa, post COVID-19 pandemic, has become increasingly digitally transformed through e-Learning and learning analytics (LA). The global expansion of e-Learning adoption has been successful due to the affordability and flexibility of Learning Management Systems (LMS), such as Moodle which is commonly used for teaching in universities. In Kenya, the adoption of e-learning in most universities' teaching, learning, was driven by government policies on social distancing to suppress the spread of the COVID-19 (en.unesco.org/covid19/educationresponse, 2020; Kibuku, Ochieng' & Wausi, 2020; Akinyi & Oboko, 2020). The term "e-learning" refers to web-based systems such as LMS which enable learners to easily collaborate, and access educational content, and activities, while obtaining support during the process of learning, with instructors delivering the curriculum and learning materials (Araka, et al, 2020; Delen & Liew, 2016).

Despite the benefits of e-learning adoption, this growth has led to an increase in e-learners' socio-cognitive challenges, especially lack of intelligent support on their Socially-Shared Regulated Learning (SSRL) skills as seen through the low interaction with e-learning activities, and collaborative platforms. SSRL skills are essential for successful quality educational experience (QEE) for the 21st century e-learning (Viberg, Khalil, & Baars, 2020). There is lack of a Learning Analytics intervention that uses prompts and feedback approaches, and maps Moodle LMS features to SSRL strategies for QEE. To provide effective instructional support to e-learners, there is need for an intelligent intervention of the learners' SSRL strategies (Akinyi & Oboko, 2020). Learning Analytics involves integrating and analyzing educational data which is collected for insights and patterns on how learners interact, and collaborate in learning activities while studying online, with a goal of supporting students by providing interventions to reinforce positive learning and improve poor learning skills (Lodge, et al., 2019).

This research aimed at investigating the effect of Learning Analytics intervention using prompts and feedback on e-learners' SSRL strategies in an e-learning context. The use of Learning analytics (LA) in education brings the

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promise of essential benefits (Akçapinar et al. 2019; Chatti, et al., 2012), such as personalized learning to each e-learner's preferences, helping learners adapt the pace and control iterations to improve the mastery of the topic and promote equity in overall learner performance. Learning Analytics-based scaffolding reduces cognitive load and increase socially-shared regulation which improves quality educational experience. Measurement of SRL using LA scaffolding techniques is categorized under the "current wave", as it serves as a tool for promoting SSRL skills in e-learners (Araka et al., 2020).

1.1 Problem Statement

There is lack of a Learning Analytics intervention that uses prompts and feedback approaches, and maps Moodle Learning Management Systems features to SSRL strategies for QEE.

1.2 Research Question

RQ1: Which instruments and approaches can be used to measure and promote SSRL in collaborative e-learning contexts?

RQ2: Which features can be mapped to LMS factors to develop a SSRLA instructional support model to best predict the performance of e-learning students based on their SSRL skills?

2. Socially-Shared Regulated Learning Model

This study was underpinned by Hadwin, Järvelä, and Miller's: Socially-shared regulated learning (SSRL) model, Figure 1. SSRL model explains self-regulation in the social and interactive learning contexts using ICT in collaborative e-Learning environments (Panadero, 2017), and focuses on the situational, contextual and motivational SRL aspects (Hadwin, et. al., 2011) to improve QEE. The operational definition of SSRL in this study, builds on Winne and Hadwin's (1998) model of SRL, which outlines four phases of self-regulation, such as task perception, goal setting/ planning, applying strategies, and evaluating/adapting (Järvelä et al. 2013).

The SSRL model indicates the existence of three modes of regulation in collaborative settings: self-regulation (SRL), co-regulation (CoRL), and shared regulation (SSRL). First, SRL in collaboration refers to the individual learner's regulatory actions that involve adapting to the interaction with the other group members. Secondly, CoRL in collaboration "refers broadly to affordances and constraints stimulating the e-learner's appropriation of strategic planning, enactment, reflection, and adaptation that occurs when interacting with other learners or group members" (Hadwin et al., 2011). Lastly, SSRL, the third category in collaboration, occurs when "deliberate, strategic and transactive planning, task enactment, reflection and adaptation" are taken within a group (Hadwin et al., 2011).

In SSRL model, SRL deploys five different facets of tasks which are identified using the COPES acronym which stands for Conditions Operations Products Evaluations Standards (Winne and Hadwin, 1998; Greene and Azevedo, 2007). The SSRL model unfolds in four linked feedback loops (Hadwin & Oshige, 2011). In the first loop, using internal and external representations of the current task, groups "negotiate and construct shared task perceptions (Winne & Hadwin, 1998). On the second loop, groups decide how they will tackle the task as a group and establish agreed goals for it. On the third loop, teams carefully plan their collaboration and strategically keep track of their advancement. In the fourth loop, groups evaluate and regulate for future performance. The groups might alter their task perceptions, goals, plans, or methods based on this monitoring activity to increase their collective activity toward the learning goal (Nguyen, et al., 2022).

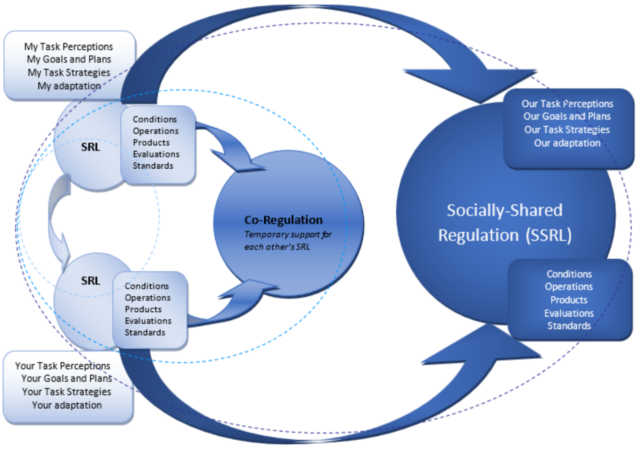

Figure 1: Socially-Shared Regulated Learning model-1 (Adapted from Hadwin et al. 2011)

2.1 SSRL Strategies used in e-Learning

SSRL strategies refer to research-based instructional techniques targeted at assisting e-learners with monitoring and management of their own learning skills and habits (Zimmerman, 2008) for ease in acquiring and retaining knowledge in a manner that is methodological and structured. They enable a learner to actively engage self-regulated processes, as different self- regulated learners utilize different strategies during learning process (Wandler & Imbriale, 2017; Alvi et al., 2016). When learners apply SRL strategies in their e-learning environments, their QEE and academic achievement projections can easily be predicted (Wang et al., 2013). For this study, the adopted SRL strategies included metacognitive, cognitive, motivational and resource management.

Cognitive strategies are used by students to optimize personal regulation, as they help students to acquire knowledge through retaining information (Akinyi & Oboko, 2020). They include: Critical thinking, Elaboration, and Organization describes a learner's capability to underscore major concepts covered during learning (Effeney et al., 2013).

Metacognitive define a learner's awareness to monitor, plan and regulate learning" (Akinyi & Oboko, 2020; Alvi et al., 2016) and are used to enhance behavioral functioning. Examples include, Time-management, the capability of applying a learner's study-time constructively while undertaking an online course (Effeney et al., 2013).

Resource Management Strategies mandate that students make the most of their surrounding learning settings, including their peers and teachers (Akinyi & Oboko, 2020). E-learners often consult a variety of sources, including books, periodicals, libraries, and the internet, ask for help and occasionally work in groups to ensure QEE. Examples include: Peer-learning, which entails teaming up with other students to help one learn (Akinyi & Oboko, 2020; Effeney et al., 2013). Help-Seeking, encourages a learner to seek assistance from lecturers or better placed peers, to overcome challenges while learning (Effeney et al., 2013). Effort-regulation refers to the students' persistence in performing their task when they encounter a difficult task (Cho & Shen 2013).

Motivational Strategies affect learners' participation in SRL and influences the behavior, motivation, and feelings by self-efficacy, a crucial motivating factor in SRL (Bandura, 2012). Efficacy is a trait shared by highly successful students who are intrinsically motivated to learn. Extrinsically driven students are more likely to be less self-motivated, which means that they will utilize less SRL methods than intrinsically motivated students (Makokha & Mutisya, 2016).

2.2 Learning Analytics Technology

Learning analytics (LA) technology is the process of measuring, collecting, analyzing and reporting learners' data in their context, so as to understand, measure, optimize student learning process, experience, and the e-learning environment, with an objective of improving QEE on the overall performance outcomes (Baars, & Viberg, 2022; Long & Siemens, 2011). With the application of LA during e-Learning, there is a possibility of measuring key indicators of learner performance, supporting development of SRL skills, improving decision-making, improving learning outcomes, motivation and informing institutional strategy (Verstege et al., 2019; Azevedo et al., 2010).

Visualizing LA data and understanding student behavior with the support of Social-cognitive LA intervention can enhance online student interactions leading to better engagements among e-learners (Kaban, 2023). With the intervention of prompts and feedback during e-Learning, the possibility of measuring key indicators of learner QEE on academic performance, encourages the development of students SSRL skills, improve decision making, learning outcomes, motivation and inform institutional strategy (Verstege et al., 2019; Azevedo et al., 2010).

3. Methodology

Our current work was carried out in the context of a SSRLA-based socially-shared regulated learning instructional support extended from a Moodle LMS. A deductive research approach was employed, whereby SSRL, an SRL theory, was developed based on literature review. The research design provided a way to analyze literature, identify SRL strategies, and measurement instruments used on LA-based interventions, and for feature selection so as to build a SSRLA instructional support. A descriptive survey was used to investigate the SSRL level of learners. The descriptive survey was adopted given its possibility to examine a situation the way it is and provide quantitative information, summarized through statistical analyses (Akinyi & Oboko, 2020; Engelhart, 1972). LA-based prompts and feedback interventions were developed and integrated within Moodle LMS, for the SSRL strategies applied by learners. The Model validation was done through experimental analyses and experimental evaluations respectively, as will be shared in the next phase of this research.

For the systematic literature review and a survey, the results obtained were SRL strategies, LA indicators as well as the established socially-shared learning factors. This study reviewed literature about LA support on SRL strategies in socially-shared e-Learning, based on clearly formulated research questions. Before conducting the systematic review, the research problem was specified in a clear and structured manner by framing it using specific keywords. Some of the keywords used included Learning Analytics instructional support for SRL, e-Learning SRL strategies and approaches, Machine Learning techniques on SRL, and e-Learning QEE on performance. Literature Analysis was based on literature, where the researcher identified various SSRL strategies and a SSRL model best suited for an e-Learning environment for improving QEE on performance.

From the SRL Models Analysis, the SSRL model (Hadwin, et. al., 2013) was analyzed together with the SRL theories selected during the systematic literature review, then the factors for the conceptual assessment framework were analyzed.

A three-months qualitative survey was conducted, on 21 Universities in Kenya, with an aim of informing more on the problem and giving more clarity on the research problem. It investigated the e-learner awareness and use of SRL strategies, LA experience, motivation, perceptions and challenges faced by e-Learners in Universities in Kenya.

In light of the e-learning challenges identified, a need for the ongoing methodological development is obvious, which entails having a real-time measurement strategy that takes place as e-learners engage in the learning process (Azevedo et al. 2017).

In order to see the extent to which the expected contribution was achieved, two research questions were addressed:

RQ1: Which instruments and approaches can be used to measure and promote SSRL in collaborative e-learning contexts?

RQ2: Which features can be mapped to LMS factors to develop a SSRLA instructional support model to best predict the performance of e-learning students based on their SSRL skills?

3.1 Participants and Sample Size

This research adopted Purposive sampling on 21 Universities in Kenya. University lecturers, through their departmental Program coordinators, were requested to provide contacts of their class representatives, for ease of facilitation. The researchers then made a formal invitation e-poster through their e-mails and via a WhatsApp invitation link, for the students to fill in a google form as a formal registration into the course. The sampled participants were informed of the purpose of the study by the researcher, and their consent was sought before responding to the survey. Such an assurance was required so as to eliminate any form of ethical issues that might come up while using university curriculum material to conduct experiments therefore intentionally disadvantaging some learners. Participation was on a voluntary basis.

The research targeted students pursuing Computer Science degree course, and were in their second, third or fourth years of study, due to the complexity of the experimental course, Laravel Frameworks for web development. Laravel was chosen due to its practical nature, hence more learning activities to measure, and also based on the challenges usually experienced by final-year students during projects development as confirmed from the pre-study findings. The experiment was facilitated by an experienced instructor, a lecturer from Technical University of Mombasa, and an academic counselor from Technical University of Kenya.

In the survey, research participants completed a mandatory course survey when enrolling into the Laravel Frameworks course for the first time. The survey included a measure of SSRL using questions adapted and customized from the MSLQ questionnaire by Duncan and McKeachie (2005). The questionnaire was distributed through e-mail invitations to the participants. The invitation e-mail contained the purpose of the Research study, a link to the URL and WhatsApp forum where the questionnaire was located. Learners were required to enter their demographics (course level, gender, education, university), time commitment (hours per week), course intentions (intend to watch all lectures; intend to complete all assessments), prior experience with the course topic, the number of prior e-Learning courses started, the number of completed courses, their SSRL strategies, and motivations. The descriptive survey was adopted as it examined the situation the way it was and provided quantitative information that would be analyzed through statistical analysis, hence providing a basis to answer our research questions (Engelhart, 1972). The researcher customized a MLSQ questionnaires using a web-based tool, Google forms. This approach was preferred because it enabled a faster collection of responses and the ease of exporting data for qualitative analysis. The Course Survey link: https://forms.gle/yUNMvDUjiimsPnb49.

4. Results

This research sought to investigate the most suitable interventional instruments, and factors that can enable LA to effectively support SSRL, based on the survey responses from MSLQ questionnaire, so as to clearly understand e-learners preferred SRL strategies. These findings would enable lecturers, LMS designers, LA researchers be more engaging in offering scaffolds to their at-risk learners. The research thus, encourages collaborative and autonomous socially-shared regulated learning for QEE.

4.1 Research Question1 Results

Research Question 1:

RQ1: Which instruments and approaches can be used to measure and promote SSRL in collaborative e-learning contexts?

The following instruments and approaches were used in this study:

4.1.1 Evidence-Centered Design (ECD) framework

Mislevy, Steinberg, and Almond developed the Evidence-centered design (ECD) framework in 2003 for designing, constructing, or implementation of educational assessments based on evidentiary arguments (Lee & Recker, 2017; Mislevy et al., 2012). This study used ECD to help draw valid inferences between the constructs of SSRL and learner trace logs that were captured in Moodle LMS, ie psychological constructs (students' cognitive processes) and individual traces (Lee & Recker, 2017). Through EDM, valid inferences were formed between the variables (e.g., detailed logs of student activities in Moodle online learning system) and the psychological constructs of interest (latent variables), based on a construct-centered approach.

The ECD framework provided explicit evidentiary linkages between the targeted assessment constructs (student model), evidential components (evidence model), and assessment tasks (task model). It measures student SRL by using trace logs captured by a learning management system. According to Lee & Recker, 2017, the ECD framework consists of five layers (domain analysis, domain modeling, conceptual assessment framework, assessment implementation, assessment delivery), in this study we focus on the core layer that is closely related to assessment implementation, the conceptual assessment framework (CAF) (Lee & Recker, 2017; Riconscente, Mislevy, & Hamel, 2005). The CAF consists of several models, and each model asks critical questions such as What are we measuring? How do we measure it? Where do we measure it? (Lee & Recker, 2017; Mislevy, Almond, & Lukas, 2003).

- Student Model: What are we measuring?

A learner or student model contains variables that are related to e-learners' knowledge, skills, or abilities that the researcher wishes to measure, (Lee, & Recker, 2017; Mislevy et al., 2012). In this study, the focus was to measure 3 types of SRL strategies: cognitive, resource management, and metacognitive. To measure student use of SRL strategies, we use the theoretical constructs from the MSLQ (Lee, & Recker, 2017; Pintrich et al., 1993). MSLQ is one of the most widely used instruments and the subconstructs of SRL are clearly defined. According to the MSLQ, students' SRL consists of four components: motivation (value, expectancy, affect), cognitive strategies (rehearsal, elaboration, organization, critical thinking), metacognitive strategies (planning, monitoring, regulating strategies), and resource management strategies (or behavior) (Lee, & Recker, 2017).

- Evidence Model: How do we measure it?

The evidence model is associated with how we measure e-learners' knowledge, skills, or abilities (Lee, & Recker, 2017). It refers to e-learners' behaviors that reveal the constructs described in the student model and also links the student model with the task model (Lee, & Recker, 2017). From Cognitive construct, the first subconstruct, Elaboration (EL) used the frequency of course viewed (COV), files downloaded (FID), e-notes read (ENR) and videos viewed (VIV). The second subconstruct used user logins (ULI). The third subconstruct, critical thinking (CT) used posts created (POC) and workshop updated (WOU).

From Resource management construct, the fourth subconstruct, Peer learning involves engaging others during learning whenever needed. Students' use of peer learning strategies was measured using the number of discussions viewed (DIV), Wikis viewed (WIV), Workshop Viewed (WOV), WhatsApp posts (WHP) and Webinar attended (WEA). The fifth subconstruct, Effort regulation refers to e-learners' regulation of their own effort, including persistence during difficult or boring activities and tasks (Lee, & Recker, 2017; Pintrich et al., 1993). Learners' use of the effort regulation strategy was measured using the number of Quiz attempt viewed (QAV), Assignment Attempt viewed (AAV) and Project submitted (PRS). The sixth subconstruct, help-seeking is about the usage of other stakeholders whenever needed during the learning process, and was measured using the number of Discussions created (DIC), Wikis updated (WIU) and Q and A Posted (QAP).

From Metacognitive construct, the seventh subconstruct, Planning and goal setting used Dashboard viewed (DAV), Most preferred day (MPD) and, Most preferred time (MPT). The eighth subconstruct, monitoring used Quiz attempt reviewed (QAR). The ninth subconstruct, Self-assessment used Quiz attempt viewed (QAV). The tenth subconstruct, time-management, refers to students' efficient use of time (Lee, & Recker, 2017; Pintrich et al. 1993), and used the regularity of log-in intervals (intervals between login points) to measure time management strategy using Quiz attempt submitted (QAS), Assignment attempt submitted (AAS), Total time spent (TTS).

- Task Model: Where do we measure it?

The task model focuses on where we measure learner abilities, knowledge, or skill. It describes the tasks, situations, or environments that elicit the behaviors described in the evidence model. This research measured students' SRL in Moodle LMS. E-learners' activities related to SRL strategies (e.g., viewing learning materials, participating in online discussions) were used to elicit the variables described in the evidence model (Lee, & Recker, 2017).

Figure 2 gives a summary of the CAF to measure students' use of Resource Management SRL strategies using Moodle LMS trace logs and how the student, evidence, and task models are related to each other.

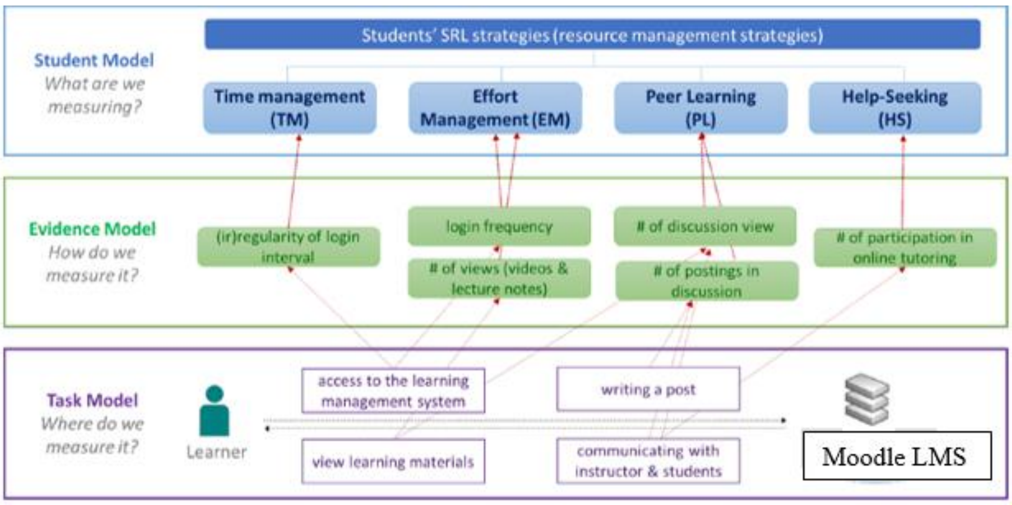

Figure 2: Conceptual assessment framework (CAF) to measure students' use of Resource Management SRL strategies (Adapted from Lee & Recker, 2017)

4.1.2 Motivated Strategies for Learning Questionnaire (MSLQ)

For this study, the Motivated Strategies for Learning Questionnaire (MSLQ) was also used to measure SRL as a self-report instrument (Pintrich et al., 1993). This instrument is considered an aptitude measure of SSRL, as it regards self-regulation as a student's typical attribute and over time, it aggregates students' responses (Zimmerman, 2008). Throughout the learning process, the ability of learners to use self-regulated strategies keeps changing and is not static (Dignath et al., 2008).

Socially-shared and self-regulated learning strategies were measured using the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, et al., 1993). It is a self-report instrument designed to assess college students' motivational orientations and their use of different learning strategies for a college course (Pintrich et al., 1993). It was used in data collection, as it has made a major contribution to the SRL field (Pintrich et al., 1993b). Researchers have indicated that MSLQ has a strong reliability and sound validity (Pintrich, Smith, Garcia & McKeachie, 1991; Pintrich, Smith, Garcia & McKeachie, 1993) within traditional higher educational settings hence can fit well in online contexts. The MSLQ is a self-reporting tool with 81 items, divided into a Motivation section with 31 items, and a Learning strategies section with 50 items which are subdivided into three general types of scales: cognitive, metacognitive and resource management (Duncan and McKeachie, 2005). The resulting questionnaire used a seven-point Likert scale ranging from 1 ("not at all true of me") to 7 ("very true of me") with no specific labels for the other response categories, as shown in Table 1 below.

Self-reported data from learners via instruments like surveys, SSRL quizzes, questionnaires, interviews, MSLQ and its subsets (Araka, et al., 2020). Some studies have found MSLQ as being the most used instrument in investigating students' motivation and SRL strategies (Honicke and Broadbent, 2016; Duncan and McKeachie (2005); Moos and Ringdal, 2012). This emphasizes the highly significant impact of Pintrich's MSLQ in SRL (Broadbent, J., & Poon, W. L., 2015). This research adopted the MSLQ questionnaire and customized it to suit the research objectives within a SRL e- Learning environment.

Table 1: Summary of the MSLQ Research Questionnaire Items Used in the Study

Item No.	Type	Information Gathered
Items 1-9	Multiple choice	Demographic information
Items 10-15	Checkboxes	Commitment And Experience With E-Learning:
Items 16-22 (1-7)	Likert Scale	Experience with Self-Regulated Learning (SRL) Strategies: Metacognitive Activities BEFORE Learning
Items 23-29 (8-14)	Likert Scale	Experience with Self-Regulated Learning (SRL) Strategies: Metacognitive Activities DURING Learning
Items 30-35 (15-20)	Likert Scale	Experience with Self-Regulated Learning (SRL) Strategies: Metacognitive Activities AFTER Learning
Items 36-40 (21-25)	Likert Scale	Time Management
Items 41-44 (26-29)	Likert Scale	Environmental structuring
Items 45-51 (30-36)	Likert Scale	Persistence
Items 52-57 (37-42)	Likert Scale	Help seeking

4.1.3 Learning Analytics dashboard using personalized feedback and prompts

Today, Learner analytics (LA) is seen as a fast-growing field that focuses on utilization of educational data which is generated from LMSs. Upon collection of learners' log data, analysis is done so as to make inferences which can generate patterns, inform and understand e-learners' interactive behavior while learning. Learning analytics (LA) technology is the process of measuring, collecting, analyzing and reporting learners' data in their context, so as to understand, measure, optimize student learning process, experience, and the e-learning environment, with an objective of improving QEE on the overall performance outcomes (Baars, & Viberg, 2022; Long & Siemens, 2011). With the application of LA during e-Learning, there is a possibility of measuring key indicators of learner performance, supporting development of students SRL skills, improving decision-making, improving learning outcomes, motivation and informing institutional strategy (Verstege et al., 2019; Azevedo et al., 2010; Davis et al., 2016).

Visualizing LA data and understanding student behavior with the support of SSRL factors on LA intervention can enhance online student interactions leading to better engagements among e-learners (Kaban, 2023). LA-based approaches could be applicable in measuring and supporting e-learners SRL (Pardo et al., 2019) with little support being offered to adopt SSRL through LA (Viberg, Khalil, & Baars, 2020). LA would be very important in supporting e-Learners in developing their ability for regulation of their own learning across collaborative e-Learning environments (Viberg, Khalil, & Baars, 2020).

Web-enabled feedback and Prompts were employed in this study to provide personalized feedback to e-learners. Such feedback was facilitated through the use of LA reports submitted to the course administrator and instructor who then used the feedback to assess e-learners' application of SSRL strategies (Cho & Shen, 2013; Winne & Hadwin, 2013).

In this study, LMS log data was collected, recorded, and carefully integrated into LA-based personalized dashboard for participants in the experiment group. The flow chart in Figure 3 illustrates how LA-based personalized interventions were generated. In this study, learning analytics included a range of log data, such as students' login records to the LMS (e.g., the days and numbers of the students' logging in and off the LMS), numbers of views of the video recording of lectures, frequencies of reading the e-book, the number of messages posted on the discussion forum, the number of weekly tests they took, and their test scores as well (Ustun, et al.,2022).

LA-based personalized dashboard interventions were provided to each student in the experimental group once a week for 10 consecutive weeks. These personalized interventions were pushed to each student via the messaging feature on the LMS (Ustun, et al.,2022). LA-based interventions were provided as individual, customized feedback and prompts to each student in the experiment group. The content of such messages was based on students online learning behaviors as reflected in the LMS log data and the records of their testing attempts and results (Ustun, et al.,2022).

The graphics in the LA dashboard was interpreted with concise explanations, and LA-based personalized messages included specific recommendations for actions (Ustun, et al.,2022). For example, the LA-based feedback and prompts read like,

> *"You have never viewed this week's Session 1 video and e-Notes.*
>
> *You need to work on the videos to be able to do Assignment 1 successfully."*

Or,

> *"You participated in the Wikis collaboration forum only once in week 4. Increased participations in discussions will be beneficial for your Quality Educational Experience."*

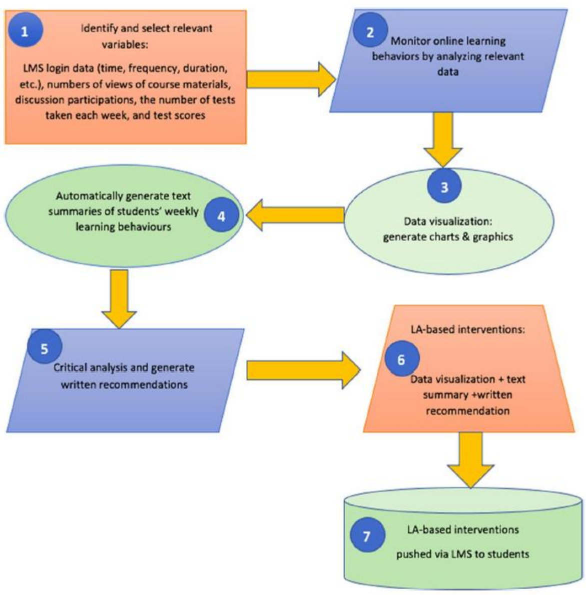

Figure 3: Creation process of LA-based personalized interventions on SSRL (Adapted from Ustun, et. Al., 2022)

4.2 Research Question2 Results

RQ2: Which features can be mapped to LMS factors to develop a SSRLA instructional support model to best predict the performance of e-learning students based on their SSRL skills?

4.2.1 *Feature mapping of SRL strategies to LMS factors*

Traditionally, the self-regulatory aspects of students' metacognition have been measured using questionnaires. However, research on SSRL measures has shown that learners can be inaccurate in calibrating their learning behaviors (Sanne et al 2019; Zhou & Winne. 2012). There is contention among some researchers (Greene and Azevedo, 2010) that students are not accurate reporters of their behaviors and therefore we should question the validity of self-reported measures. On the other hand, other researchers e.g. (Karabenick and Zusho, 2015) emphasize the importance of understanding students' conception of themselves.

Since disagreements exist regarding SSRL measurements, particularly whether self-reports represent a valid and reliable approach to measuring these processes, researchers have advocated the use of behavioral data (Zhou & Winne. 2012). Learning analytics techniques were used via Moodle LMS logs to generate simple metrics in order to assess learner's proficiency in self-regulation. This approach provided promising insight into learning processes as an alternative to traditional approaches for measuring self-regulated learning. From Table 2, this was done by examining the frequencies of students' SSRL behaviors as revealed from the system logs and the relations between SSRL behaviors and student learning performance (Zheng, Xing, & Zhu, 2019). Additionally, questionnaires were used in order to assess whether students were aware or not of the strategies they used, by comparing their answers with the observed learning sequences.

In this study, we have defined a simple, reduced set of SSRL categories so that the reported data is presented in such a way that is easy to understand and interpret (Figure 4). As for which categories to choose, we considered the ones that have been observed to be most correlated with academic performance, according to studies such as the ones just cited. Furthermore, we made sure that our available data could be directly associated to these categories. In the end, we have settled with the following five categories: cognitive strategies, resource management strategies, metacognitive strategies, learner characteristics, and QEE on performance.

Table 2: Summary of SRL Features, Strategies, Variables and Measures for LMS Log metrics (Source: Authors)

Student Model (What are we measuring?)				**Evidence Model (How do we measure it?)**
SSRL Strategy	**Description**	**Variables**	**Operational definition**	**Measures and Indicators (Moodle LMS sub-variables)**
Cognitive	Learner integrates new information with prior knowledge.	Elaboration	• The ability to link new and existing information with a goal of recalling new contents	• Course viewed (COV) • Files downloaded (FID) • E-Notes read (ENR)
	Learner selects appropriate information	Organization	• A learner's capability to underscore major concepts covered during learning	• User-logged in (ULI)
	Learners apply previous knowledge to solve problems	Critical Thinking	• Learner's ability to scrutinize online learning content carefully	• Post created (POC) • Workshop Updated (WOU)
Resource Management	Manipulating available resources and maximize	Peer Learning	• Using a study group or friends to help learn	• Discussion viewed (DIV) • WhatsApp Posts (WHP) • Webinar Attended (WEA)

Student Model **(What are we measuring?)**				**Evidence Model** **(How do we measure it?)**
	learning environments			• Wikis Viewed (WIV) • Workshop Viewed (WOV)
		Effort Regulation	• Persisting in tasks • Active participation	• Quiz attempt reviewed (QAR) • Assignment Attempt Viewed (AAV) • Project Submitted (PRS)
		Seeking Help	• Seeking help from peers or instructors when needed	• Wikis Updated (WIU) • Q & A Posted (QAP) • Discussion created (DIC)
Metacognitive	Improve performance by assisting learners in checking and correcting their behavior as they proceed on a task	Planning and Goal setting		• Dashboard viewed (DAV) • Most Preferred Day (MPD) • Most Preferred Time (MPT)
		Monitoring		• Quiz summary viewed (QSV)
		Self-assessment		• Quiz attempt viewed (QAV)
		Time management	• Using their time well • Regularity of log-in interval	• Quiz attempt submitted (QAS) • Assignment attempt submitted (AAS) • Total Time Spent (TTS)
Learner Characteristics	Showing prior-experience	Extrinsic motivation	• Average score in Motivation & experience	• Prior Experience (PRE) • Learner Motivation (LEM)
QEE on Performance	Showing improvement on activity engagements.	Scoring a grade on quiz or projects	• Setting and pursuing learning goals	• Average Quiz Grade (AQG) • Total Activity Engagements (TAE)

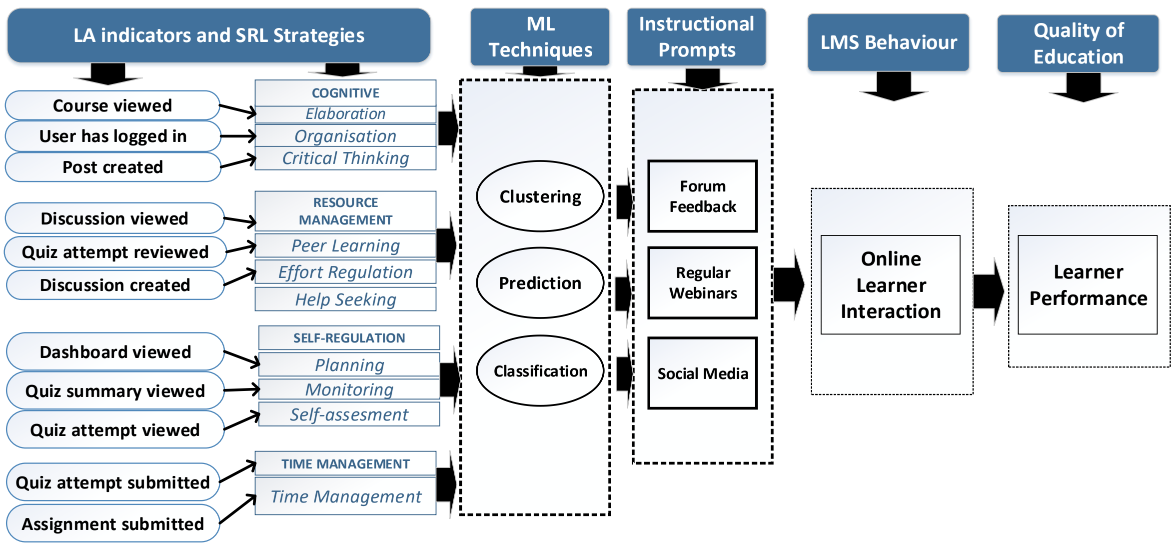

Figure 4: The SSRLA instructional support model with features mapped to LMS factors (Source: Authors)

5. Discussions and Findings

The purpose of this study was to investigate the effect of Learning Analytics intervention using prompts and feedback on e-learners' SSRL strategies in an e-learning context. The findings indicate that LA-based support has the ability for measurement and provision of intervention which would stimulate e-learners SSRL skills while learning online. Through this, the researchers were able to provide SSRL factors and strategies that could be adopted as interventions to student SRL and its implications for advanced LA-based research, concurrent with studies by Nguyen, et al., 2022, and Kim et al., 2018.

The findings confirm that LA scaffold using Prompts and Feedback can support e-Learners in developing their ability for regulation of their own learning across SSRL Moodle e-Learning environment, and this concurs with findings from Viberg, Khalil, & Baars, 2020. This can be categorized into three Strategies. First, Cognitive strategies, which describes how the e-Learner integrates new information with prior knowledge, selects appropriate information and applies previous knowledge to solve problems. Secondly, Resource management strategies, which entail manipulating available resources and maximize learning environments. The provision of consistent information on learners' use of cognitive tools during the learning process was made possible by log files traces (Malmberg et al., 2014). Third, Metacognitive strategies which improve performance by assisting learners in checking and correcting their behavior as they proceed on a task

Based on e-learners' log data from the Moodle LMS, SSRLA-based intervention can offer visual feedback that are simple to perceive and understand. As frequently advised by researchers (Ustun et al., 2022; Viberg, Khalil, & Baars, 2020; Schumacher & Ifenthaler, 2018; Yilmaz & Yilmaz, 2020; Uzir et al., 2020), they also include tailored prompts and feedback recommendations.

The study looked at how university students' QEE based on their SSRL skills was affected by LA-based interventions. In order to encourage and remind e-learners to plan, monitor, and manage their own learning progress during e-learning sessions, LA-based feedback and prompts were used consistent with Yilmaz & Yilmaz, 2020. This research confirms that LA-based feedback and prompts, along with highly individualized, informative recommendations, are necessary to maintain e-learners' engagement and motivation (Ustun et al., 2022).

It is notable that self-reported-instruments like the MSLQ are still being used to measure SSRL, so as to give a clear analysis and report on the preference and behaviour of e-learners. The feedback generated by the LA instrument will enable instructors and course administrators to provide better scaffolding to the e-learners for a more engaging and motivated learner experience. LA scaffolds will also be able to give early warnings especially to at-risk learners so as to lower the attrition rates. This proposed SSRLA model can be used in the implementation of the current "third wave" of SSRL measurement in e-learning contexts. So as to curb the challenges encountered when using self-reported instruments like MSLQ, the researchers propose the use of LA techniques to measure SSRL in collaborative e-learning environments.

6. Conclusion and Recommendation

This study was set to establish the effect of LA intervention on SSRL strategies intervention using prompts and feedback on e-learners' SSRL strategies in a socio-cognitive e-learning environment and to develop an LASSRL model based on these factors. The potential of LA techniques in measuring task-specific SSRL process on a collaborative e-learning context over time has been established in this study. The study is based on the social cognitive theory, with the most modelled SRL strategies being cognitive, resource management and metacognitive.

This research focused on Learning Analytics instructional support on learners in an e-learning context and it matters because the proposed intervention, has indicated improvement to Quality Educational Experience (QEE), performance and motivation measurement through the SSRL behavioral patterns of learners.

The success of SSRL is tied to the support from instructors and academic counselors, particularly feedback on previous problems and quizzes, which are regarded as environmental conditions (Hadwin & Oshige 2011), as well as their personal perceptions and efficacy. This study derives its motivation on the fact that without adequate utilization of the trace data, critical information about learners' behavior patterns in terms of their online interactivity with the course activities and their SSRL profiles and strategies cannot be disclosed leading to little improvement of e-Learning interventions (Lodge et al., 2019). Recent studies confirm that more experienced e-learners who make use of appropriate SSRL strategies in constructing and selecting courses of actions to improve their QEE, are believed to be better able to self-regulate during learning than inexperienced ones.

The empirical literature reviewed explicitly discussed the relevant potential of LA to measure and support SRL, but was limited to providing more options for improving learning support on SSRL. This suggested that Learning Analytics support needed to be critically examined further to understand how it could be effectively transformed into teaching to improve students' conditions for SSRL in collaborative e-Learning contexts. The potential of improving students' QEE and learning outcomes were also explicitly underlined. The proposed SSRL model will be useful in blended e-learning environments for Universities from Sub-Saharan region and beyond.

Authors' Contributions

All the authors, GLA, RO, and LM, approved and equally contributed to the final manuscript for submission. They all made substantial conceptual contributions, gathered and analyzed the data. They also drafted and critically revised the manuscript in keeping with scholarly guideline, and have provided final approval before publishing. They have agreed to be accountable for the accuracy of this publication work.

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Availability of Data and materials

Not applicable.

Competing interests

The authors declare that they have no competing interests.

Ethics

This article is original and contains unpublished material. Both the corresponding author and the co-authors confirm that they have read and approved the manuscript and that no ethical issues are involved. The authors declare that they have no competing interests. The researchers sought ethical approval from Kenyatta University Ethics Research Centre and NACOSTI. Student's participation was on a voluntary basis during the survey and experiment processes. This assurance was necessary to eliminate any ethical issues that could be raised from experimenting with curriculum material and knowingly disadvantaging some students. Before the experiment was undertaken, the study anonymized datasets and information collected, by replacing them with anonymous IDs.

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