Self-Regulated Learning and Scientific Research Using Artificial Intelligence for Higher Education Systems

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ABSTRACT

Self-regulated learning (SRL) is a very significant ability for students in the learning process, and SRL strategies are used to assist students in learning efficiently in higher education. Many SRL environments face challenges and barriers, including less immediate feedback and guidance, a high level of self-personalization, environment, and resources from teachers or learner designers. Hence, in this paper, the artificial intelligence framework for self-regulated learning (AIF-SRL) overcame the SRL environment’s challenges in higher education. Self-regulated students are active participants in their learning and may select from a strategic portfolio and monitor their progress towards the objective. The proposed artificial intelligence-based solution has been used to monitor student behavior through students’ feedback and responses. The experimental results show that the proposed AIF-SRL method improves the student’s self-evaluation, self-regulation behavior, self-efficacy, learning gain, and self-satisfaction compared to other existing methods.

KEYWORDS

Artificial Intelligence, Higher Education, Self-Regulated Learning

INTRODUCTION AND SIGNIFICANCE OF SELF-REGULATED LEARNING

In recent years, greater attention has been given to identifying and promoting students’ self-regulating learning (SRL) activity (Hooshyar et al., 2020). During interactions with these environments, student conduct is not consistently demonstrated as self-regulatory conduct, reducing potential learning contributions. This line of study is supported by evidence that self-regulating activities play a significant role overall in a student. A teacher self-report questionnaire was developed and validated to evaluate teachers’ usage of SRL-fostering teaching practices in the classroom and build a competency-based progression to represent the number of abilities instructors deploy in their SRL classroom activities. Using SRL behaviors helps students persevere with difficult tasks until a solution is found, and they gain satisfaction from their efforts as a result of this perseverance and accomplishment. By taking an
active role in their education, kids become more self-motivated, accomplish more and evaluate what they have learned. The mechanism through which students maintain cognitions, conduct, and effect (Gao et al., 2020) that are consistently oriented towards attaining their objectives can be described as the process that usually involves strategic, metacognition, and encouraging aspects (Taub et al., 2020). Unfortunately, students can show their SRL behavior across a wide range of students lying behind their fellow students across their ability to establish and track learning objectives adequately (Abdel-Basset et al., 2019; Nguyen et al., 2020). Although there are many, they have only examined the interventions whose contents were implemented in e-learning ways or supported by the new information and communication technology.

For this reason, a lot of work in the Artificial Intelligence education field centered on the ability to identify and help student SRL strategies (Chi et al., 2016). The key objective of this study has been the analysis of SRL in structured problem solving and learning environments. However, inaccessible learning environments where goals can be less evident (Taub et al., 2019), students may not always have a consistent indication of their success, and students need to recognize and prevent SRL behaviors. Students need to consciously define and choose their targets and measure their progress correctly to succeed in this learning environment (Nguyen et al., 2021). Unfortunately, students do not reliably demonstrate adequate self-regulatory actions during interaction with these environments, limiting future learning contributions.

Consequently, more research is needed to clarify the function of SRL in open-ended learning environments as useful learning resources (Abdel-Basset et al., 2019; Gambo et al., 2019). Artificial intelligence systems (AIS) are designed to deliver students with independent learning opportunities. Learning takes place by way of suggestions, mentoring, scaffolding, and feedback. There is a great deal of research on feedback and teaching forms and strategies (Ullah et al., 2020), which have been shown to enhance student results. As a teacher in the school, they have used numerous artificial intelligence systems for learning mathematics with students (Nieto et al., 2019). Over the years, these systems have benefited numerous people. The task planning and decision-making phases include the activation of learning through personality and management of underlying motives. Here, students assess a task’s components and the level of difficulty and work necessary before deciding on the conclusion. Self-regulatory learners manage their learning tactics before they begin. They do this by analyzing the learning task. However, amid all the support they get, the experienced students struggle to utilize the techniques and fail to learn. The research framework is to deal with that failure (Matcha et al., 2019; Lung-Guang, 2019). To obtain optimal results, AIS must have successful self-regulated learners for students with the system. Smart Tutoring Systems offer independent student learning opportunities. Learning takes place via tips, tutorship, tacking, and feedback on correctness.

Self-regulated learning is a three-phase progression (Tsiakas et al., 2020). The students perform a task review during the Foresight Process that involves selection and strategic design (Nuankaew et al., 2019; Molenaar et al., 2019)). Although self-motivation values, including expectations of self-efficacy, performance, job interest/value, and target orientation, play a crucial role in this process, they have significantly affected student learning (ElSayed et al., 2019; Song et al., 2020; van Gog et al., 2020)). During the learning process, students show self-control through the usage of different task policies and behaviors (Li, 2019; Zheng et al., 2020). Self-observation is essential through meta-cognitive control (Ivanova et al., 2019)). The students engage in self-reaction and self-judgment during a final period of self-reflection. The programs, which came from most direct continuum programs, focused on general self-regulatory training competencies that apply to every curricular subject. These elements must be including developing self-regulated learners. In the foresight stage, students prepare ahead by putting strategies into action and staying on top during the execution phase. Students need to keep their goals in mind throughout the course to adjust their behavior and learning practices to stay on track or even adjust their goals in response to changing conditions. Students keep track of their development and motivation through self-reflection and feedback. They can articulate and defend a particular viewpoint because they are well-restrained in their thinking. They keep track of effective
methods and processes for future reference. However, as they deal with AIS, certain aspects seem to be more important than others. Specifically, the mechanisms of self-regulated learning may resolve motivating principles, help-seeking behavior, and metacognitive self-monitoring. In this paper, the Artificial Intelligence Framework for Self-Regulated Learning (AIF-SRL) to overcome the challenges students face in higher education. Self-regulated students are active participants in their learning and may select from a strategic portfolio and monitor their progress in higher education. Hypotheses are formed from the demonstrated relationships, and particularly those contradicted results in existing research. Artificial intelligence (AI) can build capacity for learning analytics. Still, these systems demand enormous amounts of data, including confidential student or faculty information, which pose serious data protection and privacy problems.

LITERATURE SURVEY AND FEATURES OF THE RESEARCH STUDY

(Biswas et al., 2020) introduced Massive Open Online Courses (MOOCs) to study individual and community differences between students in self-directed learning in terms of expectations, patterns, and behaviors. This research explores the connections between MOOC learners’ demographics, self-regulated learning (SRL) technique, perceived learning, and satisfaction. The structural equation modeling revealed that the age, sex, the highest degrees of participants, and the amount of prior online courses have greatly forecasted their target and the climate. Using SRL behaviors helps students persevere with difficult tasks until a solution is found, and they gain satisfaction from their efforts as a result of this perseverance and accomplishment. When students take an active role in their education, they develop targets for themselves, complete tasks as expected, and reflect on what they’ve learned as a result. With the ability to self-regulate learning, students can become more self-sufficient and proficient, as well as develop, adapt, and access learning opportunities beyond what their teachers had originally imagined. By applying and staying aware of techniques employed throughout the mission statement, students use planning that began in the thought phase. Students need to keep their goals in
mind for the course to adjust their learning and behavior strategies as necessary to stay on track and accomplish them. Aside from individual differences, the environment can significantly impact how students engage in the learning experience and grow as learners. Consider an instructor who believes that government officials possess knowledge that novices do not have access to. As a result, this instructor may use more instructional classroom approaches such as speaking or explicit instruction, which could reduce student engagement and growth in learning skills. The results have contributed to independent learning settings for researchers, different learning opportunities for students of different backgrounds, SRL attitudes and education providers who discuss the increased use of SRL techniques, improved success for online learners, and cross-cultural education. Researchers, institutions, and professors need to know how to organize the resources of new technologies to develop students’ self-regulatory abilities in and outside classes.

(Azevedo et al., 2019) introduced science, technology, engineering, and mathematics (STEM) for a complex design process. The self-regulation of students plays a significant part in interdisciplinary tasks. There is a minimal study on why and how self-regulation contributes to different student learning results in engineering design. The students are categorized into four different types: knowledgeable, emotional, analytical, and minimally self-regulated learners. Competent, self-controlled learners thought they were the most vital autonomous students and had the most significant learning benefits, even if they were not strongest at work. Cognitive self-regulated learners regarded themselves as the least self-regulated learners, even as both the mission and the learning results were second-highest performed. Developing and using learning processes is a key question for teachers. The purpose of this paper is to look at previous research that tackled this broad subject. Identifying a conceptual framework that can adequately describe the intricacies of learning is an important part of the process in exploring this issue further. It is vital to understand how students self-regulate their learning before looking at how teachers might facilitate SRL. Despite the fact that the SRL discipline has given rise to numerous theoretical methods focusing on a wide range of dimensions, there are four underlying assumptions about how students can self-regulate their learning that remain constant.

(Cárdenas-Robledo et al., 2019) developed the Hidden Markov Model (HMM) used to identify and classify the behavioral trends of students from their machine activity sequences. They would detail the Hidden Markov Model (HMM) is obtained from the operation logs. They prove that the composition of the HMM fits the collective activity trends of students in the learning context. Overall, the HMM approach helps one move beyond necessary frequency and series analyses, including individual behavior and predefined pattern counts, and explore how certain behaviors cohere more in complex trends over time, utilizing discovery techniques. The results show that those who teach an agent have higher learning output and greater value than students who learn about themselves. They integrate content, monitoring the learning process, collaboration tools, communication tools, management, evaluation, feedback, etc., in a single media-pedagogical instrument, which requires and facilitates greater user involvement and management.

(Azevedo et al., 2019) introduced Computer-assisted learning systems (CALSs) technologies such as smart tutoring, game-based learning experiences, and virtual reality (VR) to improve instructional performance by helping and the capacity of learners to effectively identify and control cognitive, affective, metacognitive, motivational and social processes in several areas. The research presents self-regulation in CALSs by examples of contemporary CALSs and how they use multimodal multichannel data to analyze self-regulatory strategies in perceptual, affective, and metacognitive frameworks. The study is primarily based on how CAM mechanisms play a part, assess, and assist in analyzing and resolving CALSs problems. It presents a brief overview of self-regulated learning (SRL) studies with CALSs and addresses the usage of various CALSs to analyze and promote SRL.

(Cárdenas-Robledo et al., 2019) proposed a Smart Sequencing Approach, which allows Technology-enhanced learning (TEL) systems to improve student learning. The proposal’s essence is an overall self-regulated learning (SRL) model that allows students to build higher-order reasoning through exercising their learning skills, interests, and actions. The technique was used in the U –
Learning framework sequencing module, where students adopt their recommended cognitive strategies to help them through control unit programming.

To overcome these issues, in this paper, the Artificial Intelligence Framework for Self-Regulated Learning (AIF-SRL) to overcome the challenges faced by the SRL environment in higher education. The present research has observed the following hypotheses.

ARTIFICIAL INTELLIGENCE FRAMEWORK FOR SELF-REGULATED LEARNING (AIF-SRL)

The present document addresses the challenge for the SRL environment in higher education through an Artificial Intelligence Framework for self-regulated learning (AIF-SRL). Auto-Regulated learning is defined as the control and monitoring of one’s performance before, during, and after a learning process. It is an embedded learning process guided by several motivational philosophies and conduction, metacognitive and cognitive activities adapted and designed for personal objective detection. In SRL, various metacognitive processes include target setting, self-assessment, support, self-monitoring, choice of study, etc. Evaluation and study higher self-assessment will lead to a better choice of study, which may render learning more efficient and effective. Universities should consider how AI-driven software and data processing techniques will assist existing students. This is partially done by finding students who are at risk of dropping out of education. Over time, the models used in these machine applications are steadily improving, while students who require help are zeroing in. Artificial Intelligence-assisted SRL is intended to deliver independent learning occasions for students. Learning arises via tutoring, hints, and precision feedback. Great research exists immediate types and timing of tutoring and feedback found to enhance student results. Artificial Intelligence assisted SRL in providing various structures to support student learning.

Figure 2 shows the architecture of the suggested AIF-SRL method. Self-regulated learning has become a very attractive research field. Self-regulation entails observing and maintaining cognitive functions and monitoring emotions, motivations, behavior, and environment relating to learning. The proposed method has shown that self-regulated learning increases learning output, enhances student thought, emphasizes learning, and enhances reflexive and conscientious professionalism. The acquisition of lifelong learning skills is crucial for self-regulation. Self-
regulated learning is influenced by strategic action, meta-cognition, and the motivation to learn, according to psychologists, in schooling. Students are proactive about their learning in this relation. There is support for further academic accomplishment for students with inherent motivation, initiative, and personal responsibility concerning learning results. The cognitive psychology theory defines self-regulatory efficacy (SRE) as the efficacy of competent self-regulatory processes like self-judgment, self-observation, and self-response. Self-observation is characterized as the intentional focus on different aspects. It offers information based on evaluating one’s performance and the establishment of goals, includes independent roles to determine the success of the activities, and induces changes in behavior. Self-judgment disparities the ambitions of the learner with their present achievement. Furthermore, self-response is described by motivating oneself to change and regulate the actions to achieve the aim. Students are presumed to be able to keep track of and govern their own cognitive processes as well as behaviors and motivations. This assumes that each student is unique and has a set of challenges. According to a second hypothesis, students actively create their own unique goals and meaning based on both the learning setting and past information they bring to the table.

The automated measurement of the learner’s ability to learn is called self-regulatory efficacy. Self-response is often calculated by the faith of oneself in mastering a topic as strong as the will to achieve by self-regulatory efficacy learners. Confidence encourages learning through endorsing individual goals, such as the conventional psychology of education, for academic achievement completed via self-directed learning with SRL. Self-regulated learning is characterized as a student’s goal for the basis of studies. It is systemic management of our perception, emotions, and conduct concerning our personal goals and achievements. Conventional adaptive systems inevitably adjust the content and system behavior to the learner by utilizing the data from the user model, which is known as personalization. However, this method might be very operative for obtaining domain knowledge, and it does not allow for learning aspects relevant to self-regulated.

Consequently, they learn positively. As a result, it comes as no surprise that all student conduct is goal-directed and that self-regulation includes changing actions to achieve goals. Finally, it is presumed that self-regulatory behavior modulates the link between a student’s performance, environmental circumstances, and individual traits.

For instance, planning contains the task of selecting learning resources seeing their own goals. Thus, the proposed AIF-SRL method concentrates on recommendations, which provide guidance and control to users simultaneously. Similar to traditional adaptation, the recommended method is based on a user model and a recommendation plan. The proposed artificial intelligence framework for the self-regulated learning method has three types of resources. These are learning activities, learning tools, and learning or content objects. This recommendation is generated by exploiting the relationships between learning techniques and strategies. The learner model data is utilized to rank the learning tool. For instance, if a learner has the objective to enhance students’ reflection competence, learning tools are ranked greater if they are connected with learning methods being part of the reflection plans. The recommendation for learning activity is a trait that directs the learner in the learning stage. A sequence and frequency of learning, the methods, and procedures to make sure all forms of learning tasks are covered would be recommended. The student model is updated, and new guidelines are given based on the activities applied. The learner may decide not to participate or choose an activity and ask for further work at a deeper level. The content recommendation is focused on ideas that the student has or needs to build in the domain skills. The learner model contains such skills. As domain capabilities include definitions of the concept, this information is utilized to scan for learning repositories of objects.

**Case Analysis 1**

This study has tested with the hypothesis model below:
**Hypothesis 1:** Low- and high self-regulated students have an important relationship between academic performance and multiple intelligences.

**Hypothesis 2:** There is an important relation among low and high self-controlled learners between levels of academic self-regulation and several bits of intelligence.

**Hypothesis 3:** There is a substantive relationship between university performance and academic self-regulation levels among low and self-regulated students.

**Hypothesis 4:** Higher education has a strong relationship between academic achievement, self-regulated learning, and self-image.

**Hypothesis 5:** There is a relationship between intrinsic motivation of academic achievement and self-concept in higher education.

Figure 3 shows the research model. Multiple Intelligences and self-regulation are the building blocks of academic curriculum design and educational psychology since self-regulated strategies are linked with students’ multiple intelligences and other factors related to personality. Multiple Intelligence enables the teachers to integrate various creative approaches in classroom instruction, where differentiated activities enable the students to navigate their learning. Multiple Intelligence approach to increase the level of academic self-regulation. Self-concepts should be understood as a dynamic system, which refers to individual values, desires, talents, and abilities developed due to individual encounters with the world and their interactions with other self-concepts. These factors determine how people are motivated. Academic self-concepts are likewise processes in which self-concept evaluations are focused on learning experience and the understanding of the educational environment of students, and they reflect the awareness and perception of serious deficiencies of the willing participant and in a specific academic discipline and their confidence in the capability to perform academic tasks on planned levels effectively. It is one of the main mediators and predictors for efficacy and ineffectiveness of motivation and one of the most significant and relevant variables.
in the learning progression. Academic self-concept relies heavily on relative social knowledge and represents the interpretation made by others in a normative way. On the other hand, a distinction between the academic self-concept of every person and the others. The high-self-regulated students use goal redefining methods and techniques in motivating activities to define educational goals and targets to perform tasks associated with these priorities. This includes making a calendar of activities in each course, taking into account the ultimate goal of each activity they participate in, and keeping an eye on how they achieve the objectives.

Case Analysis 2

Hypothesis 6: There is a relationship between lack of academic achievement motivation and self-concept in higher education.

Hypothesis 7: There is a relationship between intrinsic motivation of academic achievement and self-regulated learning in higher education.

Hypothesis 8: There is a relationship between extrinsic motivation of academic achievement and self-regulated learning in higher education.

Hypothesis 9: There is a relationship between lack of academic achievement motivation and self-regulated learning in higher education.

Figure 4 shows the impact of key component processes of SRL. In the way students learn and succeed in school, motivation plays an important role. However, failure to understand and engage students correctly can have the opposite effect. Therefore, the fact that motivation is a dynamic concept is important to consider. Psychologists generally define two distinct forms of motivation: external and intrinsic motivation. Extrinsic motivation allows students to become inspired and competitive while inspiring them implicitly leads to the quest for understanding. In the end, encouraging both kinds of motivation helps students build good study practices and learning investments. There were positive relationships between SRL and intrinsic learning and relationships of high school students between self-regulated education and external encouragement to achieve academic achievement. The relationship between independent learning and lack of academic motivation was negative and inverse proportion. Intrinsic and extrinsic motivation affect students learning and academic performance.

Table 1 shows the hypothesis testing result. These learners use broader and more self-regulated strategies such as analyzing, planning and reflecting to make sense of problem situations. They have

Figure 4. Self-regulated learning component
an effective set of strategies that they can readily utilize when rechecking class works, writing an essay in math, answering homework at home, preparing for an exam, solving difficult tasks, rechecking works once finished, and rearranging the learning environment. Poor self-regulation indicates that these learners fail to utilize motivational and metacognitive strategies and the behavioral strategies necessary to regulate their learning. It further suggests that low self-regulation among students is associated with low performance.

As a consequence, they become dependent and ineffective learners. In the academic setting, one of the objectives is to mold the students to become self-reliant to attain higher academic achievement in math. Thus, learners need to have high self-regulation and become independent learners who have obtained higher academic outcomes. The result expresses that high self-regulated students have higher academic performance compared to their low self-regulated peers. It is found that the settings of these variables are supported; thus, parametric testing has been used in the analysis of the details. The distribution of the sampled responses is important in each of these variables.

**RESULTS AND DISCUSSION**

This research aimed to simultaneously investigate the relationships between demographics, the use of an SRL approach, perceived learning, and satisfaction in learning contexts using an AIF-SRL model. The AIF-SRL is consistent with student self-evaluation and encourages learners to take part as much as possible in developing their knowledge. In addition to creating learning needs and increase success and performance, student self-evaluation represents each student’s strengths and weaknesses.

Student self-evaluation is a method that represents each student on their strengths and deficiencies such that learning requirements are established and defects to improve achievement and performance. Student self-evaluation is compatible with the AIF-SRL and supports learners for maximum participation in developing their knowledge. AIF-SRL is a system for self-regulation learning. To create new, real information, students must review the knowledge to fill gaps and maintain links between its elements. There is no proper information development in the absence of these revisiting trials. Therefore, Student self-evaluation is essential to the development of reasonable understanding. The proposed AIF-SRL creates knowledge of their learning and thought processes and gives support for future learning, sensitize teachers to the interests of their students, and giving them an external perspective for their achievement, allowing students to recognize their learning differences and motivating themselves to improve their learning towards the learning goal. Figure 5 illustrates the Student self-evaluation ratio of the proposed AIF-SRL model.

| Variable                  | Mean | Standard deviation | Probability | Result    |
|---------------------------|------|--------------------|-------------|-----------|
| Self-regulated learning   | 34.2 | 4.9                | 0.01        | Supported |
| Self-concept              | 24.1 | 5.4                | 0.01        | Supported |
| Lack of motivation        | 40.2 | 4.5                | 0.02        | Not supported |
| Intrinsic motivation      | 22.4 | 6.7                | 0.01        | Supported |
| Extrinsic motivation      | 29.4 | 7.8                | 0.01        | Supported |
| Academic achievement      | 35.2 | 6.9                | 0.01        | Supported |
| Multiple intelligence     | 35.9 | 6.3                | 0.01        | Supported |
| Higher education performance | 40.1 | 5.3            | 0.01        | Supported |
The students about their persistence intent to examine potential relationships between student self-regulation and perceptions of academic persistence. The proposed AIF-SRL explored students’ expectations of success by their decision to complete the course. To determine how the variables described earlier could affect how often a student will continue or leave its current path with the AIF-SRL model. Personal attributes are very significant for studying information, motivating values, and effective usage of cognitive skills in the framework of AIF SRL self-regulated learning analysis. However, these attributes are used in conjunction with theories and self-regulation contexts based on AIF-SRL. The elements of motivation and self-regulated learning differ widely based on the numerous specific areas and courses to understand better art college students’ independent behavior and the relation between autonomous and academic activity. The proposed AIF-SRL model has higher self-regulation behavior prediction for self-regulatory learning in higher education. Figure 6 illustrates the Self-Regulation Behavior Prediction of the proposed AIF-SRL model.

The proposed AIF-SRL model has provided better self-efficacy for self-regulatory learning in higher education. While significant data confirm the specific effects of self-efficacy belief on academic achievement, relatively few researchers have investigated the motivating process for mediating self-efficacy and achievement relationships and are required to explain how and why self-efficacy influences students’ academic achievement. This AIF-SRL model looks at the relationships between academic self-performance, the desire value beliefs of students, the satisfaction of the educational processes, and academic success, focused on a social-cognitive motivation viewpoint. This proposed method is utilized in analyzing the connections and consequences of these motivating beliefs on the output of the students, in planning activities and programs aimed at enhancing instructor efficiency and student results, and in clarifying the connection between self-efficacy and expectative variables in the prediction of student outcomes. Figure 7 illustrates the Self-efficacy of the proposed AIF-SRL model.

The satisfaction of students in learning is significant, and sometimes it is beneficial for learning outcomes. One of the crucial reasons for students’ success and expected education in online courses is the design and structure of systems. Perceived research has shown that the amount of previous online classes, gender, and grade levels (students or undergraduates) has precisely predicted self-performance and has predicted that students will satisfy themselves significantly. The AIF-SRL model recognizes
the potential link between SRL and student satisfaction, and many efforts have been made to address it. Since self-regulated students continually track their success and performance to adapt their plans to their priorities, they are satisfied with their learning experiences. Based on the proposed model, the learner’s experience with the content of the course forecast its expected learning, the student’s experience with the subject, indicate their use of the other process, and the satisfaction of the time. The proposed AIF-SRL model has provided better student satisfaction for self-regulatory learning in higher education. Figure 8 illustrates the student satisfaction of the proposed AIF-SRL model.

The AIF-SRL model has been proposed to include cognitive, affective, computational, and motive processes to quantify proportional learning improvements in connection with sub-targets, cognitive strategy, and metacognitive processes to improve learning among students. There is a significant need to
support students build their classroom environments and be mindful of and accountable for monitoring and assessing their learning processes. AIF-SRL is a useful model that encourages students to actively participate in awareness, self-regulation, and metacognition and resolve their behaviors, motives, and social actions to accomplish learning goals. The proposed AIF-SRL paradigm contributes to the classical contributions of educational and expert systems. It seeks a dual-target that considers various and complex cognitive functions concurrently carried out by users as a multi-task brain-machine aimed at learning. The proposed AIF-SRL model has provided better learning gains for self-regulatory learning in higher education. Figure 9 illustrates the learning gain of the proposed AIF-SRL model.

Figure 8. Student satisfaction analysis

Figure 9. Learning gain
The proposed Artificial Intelligence Framework for Self-Regulated Learning (AIF-SRL) achieves high student’s self-evaluation, self-regulation behavior, self-efficacy, learning gain, and self-satisfaction in the SRL environment when compared to other existing Massive Open Online Courses (MOOCs), science, technology, engineering, and mathematics (STEM), Hidden Markov Model (HMM), Computer-assisted learning systems (CALSs) methods.

CONCLUSION

This paper presents the Artificial Intelligence Framework for Self-Regulated Learning (AIF-SRL) to overcome the challenges faced by the SRL environment in higher education. The present research hypothesized that students’ self-regulated learning (SRL) capability suggestively affects their academic achievement in the learning process. The results that were generated showed that SRL influences satisfaction and academic performance. The dimension of goal-setting proved not to influence either of the two variables. It has proven to be difficult to monitor those behaviors in real-time. This paper presents a study of autonomous learning in a game-based learning environment. Therefore, artificial intelligence-based different self-regulated learning strategies have been effectively utilized, like searching for help, choosing goals, and appropriate cognitive and metacognitive strategies. By comparing and assessing their actions in the self-reflection and self-judgment stages, they could reform their provenance to an extent. According to the significances of the study, in the higher educational system, academic self-regulated learning and self-concept can be enhanced by multiple Intelligence to grow learners’ academic achievement.
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