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Understanding Self-Regulated Learning Dynamics Through Computer Simulation: A Model-Based Approach

Kyffin Bradshaw*

Division of Natural Sciences, Barbados Community College, BB11058 St Michael, Barbados

* Correspondence: Kyffin Bradshaw (Kyffin.bradshaw@icloud.com)

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Abstract: Self-regulated learning (SRL) is conceptualized as a series of interrelated cognitive and affective processes rather than as isolated events. To elucidate the relationship between students' cognitive engagement and their comprehension of self-regulation strategies, a conceptual model was developed to examine learner engagement during a hypothetical learning scenario. The model posits that the learning environment can be represented as a social network in which the mechanisms of knowledge diffusion significantly influence a learner's adoption of self-regulatory processes. The results obtained from this model corroborate the modes of cognitive engagement as predicted by the Interactive, Constructive, Active, and Passive (ICAP) framework, manifesting as absorbing-state phase transitions. These transitions are interpreted as self-tuned phase changes associated with self-schema and personal adaptive and reflexive learning thresholds. This framework suggests that learners engage in retrospective monitoring processes that activate SRL mechanisms. It is inferred that learning occurs through continuous change; wherein self-regulated practices can be viewed as processes leading to specific events that subsequently trigger further learning. This conceptualization underscores the dynamic nature of SRL and highlights the potential for computer simulations to model and understand these processes.

Keywords: Self-regulated learning (SRL); Cognitive engagement; Social network; Absorbing-state;Pphase transition; Reflexive learning

1 Introduction

Learning, according to Daneshgar and Pariokh [1], constitutes gaining a skill in something or acquiring knowledge through either some course of study, experience, or tuition. However, quantifying this level of learning and evaluating the knowledge competences of learners through their self-development and behavior as they navigate a learning environment is quite challenging since human beings are known to characteristically interpret their environment using some type of schema. And any information they perceive not to fit their schema is either dismissed or treated as extraneous content. Consequently, developing the appropriate assessment tools that reliably reflect conceptual knowledge schema and the extent to which individual learners benefit from a learning event is extremely challenging. The difficulty lies with quantifying conceptually a learner's thinking and the level of acceptance or rejection of subject content that occurs due to their schema.

Given that each learning process is unique to an individual and occurs via knowledge structure, it is reasonable to assume that individual schema may significantly influence student learning and academic achievement since learning environments, especially those in higher education, inherently challenge a learner's cognitive structures and processes. If learners interpret their surroundings according to predefined rules, we can argue that SRL, a theory about how learners interpret, organize, and store information, is similar to theorizing about the role of self-schema in the task at hand.

Schema theory suggests that cognitive structures act as mental frameworks that guide the interpretation and organization of information [1]. In particular, Daneshgar and Pariokh [1] articulate that schemas dictate how individuals perceive, interpret, and integrate new information. According to schema theory, schemas develop and change based on new information and depend on a learner's experiences and cognition.

Figure 1, as conceptualized for the purposes of this study, depicts the agents believed to be relevant to knowledge schema and SRL. It is a composite of the three-layered model of learning and an adapted version of Nonaka's model of knowledge creation [1]. It is believed that combining these two models into a singular framework provides the means for developing a first-approximation theoretical framework of how SRL may be inextricably related to self-schema and the various applied forms of cognition. It is assumed for this investigation that Figure 1, in the most basic sense, visually illustrates the components believed to be indispensable prerequisites for learning and the transfer of knowledge in a learning environment.

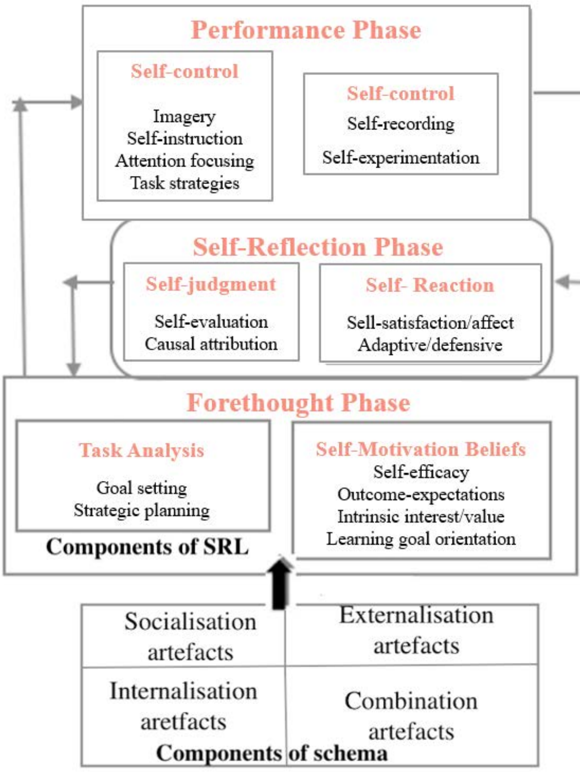

Figure 1. Knowledge creation and SRL schematic

According to Ŝteh and Ŝarić [2], certain teaching strategies suit certain students better than others because teaching strategies can interfere with the learning strategies that learners already possess and bring into a learning environment. It is reasonable to assume that Ŝteh and Ŝarić were attempting to convey that not all strategies work the same way for every learner because of the individuality component associated with learning.

In the study of Boud et al. [3], learners are believed to experience different learning effects in a learning environment depending upon the extent to which they practice some kind of self-monitoring. According to Boud et al., self-evaluation is necessary for learners to improve and build the skills they need to join the workforce. According to Woodland et al. [4], the learning environment may be conceived as a complex social network that connects the learner with the lecturer in a collaborative knowledge exchange process that is equivalent to a network diffusion process.

Social networks may be thought of as environments where individuals connect with each other and inform, spread ideas, and influence opinions. According to Woodland et al. [4], people and groups of people within organizations are embedded within social networks, where their mutual connections act as conduits for the exchange of ideas and resources. In these circumstances, social network analysis may be used to measure and visualize the presence or absence of connections between individuals and the facilitators disseminating the information to the network.

Using the concept of a social network and the concepts of teaching what to learn and how to learn, this study introduces a conceptual model of knowledge sharing and schema as a theoretical approach to the analysis of student learning as it relates to the acquisition of self-regulation practices in a learning environment. To construct the conceptual model, the assumption was made that the learning environment may be modeled using the theoretical constructs associated with knowledge collaboration organizations [5]. And that knowledge collaboration organization could be translated into a learning environment where the interactions are between learners of different backgrounds, knowledge domains, and cultures. According to Sun et al. [5], there are basic asymmetries of knowledge that exist among the members of knowledge collaboration organizations, and these asymmetries can lead to frequent and extensive knowledge diffusion. In the study of Sun et al. [5], knowledge diffusion is considered conducive to improving knowledge and stimulating knowledge among members of the organization. Drawing from the construct of Sun et al. [5], it is assumed that the knowledge processes operating in a learning environment may be distributed via network diffusion. A diffusion process consists of three main components [6]: 1) the population on which they unfold; 2) the mechanisms that describe their evolution; and 3) the content of the diffusion. Diffusion, as a construct, is a transport process from an area of high concentration to an area of low concentration [7]. Alternatively, diffusion may be seen as a process by which innovations or technologies are communicated through certain channels over time to the members of a social system.

The concept of knowledge diffusion has been widely studied in various scenarios. However, as highlighted by Sun et al. [5], not many quantitative methods and models exist that adequately give context to the fundamentals of knowledge diffusion as a construct. Sun et al. [5] contends that mainstream knowledge diffusion researchers have mainly focused on qualitative analysis of the diffuse process only at the macrolevel. To Sun et al. [5], this is unacceptable since knowledge diffusion is a complex process that is generated by the micro-knowledge exchange activities between a knowledge sender and receiver that may result in interactions that are missed on the macroscale.

To improve upon this, Sun et al. [5] devised a quantitative model to investigate the knowledge diffusion process and rules in a knowledge collaboration organization using cellular automata. In that study, Sun et al. [5] used cellular automata to investigate knowledge diffusion from the perspective of micro-knowledge exchange activity among members of the knowledge collaboration organization. Such a model can provide improved insights into the nature of knowledge diffusion mechanisms while providing theoretical support for improving knowledge diffusion efficiency and knowledge management performance in knowledge collaboration organizations. Given the parallels that exist between the functioning of knowledge collaborative organizations and the functioning of a learning environment, this research attempts to utilize cellular automata in the theoretical context presented by Sun et al. [5]. However, some adjustments had to be made to analyze the distribution pattern of knowledge and knowledge accessibility among learners in a learning environment. It is believed that adapting the constructs of learning can potentially help educators develop a holistic view of education so that concrete steps may be taken in developing adequate quality assurance and performance management strategies to support and promote SRL [5].

A key component of higher education that highlights is the notion of guiding learners on how to self-regulate their own learning [2]. According to Milli et al. [6], SRL pertains to the ability to develop knowledge, skills, and attributes that are transferable from one learning context to another. In contrast, Boekaerts [8] describes SRL as an active constructive process in which learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior based on their set goals and the contextual features in their environment. However, according to Boekaerts [8], the most popular definition of SRL is having self-regulated thoughts, feelings, and actions that are systematically guided by personal goals. This concept of guiding students to self-regulate contrasts well with the argument posited by Schunk [9], who claims that knowledge can be diffused using direct interactions between agents operating in a social system and a social network. The works of Schunk [9] suggest that even with the existence of many definitions for SRL, the best strategies for developing SRL are still relatively unknown. Thus, to Rodriguez-Gomez et al. [10], it is vital that researchers design a variety of models geared toward learning how to best promote SRL in academic programs and subjects. This call for better models of SRL is also supported by Toth et al. [11], who argues that more reliable instruments for assessing SRL are needed, especially given that SRL as a concept is a function of interwoven elements relating to metacognition, motivational, and behavioral competencies that underlie the ability of learners to acquire academic mastery.

The concept of developing academic mastery has led to some pertinent questions being raised about the nature of SRL. For example, Boud et al. [3] ask student engagement in self-assessment really calibrate their judgment over time? As an extension to the question posed by Boud et al. [3], this study develops a conceptual model geared toward gaining insight into the elements of learning that will allow educators to answer three specific questions:

1) If SRL is a series of reciprocally related cognitive and affective processes rather than a singular event, are these processes perceptual, attentional, or motivational?

2) If SRL is an event, is there any quantifiable transition point between a learner not being able to self-regulate and a learner adopting a self-regulatory process?

3) Does self-schema affect the ability to self-regulate, and if it does, in what way?

It is believed that to potentially answer these questions, it is vital to replicate student self-assessment in a real-time learning event to map how self-monitoring works for different learners as they navigate the learning environment. However, this work focuses on determining whether schema may be used to predict a learner's ability to adopt an SRL process. The section that follows provides the details for constructing the modeling technique.

2 Constructing the Conceptual Model

To construct a hypothetical structure of learning, the three-layered formulation of learning and an adapted version of Nonaka's model of knowledge creation were selected as the base framework. Figure 2 depicts a combined adaptation of the three-layered model of learning as presented by Boekaerts [8] and Nonaka's model of knowledge creation.

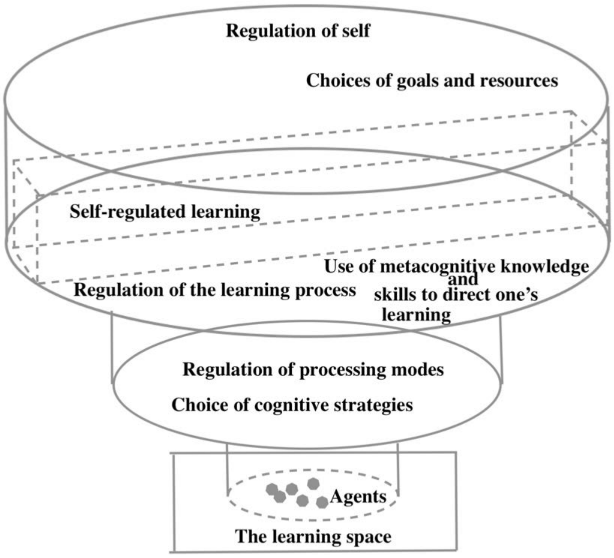

Figure 2. Three-layered model of SRL

Figure 3 shows the various components used to make up the agents of the network that will facilitate the diffusion process. It is believed that combining these components will merge well-established constructs related to SRL and knowledge creation.Theoretically, Figure 3 should be interpreted as constituting the population on which the collaborative knowledge exchange process unfolds, the mechanisms that describe their evolution, and the content of the diffusion. The home learning environment (HLE), shown in Figure 3, is assumed to be the impact source responsible for the initial learning ability a learner enters the learning environment with. Although it is generally accepted that the HLE does not prevent learning, the previous studies [11–13] have highlighted how families from lower socio-economic backgrounds are more likely to produce individuals with anxieties towards learning, and hence these individuals are more likely to face barriers in the learning environment that are different from their counterparts coming from higher socio-economic backgrounds.

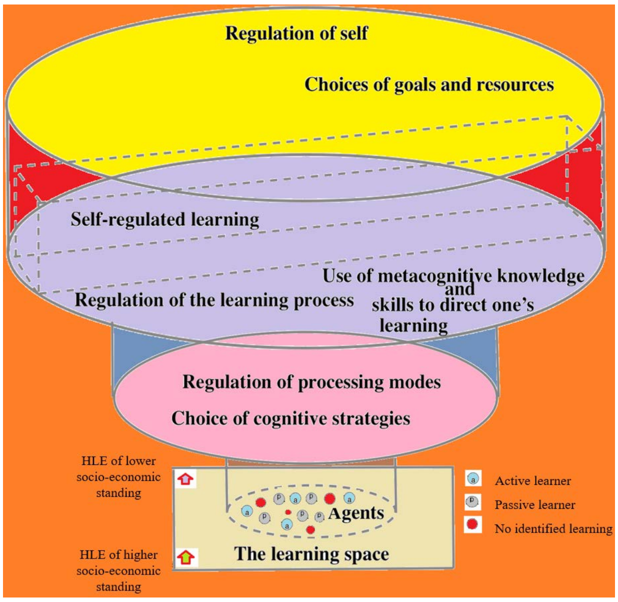

Figure 3. Learning environment as a knowledge flow system

The HLE consists of three major components. 1) The structural characteristics, which describes as the characteristics of the family [11]; 2) The parental educational beliefs; and 3) The educational process. These processes, in the view of Kluczniok et al. [12], pertain to the nature of the interactions in the family. According to Kluczniok et al. [12], the family represents the most influential learning context, and hence the HLE represents the educationally oriented activities that a learner will identify with in a learning environment.

Based on the works of Kluczniok et al. [12], it is reasonable to assume that the influences of the HLE most likely will have some impact on the process of a learner self-regulating. For the purposes of this investigation, it is assumed that the capacity to which the HLE sustains and supports the acquisition of SRL pertains to the extent to which it impacts learner neutrality, passivity, or activeness in a real learning event.

Understanding the attributes of learners is an important consideration to make, as Meiiua and Kaili [14] and Alqahtani et al. [15] suggest that self-adaptive learning is required for learners to maximize their learning experiences. According to Meiiua and Kaili [14] and Alqahtani et al. [15], self-adaptive learning involves a learner reflecting on their actions or self-concept through an objective lens. And hence, the process of reflection is characteristic of learning. This concept of learner reflection has sparked many interesting debates concerning the differences between a learner showing reflection and a learner being reflexive. Being reflexive and showing reflexivity may be viewed as being strongly interrelated, even though they feature different components. Being reflective is considered having the mental capacity to connect with experiences and learn from them. In contrast, being reflexive, according to the literature, is where a learner develops a working theory about the situations, they engage in so that their perceived realities might be modified. As a result, reflection is believed to be a necessary step for becoming reflexive [16]. Therefore, it is believed that the reflection process is an important component of reflexive management learning (RML). According to Denton [16], RML is used to describe both reflective and reflexive components existing within various pedagogical contexts. The works of Zimmerman [17] purport that there are some essential qualities of academic self-regulation that describe the structure and function of the self-regulatory process and methods required for guiding students to learn on their own. According to Ŝteh and Ŝarić [2], self-regulation is a self-directed process by which learners transform their mental abilities into academic skills. And the structure and functioning of self-regulation may be represented via the various phases and processes as depicted in Figure 1. Recall that the phases represented in Figure 1 are: 1) the forethought phase, which refers to the processes and beliefs that occur before efforts to learn. This phase may be further subdivided into task analysis and self-motivation phases. Task analysis is associated with setting goals and strategic planning. In contrast, self-motivation pertains to self-efficacy beliefs. 2) the performance phase, which refers to the processes that occur during behavioral implementation. This phase, as described by Zimmerman [17], features a two-step process. These include self-control and self-observation. The self-control phase focuses on the deployment of specific methods or strategies that were adopted during the forethought phase. Self-observation, on the other hand, focuses on the self-recording of personal events or self-experimentation to ascertain the cause of these events. 3) the self-reflection phase, which refers to the processes that occur after each learning effort. The self-reflection phase is classified as a self-judgement and a self-reaction phase process. The self-judgement phase relates to making comparisons of self-observed performance against a standard of measurement. Self-judgment may also take the form of causal attribution, which refers to beliefs about the cause of an individual's failures or successes [17]. Self-reaction comprises self-satisfaction and positive effects surrounding one's own performance. Self-reaction, according to Zimmerman [17], may manifest through what are called adaptive or defensive responses. Adaptive reactions refer to adjustments designed to increase the effectiveness of an individual's method of learning, while defensive reactions refer to the efforts an individual makes to protect their self-image.

In this work, it is assumed that the three-layered model of SRL as described by Boekaerts [8] and Nonaka's model of knowledge creation give a general enough representation that supports all the ideas expressed by Zimmerman [17]. As a result, it is further assumed that using the three-layered model and Nonaka's model of knowledge creation as a theoretical basis for this work presents a reasonably solid foundation for modeling the elements contained in a learning environment. The innermost layer of the tree-layered model of SRL pertains to the regulation of the processing modes, while the middle and outermost layers represent the regulation of the learning process and the regulation of self, respectively [8]. Figure 3 is a reinterpretation of the three-layered model of SRL proposed by Boekaerts [8]. This reinterpretation, along with Nonaka's model of knowledge creation, is used to build the theoretical learning environment presented in this work.

To convert the elements of Figure 3 into a usable domain in which knowledge-flow and knowledge-change processes of theoretical learners could be simulated, the conceptual ideas used in the work of Nakanishi et al. [18] were utilized and modified for this specific investigation. Specifically, Figure 3 had to be adapted such that information along with its mechanisms of spread over the purposed synthetic social network could be simulated in a way to reveal any phenomena that could be potentially used to make abstractions regarding schema and the concept of SRL. To accomplish this, active and passive diffusion, as described by Milli et al. [6], were used as constructs to discriminate the degree to which individual choice affects the overall spreading of content over a social graph. In the study of Milli et al. [6], spreading processes describe different kinds of contents that must be vehiculated by interacting agents to diffuse. According to Milli et al. [6], agents can include individuals connected by a complex network describing their relationship. The work of Milli et al. [6] further suggests that the degree of activeness is a characteristic feature of diffusion processes that affects the way in which the process itself evolves. Active agents, as described by Milli et al. [6], voluntarily adopt a given behavior or idea simply because they may feel it to be right. In contrast, passive agents are doomed to suffer a diffusion process [6].

To remove some of the abstraction of the synthetic learning environment constructed in this study, a parallel is made between the concepts of a social network and real-world geological flow media. Information associated with a social network is paralleled by the flow characteristics of fluid percolating through a porous medium. Thus, the mechanics of fluid flow in a porous medium are being used in this work to construct synthetic learners interacting and exchanging information in a learning environment in the same way fluid interacts with material properties to channel flow. It is believed that using physical geological media as a reference paints a better picture of agents spreading across a domain. However, it is important to keep in mind that although diffusion is introduced with respect to geological constructs, terms such as activeness, passiveness, blocked nodes, and dead ends do not hold their usual geological meaning but are to be interpreted in the context of the learning environment and in relation to the phenomenon of social contagion. The geological setting is used only to illustrate how flow is dependent on connectivity and neighboring network structure in the same way social decisions can depend on the social network structure and the details of the network neighborhood structure. This parallel is also used to illustrate how structure dynamics may be used in predicting the decisions of individuals in a learning environment. Therefore, an attempt is made in this conceptual model to capture via computer simulation how some learners can autonomously adopt a self-regulatory process independent of their peers' inability or ability to adopt any self-regulatory process for themselves by introducing the concepts of the backbone and dead ends associated with porous media. Conceptually, this means that in this study, the learning environment is theoretically approximated to flow through porous media with characteristics like the interactions occurring between learners in a learning environment and the way knowledge diffuses among them. Note that it is reiterated that although the same constructs of flow in porous media are used, some terms, as previously stated, do not carry the same meaning. For example, whereas the term matrix in a geological setting represents solid, unfractured rock, its usage in this study represents the agents making up the learning environment, and hence it essentially depicts the knowledge-flow domain in that context. Also, in geological settings, rock masses contain large fractures or fractal objects with fractal properties in the form of complex interconnected voids that enable fluid flow across the rock matrix. Fractal objects may be viewed as infinitely complex patterns that are self-similar across different scales [18]. However, voids in the context of their application to the learning environment are assumed to represent the mechanisms or pathways in the learning environment that allow content knowledge provided by the lecturer to diffuse across the learning environment.

Figure 4 shows the learning environment matrix representation of the elements presented in Figure 3. It represents the population of learners to whom the content knowledge will be supplied and the mechanisms that will facilitate how this knowledge flows across the domain. The simulation is designed such that when the results are interpreted in the context of the learning environment, the active and passive schemas of learners are characterized in the context of SRL. Additionally, it is designed to capture such behaviors as spontaneous adaptation and mechanisms such as dead ends or blocked nodes that may affect the diffusion of knowledge in the network. It is believed that this approach is viable theoretically for linking schema to SRL, as SRL is viewed as an active, constructive process by which learners set goals for their learning and attempt to regulate, monitor, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features in the environment [9]. It is because of this that the diffusion process simulated in this work is believed to be a direct reflection of the active and passive diffusion schema mechanisms of individuals that might result in achievement differences among learners during a learning event.

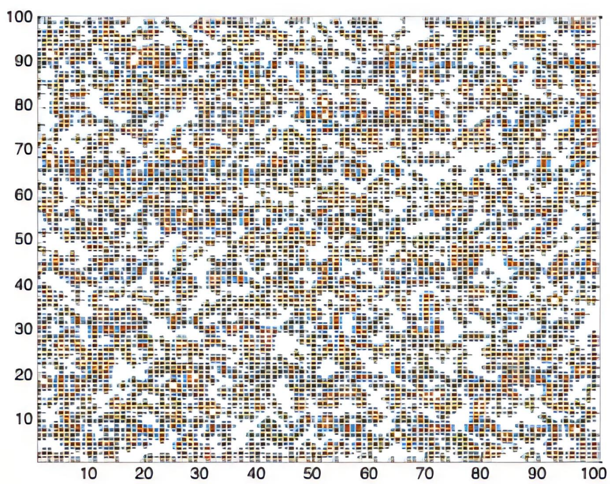

Figure 4. Learning environment as a knowledge flow system

The spaces visible in Figure 4 represent the mechanisms and pathways by which knowledge can diffuse. Some of these "voids" form "dead ends" that do not allow for knowledge flow, and hence these voids are simply a part of the network. As previously stated, dead ends contain stagnant information. The colored portions of Figure 4 represent the different learners that were created by assigning random values to represent the different assumed learning abilities that learners might bring with them to the learning environment. For the purposes of this study, the computer-generated learners were assigned random numbers representing whether a learner had no predefined learning style or was passive or active. The learning styles used in this investigation are assumed to be a function of the cognitive distortions and self-efficacy of each individual learner. The axis labels in Figure 4 serve only as an indicator of the size of the of the lattice constructed. This is in acknowledgement that in numerical computer simulations such as the one presented in this study, simulations are always restricted to a finite sample, and hence they are expected to suffer from what are called finite size scaling effects. These effects pertain to critical fluctuations that occur because of increasing the system size.

When studying flows through a complex network such as the one created in Figure 4, the backbone of that system is said to be the only part of the system that needs to be investigated [19]. The backbone of a medium, according to Onody and Zara [19], is the part of a percolation cluster where there is non-zero flow. Alternatively, the backbone may be described as a fractal object that obeys a scaling law with known dimensions that can be estimated via simulation [20]. However, for the purposes of this study, it is assumed that the backbone is linked to the collective learning dynamics of the simulated learning environment.

There are three main theories that are believed to operationalize the understanding of collective learning. 1) capacity development; 2) functions of education and learning; and 3) onto-political proceedings [21]. Collective learning, as described by Schreurs et al. [21], is a concept used to help understand how the processes of collective learning are managed. Collective learning considers the ability to commit, engage, perform functions or tasks, relate, get resources and support, adapt and self-renew, and balance coherence and diversity as the core elements that define the ability of a group of learners to organize themselves. According to Schreurs et al. [21], the status of each of these elements reveals the overall capacity of a group to engage in a process of learning. Learning, as described by Schreurs et al. [21], provides an individual or group with knowledge and skills to perform a task. It is fair to assume that Schreurs et al. [21] believes that this type of learning constitutes a form of organized learning. Additionally, one may argue that Schreurs et al. [21] suggest that different modes of learning coexist with the processes of collective learning, and their balance is a function of certain requirements of learning that are defined through time.

In the context of this study, skills and knowledge, as highlighted in the study of Schreurs et al. [21], are assumed to be attributes learners initially acquire from their respective HLEs. It is also assumed that once learners enter the learning environment, their interactions with other types of learners further determine how they develop and how they attain a state of self-regulation.

To investigate the processes that may lead a learner to self-regulate, this work looks at the feasibility of using network diffusion in the form of a cellular automaton to explore how learning unfolds during a learning event. Cellular automaton is a discrete model of computation that constructs a discrete lattice of cells in which each cell is characterized by a state that is taken from a finite set of states. That is, it is a collection of cells on a grid of specified dimensions that evolves through a set of discrete time steps. Each cell state is updated using a predefined update rule that depends only on the state of each neighboring cell. The automaton updates via a sequence of discrete time steps, as previously mentioned, such that the state of the cells evolves simultaneously. All cells of the automaton are constrained to the same update rule, and the cells are arranged so that each cell is surrounded by four neighboring cells that influence each evolution. Since cellular automaton is a model of computation, computational modeling is employed in this study. Therefore, the proposed model contains numerous variables that are used to characterize the learning environment as a social network facilitating network diffusion. As such, the information that follows contains unavoidable technical jargon and complex descriptions associated with computational modeling and cellular automata. However, the expected takeaway from such technical descriptions is that the learning environment is recast as a network of elements with short-range relationships in parallel that display emergent behavior. It is this emergent behavior that this research attempts to quantify in relation to schema and its role in the self-regulation process.

In this implementation of cellular automation, reactions are assumed to occur in the learning environment each time knowledge or information is diffused. The content knowledge to be diffused is assigned randomly to a cell, as depicted in Figure 5 of the results section. This information may be passed to cells assigned as leaners in the environment. Learners may either be passive, neutral, or active. Different numbers of indexes were assigned to each cell to represent the ease or difficulty with which a passive, active, or neutral learner collects and transmits this information to a neighboring cell. The cells were initialized such that at least one of the neighbors is empty. Therefore, in this model, the state of any cell is described in terms of its learner type and knowledge acquisition state. Each state represents the different entities involved in the process. Knowledge passing between learners is simulated by using the simplistic view that a cell could be a learner that may be characterized as an active learner, a passive learner, or a learner with no predefined learning style. Each cell was divided into four quadrants (North, South, East, and West). For the automaton, it was assumed that center cells were located on modes (i, j) with $0 \leq i < M$ and $0 \leq j < N$, where M was the number of rows in the automaton and N the number of columns. The cells that were located on node (i, j) were referred to as the $C(i, j)$ cell and the corresponding neighboring cells were denoted by $C(i-1, j), C(i+1, j), C(i, j-1)$, and $C(i, j+1)$. The state of each cell $C(i, j)$ in the automaton was defined by a set of variables: $C(i, j) = \langle I, N, S, W, E, F \rangle$ where: I represents the state of the cell. That is, I could indicate a neutral learner, passive learner, or active learner. N, S, W, E are integer variables that indicate the strength or intensity of the learner ability present in each segment of the cell. $F = \langle u, d, l, r \rangle$ represents a set of one-bit flags that were used to simulate the movement of content knowledge in the network. The notation $N_{i,j}, W_{i,j}, E_{i,j}$ and $S_{i,j}$ used in the original automation to describe the number of particles in each four sections of the cell was retained for this simulation. The notation $u_{i,j}, d_{i,j}, I_{i,j}$ and $r_{i,j}$ was used to represent the movement flags for each cell and $I_{i,j}$ as the cell identification.

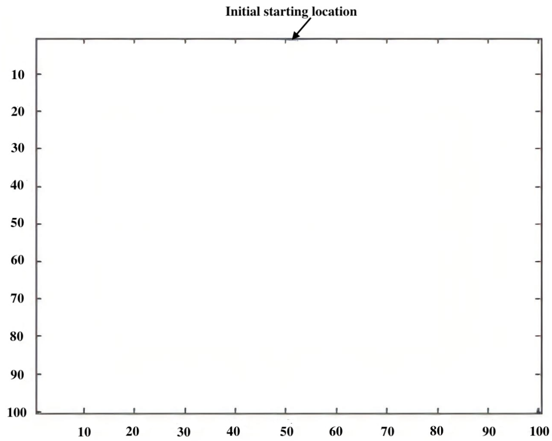

Figure 5. Introduction of content knowledge

Another way to view the simulation presented in this study is via the generalized susceptible-infected-susceptible (SIS) model. The SIS model examines how spread occurs over large networks [22]. Specifically, SIS is used to model the outbreak of diseases that do not give immunity upon recovery [22]. The SIS model divides the population into susceptible groups. Infected such that links between and transmit the disease at a rate. In this work, knowledge is transmitted via links at some unspecified rate. According to Cai et al. [22], and can be reduced to represent the rate of new infections per link per recovery, or the effective infection rate. Also, the SIS model in the thermodynamic limit experiences a phase-transition phenomenon when tuning. As a result, the SIS model is said to play an important role as one of the simplest models undergoing an epidemic phase transition between an absorbing, healthy phase, where infection rapidly disappears, and an active phase, with a stationary endemic state characterized by a finite fraction of individuals [23]. The works of Ferreira et al. [23] showed that when was less than some critical value, the disease died out spontaneously. When was greater than, the disease reached an endemic state where the prevalence or fraction of infected nodes were non-zero [22]. This zero/nonzero epidemic threshold in the mind of Lee et al. [24] was inherited from a zero/nonzero percolation threshold in a model where nodes were occupied in the degree-descending order.

However, some researchers believe that the SIS model is too restrictive in considering a single state since many factors such as environmental changes, social factors, intrinsic fluctuations, discreteness of reacting agents, and the random character of their interactions can influence the most probable, or optimal, flow across the network. Therefore, a general principle is needed to expand the susceptible state for cases where more than one contagion, ideas or. Behaviors spread in the network. Here the idea is that this extension allows for comparison of the interaction between competing multiple sources. To generalize the SIS, Lin et al. [25] made provisions for the number of infected states k to be greater than 1 such that states may range from 0 to k-1. In this formulation, k-1 was defined to be an infected state where an infected node can influence its neighboring nodes. In contrast, nodes in state 0 to k-1 may be elevated to a higher state if exposed to its infected neighbor. Although the model presented in this study employs a similar generalization to that of the study of Lin et al. [25], where Lin et al. [25] used multidimensional mean-filed to analyze the spreading dynamics and general graphs to determine the condition of the phase transition, this work reserves such for a future investigation. For this study the focus was on construction of a conceptual model capable of reproducing already established results. Another area addressed by Lin et al. [25] that is also not explored for this investigation was the dynamics and behavior of the two competing sources with one source being the dominant and the other being recessive. This part of the analysis is planned for future research as the study of Lin et al. [25] already showed that factors such as initial condition and transmission rates may affect the phase transitions and the final equilibrium of the network.

Once the constructed learning environment is initialized, content knowledge is added to the environment by setting the identity of certain boundary cells to knowledge and the identity of others to active. This allowed for the immediate flow of knowledge. The update rule was implemented in three separate steps: 1) the reaction step, 2) the balance step, and 3) the movement step [26]. The reaction step simulated the passing of knowledge between learners after interaction during a learning event. During the reaction step, the amount of knowledge content present in each cell portion was balanced with the amount of knowledge content contained in the adjacent portions of the neighboring cells. For example, if cell $C(i,j)$ contain $N_{i,j}$ particles in its northern portion and its northern neighbor $C(i-1,j)$ contain $S_{i-1,j}$ particles in its southern portion then at the end of the interaction each portion contain $\lceil (N_{i,j} + S_{i-1,j})/2 \rceil$ knowledge particles.

The same update rule was simultaneously executed in the other portions and corresponding neighbors. For the purposes of this study, the reaction only occurs when there are two adjacent nodes or active learner cells, two adjacent active and neutral learners, or when there was an adjacent active and passive learner cell. No reactions are allowed to take place between two passive or two neutral learners. This was to ensure that activeness was the dominant agent in the simulated learning environment. Activeness was chosen as the dominant agent so that the simulation accounted for could mimic any reflective and reflexive processes learners would have to undertake to transition to the next higher phase of learning or a self-regulatory process. The balance step was used to make sure that the concentration of the content knowledge remained uniform during learner interactions. Once the interaction occurred, the number of particles contained in each cell was assigned $[(N_{i,j} + W_{i,j} + E_{i,j} + S_{i,j})/4]$ and again, the particles corresponding to the remainder were assigned randomly to the four portions [26]. The transfer of knowledge between learners was simulated during the movement step of the cellular automaton. Knowledge during the movement step was always in response to an active learner passing information to their southern neighbor. If the southern neighbor was occupied by another active learner, then knowledge flowed laterally. If both adjacent neighbors were occupied by passive learners, no knowledge flow occurred. The steps performed by the automaton may be summarized as follows:

(1) Set up the diffuse network
(2) Add content knowledge
(3) Update:
a) The reaction was modified to consider the saturation constants.
b) Balance.
c) Movement:
i. Movement neighbor 1.
ii. Movement neighbor 2.
iii. Movement neighbor 3.

The remaining steps included removing knowledge from the bottom row and updating the simulation status. Once completed, step 2 was revisited. The time required for an active learner to positively influence a neutral and passive learner was simulated by arbitrarily reducing the particle number representing the intensity for a learner to resist change as they interacted with an active learner. This arbitrary decrement was assumed to be governed by the known dissolution rates of limestone media F_1 such that:

$$F_1 = k_1 \left(1 - \frac{c}{c_{eq}}\right) \tag{1}$$

And

$$F_n = k_n \left(1 - \frac{c}{c_{eq}}\right)^n \tag{2}$$

Dissolution as governed by these rates pertains to the detachment rates of minerals in a limestone dissolution process. Using these rates was in an acknowledgement that the proposed model must account in some way for the process of time involved with learners modifying or changing their perception of their own learning. Since dissolution rates for limestone occur over relatively long periods of time, the dissolution rate formulation was used to specifically show that the phases of learning require significant evolution in time.

3 The Results of the Conceptual Model

The objective of this study was to show how a learner's knowledge management was related to the dynamic character, attitude, and behavior of the learner during a learning event. Specifically, this was represented as knowledge diffusion across the synthetic domain, represented by Figure 4. Figure 5 shows an injection of content that a lecturer wants a cohort to assimilate. Figures 6-8 illustrate how content knowledge diffuses across the theoretical learning environment using cellular automation, as described in Section 2.

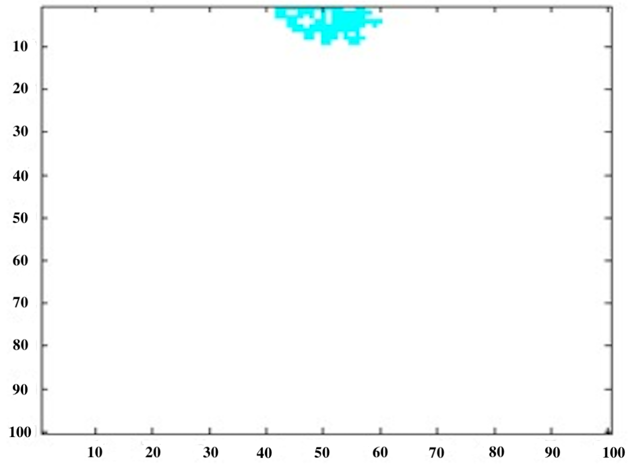

Figure 6. Knowledge diffusion after 10^3 lattice updates

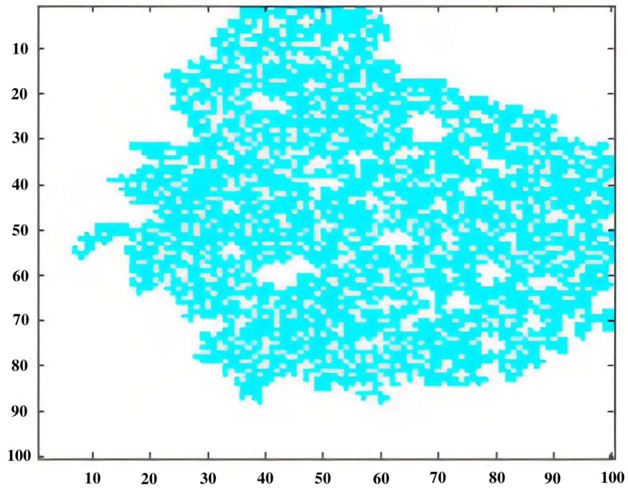

Figure 7. Knowledge diffusion after 10^4 lattice updates

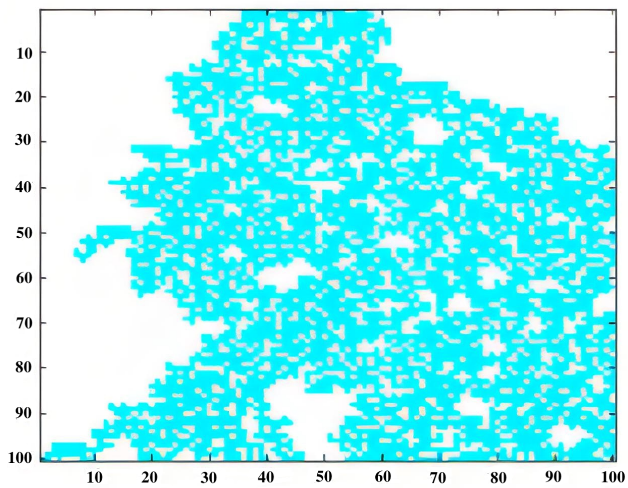

Figure 8. Knowledge diffusion after 10^5 lattice updates

What these figures appear to show is that knowledge is initially acquired by a learner or learners and transmitted to other learners until some steady state or equilibrium point is reached. Since numerical techniques were used for this knowledge-flow simulation, Figure 9 was included to show that the scaling properties of the system could be ascertained.

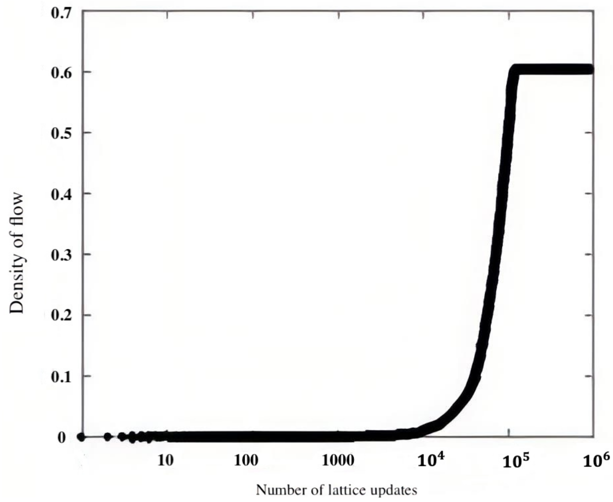

Figure 9. Density of knowledge flow as a function of updates

Spreading of knowledge across the network follows the order parameter for a spreading process; $\rho(t)$, which is defined as the density of "wet sites" and is denoted by the equation [27]:

$$\rho(t) = \left\langle \frac{1}{N} \sum_i s_i(t) \right\rangle \tag{3}$$

In Eq. (3), $s_i(t)$ represents a local binary variable that is attached to each site of the lattice. When $s_i = 1$, the site is considered active (occupied), while $s_i = 0$ means that the site is inactive. The total number of sites in the sample is denoted by N. The number of sites in the lattice is sufficiently large to ensure that in the simulation, the cluster of wet sites remains much smaller than the system to avoid finite-size effects in the time intervals being considered. The spreading of knowledge on the lattice is computed for $N = 1000$. The results are shown as follows:

Figure 10 appears to display the known behavior associated with absorbing-state phase transitions. An implication of this result in the context of learning would suggest that learning is a process involving knowledge change such that when learning occurs, the learner attains a new phase in the learning process and maintains this phase until another learning cycle takes place. It may also be showing how the configuration of the learning environment with respect to the organization or layout of the classroom neighbors can play a significant role in predicting the decisions of other learners. It is further believed that the apparent absorbing-state phase transitions in Figure 10 may very well depict learners who autonomously adopt an idea or information without influence from their neighbors or other individuals who have decided not to adopt that idea.

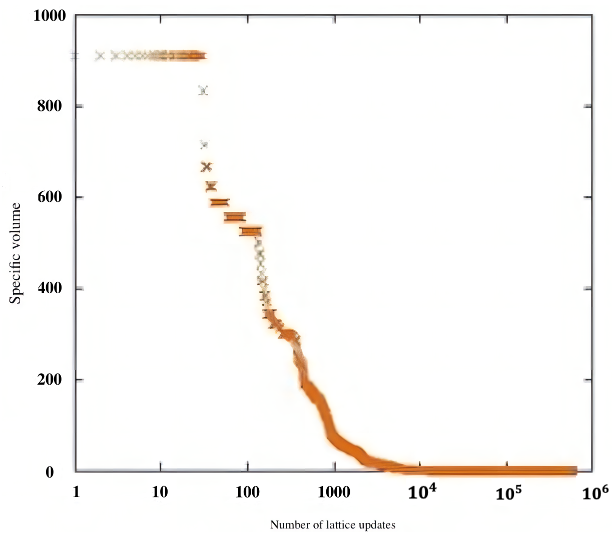

Figure 10. Knowledge flow after 10^6 lattice updates

This is a reasonable interpretation since phase transitions are known to occur with ordering processes and can occur because of many different parameters. Phase transitions can be either first- or second-order and each phase transition has an associated order parameter. First-order transitions are an abrupt discontinuous jump in the order parameter that signals an abrupt change in the properties of a system. In contrast, second-order phase transitions are continuous in their behavior. Given what appear to be discontinuous jumps in Figure 10, interpretations will be given in terms of absorbing-state behavior.

Absorbing-state behavior is generally associated with lattice models and elastic interfaces in random environments [28]. For elastic interfaces, the dynamics are said to be frozen whenever the interface is pinned by the disorder. The non-trivial, on the other hand, is said to be the moving or de-pinned phase. With respect to lattice models, many researchers have shown that there exists some type of phase transition separating what is called a non-trivial phase from a frozen phase. According to these studies, discrete particles originally with some activity over time eventually reach frozen states with non-activity. These frozen states are called absorbing states [28]. According to Alva and Munoz [28], absorbing-state phase transitions are typical for cellular automaton, reaction diffusion systems, directed-percolation type systems, and the fixed energy ensemble of sand pile cellular automaton. If it is accepted that the presented model is characteristic of absorbing-state phase transitions, then the challenge becomes how to interpret Figure 10 in terms of SRL and the general learning environment.

To interpret Figure 10 in the context of phase transitions, it is important to understand that absorbing-state phase transitions represent a special type of transition between an active phase and an inactive phase where particles are absorbed into a state without fluctuations. Hooyberghs et al. [29] describes absorbing states as robust and address models with a scalar parameter, the absence of conservation laws, and short-range interactions. Well-known models with a phase transition of this class are referred to as the contact process and the Ziff-Gulari-Barshad model of catalytic reactions. In systems with special structures, phase transitions are associated with what is called self-organized criticality [30]. Self-organized criticality, as described by Adami [30], refers to phenomena that naturally evolve to a critical point. The behavior of such systems tends to follow a power law in which the exponents are a function of the geometry and the spatial structure. The concepts of self-organized criticality and the ICAP formulation are explored with respect to giving interpretation to Figure 9. According to the works of Chi and Boucher [31], the ICAP formulation gives insight into the different types of learning activities and their effectiveness in advancing learning. The ICAP is further described as quantifying physical and cognitive engagement. Physical engagement addresses learner actions as they interact with the learning environment. In contrast, cognitive engagement covers the learner's thinking process while learning [31]. Therefore, the ICAP formulation is said to be a theory about the process of how students ultimately learn.

Two areas where it is believed that the model presented points to the ICAP relate to the main characteristics of the ICAP hypothesis and the physical interactions it indexes. The ICAP, as reported by Chi and Boucher [31], is based on combining the physical interactions and actions of students with the instructions they receive in conjunction with an analysis of the corresponding student-produced outputs to define the different modes of student engagement. The ICAP is further accepted as providing quantifiable indices that can be used in a real-time classroom context to identify the levels of learning outcomes that may be predicted sequentially, ordering learner ability from passive all the way up to interactive. Therefore, it is posited that the ICAP is based on including the rankings of physical interactions and the plausible hypothetical thinking processes underlying associated learning modes. The ICAP defines a passive learner as a learner interacting with the content material and paying attention to instruction, but there is no output produced [31]. The active learner is described as someone who is engaged with the content material and capable of utilizing its content such that there is visible student-produced output. In contrast, the constructive learner under the ICAP is a learner physically capable of generating external outputs that feature components that were not originally in the content material. The interactive learner is described as learners who interact and collaborate with each other in reciprocally co-generative behavior, producing student output that goes beyond the content material and beyond what each learner contributes individually.

4 Conclusionss

A key component of higher education is guiding learners through the process of self-regulating their own learning [2]. Underlying this concept is the belief that self-regulation can be learned through interactions with others and through some process of knowledge transfer and change. Given the importance that 21st century educators have placed on promoting SRL and practices in the learning environment and understanding how learners codify, store, and transmit knowledge so that they synthesize the relevant information needed to shape and direct their own learning, it has become necessary to assess how different variables influence learning outcomes. To examine how variables such as self-schema and student cognitive engagement relate to and impact the degree to which a learner mediates and organizes their own experiences of learning, this study examined the feasibility of creating a conceptual model of the learning environment that captures information processing and filtering as it relates to schema and how learners are propelled into developing personalized learning strategies.

The results suggest that the conceptual model offers computational potentialities in its ability to capture the engagement modes that are associated with the different phases of learning during a learning event. This claim is substantiated as the results of the simulation appear to be reproducing the hierarchical sequence of learning as specified by the well-known ICAP hypothesis. The ICAP formulation hypothesizes that in any learning environment, learning progresses from passive to active, then from active to constructive, and finally from constructive to interactive. The active mode, according to Vosniadou et al. [32], leads to better learning outcomes than the passive mode because the active mode engages the learner in activities that facilitate the retention of new information. In the case of the constructive mode, Vosniadou et al. [32] claim that it is better than the active mode because it encourages activities such as providing explanations, drawing inferences, and raising critical questions that can lead to the formulation of new knowledge. The interactive mode, as described by Vosniadou et al. [32], is better than the constructive mode because it is related to co-constructive activities between two or more learners. These activities include arguing, debating, critiquing, and questioning that can inspire the creation of new knowledge beyond that which could be attained individually.

This sequence of learning, as explained by Vosniadou et al. [32] and purported by the ICAP hypothesis, is associated with different knowledge change processes and the corresponding learning outcomes [32]. This important association is revealed in this study in the form of absorbing-state phase transitions, as indicated in Figure 10. The significance of these transitions in the context of learning suggests that in any learning event, there exists some transition point between a free state and an active stationary state. An important feature of systems with absorbing states is the existence of a non-equilibrium phase transition between an active state in which the activity continues in the thermodynamic limit and an absorbing state in which the activity is absent. The behavior in Figure 10 is believed to be characteristic of an activity being present for some period and then absent at some later point in time. The distinct transitions in Figure 10 may be alluding to the passive to active, active to construction, and constructive to interactive processes associated with learning.

However, it is important to note that this link is speculative since the data is synthetic. More research is required to further develop the proposed model to input larger and more diverse real-world data. As such, a circumspect approach is taken in professing the real-world application propensities since, for simplicity, the original network configuration assumed homogeneity in the likelihood of how neighbors interacted in the learning environment. Given that in a real-world setting heterogeneity is more likely to occur, it is accepted that interpretation of the results in the absence of further model testing could lead to biased or incorrect simulated outcomes with respect to the psychometric properties underlying the schema. Therefore, future research is planned to extend the current conceptual model to incorporate empirical evidence that could speak to the psychometric validity, reliability, and predictive validity of the model. The initial plan is to utilize some type of schema questionnaire designed to report the psychometric properties associated with SRL and perform factor analysis on a student sample collected at the same time and from the same subject pool to construct a schema map that may be used as real-world inputs to the current model.

However, the present research focused on introducing schemas as a variable in the investigation of promoting SRL. The implication of this approach is that SRL may be directly studied in terms of information processing. A challenge with assessing schema indirectly in the way done in this research is that schemas are considered unconscious cognitive structures that inform an individual's experiences, and as such, no one can be certain of the engagement mode in which learning occurred. However, if it is possible for a schema map to be identified, then targeted interventions may be constructed to correct cognitive distortions that may hinder learners from attaining academic mastery. If this is accepted to be true, then schemas may be considered salient to a learning event since schemas may reflect learning ability. Given the initial results of this computer model, it is concluded that SRL is a function of a learner's desire to reach a specific goal and hence is a function of an individual self-schema, and it occurs via a process of change that leads to an event that compels the learner to a new phase of learning until they reach the interactive phase, where they acquire a steady state of learning. Therefore, it is believed that this study provides supporting evidence that SRL as a series of reciprocally related cognitive and affective processes rather than a singular event is a valid construct.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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