Online Adaptive Learning:
A Study of Score Validity of the Adaptive Self-Regulated Learning Model

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ABSTRACT

Adaptive Learning (AL), a new web-based online learning environment, requires self-regulated learners who act autonomously. However, to date, there appears to be no existing model to conceptualize different aspects of SRL skills in Adaptive Learning Environments (ALE). The purpose of this study was to design and empirically evaluate a theoretical model of Self-Regulated Learning (SRL) in ALE's and the related questionnaire as a measurement tool. The proposed theoretical model, namely, "Adaptive Self-Regulated Learning (ASR)", was specified to incorporate the SRL skills into ALE's. Based on this model, the Adaptive Self-regulated Learning Questionnaire (ASRQ) was developed. The reliability and validity of the ASRQ were evaluated via the review of a content expert panel, the Cronbach's alpha coefficients, and confirmatory factor analysis. Overall, the results supported the theoretical framework and the new ASRQ in an ALE. In this article, the theoretical and practical implications of the findings were discussed.

KEYWORDS

Adaptive Learning, Adaptive Self-Regulated Learning Model, Adaptive Self-Regulated Learning Questionnaire, Questionnaire Development, Self-Regulated Learning, Validation

INTRODUCTION

The Internet has become a robust, dynamic, and flexible way of communication and a medium of learning which develops "learning-on-demand and learner-centered instruction and training" (Khan, 2001, p. 4). Additionally, it can be easily integrated into educational settings to offer open, web-based, interactive, and innovative learning for anyone, anytime, and anywhere. The online learning, or e-Learning, is a ground-breaking evolution in the education industry, however, one of the challenges is the high attrition rate due to its static learning environment using one-fits-all curriculum (Karampiperis & Sampson, 2005). Adaptive Learning (AL) can be an alternative to the traditional one-size-fits-all curriculum of online learning (Brusilovsky, 2001) and it can personalize the learning experience for each learner (Karampiperis & Sampson, 2005).

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In Adaptive Learning Environments (ALE), learners need to go through a complicated process to learn the materials. Therefore, it requires learners to be equipped with skills to perform well and incorporate different resources into their learning process. Self-Regulated Learning (SRL) would be one of the skills which could help learners construct knowledge, complete tasks, and improve performance.

SRL skills are critical factors in student success in online learning environments (OLE) (Barnard-Brak, Lan & Paton, 2009; Chen & Huang, 2013; Bambacas, Sanderson, Feast, & Yang, 2013). Zimmerman (2008) indicated the importance of SRL in the performance and achievement of students in face-to-face, online, or blended learning. The SRL skills in OLE are vital which require autonomous and self-regulated learners (Ally, 2004; Kramarski & Gutman, 2006; Barnard, Lan, To, Paton, & Lai, 2009). When SRL skills are essential to the success of online learners, they could be even more indispensable in ALE's where learning tasks and materials are individualized according to the cognitive ability of each learner. AL learners work alone with the system which may require more autonomy, internal control, and SRL skills. AL Learners with low SRL profiles may not be able to accomplish complicated learning tasks autonomously. AL Learners' SRL skills can be considered as their ability to cope with the potential problems of "managing the breadth and depth of electronic resources" (Hoe & Joung, 2004, p. 1).

However, the role of SRL skills in ALE's has not received the same attention as it does in OLE's. Consequently, a few bodies of research have yet examined the SRL skills of AL learners. The present models of SRL skills in face-to-face learning environments (such as MSLQ; Pintrich, Smith, Garcia, & McKeachie, 1993) or in OLE's (such as OSLQ; Lan, Bremer, Stevens, & Mullen, 2004; Barnard, Paton, & Lan, 2008) might be irrelevant in ALE's due to the differences between these learning environments and the context-specific process of self-regulation (Ally, 2004; Zimmerman, 1998). Despite these facts, a conceptual framework of SRL within ALE and an empirically validated instrument to examine the trustworthiness of this conceptual framework are not available. Therefore, a theoretical framework and a valid instrument specifically designed for this environment are needed at this point.

The purpose of this study was to propose a conceptual framework of SRL skills within ALE's which is called 'Adaptive Self-Regulated Learning' (ASR) model. Based on this model, a new instrument, namely, the Adaptive Self-Regulated Learning Questionnaire (ASRQ), was developed, validated, and implemented to test the validity and trustworthiness of the proposed theoretical framework. The factor structure of the ASR model was tested with a confirmatory factor analysis (CFA) of the ASRQ scores. The result of the CFA will shed light on the score validity of the instrument.

BACKGROUND

What is Adaptive Learning?

The history of distance education goes back to the first correspondence program course offered at the University of Chicago. The reason behind the expansion of these courses was the democratic movement in education with the aim of equal access of everyone to educational opportunities. In the 1980s, virtual education was expanded to meet economic and commercial needs in the U.S. Also, with the introduction of the Internet in the field of education, Open Learning shifted to more online or networked learning and was more widely used (Gunawardena & McIsaac, 2003). But online learning as an evolution in the education industry faces some challenges such as the high attrition rate and one-fits-all curriculum (Karampiperis & Sampson, 2005). Adaptive Learning System (ALS) as a new innovative learning instrument has been increasingly utilized to address these challenges.

As an online learning system, ALS has become more widespread from the early 1990s. The expansion of the World Wide Web with its adaptive nature for diverse audiences followed by the accumulation of research in the field of adaptive technologies were the main driving forces behind the growth of adaptive technology as both attractive and challenging platforms for educators and researchers (Brusilovsky, 2001). This new technology is considered as the next generation of the digital learning environment.

By the emergence of "Artificial Intelligence" (AI) and the advancement of technologies as a research field in laboratories, integration of ALS's has been growing since 1996. ALS's as the "computer-based systems" employ AI to emulate the teacher-guided learning experience and adjusting instructional strategies based on the interaction with learners" (Murray & Perez, 2015, p. 114).

ALS's incorporate hypertext/hypermedia systems based on the characteristics of users in the so-called 'user model' and apply that model to adapt different parts of the content for each user (Brusilovsky, 1995). ALS's give a presentation specifically modified to fit a user's knowledge of subjects (De Bra & Calvi, 1998), suggest a set of links for next steps, and provide different learning pathways of navigation in each user model (Brusilovsky, 2001).

Unlike any other online learners, AL learners are immersed in a modular learning environment in which all their actions in working with the system are captured, saved, and analyzed, including the right or wrong answers, time in a task, and decision-making strategies. The priority of ALE over any other traditional OLEs is the capability to use all these data to place learners at a right difficulty level, offer required scaffolding, and provide formative or summative data to instructors (Intelligent Adaptive Learning, 2014). Unlike online learning systems which require an instructor to monitor learners constantly, ALS's work as constant tutoring tools that check the wide range of knowledge and understanding in real-time (Kuntz, 2010), identify the sources of errors in performance (Park & Lee, 2003), provide intelligent feedback to both learners and instructors (Teich, 2016), and help learners to reflect on their errors (Horizon Report, 2016). They also provide navigational help for novice learners to avoid getting lost (Brusilovsky, 1995). As traditional OLE provides "one-fits-all-curriculum", AL, as a byproduct of ALS, is useful for users with different interests, knowledge, or goals. AL as a dynamic learning environment with learners at the center of their learning process (Kuntz, 2010) presents an "Adaptive Curriculum".

What is Self-Regulated Learning?

Self-Regulated Learning (SRL) is the process through which learners "transform their mental abilities into task-related academic skills" (Zimmerman & Schunk, 2001, p.1) with the help of personal initiatives, perseverance, and adaptive skills. SRL is "an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior" (Pintrich, 2000, p. 453). Self-regulated learners are active meta-cognitively, behaviorally, and motivationally in their own learning process (Zimmerman, 1989). Learners who heavily use SRL skills are responsive to self-oriented feedback about learning effectiveness and they are active agents in their learning process (Zimmerman, 1990; Barnard-Bark, Lan & Paton, 2010).

Zimmerman (1989) conceptualized three cyclical processes for SRL. The first phase is forethought in which learners have the predefined set of cognitions and self-beliefs. In this phase, they set goals and plan the next steps. In the second phase, performance, learners actively get involved in the behavior required to successfully attain their goals. In the last phase, self-reflection, learners use self-monitoring to evaluate and judge their own performance (Barnard-Bark, et al., 2010; Dabagh & Kitsantas, 2012).

Bodies of research indicate that higher SRL leads to a better performance and achievement of learners (Barnard-Bark et al., 2010; Bai, 2012; Bambacas et al., 2013) and fosters autonomous and independent learners (Ally, 2004) who are able to influence their outcomes and experiences (Barnard-Bark, et al., 2010). Therefore, improving these skills in more independent learning environments is vitally important.

Self-Regulated Learning in the Adaptive Learning Environment (ASRL)

SRL has been researched in different fields of study due to its effect on improving students' grades and motivation (Kizilcec, Pérez-Sanagustín, & Maldonado, 2017), confidence (Alexiou & Paraskeva, 2010), and understanding learning materials (Bergin, Reilly, & Traynor, 2005). SRL is crucial especially in less controllable learning environments with low levels of support and guidance like Online Learning (OL) (Kizilcec et al., 2017; Garcia, Falkner, & Vivian, 2018; Barnard-Bark et al., 2010). Due to similarities of OL to AL, SRL might also be a prominent factor in this new environment. However, to date, there is not a theoretical model to demonstrate the SRL factors in ALE's. This study attempted to develop, validate, and implement a conceptual framework to incorporate these factors in ALE's. The modified definitions of SRL factors used in this study based on Zimmerman and Martinez-Pons (1986) and Pintrich (2000) explanations are as follows.

Goal setting is to specify intended actions or outcomes by learners according to ALS instructions and procedures. Often, AL learners assume that the goals are set for them by the system and they do not have to set goals for their own achievement. This dimension in ALE's illuminates the need for specifying intended objectives by learners in the learning process.

Environmental Structuring is selecting or creating an effective setting for learning. ALS usually has a fixed learning environment, namely, the dashboard, without offering much room for changes based on learners' preference. AL learners, more than any other learners, need to boost this skill to manage their learning environment outside of the system.

Task Strategy represents the analysis of tasks and identification of specific advantageous methods for learning. ALS can evaluate if the task strategies chosen by each learner are effective or not. This skill is not easy to be identified directly by instructors or even learners. However, ALS can track students' progress based on their selected task strategies and it can depict their success through progress indicators.

Time Management is the estimating and budgeting use of time. ALS usually offers more robust subject matters with a diverse range of assessments, tasks, and activities. Therefore, it requires learners to devote more time to finish a course. Specifically, certain students need to spend more time on tasks and course requirements to achieve an expected level of mastery, finish a module, or proceed to the next one. ALS can record and inform each learner's time budgeting behavior throughout the course.

Help-seeking refers to choosing specific models or sources to assist oneself in learning. Since AL learners are alone in the system without social interaction with peers, they might feel isolated in their learning process. Furthermore, these learners may not even know other learners in the same course if AL is delivered fully online. AL learners need to seek help through exploring the ALS help button, calling the help center, referring to the explanation bar, or asking the instructor.

Another SRL skill in ALE is persistence. Persistence is the effort in completing tasks. ALS's measure the learners' persistence through identifying the average progress of each learner in each topic and the percentage of attempted but not learned topics. The complicated and sometimes frustrating environment of ALS requires more persistent learners than any other types of learning environments.

ALS's provide various progress bars and graphs to facilitate self-evaluation. Self-Evaluation refers to setting standards and using them for self-judgment. ALS through data-informed learning instructs learners how to use the system data in the learning context to communicate the materials better and to measure their own performance. Data informed learning "emphasizes learning as an outcome of engaging with information" (Maybee & Zilinski, 2015, p. 3). ALS provides information about learning behaviors while learners read materials, do assignments, complete tasks, or take tests. This data-informed information can be used critically by learners to self-evaluate their performance.

ALS's have not yet been designed to track how learners feel and how their experience is while working with the system. To know more about AL learner emotions or experiences, researchers need to design a self-report questionnaire outside of the system.

METHODOLOGY

Participants

Three hundred and fifty students who enrolled in a Chemistry Course at a university in the Southwestern of the U.S. were invited to participate in this study. The researcher attended each class, described the intention of the research, and explained the purpose of the Adaptive Self-Regulated Learning Questionnaire (ASRQ). Participants voluntarily attended and filled in this newly designed questionnaire (it will be discussed below) which took around 15-20 minutes. The total number of participants was one hundred and sixty (N = 160) and most of them were female (n = 108, 67.5%). In terms of ethnic composition, 66.3% were white (n = 106), 16.2% Hispanic or Latino (n = 26), 6.9% two or more races (n = 11), 4.4% Middle Eastern or Asian (n= 7), 3.1% black (*n* = 5), and 3.1% American Indian or Alaska Native (*n* = 5). Furthermore, more than half of the participants were freshmen (*n* = 87, 54.4%) and aged from 18 to 24 years old (*n* = 154, 96.3%). More detailed demographic information of the participants is listed in Table 1.

Table 1. Demographic information of participants (N = 160)

Variable	Frequency	Percent
Gender		
Male	52	32.5
Female	108	67.5
Ethnicity		
White	106	66.3
Hispanic or Latino	26	16.2
Two or more races	11	6.9
Middle Eastern or Asian	7	4.4
Black or African American	5	3.1
American Indian or Alaska Native	5	3.1
Age		
18 - 25	54	96.3
26 - 35	4	2.5
36 +	2	1.2
Grade		
Freshman	87	54.4
Sophomore	57	35.6
Junior	13	8.1
Senior	3	1.9

Development of the Adaptive Self-Regulated Learning Questionnaire (ASRQ)

In order to conceptualize SRL factors in ALE's, this study proposed a theoretical framework, namely, the *Adaptive Self-Regulated Learning (ASR) model.* The factor structure of this model was empirically evaluated through developing an *Adaptive Self-Regulated Learning Questionnaire (ASRQ)*. The first draft of ASRQ was developed based on the existing SRL models in the literature, namely, the

Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich, Smith, Garcia, & McKeachie, 1991), the Online Self-Regulation Questionnaire (OSRQ) (Barnard, et al., 2009), and the Metacognitive Awareness Inventory (MAI) (Schraw & Dennison, 1994).

Given the need to measure the SRL skills in an ALS, all ALEKS[1] features (i.e., the ALS in this study) and its task models[2] were studied, extracted, and analyzed. Then, those SRL skills supported by the existing literature and aligned better with the ALEKS features were selected. As a result, seven SRL skills best depicting the features of ALEKS were chosen. These SRL skills included goal setting, environment structuring, task strategies, time management, help-seeking, persistence, and self-evaluation. Then, another factor (i.e., emotions and experiences) was added to the model to tap into students' feeling in their learning experience in ALEKS (Table 2).

Table 2. ALEKS task models

Student Model (What Are We Measuring)	Task Model (Where Do We Find It)
Goal-setting	ALEKS Time and Topic Report ALEKS Assignment Report
Environmental structuring	ALEKS Help Center
Task strategies	ALEKS Time and Topic Report ALEKS Pie Graph
Time management	ALEKS Time and Topic Report
Help-seeking	ALEKS Time and Topic Report ALEKS Help Center
Persistence	ALEKS Report Page
Self-evaluation	ALEKS Help Center
Emotions and Experience	Student self-report

Based on ALEKS task model and the existing literature, the questionnaire items for each SRL skill were designed. The first draft of ASRQ contained 49 items divided over eight skills. All items had to be answered on a 5-point Likert scale, ranging from "Strongly Disagree" (=1) to "Strongly Agree" (=5). Some notes were added to help the participants understand better into which part of the system the item was tapping. Should other researchers use this questionnaire for a different ALS, they can use different notes to let learners better understand the focus is on which part of the system.

Validation Procedures

To validate the new ASRQ, the expert panel review, the Cronbach alpha analysis, and the confirmatory factor analysis were implemented to collect the empirical data on content validity, internal consistency, and construct validity.

Content Validity

The actual content of the ASRQ was evaluated based on the degree of agreement among three expert evaluators. Three experts in the field reviewed the questionnaire items and commented on how to improve each of them. The experts also evaluated how effectively each item could measure the selected SRL skills in the ALE. Specifically, each item was assessed with four criteria including relevance, clarity, simplicity, and ambiguity on a scale of 1 to 5.

Internal Consistency

The internal consistency of the items measuring the same factor was assessed with the Cronbach's Alpha coefficient (Field, 2009). Generally, a newly developed questionnaire with the Cronbach's Alpha coefficient .70 or higher will be considered as reliable (Nunnally, 1978).

Confirmatory Factor Analysis (CFA)

The construct validity of a new questionnaire can be assessed with confirmatory factor analysis (CFA) (Bornstedt, 1977; Ratray & Jones, 2007). There are a variety of fit statistics to assess the overall model fit in CFA but with no uniform cutoff values of the approximate fit indices for a so-called acceptable model fit (Byrne, 2016; Kline, 2016; West, Taylor, & Wu, 2012). The results of the CFA show if various items in a new questionnaire measure the constructs as hypothesized by the underlying theoretical framework. In other words, CFA generates the empirical evidence of score validity for the instrument based on the established theoretical framework (Field, 2009). In CFA, 1) the Chi-square test statistic, 2) the Normed Chi-Square (NC), 3) the Root Mean Square Error of Approximation (RSMEA), and the 4) Comparative Fit Index (CFI) (Kline, 2016; Comrey & Lee, 1992) were calculated to assess the model fit of the model under study.

The Chi-square statistic, NC, and RMSEA as the absolute fit indices could be used to provide the indication regarding the quality of the theoretical model being tested (Hooper, Coughlan, & Mullen, 2008; Kline 2016). The Chi-square test indicates the difference between observed and expected covariance matrices; therefore, the smaller values indicate the better model fit (Gatignon, 2010). The Chi-square test should be non-significant for a model with an acceptable fit. However, the statistical significance of the Chi-Square test results is highly sensitive to the sample size (Kine, 2016). Hence, the NC should also be considered. The NC is equal to the Chi-square divided by the degrees of freedom. Smaller NC values suggest the better model fits and an NC value equal to or less than 5 supports an acceptable model fit (West, et al., 2012). Another model fit index was also utilized in this study, i.e., Root Mean Square Error of Approximation (Steiger & Lind, 1980). The RMSEA qualifies the difference between the population covariance matrix and the theoretical model. Smaller RMSEA values indicate the better model with .08 as the cutoff for an acceptable model fit (Gatignon, 2010, Blunch, 2013; West, et al., 2012). The CFI (Bentler & Bonett, 1980; Bentler, 1990) was also used to assess the model fit in this study. If the value of CFI is larger than .90, an acceptable model fit is indicated (Kline, 2016; Blunch, 2013; West, et al., 2012). The α level in this study was set at .05 for the χ^2 goodness-of-fit test.

RESULTS

The Result of Content Validity

The content of items in the instrument was revised based on the degree of agreement among a panel of experts in the field. The best items with the highest rate of clarity, simplicity, relevance to the related scale, and non-ambiguity were selected. Also, the evaluator comments on how to improve each item and their related ratings were aggregated, and the items were revised, modified, or tossed out accordingly. Next, the revised questions were designed in an online form with demography questions. The total number of questions after the content analysis was deducted to 39 for eight SRL skills.

The Result of Internal Consistency

The internal consistency of the questionnaire's items under the same factor was measured with the Cronbach's Alpha coefficients. The Cronbach's Alpha coefficient of this questionnaire (i.e., .94) was greater than the .70 cutoff value (Nunnally, 1978) for a reliable instrument and supported the internal consistency of the items. Furthermore, the internal consistency of each subscale was evaluated. Most of the subscales showed acceptable internal consistency. The Cronbach's Alpha coefficients of the subscales are as follows: Goal Setting (.668), Environmental Structuring (.707), Time Management (.700), Help Seeking (.642), Persistent (.817), Self-Evaluation (.791), Task Strategy (.749), and Emotions/Experiences (.905).

The Result of Confirmatory Factor Analysis (CFA)

The content validated questionnaire was distributed among AL learners to collect data for the subsequent analyses to evaluate the construct validity of it. The Amos 24 program (Arbuckle, 2003) was used to implement a confirmatory factor analysis (CFA) using structural equation modeling (SEM). The theoretical model of ASR (39 items, eight scales) was assessed with various statistical tests and fit indices.

In the current study, the items with the factor loadings not less than .4 onto the related factors were kept and the others with loadings lower than .04 were eliminated. The statistically significant Chi-square test results (CMIN= 478.988, $p < .5$) showed a poor model fit. However, the NC of the theoretical model (i.e., 1.77) was less than 5 and indicated a reasonable model fit (West et al., 2012). The RMSEA analysis shows how well the theoretical model fits the population covariance matrix. The theoretical model in this study showed an acceptable fit (RMSEA= .07 < .8). Therefore, both absolute fit tests (i.e., RMSEA & NC) supported a reasonable fit of the theoretical model to the data.

The CFI was also used to determine if the model adequately fitted the data. The CFI compares the fit of the theoretical or tested model to that of the independence model in which all latent variables are not correlated (Blunch, 2013; Hooper et al., 2008). In this study, the CFI was 90 and suggested the acceptable model fit. An overview of the fit indices in the CFA model can be found in Table 3 and the standardized factor pattern coefficients in Figure 1.

Individual Item Loading

The theoretical ASR model (Figure 1) had an acceptable model fit according to the results of various fit indices discussed before. The examination of the correlation between various factors showed that the factors were highly correlated. The standardized factor pattern coefficients (i.e., correlations or loadings) between the factors and test items suggested there were no loadings lower than the cutoff of a poor loading (i.e., .40), five out of twenty-six items with the loadings higher than the cutoff of a fair loading (i.e., .45), and the remaining twenty-one items with the loadings higher than the cutoff of a good loading (i.e., .55) (Comrey & Lee, 1992).

Those items with fair loading (i.e., .45) include the questionnaire items #1 (Goal Setting), # 6 (Environment Management), #9 (Time Management), #12 (Help-seeking), and #22 (Task Strategy). Further inspection of these test items or their removal might not be necessary since they loaded fairly on their designated factors as strongly as theoretically expected. Goal Setting and Environment Management have just "*three-items*" which is the minimum requirement of a CFA. Therefore, it will be advisable to add new items to avoid potential specification issues and to develop a better model of ASR.

In a nutshell, based on the result of this study, the current eight-factor ASR model is an appropriate theoretical framework of SRL in ALE's given no items with the loadings lower than the cutoff of .40 for a poor loading.

DISCUSSION

Due to lack of an empirical framework and a validated instrument to measure AL learners' SRL skills in the new ALE and the fast-growing spread of this type of instruction at different universities in the U.S., this study proposed an eight-factor ASR Model. To validate the theoretical framework of this model, a new instrument, ASRQ, was developed based on the available literature of both face-to-face and OL environments. This instrument was administered in chemistry courses equipped with ALEKS Adaptive System. The statistical indices, analyzed from the ASRQ data, empirically supported the

Figure 1. ASR model with standardized factor pattern coefficients

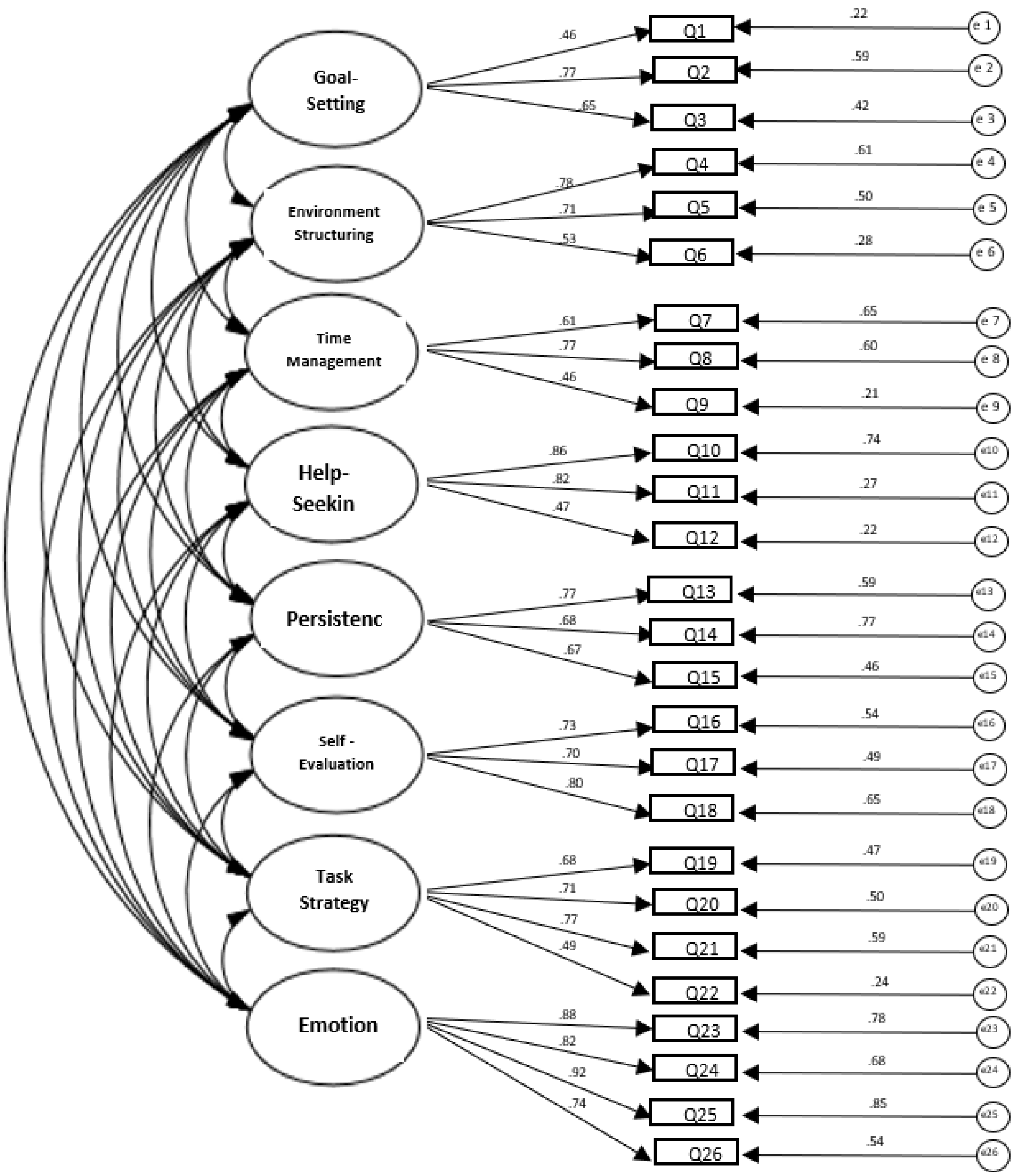

Table 3. Fit indices for CFA model

Model	*CMIN*	*NC*	*RMSEA*	*CFI*	*df*	*P*
Theoretical SRL-AL Model	478.988	1.767	.069	.897	271	.000

Note: CMIN= Chi-square value; *df*= Degree of freedom; NC= Normal Chi-square; RMSEA = root mean square error of approximation; CFI=Comparative fit index; *p < .05.

factor structure specified in the theoretical ASR model with eight SRL factors; Furthermore, the results of this study empirically supported the validity and reliability of the newly developed instrument and the validity of the underlying theoretical framework of ASR. This conclusion is based on the result of the absolute model fit and the comparative fit indices of CFA which suggested an acceptable fit of the model.

The multidimensional eight-factor model of ASR in this study is a plausible theoretical framework to understand how AL learners perceive and manage SRL skills in an ALE. This model can be used in similar studies to develop new questionnaires focusing on other SRL items. Furthermore, the ASRQ also can be used by researchers of ALE's as an instrument to collect AL learners' SRL data.

Table 4 shows the eight factors proposed in the ASR model and the definition of each factor based on ALEKS features. It also displays the items corresponding to each skill and the related standardized factor pattern coefficients (loading).

IMPLICATION OF THE STUDY

Based on the design and results of this study, there are several implications for educational theory and practice around self-regulated learning in ALE's. The empirical results of this study are useful for instructors, learners, and instructional designers in several ways.

Several studies found that SRL is an effective predictor of students' performance (Kitsantas & Zimmerman, 2008; Yukselturk & Bulut, 2007; Bell, 2007; Morris, Wu, & Finnegan 2005; Waschull, 2005). Therefore, AL instructors can use the ASRQ to predict the success or failure of students at the beginning of the course and accommodate students' needs before it gets late. In addition, this prediction would help instructors to prepare students' adaptive self-regulated learning skills.

Barnard, et al., (2008) indicated there is a positive relationship between learners' perception of online courses and collaboration with academic achievement. Thus, the perception and experience of AL learners would be also a determining factor in their achievement. The ASRQ is a useful tool for instructors as one of the data sources to assess students' perception and experience while using this new learning environment. The ASRQ can also help instructors to assess learners' self-regulated use of SRL at different points of the course and identify their areas of incompetency. Quince (2013) also found that assessment of SRL behaviors before and after a guided instruction affects positively on online learners' academic success. Furthermore. the ASRQ can be used as a pretest-posttest tool by instructors to assess and monitor students' growing SRL skills in AL courses.

Additionally, the AER model has some implications for AL learners. Bodies of research indicated that SRL skills have a positive effect on the academic success of learners (Bail, Zhang, & Tachiyama, 2008; DuBois & Staley, 2007; Hofer & Yu, 2003). AL Learners can use the ASRQ as an effective instrument to improve their SRL skills directly and their achievement indirectly.

OLE's require higher levels of self-regulation for autonomous and independent learning (Kollar & Fischer, 2006). Due to similarities of ALE to OLE, ALE's might also need autonomous learners with higher levels of self-regulation. The use of the ASRQ as an assessment tool would enable AL learners to enhance the strategies conducive to the autonomy and self-directedness. Besides, due to the complexity of ALS's, AL learners need a high level of perception and attitude enabling them to finish modules successfully. The ASRQ, as a self-awareness raising tool, can positively raise learners' attitude and perception in AL courses.

The instructional designers in the field of ALS and ALE will also benefit from the results of this study. The use of this model can inform ALS instructional designers on how to improve this system to facilitate the learning autonomy in the AL personalized environment. Moreover, previous research identified the positive role of scaffolding on learners' academic success (Bail, et al., 2008; Cukras, 2006; Whipp & Chiarelli, 2004; Hofer & Yu, 2003). AL instructional designers can incorporate the ASR model in the ALS's as a strategic instruction to reinforce SRL strategies and support learners'

Table 4. Eight-factor ASR model, definitions, and factor loadings

SRL Variable/ Skill	Definition	Items	Loading
Goal-setting	Self-initiated plan-making based on ALS instructions	• I set academic goals for my adaptive courses.	.46
		• I create a study plan for my adaptive courses.	.77
		• I track my progress in my adaptive courses.	.65
Environmental structuring	Arrangement of ALS dashboard to make it more favorable to pursue learning objectives	• I choose a certain time to study for my adaptive courses.	.78
		• I choose a special place to study for my adaptive courses.	.71
		• I avoid any distractions when I am studying for my adaptive courses.	.53
Task strategies	Learners' strategies to tackle with the ALS complexity and complete the tasks	• I use a variety of learning strategies in my adaptive courses.	.68
		• I manage the content and technology challenges in my adaptive courses.	.71
		• I fill-in my knowledge gaps in the subject matter by using the adaptive learning system (Note: ALEKS system).	.77
		• I try to take more notes because they are more important for learning in the adaptive course than in a regular classroom.	.49
Time management	Learners' setting the time aside for tasks based on ALS time-table	• I have a specific schedule to study for my adaptive courses.	.61
		• I allocate specific studying time for my adaptive courses.	.77
		• I use my time efficiently to finish my exercises in my adaptive courses.	.46
Help-seeking	Self-initiated seeking the knowledge resources to better understanding of ALS objectives and tasks	• I contact the 'Help-Center' to solve my technical problems in my adaptive courses.	.86
		• I use 'Tutorials' and/or 'Help Page' to solve my technical problems in my adaptive courses.	.82
		• I contact the instructor and/or knowledgeable peers to help me solve problems with content in my adaptive courses.	.47
Persistence	Learners' effort to accomplish ALS materials	• I make an extra effort to complete difficult exercises in my adaptive courses.	.77
		• I am persistent in working on topics that I have not learned in my adaptive courses (Note: ALEKS indicates your mastery level in each topic).	.68
		• I do not give up until I finish all exercises in my adaptive courses.	.67
Self-evaluation	Self-initiated tracking the ALS assessment bars and graphs	• I evaluate the usefulness of the learning strategies that I use in my adaptive courses.	.73
		• I evaluate my performance in my adaptive courses every time I login into the system.	.70
		• I study the materials more than once to figure out my problems in my adaptive courses.	.80
Emotions and Experience	Reflection of learners on their emotions and experiences throughout the learning process	• I feel my adaptive courses are engaging.	.88
		• I am confident in the level of my knowledge in my adaptive courses.	.82
		• I have a positive learning experience in my adaptive courses.	.92
		• The system feedback meets my expectations.	.74

success in ALE's. Finally, AL instructional designers can focus on areas of SRL incompetency through incorporating the ASRQ into the system and try to improve it accordingly.

Limitations of the Study

One of the limitations of this study is that it used the data of the ALEKS system of a chemistry course. A more detailed study of current ALS practices in various courses with different ALS's is required to improve ASR theoretical model. The researchers need to establish the effect of AL technologies on SRL skills in other AL courses at different universities with different instructors and systems. Also, the ASRQ, developed based on the ASR conceptual framework, is a self-report instrument which might contain biases, dishonesty, lack of consciousness, or proper understanding of the questions.

Suggestions for Further Research

Even though ALS's can track learners' behaviors, they are not equipped with an application or program to collect students' SRL behaviors automatically. Researchers who would like to use the system data to support their research need to collect the required data from the system manually. Therefore, it is suggested ALS instructional designers embed this capability to newly developed systems. With newer ALS's evolving, a newer ASRQ model should be re-examined and re-evaluated. It is also suggested that the researchers focus on students' choice of certain SRL skills over others to identify which strategy is more common and is used among learners and which one needs to be reinforced.

CONCLUSION

This study concluded that the eight-factor ASR is an acceptable model fit to measure SRL skills in an ALE through the ASRQ. The results of this study would shed lights for those institutions, educators, and instructional designers who intend to integrate AL to support effective teaching and learning. The ASR model guides them to select an effective system in the future or help them to improve the current ones. ASR model is beneficial for educators planning to use a "data-informed" learning tool to contextualize the learning experience. This theoretical model is a foundation for educators to comprehend better the psychological SRL behaviors of AL learners. Educators also can assess AL learners' SRL skills through this model based on which they can create effective AL instructions and scaffolding. The objective of this model is to provide "data-driven" information through collecting learners' SRL behaviors and help the educators to predict students' achievement. ALS's are isolated learning environments; therefore, AL instructional designers should strategically focus on reinforcing SRL skills through accommodating the ASR model in future systems. This will provide educators and educational institutions with students SRL behaviors in ALS's.

AL is the next generation of learning environments and should be designed in a way to assist the future generation of learners both psychologically and cognitively. This study points to the necessity of the ASR model in designing effective digital adaptive learning environment to enable learners to enhance their self-regulation, internal control, and autonomy.

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ENDNOTES

[1] Assessment and Learning in Knowledge Spaces System (ALEKS).

[2] Task model refers to “where we measure student knowledge, skills, or abilities. It describes the tasks, situations, or environments that elicit the behaviors described in the evidence model.” (Lee & Recker, 2017, p. 5) Evidence model refers to how we measure learners’ knowledge, skills, or abilities. The evidence models might include regularity of log-in intervals, persisting on difficult tasks, login frequency, time on task, and the number of views of materials (Lee & Reckor, 2017). Some of the task models in this research include Time and Topic Report, System Help Center, and Report Page.

APPENDIX: ADAPTIVE SELF-REGULATED LEARNING QUESTIONNAIRE

Goal Setting

1. I set academic goals for my adaptive courses.
2. I create a study plan for my adaptive courses.
3. I track my progress in my adaptive courses.

Environmental Structuring

4. I choose a certain time to study for my adaptive courses.
5. I choose a special place to study for my adaptive courses.
6. I avoid any distractions when I am studying for my adaptive courses.

Time Management

7. I have a specific schedule to study for my adaptive courses.
8. I allocate specific studying time for my adaptive courses.
9. I use my time efficiently to finish my exercises in my adaptive courses.

Help-Seeking

10. I contact the 'Help-Center' to solve my technical problems in my adaptive courses.
11. I use 'Tutorials' and/or 'Help Page' to solve my technical problems in my adaptive courses.
12. I contact the instructor and/or knowledgeable peers to help me solve problems with content in my adaptive courses.

Persistence

13. I make an extra effort to complete difficult exercises in my adaptive courses.
14. I am persistent in working on topics that I have not learned in my adaptive courses (Note: ALEKS indicates your mastery level in each topic).
15. I do not give up until I finish all exercises in my adaptive courses.

Self-Evaluation

16. I evaluate the usefulness of the learning strategies that I use in my adaptive courses.
17. I evaluate my performance in my adaptive courses every time I login into the system.
18. I study the materials more than once to figure out my problems in my adaptive courses.

Task Strategies

19. I use a variety of learning strategies in my adaptive courses.
20. I manage the content and technology challenges in my adaptive courses.
21. I fill-in my knowledge gaps in the subject matter by using the adaptive learning system (Note: ALEKS system).
22. I try to take more notes because they are more important for learning in the adaptive course than in a regular classroom.

Emotion and Experience

23. I feel my adaptive courses are engaging.
24. I am confident in the level of my knowledge in my adaptive courses.
25. I have a positive learning experience in my adaptive courses.
26. The system feedback meets my expectations.

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