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Developing a Learning Analytics Intervention in E-learning to Enhance Students' Learning Performance: A Case Study

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Abstract
The emergence of Learning Analytics has brought benefits to the educational field, as it can be used to analyse authentic data from students to identify the problems encountered in e-learning and to provide intervention to assist students. However, much is still unknown about the development of Learning Analytics intervention in terms of providing personalised learning materials to students to meet their needs in order to enhance their learning performance. Thus, this study aims to develop a Learning Analytics intervention in e-learning to enhance students' learning performance. In order to develop the intervention, four stages of Learning Analytics Cycle proposed by Clow: learner, data, metrics and intervention were carried out, integrating with two well-known models: Felder-Silverman's and Keller's Attention, Relevance, Confidence and Satisfaction (ARCS) models in e-learning, to develop various Learning Objects in e-learning. After that, a case study was carried out to assess this intervention with various validated research instruments. A quantitative approach involving a one-group pre-test–post-test experimental design was adopted, which consists of a population of 50 undergraduate students who enrolled in the Information System Management in Education course. The results indicated that the Learning Analytics intervention is useful, as it overall helped the majority of students to enhance their motivation, academic achievement, cognitive engagement and cognitive retention in e-learning. From this study, readers can understand the way to implement the Learning Analytics intervention which is proved to made positive impact on students' learning achievement with the Cohen's d of 5.669. Lastly, this study contributes significant new knowledge to the current understanding of how Learning Analytics intervention can perform to optimize students' learning experience and also serves to fill a gap in research on Learning Analytics, namely the lack of development of interventions to assist students.

Keywords Learning analytics intervention · Personalised learning objects · e-learning · At-risk students

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1 Introduction

Due to the rapid emergence of technology, e-learning has become typical important in the education sector, as it has been vastly implemented in university (Al-Fraihat, 2020). E-learning platform should meet the needs of students (Mpungose, 2020) and some previous studies have reported the challenges faced by students in e-learning that need to be tackled. Czerkawski (2015) highlighted that it needs to customize instruction for individual needs and identify learning difficulties. This is because students learn at different speed and level, and their progression differs from student to student (Dietz-Uhler & Hurn, 2013). Also, different students have different learning preference and styles. Hence, different appropriate learning resources should be provided for students in e-learning in order to meet the demands of students. Zhu et al. (2018) emphasised that educators should design various and suitable learning resources for students in order to enhance the attractiveness of learning, and to cater for students with different learning styles. Besides that, motivation is an important role in e-learning that cannot be neglected. Lack of motivation leads to engagement, and decreased engagement can cause students to withdraw from the course (Andersson & Grönlund, 2009) and to become at-risk students in e-learning. The studies about online learning environments also reveals relationships between motivation and performance (Kew et al., 2018; Na et al., 2020; Saadé et al., 2007), as these results emphasize the significance of motivation for online learning. Therefore, it is highly vital to look into its effect on motivation in e-learning. This is because demotivating e-learning environment might affect students' learning performance (Teo, 2010), especially at-risk students.

Moreover, engagement is another critical aspect to determine students' success in e-learning. To ensure students' engagement in their online learning, cognitive engagement, specifically, is discovered to be an achievement predictor (Barlow, 2020). Nonetheless, poor engagement problem is still happening in e-learning (Kew & Tasir, 2021a, b). The reason is it has been found that students' level of cognitive engagement remains relatively low, although education has evolved alongside technology (Ma, 2009). Apart from that, retention is another important element in e-learning. Nevertheless, some studies conducted by Sana et al. (2013) found that the use of technology had no effect on students' retention and their academic performance. In a study examining relations among student motivation, engagement, and retention in an online learning (Xiong et al., 2015), the findings showed that motivation is significantly predictive of student course engagement and engagement is a strong predictor of retention. Moreover, the findings also proposed that course retention might be enhanced by stimulating students' motivation and monitoring their online activities. These learning issues such as motivation, engagement, retention and the problem with one-size-fits-all can affect the effectiveness of e-learning and students' learning performance. Particularly, students who were demotivated, disengaged and gained low test scores fall in to the at-risk group and might drop out of course (Hammond et al., 2007). Therefore, these learning issues such as motivation, engagement, retention, learning performance and the problem with one-size-fits-all that can place students at risk require a solution to solve them.

In fact, these problems can actually be tackled by using Learning Analytics (LA), as there have also been positive findings concerning the potential of LA to support students in the self-regulated learning processes of planning, monitoring, and assessment (Winne & Hadwin, 2010) through intervention, and thus enhancing their retention, engagement and motivation as well as academic achievement. LA "uses analytic techniques to help target instructional, curricular, and support resources to investigate students' learning behaviours and intervene in their learning environments" (Van Barneveld et al., 2012, p. 8). It mainly serves to collect and analyse educational data to discover more useful information about the activity and behaviour of students in e-learning (Van Leeuwen et al., 2015), and it becomes more important because it can provide evidence-based understanding of what is happening in the e-learning environment. Students create a large number of data-laden footprints, such as number of clicks and number of posts, when they interact with e-learning activities in their course of study. These digital traces can be downloaded, tracked, and analysed by educators to discover information about the students and solve the problems that arise in online learning, and to assist in intervention support for students. It can especially lead to improvement through enhanced educational decision-making (Vatrapu et al., 2011), the personalization of teaching and learning (Beck & Mostow, 2008) and the development of early intervention systems (Kew & Tasir, 2021a, b; Wong & Li, 2020).

With the advance of LA, in particular, instructors can have better insights to understand students in e-learning by analysing the data in e-learning, and provide intervention to assist the at-risk groups. This makes LA intervention important because a key application of LA involves observing students' learning performance and identifying potential learning problems early so that interventions can be provided to recognize and support students at risk (Johnson et al., 2011). Wong and Li (2020) also claimed that students' learning can be improved by LA interventions through the evidence-based decision making. LA can then conclude the intervention of learning content and program design, enhancement of students' motivation and the early detection of at-risk students. As a matter of fact, more interventions are literally needed, as LA intervention has long been implemented in university to assist at-risk students (Kew & Tasir, 2021a, b; Wong & Li, 2020). Nonetheless, even though the implementation of LA is on the rise, there is lack of studies indicating whether these are useful in improving students' learning performance (Bodily & Verbert, 2017) and whether can meet the needs of students. Therefore, this research sheds light on this aspect of LA intervention, which is an under-investigated but important area in LA to solve the aforementioned learning issues in e-learning such as motivation, academic achievement, cognitive engagement and cognitive retention of students as well as the problem with one-size-fits-all. This research aims to design and implement a LA intervention in e-learning based on the log file data collected from e-learning to provide personalised and motivating learning objects (LOs) for students. In line with these aims, the following is the research questions:

1) To design and develop an e-learning environment embedded with Learning Analytics intervention based on students' learning styles to enhance motivation, academic achievement, cognitive engagement and cognitive retention.
2) To analyse students' overall learning performances such as motivation, cognitive engagement, cognitive retention and academic performance in e-learning embedded with the LA intervention

2 Literature Review

LA's role is increasingly important, as it enables data-driven decisions at the administrative level of universities (Sclater et al., 2016) and aids in teaching and learning practices by providing direct evidence of students' learning behaviour (Zhang & Kew, 2021; Viberg et al., 2018). These data and evidences can reflect the real situation in students' learning process. LA mainly aims to help teachers and schools to adapt teaching and learning practices and strategies depending on the ability and demands of students (van Harmelen & Workman, 2012) and to provide intervention. Coffrin et al. (2014) confirmed that key to the effectiveness of LA is the capability to deliver data to educators in ways that can help inform their decision-making about educational interventions. Based on review studies concerning LA intervention used in e-learning, the findings revealed that the types of learning issues being tackled by implementing LA intervention were students' engagement (cognitive engagement and participation), retention, cognitive retention, performance outcomes, motivation, and satisfaction (Kew & Tasir, 2017; Lonn et al., 2015). Thus, LA is useful in teaching and learning, for example, to spot potential issues and to provide intervention to optimize students' learning to meet their needs.

LA can offer "increased accountability at all levels of education" (Dietz-Uhler & Hurn, 2013, p. 20) and provide insights into how teaching and learning materials best suit to each individual student and the useful intervention. LA is especially used to help educators understand and optimize learning via an environment tailored to each student's level of need and ability in close-to-real-time (Aguiar et al., 2014). This brings benefits to e-learning because LA can be used to solve learning issues by designing personalized learning objects for students based on their learning styles. Similarly, van Harmelen and Workman (2012) said that identifying at-risk students and providing them with interventions designed to improve retention is one of the most promising uses of LA in education. Accordingly, by developing an LA intervention, the learning problems faced by students with different learning styles can be solved by giving them proper support to meet their needs, and consequently, the quality of online learning can be improved. Indeed, the development of the LA intervention to identify and support change as a process that happens over time is important (Kew & Tasir, 2021a, b; Wise et al., 2014; Wong &

Li, 2020). By using LA techniques, educators can foster logical thinking that helps them make better decisions, hence refining their interventions in students' learning. This makes learning more meaningful to students, especially giving them more personalised learning objects in e-learning to meet their demands. Therefore, LA constitutes a crucial device for supporting learning design, and the interventions should be developed to improve the teaching practices in e-learning.

2.1 Examples of Existing Learning Analytics Intervention

Many institutions have developed interventions using LA to support students' learning, focusing mainly on their academic achievement. For example, Purdue University provides the Course Signals System to detect at-risk students and then provide intervention to them through emailing and texting. Similarly, Northern Arizona University uses Grade Performance Status to give support to students by receiving the alert and feedback. These interventions are useful for teaching and learning practices and demonstrate the important role of LA interventions, especially in tertiary institutions. Also, some previous studies related to LA interventions show how they assist in the educational field. For instance, Wise et al. (2014) examined the application of LA in investigating how learners contribute and respond to peers' messages in online discussions, and an intervention was designed to support the discussion activities. Similarly, Lonn et al. (2015) investigated students' motivation in the context of LA interventions during a summer bridge program, while Cho, Lam, Li & Wong (2018) used a self-designed classroom responses system to collect students' click data to provide a proposed systemic proactive intervention such as emails, phone calls, and face-to-face consultations to assist at-risk students.

Although these LA interventions can affect learning and teaching practices, previous systematic reviews of LA interventions contributing to student success in e-learning found that only a limited number of LA interventions have been developed to assist students (Kew & Tasir, 2021a, b; Wong & Li, 2020). It is especially the intervening learning objects and materials in e-learning based on students' learning styles to solve the one-size-fits-all problem. Meanwhile, the keywords "Learning Analytics Intervention Framework" and "Learning Analytics Intervention Model" were searched in databases. Table 1 shows the summary of research conducted on the development of LA intervention frameworks or models in e-learning, noticing that LA interventions are still at a development stage because the number of studies is still limited. Thus, more studies are required to develop new interventions to tackle the problems different students face due to their different demands in their learning process. For example, as Tie & Umar (2010) reported, the diversity of learning styles affects students' engagement in understanding the course, significantly influencing information retention and finally their academic achievements. Gašević et al. (2016) also pinpointed that LA interventions should be designed to meet students' needs.

Table 1 Studies of LA intervention design in e-learning

Research Title	Research Purpose
1. The Learning Analytics Cycle: Closing the Loop Effective (Clow, 2012)	This paper articulates the LA Cycle for closing the feedback loop through interventions
2. Designing Pedagogical Interventions to Support Student Use of Learning Analytics (Wise et al., 2014)	This article shows the design of LA interventions for students' participation in discussions
3. The Design of an Intervention Model and Strategy based on the Behavior Data of Learners: A Learning Analytics Perspective (Wu et al., 2015)	This paper shows an intervention model involving means of intervention and the content of this intervention
4. Integrated Representations and Small Data towards Contextualized and Embedded Analytics Tools for Learners (Harrer & Göhnert, 2015)	This paper describes an approach to support learners by means of visualization and contextualization of LA interventions
5. A Conceptual Framework Linking Learning Design with Learning Analytics (Bakharia et al., 2016)	This paper shows an LA conceptual framework that supports enquiry-based evaluation of learning designs
6. Implementing a Learning Analytics Intervention and Evaluation Framework: What Works? (Rienties et al., 2016)	This study describes a proposed Learning Analytics Intervention and Evaluation Framework (LA-IEF model)
7. The Framework of Intervention Engine based on Learning Analytics (Şahin and Yurdugül, 2017)	This study shows LA Intervention engine framework based the learning outputs of the learners and their learning experiences
8. Developing a Learning Analytics Intervention Design and Tool for Writing Instruction (Shibani, 2018)	This paper shows a proposed Learning Analytics Intervention design for rhetorical writing instruction by providing automated feedback from a writing analytics tool

Table 1 shows no intervention is being developed to cater for students' learning styles. Therefore, this research develops an LA intervention based on learning style models in e-learning to enhance students' learning performance in terms of motivation, academic achievement, cognitive engagement, and cognitive retention.

3 Research Methodology

3.1 Research Design and Population

In this research, a one-group pre-test–post-test design was applied. Students were pre-tested (O1) in order to identify at-risk students in e-learning. It is followed by the implementation of the LA intervention which is integrated with the Felder-Silverman model and Keller's ARCS model in an e-learning environment. Finally, the post-tests (O2) were carried out to examine the students' learning performance. This design was used because it lets the researcher measure the change in variables over time and, in particular, reveals the changes in individuals' performance. In this research, the sample is the population in this research; all Year Two undergraduate students who enrolled in a computer-based course were selected as the participants (N = 50) with both male (N = 20) and female (N = 30) students. All had experience in using e-learning since year one and they were active in e-learning.

3.2 The Learning Analytics Intervention Development

As mentioned previously, learning style and motivation are two important factors in e-learning to optimise the learning process of students (Sfenrianto et al., 2014). Consequently, the development of LA intervention in e-learning in this research is integrated with learning style model and motivational model. Figure 1 shows the model used to develop LA intervention. Four stages of Learning Analytics Cycle proposed by Clow: learner, data, metrics and intervention were explained in this section.

3.2.1 Step 1: Learner

In this research, the numbers of male and female students were 20 (40.00%) and 30 (60.00%) respectively. The total number of learners was 50 in the aforementioned research population section They were active in using e-learning.

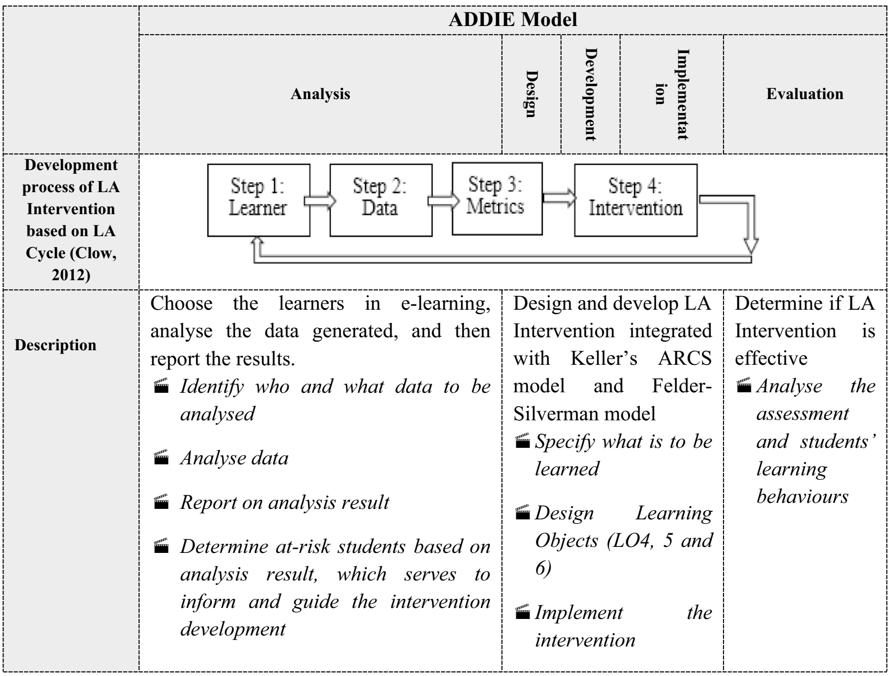

Fig. 1 ADDIE model and LA Cycle

Table 2 Learners' learning status data

No	Learners' learning status data	Description	Examples
1	Learning behaviour data	Data among learners and learning platforms or learning resources	As log-in times, study time, numbers of clicks and views
2	Learning network data	Learners' interactive data, including network relationships and discourse content with others	Reply, post
3	Learning level data	Learners' exam or program scores, reflecting learners' learning status directly	Grade
4	Others	Other instruments used to discover the other type of student data	Questionnaire

3.2.2 Step 2: Data

In this step, by adapting and referring to Wu et al. (2015), several types of data were chosen in order to identify at-risk students (refer to Appendix 1) and understand more about their learning behaviour, which then helped to inform the design of the LA intervention. Based on Table 2, in terms of learners' learning data, number of views and time spent on activity were used to discover students' learning style through automated detection of learning style, adapted from Dung and Florea (2012). Questionnaires were used to measure students' motivation level and learning style respectively. In term of learners' level data, grades and test results were used to find students' cognitive retention and academic achievement. In terms of learners' network data, number of replies and posts in forum discussions were used to discover the students' cognitive engagement level. All these data help to identify at-risk students and then classify them according to their learning style. These were collected and the analysis results are reported in the next stage of the metric.

3.2.3 Step 3: Metric

In this step, it is to report the results of the data analysis to identify at-risk students, which serves to guide the LA intervention in the subsequent stage. The indicators for at-risk students are shown in Appendix 1, adapted from past studies (e.g. Archambault et al., 2010; Bainbridge et al., 2015; Baker et al., 2015; Er, 2012; Hammond et al., 2007; Hu et al., 2014; Tarimo et al., 2016). According to Hammond et al. (2007), students who experience low achievement and low-test scores fall into the at-risk population, and academic performance data serve as a good predictor (Ortiz-Lozano et al., 2020; Ivankova and Stick, 2007). Students at risk of dropping out will also show early signs of inactivity in the course, and this research has used it as one of indicators in determining the at-risk students. Subsequently, WEKA was used to classify students who were at-risk and not at-risk based on a number of attributes through classification data mining technique- Decision Tree, shown in Fig. 2.

The result of the decision tree in Table 3 shows that the correctly classified instances are 100%, and the mean absolute error is 0.008. Thus, a total of 30 students (60.00%) were deemed to be at risk in this study and were classified based on

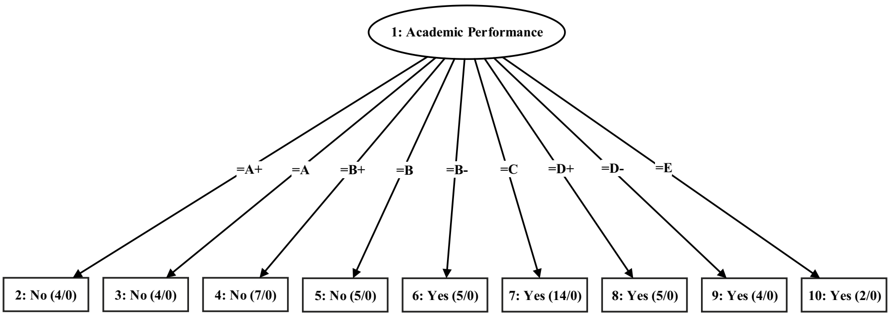

Fig. 2 Results of decision tree

Table 3 The result of data mining

Items	Results
Confusion matric	=== ConfusionMatrix === a b <-- classified as 30 / a = Yes 0 20 / b No

their learning style. The other 20 students (40.00%) were deemed not to be at risk. Besides that, in this step 3, the students' learning styles were also analysed and identified, which is shown in Appendix 1. The results gained in this step were then used to inform and guide the development of the LA intervention in the step 4.

Meanwhile, this step has also categorised the students who were at risk based on their learning style. Several types of learning style were found among these at-risk students: intuitive, sequential, active, global, verbal and visual. This meant that in step 4 the LA intervention would be designed to add more of the LOs preferred by these learning styles (intuitive, sequential, active, global, verbal and visual) with elements of the motivational model for the whole class students to enhance their motivation, academic achievement, cognitive engagement and cognitive retention.

3.2.4 Step 4: LA Intervention

In step 4, after identifying at-risk students in Step 3, the LA intervention was then designed and developed before being implemented in e-learning, which is related to the last step of the LA Cycle, namely intervention. In order to design an effective LA intervention, Keller's ARCS model (adapted from Keller & Suzuki, 2004) and the Felder-Silverman model (adapted from Graf, 2007) are integrated with the LA intervention by providing students preferred LOs based on students' learning styles. It is aimed to enhance their motivation, academic achievement, cognitive engagement and cognitive retention by adding motivational element and more learning style elements in LOs for them, shown in Appendix 2.

When developing the intervention, Felder-Silverman model and Keller's ARCS model were integrated by adding more learning style elements and motivational models to LOs (e.g. LO4 for topic 4, LO5 for topic 5 and LO6 for topic 6). Thus, during intervention, one preferred LO was added to the learning style of at-risk students for each topic of the lesson. All LOs were added motivational elements and

Table 4 Keller's ARCS model (adapted from Keller & Suzuki, 2004)

Category	Basic Strategies
Attention	Inquiry arousal: stimulating an attitude of inquiry
Relevance	Goal orientation: meeting students' needs
Confidence	Learning requirements: building a positive expectation of success; Success opportunities: increasing students' beliefs in their competence
Satisfaction	Positive results: providing reinforcement to students' success

Table 5 Recommended activities from Felder-Silverman model (adapted from Graf, 2007)

Learning style	Recommendations in learning
Active	Making a guess in possible questions and answering them
Reflective	Chances to write short summaries about the already learned material
Sensing	Facts, concrete material, and data and linear text
Intuitive	Facts and lesson objectives and linear text
Visual	Graphics, video, and images
Verbal	Text-based material
Sequential	Guidance
Global	Summaries

learning style model. Lastly, a total of 21 LOs was created for each learning style of at-risk students while 18 LOs for those learning style of not at-risk students, shown in Appendix 2. Table 4 shows the motivational strategies of the ARCS model used to develop the LA intervention.

Another well-known model used in e-learning is the Felder-Silverman model to cater for students with different learning styles and solve the one-size-fits-all problem. Several recommendations for learning are suggested, and this study uses them to meet the learning demands of students with different learning styles, as shown in Table 5.

To make it clear, Fig. 3 shows the steps to develop LOs, and intuitive learning style was as the example in this figure. Three topics were taught before the intervention, and the LOs without intervening (e.g. LO1 for topic 1, LO2 for topic 2 and LO3 for topic 3) for each learning style were developed to identify at-risk students and their learning styles. Every learning style initially had two LOs, but due to the overlapping of learning styles, the total of LOs for each learning style

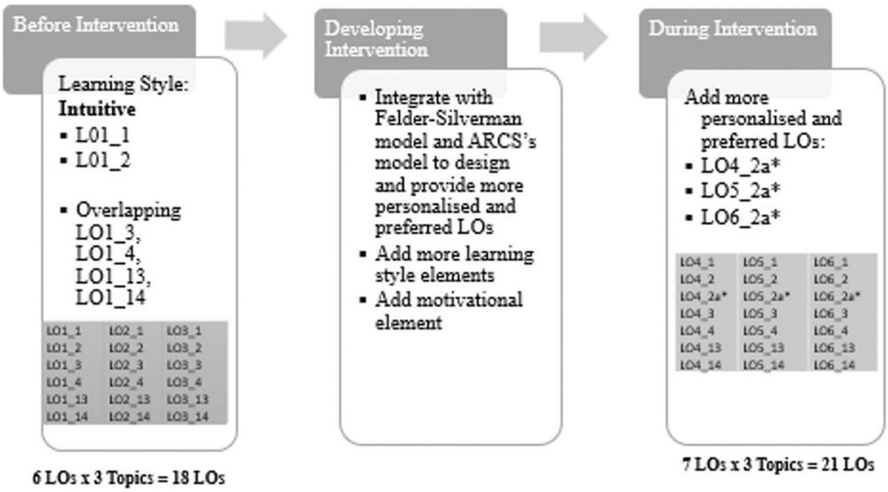

Fig. 3 Learning Objects development process (Sample of Intuitive learning style)

was six for one topic of the lesson. This is because different LOs have different learning style elements; thus, it is expected that there will be some overlapping LOs that are preferred by more than one learning style (Dung & Florea, 2012).

Hence, a total of sixty LOs of the LA intervention were developed in this study after four stages were carried out. Some LOs overlap more than one learning style. Appendix 2 shows the LOs of the LA intervention based on the ARCS model and FSLSM according to different learning styles. Among these, more LOs (marked with *) were added for the specific learning styles of students who were found to be at risk in Step 3. These LOs of the LA intervention were then uploaded to the e-learning environment for all students to access freely. On the other hand, Fig. 4 shows one sample of LOs which were developed by adding preferred learning style elements and motivational elements, and uploaded to the e-learning. Next section will explain the ways to implement this developed LA Intervention in e-learning in this study.

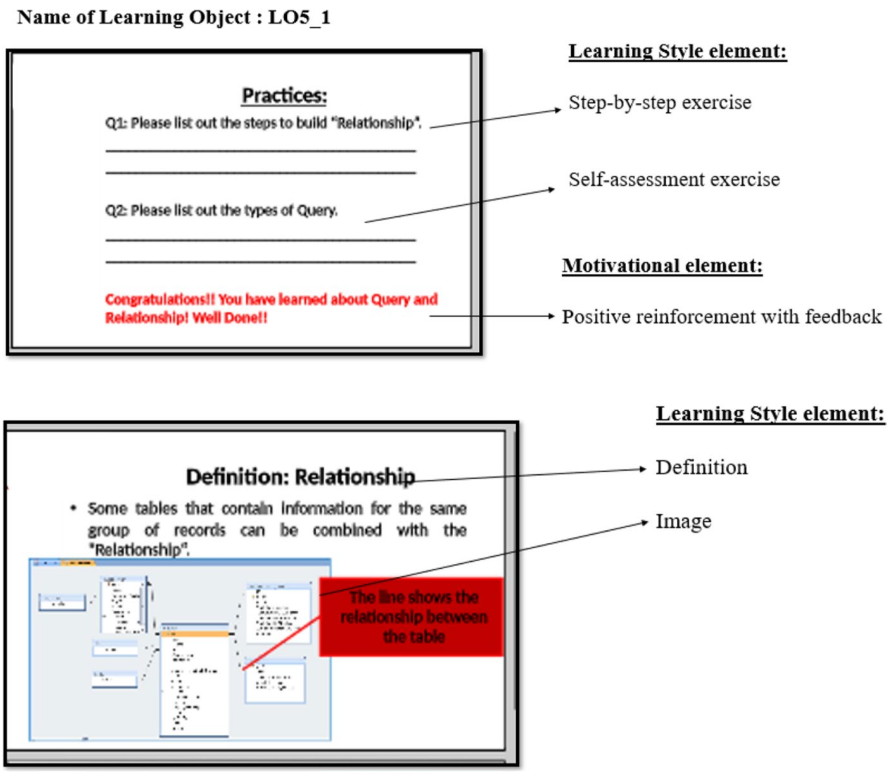

Fig. 4 Sample of Learning Object (LO)

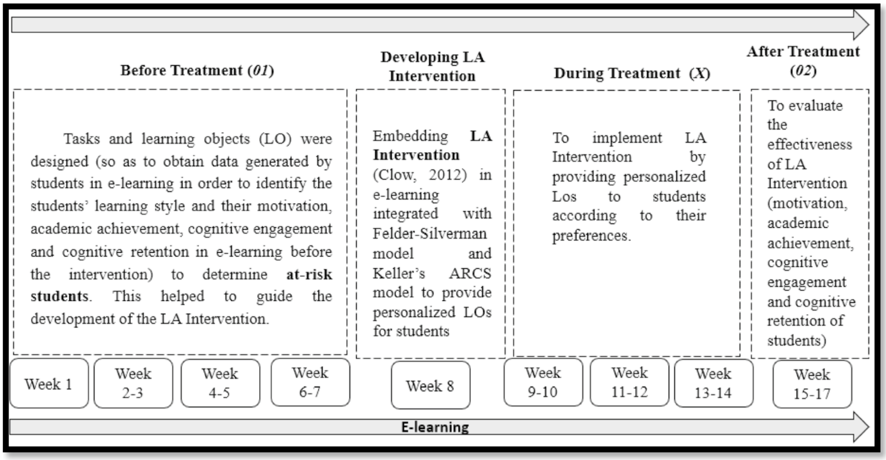

Fig. 5 Procedure of research

3.3 Implementation of LA Intervention in E-learning

Figure 5 shows the research procedure of the implementation of Learning Analytics intervention in e-learning. From Week 1 to 7, every two weeks, different Learning Objects (LOs) without intervening were uploaded (e.g. LO1, LO2 and LO3) and students were given freedom to access them via e-learning. This stage was aimed to use and analyse the data that were generated in e-learning to identify students' learning styles, and to measure their motivation, academic achievement, cognitive engagement and cognitive retention. This then helped to identify which students were at risk in areas such as low motivation, academic achievement, cognitive engagement and cognitive retention by using data mining technique, and to categorize them based on the learning style. This phase was then followed by an intervention development at Week 8, which is based on the LA Cycle (Clow, 2012). This LA intervention was integrated with the Felder-Silverman model (1988) and Keller's ARCS motivation model (1987) to provide new intervening LOs such as LO4, LO5 and LO6 in different weeks by adding motivational elements and more learning style elements according to the lesson topics for students. Next, in the following weeks, students continued to access the e-learning embedded with the LA intervention. Their learning data generated via e-learning were collected and analysed in order to evaluate the effectiveness of the LA intervention by measuring students' motivation, academic achievement, cognitive engagement and cognitive retention.

3.4 Instruments and Data Analysis

In order to investigate the implementation of LA Intervention in e-learning, different validated research instruments are used to analyse the students' overall learning performances such as motivation, cognitive engagement, cognitive retention and academic performance in e-learning embedded with the LA intervention. The pilot study test was carried out to validate these instruments.

3.4.1 Index of Learning Styles (ILS) and Automated Detection of Learning Style for Examining Learning Styles

ILS has 44 questions, which are designed to determine preferences of a learning style model formulated by Felder and Silverman. The ILS comprises four scales, each with eleven items, including active-reflective, visual-verbal, sensing-intuitive, and sequential-global. Students completed the questionnaires, and the result of the ILS was compared with the outcome of the automated detection of learning style which involved the use of a literature-based approach (where students' behaviours were measured to obtain hints about their learning style preferences) adapted from Dung and Florea (2012) to determine the students' learning style.

3.4.2 Instructional Material Motivational Survey (IMMS) for Examining Motivation Level

The IMMS was adopted in this study to measure students' motivational level. It consists of thirty-six items which are separated into four different subscales: (i) Attention (ATT), which includes twelve items determining the degree to which the materials stimulated and sustained students' motivation; (ii) Relevance (RELE), which involves nine items determining the materials' perceived value and utility to the students; (iii) Confidence (CONF), which comprises nine items determining the degree to which students felt they could successfully achieve the goals and tasks laid out in the materials; and (iv) Satisfaction (SAT), which comprises six items determining feelings of accomplishment and the intrinsic appeal of the materials. Each item is answered to measure different degrees of agreement (1–5), and then determine the level of motivation: low level (less than 3.00), medium level (3.00–3.49), upper medium level (3.50–3.99), and high level (4.00–5.00).

3.4.3 Online Discussion Forum Transcripts as Log Files from LMS for Examining Cognitive Engagement

In this research, online discussion scripts were collected from students' discussion forum in e-learning. The collected data were then used to explore students' levels of cognitive engagement, and content analysis was applied to students' online discussion scripts in e-learning based on a coding scheme proposed by Van der Meijden (2005). The reliability of the coding process was calculated by measuring the inter-rater reliability value between the researcher and an expert, in terms of percentage agreement based on Cohen's Kappa. The inter-rater reliability was 87.93%, and the Kappa value was 0.951, which is reliable. Units of meaning were counted for objectivity, which finally led to the descriptive data analysis, which showed the outcomes in terms of frequencies and percentages. Students' level of cognitive engagement was identified by comparing the percentages of low-level cognitive contributions to the percentages of high-level cognitive contributions (Shukor et al., 2014, cited in Kew & Tasir, 2021a, b): (i) a high cognitive engagement level is when the high-level cognitive contribution is higher than the low-level cognitive contribution, (ii) a high-low cognitive engagement level is when the high-level cognitive contribution is equal to the low-level cognitive contribution, and (iii) a low cognitive engagement level is when the high-level cognitive contribution is lower than the low-level cognitive contribution.

3.4.4 Cognitive Retention Test for Examining Cognitive Retention Level

This research analysed students' test scores to identify their cognitive retention levels in e-learning. Two sets of tests given to students after delivery of the lesson were used to measure cognitive retention in which the subject instructor and the researcher developed a quiz using a short essay with three questions based on the topic taught to measure cognitive retention with a total of ten marks. The scores from the cognitive retention pre-test and post-test were marked through descriptive analysis based on the university grading system: A+(90–100), A (80–89), A- (75–79), B+(70–74), B (65–69), B- (60–64), C+(55–59), C (50–54), C- (45–49), D+(40–44), D (35–39), D- (30–34) and E (00–29). Individual scores from these two tests were compared and the scores were entered into SPSS version 18 for analysis using the correlation and t-test.

3.4.5 Academic Performance Test for Examining Academic Performance

The researcher developed the pre- and post-performance tests according to the learning outline and content of the subject taught. The performance tests included 15 multiple choice questions and 3 essay questions with a total of 30 marks, which were then converted to percentages. The university grading system was used to grade the result of the students' academic performance test. Individual scores from the tests were calculated to obtain the mean and standard deviation. Individual scores from these two tests were compared and the scores were entered into SPSS version 18 for analysis using the paired sample t-test.

Table 6 Motivation level of students

Item	Before Intervention		After Intervention	
	Mean	Std. Deviation	Mean	Std. Deviation
Overall	3.59	0.18	4.05	0.31

*n = 50.

Table 7 Range of motivation level and number of students

Motivation Level	Scores	Before Intervention		After Intervention	
		Number	Percentage	Number	Percentage
High	4.00–5.00	1	2.00	23	46.00
Upper Medium	3.50–3.99	37	74.00	27	54.00
Medium	3.00–3.49	12	24.00	0	0
Low	< 3.00	0	0	0	0
Total		50	100	50	100

Table 8 Wilcoxon Signed-Rank Test of motivation level

	postMot—preMot
Z	-5.954
Asymp. Sig. (2-tailed)	0.000

4 Findings

4.1 The Effects of LA Intervention towards Students' Motivation

Table 6 show that students' overall motivation level was enhanced from a mean of 3.59 to 4.05 after the LA intervention was provided. In other words, these students' mean motivation level was increased from an upper medium to a high level.

Motivation was categorised into four levels – high, upper medium, medium and low – which can be used to find out more specific and detailed information on the motivation levels of students. In this research, it was found that the number of students with high levels of motivation increased from 1 (2.00%) to 23 (46.00%) after the LA intervention, and there were no students with low or medium motivation levels, as shown in Table 7.

Furthermore, a normality test was carried out. The significance values of the Shapiro–Wilk normality test are 0.061 before and 0.011 after the intervention. In Table 8, the Wilcoxon signed-rank test shows that the LA intervention did elicit a statistically significant change in students' motivation level ($Z = -5.954$, $p = 0.000$). Hence, it can be concluded that there is a significant difference in the mean motivation level before and after the LA intervention. The effect size for this study is 0.59. Thus, we can conclude that the LA intervention can help to enhance the motivation level of students in e-learning.

Table 9 Descriptive analysis of student in pre-test and post-test

	Academic performance pre-test	Academic performance post-test
Mean	34.28	88.56
Std. Deviation	8.60	4.30
Minimum Score	20.00	78.00
Maximum Score	53.00	95.00

*n = 50.

Next, a Shapiro–Wilk normality test was conducted and the significance value are 0.129 and 0.092 respectively. A paired-sample t-test analysis was then conducted, shown in Table 10, and the significance value is 0.000. This shows that there was a statistically significant difference between the mean of students' pre-test and post-test marks. In other words, the treatment, namely the LA intervention, has a positive impact on students' academic achievement in e-learning. Subsequently, the effect size gave a value of 5.669. The d value of 5.669 ($d > 0.80$) suggests that the effect of the LA intervention towards students' performance in learning is large.

4.2 The Effects of LA Intervention towards Students' Academic Achievement

As shown in Table 9, the average score for the pre-test is 34.28%, with a range from 20 to 53%, whilst the average post-test score is 88.56% with a range from 78 to 95%. The differences in the mean scores show that students' academic performance improved after receiving the LA intervention.

4.3 The Effects of LA Intervention towards Students' Cognitive Engagement

Table 11 shows that the number of students with high-level cognitive engagement has increased from 16 to 48 after the LA intervention, and the number with low-level cognitive engagement has fallen from 17 to 2. This means that these students gained benefits from the LA intervention.

By referring to the coding scheme of Van der Meijden's analytical framework, the results in Table 12 show that high-level contributions were enhanced from 36.44% to 57.96%, whilst low-level contributions dropped from 42.91% to 23.64%, which indicates that students had enhanced their higher levels of thinking in cognitive engagement after the intervention was provided.

4.4 The Effects of LA Intervention towards Students' Cognitive Retention

Table 13 shows that the average score for the cognitive retention pre-test is 82.60%, with a range from 50 to 95%, while for the cognitive retention post-test 2, after the LA intervention, the average score is 90.20%, with a range from 75

Table 10 Paired sample t-test for pre and post-test scores

	Paired Differences					t	df	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
				Lower	Upper			
Academic_performance_post-test_-Academic_performance_pre-test	54.28000	9.57	1.35	51.56	57.00	40.09	49	0.000

Table 11 Students' cognitive engagement levels before and after the LA Intervention

Range of cognitive engagement	Before Intervention		After Intervention	
	Number of Students	Percentage (%)	Number of Students	Percentage (%)
High level of cognitive engagement	16	32.00	48	96.00
High Low level of cognitive engagement	17	34.00	0	0.00
Low level of cognitive engagement	17	34.00	2	4.00
Total	50	100.00	50	100.00

Table 12 Cognitive contributions of cognitive engagement

Before LA Intervention		After LA Intervention	
Cognitive contributions	%	Cognitive contributions	%
High-level contributions (*)	36.44	High-level contributions (*)	57.96
Low-level contributions	42.91	Low-level contributions	23.64
Total	100	Total	100

Table 13 Descriptive statistics for cognitive retention

	Cognitive retention pre-test	Cognitive retention post-test
Mean	82.60	90.20
Std. Deviation	8.88	4.62
Minimum	50.00	75.00
Maximum	95.00	95.00

*n = 50.

Table 14 Spearman Test

			RETENTION_PRE	RETENTION_POST
Spearman's rho	RETENTION_PRE	Correlation Coefficient	1.000	0.450**
		Sig. (2-tailed)		0.001
		N	50	50
	RETENTION_POST	Correlation Coefficient	0.450**	1.000
		Sig. (2-tailed)	0.001	
		N	50	50

to 95%. The difference in the mean percentage indicates that the students had retained their knowledge about course.

A Shapiro–Wilk normality test was carried out, and the significance value of this test for cognitive retention scores is 0.000. The Wilcoxon test show that the LA intervention elicited a statistically significant change in cognitive retention ($Z = -5.390$, $p = 0.000$). The effect size for this retention test is $r = 0.539$. Hence, the LA intervention has significant effect on students' cognitive retention. Furthermore, Spearman's rank-order correlation was run to determine the relationship between cognitive retention pre- and post-test, and there was a moderate, positive correlation between these two tests, as Spearman's correlation coefficient, rs, is 0.45, and this is statistically significant ($p = 0.001$). This result shown in Table 14 confirms again that the LA intervention helps to enhance students' cognitive retention.

5 Discussions

The findings have proved that the new designed LA intervention is successfully implemented in e-learning and significantly helps to enhance students' motivation, academic achievement, cognitive engagement and cognitive retention. It is clear that capturing and maintaining student' attention, motivation and engagement in e-learning are critical aspects of the learning process towards enhancing outcomes for all students. In this research, by implementing LA intervention, motivational changes were visible among students involved in this research across the duration of the course. In particular, the LA intervention had clear content structure, preferable LOs and relevant information, which contributed to ensuring that students were motivated towards the e-learning. Hence, it has been demonstrated that the preferred LOs of good learning quality with an effective instructional design of the LA intervention in this research kept students highly motivated and engaged, and then encouraged them to remain in the environment where their preferred LOs were found to meet their demands.

Besides that, one function of Learning Management System is to provide a wide range of data and indicators that have the potential to inform meaningful decisions and provide more precise and accurate info. This research has monitored and achieved early identification of students who were at risk of falling behind in e-learning. The outcome of the LA analyses is a key factor in improving motivation, engagement and success by providing at-risk students with the LA intervention based on their learning style and to enhance their learning performance. Baepler and Murdoch (2010) highlighted that LA has been implemented at universities and enables data-driven decision-making (Sclater et al., 2016), and it also aids in teaching and learning practices, since LA delivers direct evidence of student learning. This research has referred to the outcomes of the data analyses to identify at-risk students and then added more preferred and appropriate LOs integrated with motivational elements to e-learning in order to meet these students' needs. Hence, this research has shown the importance of LA and precision education.

Moreover, among the thirty at-risk students, it is interesting to find that the majority showed greatly increased motivation levels after the LA intervention, indicating that this intervention was useful for them. This is in line with the findings Gonzalez (2015), as the respondents in their research seem to have the potential to enhance their learning performance once their motivation is boosted by effective instructional design. This is because students who used LA intervention had an expectancy of being successful in LOs, and possessed a value for engaging in e-learning, making them became more motivated and engaged to complete their e-learning tasks punctually. Students' motivation to learn derives from the meaningful nature of these learning settings and activities (Shroff et al., 2007), which makes them more engaged. The use of LOs which reflected their learning style, integrated with motivational elements, successfully attracted their attention and interest. Hence, this research has made an important contribution to the field of LA by showing how LA intervention can enhance students' motivation.

Based on the results, LA intervention was also found to have a significant influence upon students' academic achievements. The paired-sample t-test showed a significant difference in students' academic achievement before and after using the LA intervention, with a large effect size, which means that the LA intervention had an impact on students' academic achievement. This result is parallel to the outcomes of the Course Signals and OAAI projects, demonstrating that interventions using LA can successfully improve students' course performance (Bainbridge et al., 2015). This finding is mostly related to the benefits of early identification of at-risk students and then the design of meaningful LOs for the LA intervention and to help them to enhance their learning performance. These results seem to be consistent with previous research which recommends that the online provision of teaching and learning materials that meet the needs of students can have a positive influence on students' academic performance, as reported by Perera and Richardson (2010). In particular, this LA intervention leads to self-engagement, where students are intrinsically motivated by curiosity, interest, and enjoyment. As a consequence, they are able to complete e-learning tasks and absorb knowledge efficiently.

It is also interesting to know that all students, including those identified as being at risk, improved their academic achievement. Students chose the suitable and motivating LOs and activities from the learning environment to meet their needs, as LA intervention provided the students' suitable and appropriate LOs to meet their needs based on the outcome of data analysis. In this respect, they can acquire knowledge easily when they access LOs they like. Therefore, educators should provide enough different motivating and correct learning materials in the e-learning environment so that all students are satisfied. Specifically, Saeed et al. (2009) highlighted the significant relationships between students' learning styles and their impact on academic achievement, and Graf (2007) used the Felder–Silverman learning style model to identify students' learning styles based on their behaviours and actions, and demonstrated that considering students' learning styles improves their performance. Topçu (2008) also pinpointed that the awareness of instructors on learning styles may bring beneficial to enhance students' learning performance in e-learning. This is parallel to the result gained by this research, which found that motivating and matched learning materials had an impact on students' academic achievement, and that motivated students became more active in e-learning and thus acquired knowledge more easily.

The findings also reveal that the students' cognitive engagement increased after the LA intervention was provided, which directly shows that in the forum discussion, students had achieved high levels of knowledge construction, which involves cognitive effort in elaborating facts and arguments (Van der Meijden, 2005). Previous research (Miller et al., 1996) has found that cognitive engagement has a positive relationship with students' motivation. In this regard, the findings discussed in the previous section show that the majority of students had reached high levels of motivation, which in turn has contributed to making improving their cognitive engagement. Richardson and Newby (2006) also explained that students' cognitive engagement in e-learning is vital, as the students acquire experience and take more obligations for their own learning. Students' level of engagement will affect their motivation and learning performance and vice versa. This view concurs with the results of the study conducted by Joo et al. (2014), who found that cognitive engagement could be connected to the enhancement of students' motivation and learning outcomes. In the previous section, it was shown that the students' motivation and academic achievement increased, which might indirectly enhance cognitive engagement. Similarly, Lyke and Young (2006) also reported that motivation may act as a mediator of the positive relationship between instructional design and deep-level cognitive engagement. Thus, it is believed that the increase in students' motivation level may have contributed to improving their cognitive engagement.

In order to enrich their learning process and experiences, it is important for students to retain the information and knowledge they have learned so that they can successfully apply it. In this respect, the LA intervention was designed to help students to retain information by providing them with more appropriate and precise LOs integrated with motivational elements so that they could acquire the knowledge effectively. Students' overall cognitive retention improved after the intervention, indicating that the intervention has helped to improve students' cognitive retention. It also reflected how well these students retained the information after the lecture, demonstrating that most of the students remembered and retained information from the LOs in the e-learning environment. Several variables could contribute to these findings. For example, the students' enhanced motivation in e-learning might have helped them to acquire and retain the information more easily. They paid attention to the LOs that they found satisfying and relevant, and felt confident that they could achieve success in their learning, thus encouraging them to make more effort to absorb the knowledge.

Another possible reason is their interest in the subject being taught and the provision of sufficient numbers of their preferred and matched LOs to meet their needs via the LA intervention that provides evidence, which enabled them to successfully acquire knowledge and retain it. This concurs with previous research which concluded that educators or instructors should design and deliver the most appropriate and meaningful activities to suit a particular student group and to match their learning style (Zhou, 2011) so that they can build their knowledge efficiently. Additionally, the results of the Wilcoxon test show that the intervention had an important impact on students' cognitive retention. Students found the LA intervention helpful in knowledge retention, especially given that the intervention accommodates different types of learning styles and provides different motivational elements. Additionally, Spearman's rank-order correlation also shows that both cognitive retention tests carried out in two different weeks to measure students' cognitive retention during the treatment were moderately and positively correlated, confirming that the LA intervention is useful. This intervention was specifically developed to meet the needs of students with different learning styles, providing favourable and motivating LOs which helped the students to construct and retain knowledge effectively, thus enhancing their engagement and motivation level.

6 Conclusion, Limitation and Future Research

To conclude regarding the impact of the LA intervention on students' motivation, academic achievement, cognitive engagement and cognitive retention, the results clearly show that such intervention greatly helps to enhance students' learning performance. This research would like to highlight the usefulness of the precision education and LA which provides evidence based on the data analysis and accordingly informs the development of intervention which integrated with both learning style and motivation models for students, especially at-risk students. The results also clearly indicate that early identification of at-risk students, leading to LA intervention with supplementary LOs which are more suitable and preferred by students, can greatly enhance students' motivation, cognitive engagement, cognitive retention and academic achievement. Moreover, several important perspectives have been gained from the analysis of findings regarding how the LA intervention influenced students' learning performance. This research has proven that the LA intervention has the potential to provide "learner-centred learning" by firstly analysing students data' to identify those who are at risk, and then, based on the results of metrics, developing an effective LA intervention that takes into accounts the needs of students. Also, this approach can truly help instructors or lecturers to adopt suitable and appropriate learning materials for efficient learning and to best fit with students' preferences.

Several limitations of this research must be addressed. One of the limitations was the participants selected in this research. More different programs or disciplines should be taken into considerations in the future. It is possible that in other disciplines or subjects, the LA intervention used by the instructor might differ from that of the current study. Also, the number of samples should be added. It is then suggested that further research can thus shed light on the effectiveness of LA intervention in other disciplines or subject areas with greater demographic profiles. Another limitation is LA is relatively new (West et al., 2018) and serves as a basis for interventions to provide more personalized LOs to meet the needs of students; thus, this research only utilized quantitative research to answer the research questions. Future studies could consider to use qualitative research method such as interview to make an in-depth investigation of students' perceptions on LA intervention. Also, if the research were to be replicated, it is suggested that it should use more types of data mining techniques to generate more precise and different results, such as using clustering or association rules to learn more about students' learning behaviour in e-learning.

Appendix 1

Tables 15, 16 and 17

Table 15 Indicators for at-risk students

No	Motivation Level	Cognitive Engagement Level	Cognitive Retention Level	Academic Achievement	At-risk student
1	Low	Low	Low	Low	Yes
2	Low	Low	Low	Low	Yes
3	Low	High Low	Low	Low	Yes
4	Low	High Low	Low	Low	Yes
5	Low	High	Low	Low	Yes
6	Low	High	Low	Low	Yes
7	Medium	Low	Low	Low	Yes
8	Medium	Low	Low	Low	Yes
9	Medium	High Low	Low	Low	Yes
10	Medium	High Low	Low	Low	Yes
11	Medium	High	Low	Low	Yes
12	Medium	High	Low	Low	Yes
13	Upper Medium	Low	Low	Low	Yes
14	Upper Medium	Low	Low	Low	Yes
15	Upper Medium	High Low	Low	Low	Yes
16	Upper Medium	High Low	Low	Low	Yes
17	Upper Medium	High	Low	Low	Yes
18	Upper Medium	High	Low	Low	Yes
19	High	Low	Low	Low	Yes
20	High	Low	Low	Low	Yes
21	High	High Low	Low	Low	Yes
22	High	High Low	Low	Low	Yes
23	High	High	Low	Low	Yes
24	High	High	Low	Low	Yes

*Low in cognitive retention and academic achievement means B- and below

Table 16 At-risk students' details

Student	Learning Style	Motivation Level	Cognitive Engagement Level	Cognitive Retention	Academic Achievement	At risk
1	visual	high	H	B	B	No
2	visual	medium	HL	B	A+	No
3	reflective	high	H	A-	A+	No
4	intuitive	medium	L	C	D-	Yes
5	verbal	high	H	A-	B+	No
6	visual	medium	HL	B	B+	No
7	intuitive	medium	H	B	B	No
8	visual	upper medium	L	C	C	Yes
9	visual	upper medium	L	C+	D-	Yes
10	reflective	medium	H	A-	A	No
11	visual	low	H	B+	A	No
12	reflective	medium	HL	B+	B+	No
13	intuitive	upper medium	H	A-	A	No
14	visual	upper medium	L	C+	E	Yes
15	visual	low	HL	D+	D+	Yes
16	visual	high	HL	A-	A+	No
17	sequential	upper medium	H	C-	C	Yes
18	visual	upper medium	L	C-	D-	Yes
19	reflective	upper medium	HL	B+	B	No
20	visual	upper medium	L	B	B+	No
21	visual	upper medium	HL	C	D+	Yes
22	visual	upper medium	H	B	B	No
23	reflective	high	HL	B	A+	No
24	visual	upper medium	HL	C+	C	Yes
25	visual	medium	H	B-	B-	Yes
26	active	upper medium	HL	B-	B-	Yes
27	visual	medium	H	C-	E	Yes

Table 16 (continued)

Student	Learning Style	Motivation Level	Cognitive Engagement Level	Cognitive Retention	Academic Achievement	At risk
28	intuitive	High	L	D	D+	Yes
29	visual	High	HL	C+	C	Yes
30	visual	medium	L	C+	C	Yes
31	visual	High	H	C	C	Yes
32	intuitive	upper medium	L	C+	C	Yes
33	active	medium	H	C	C	Yes
34	intuitive	upper medium	L	D	C	Yes
35	global	upper medium	L	B	B+	No
36	visual	medium	HL	C-	D+	Yes
37	visual	upper medium	HL	B	B	No
38	global	medium	HL	D-	C	Yes
39	visual	medium	L	B-	B-	Yes
40	visual	low	L	B-	B-	Yes
41	visual	upper medium	HL	B	B+	No
42	global	upper medium	H	B	A	No
43	visual	medium	H	C-	C	Yes
44	visual	high	L	B	B+	No
45	visual	upper medium	HL	D-	C	Yes
46	visual	High	L	C	C	Yes
47	visual	upper medium	L	C	C	Yes
48	verbal	low	HL	B-	B-	Yes
49	visual	medium	L	C+	D+	Yes
50	visual	low	H	C+	D-	Yes

Appendix 2

Table 17 Learning objects based on the adapted Keller's ARCS model and Felder-Silverman Learning Style model

Learning Style	Learning objects of LA Intervention			Learning style model elements	Motivational model elements
Active	LO4_1	LO5_1	LO6_1	Self-assessment exercises, multiple question-guessing exercises or making a guess in possible questions and answering them	1. Perceptual arousal: capturing students' interest; Inquiry arousal: stimulating an attitude of inquiry (Ask question)
	LO4_2	LO5_2	LO6_2		2. Goal Orientation: meeting students' needs: Familiarity: trying instruction to students's experiences (Set Goal)
	LO4_5	LO5_5	LO6_5		3. Learning Requirements: building a positive expecation for sucess; Success opportunities: increasing students's beliefs in their competence (Give instruction)
	LO4_6	LO5_6	LO6_6		4. Positive results: providing reinforcement to student's success(positive reinforcement)
	LO4_6a*	LO5_6a*	LO6_6a*		
	LO4_7	LO5_7	LO6_7		
	LO4_8	LO5_8	LO6_8		
Reflective	LO4_9	LO5_9	LO6_9	Examples, Summaries or chances to write short summaries about the already learned material	1. Perceptual arousal: capturing students' interest; Inquiry arousal: stimulating an attitude of inquiry (Ask question)
	LO4_10	LO5_10	LO6_10		
	LO4_11	LO5_11	LO6_11		2. Goal orientation: meeting students' needs; Familiarity: trying instruction to student's experiences (Set Goal)
	LO4_12	LO5_12	LO6_12		3. Learning requirements: building a positive expectation for success; Success opportunities: increasing students' beliefs in their competence (Give instruction)

Table 17 (continued)

Learning Style	Learning objects of LA Intervention			Learning style model elements	Motivational model elements
	LO4_13	LO5_13	LO6_13		4. Positive results: providing reinforcement to student's success(positive reinforcement)
	LO4_14	LO5_14	LO6_14		
Visual	LO4_1	LO5_1	LO6_1	Images, videos or graphics	1. Perceptual arousal: capturing students' interest; Inquiry arousal: stimulating an attitude of inquiry (Ask question)
	LO4_2	LO5_2	LO6_2		2. Goal orientation: meeting students' needs; Familiarity: trying instruction to student's experiences (Set Goal)
	LO4_3	LO5_3	LO6_3		3. Learning requirements: building a positive expectation for success; Success opportunities: increasing students' beliefs in their competence (Give instruction)
	LO4_4	LO5_4	LO6_4		4. Positive results: providing reinforcement to student's success(positive reinforcement)
	LO4_4a*	LO5_4a*	LO6_4a*		
	LO4_10	LO5_10	LO6_10		
	LO4_12	LO5_12	LO6_12		
Verbal	LO4_1	LO5_1	LO6_1	Text	1. Perceptual arousal: capturing students' interest; Inquiry arousal: stimulating an attitude of inquiry (Ask question)
	LO4_2	LO5_2	LO6_2		2. Goal orientation: meeting students' needs; Familiarity: trying instruction to student's experiences (Set Goal)
	LO4_11	LO5_11	LO6_11		3. Learning requirements: building a positive expectation for success; Success opportunities: increasing students' beliefs in their competence (Give instruction)
	LO4_12	LO5_12	LO6_12		4. Positive results: providing reinforcement to student's success(positive reinforcement)
	LO4_12a	LO5_12a*	LO6_12a*		
	*LO4_13	LO5_13	LO6_13		

Table 17 (continued)

Learning Style	Learning objects of LA Intervention			Learning style model elements	Motivational model elements
	LO4_14	LO5_14	LO6_14		
Global	LO4_1	LO5_1	LO6_1	Outlines or summaries	1. Perceptual arousal: capturing students' interest; Inquiry arousal: stimulating an attitude of inquiry (Ask question)
	LO4_2	LO5_2	LO6_2		2. Goal orientation: meeting students' needs; Familiarity: trying instruction to student's experiences (Set Goal)
	LO4_9	LO5_9	LO6_9		3. Learning requirements: building a positive expectation for success; Success opportunities: increasing students' beliefs in their competence (Give instruction)
	LO4_10	LO5_10	LO6_10		4. Positive results: providing reinforcement to student's success(positive reinforcement)
	LO4_13	LO5_13	LO6_13		
	LO4_14	LO5_14	LO6_14		
	LO4_14a*	LO5_14a*	LO6_14a*		
Intuitive	LO4_1	LO5_1	LO6_1	Definitions or facts and lesson objectives and linear text	1. Perceptual arousal: capturing students' interest; Inquiry arousal: stimulating an attitude of inquiry (Ask question)
	LO4_2	LO5_2	LO6_2		2. Goal orientation: meeting students' needs; Familiarity: trying instruction to student's experiences (Set Goal)
	LO4_2a*	LO5_2a*	LO6_2a*		3. Learning requirements: building a positive expectation for success; Success opportunities: increasing students' beliefs in their competence (Give instruction)
	LO4_3	LO5_3	LO6_3		4. Positive results: providing reinforcement to student's success(positive reinforcement)
	LO4_4	LO5_4	LO6_4		
	LO4_13	LO5_13	LO6_13		
	LO4_14	LO5_14	LO6_14		

Table 17 (continued)

Learning Style	Learning objects of LA Intervention				Learning style model elements	Motivational model elements
Sequential	LO4_1		LO5_1	LO6_1	Step-by step exercises or guidance	1. Perceptual arousal: capturing students' interest; Inquiry arousal: stimulating an attitude of inquiry (Ask question)
	LO4_2		LO5_2	LO6_2		2. Goal orientation: meeting students' needs; Familiarity: trying instruction to student's experiences (Set Goal)
	LO4_7		LO5_7	LO6_7		3. Learning requirements: building a positive expectation for success; Success opportunities: increasing students' beliefs in their competence (Give instruction)
	LO4_8		LO5_8	LO6_8		4. Positive results: providing reinforcement to student's success(positive reinforcement)
	LO4_8a*		LO5_8a*	LO6_8a*		
	LO4_13		LO5_13	LO6_13		
	LO4_14		LO5_14	LO6_14		
Sensing	LO4_1		LO5_1	LO6_1	Examples, explanation or facts and linear text	1. Perceptual arousal: capturing students' interest; Inquiry arousal: stimulating an attitude of inquiry (Ask question)
	LO4_2		LO5_2	LO6_2		2. Goal orientation: meeting students' needs; Familiarity: trying instruction to student's experiences (Set Goal)
	LO4_3		LO5_3	LO6_3		3. Learning requirements: building a positive expectation for success; Success opportunities: increasing students' beliefs in their competence (Give instruction)
	LO4_4	LO5_4		LO6_4		4. Positive results: providing reinforcement to student's success(positive reinforcement)
	LO4_11	LO5_11		LO6_11		
	LO4_12	LO5_12		LO6_12		

* Learning Objects added in LA intervention for at-risk students in e-learning.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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