IOSR Journal of Research & Method in Education (IOSR-JRME)
e-ISSN: 2320–7388, p-ISSN: 2320–737X Volume 5, Issue 4 Ver. II (Jul. - Aug. 2015), PP 104-119
www.iosrjournals.org

Adaptive Remediation Solutions Design Framework and Implementation for Student Success

Bhushan Talwar[1], Shradha Kanwar[2], Vijay Mandke[3]
[1] *(Educational Technology, NIIT University, India)*
[2] *(Educational Technology, NIIT University, India)*
[3] *(Educational Technology, NIIT University, India)*

Abstract: *E-learning has established a critical presence in the 21st century learning environment. With the rise of convergence technologies, different models of e-learning have emerged obliterating the barriers of time and space and delivering deep learning. Teaching-learning interplay has been further enhanced because of novel interactive process centric interventions and e-tutoring is emerging as an effective teaching learning solution. Specifically, the paper addresses the current e-learning challenges by designing and implementing Adaptive Remediation Solutions Framework to e-tutoring. The e-tutoring Adaptive Remediation Solutions Framework deals with improvement of the overall learning experience by identifying the gap and adopting Learning to learn driven remedial interventions with the specific cognitive requirements of the learner traditionally not catered to in a standard (conventional) e-learning environment. The paper ascertains the improvement in the student success rate by early identification of learners at-risk followed by timely, continuous and multi-tiered teaching-learning interventions. Convergence Technology (CT) enabled Educational Technology (ET) has been leveraged to offer innovative pedagogies by matching learning model in Adaptive Remediation Solutions Framework with learners abilities & differentiated assessment. This has been evaluated through data obtained from an e-learning course offered by a leading e-learning institute. The results clearly demonstrate that the Adaptive Remediation Solutions Framework assists in creating an effective learning environment resulting in improved student success rate.*

Keywords: *Adaptive Remediation Solutions Framework, Differentiated Instructions, e-Tutoring, Innovative Pedagogies, Personalized learning*

I. Introduction

Convergence Technology (CT) constitutes convergence of computing (Net and Mobile Computing included), wireless sensory networks and telecommunications, consumer electronics and content. CT enabled ET has productized the classroom and provided abundant opportunities for higher education worldwide in the form of e-learning supporting teacher-learner, learner-learner, and learner-content communication. Over the past ten years, e-learning has become a popular form of learning and more and more training organizations have incorporated e-learning into their training delivery. According to the Australian Flexible Learning Framework's 2009 E-learning Benchmarking Report, 90 per cent of training students and 87 per cent of trainers in the national training system use some form of e-learning . In Western Australia, the number of units involving e-learning at registered training organizations jumped 13 per cent from October 2008 to October 2009. So strong is its demand that it is now a significant deciding factor for students thinking of enrolling in a particular course (the rise of e-learning, 2009) [1]. Different models of e-learning have emerged over a period of time and gained popularity and acceptance because of their ability to obliterate the barriers of time and space. As a result, enrollments in higher education institutes having e-learning has been increasing with better accessibility opportunities to almost everyone. However, the student dropout rate has increased with time. In 2009, according to a U.S. Department of Education study, over one-third of first-year undergraduate students reported enrolling in remedial or developmental courses (2011)[2]. This is an indication of the dip in higher education standards. Therefore, retaining students remains a top priority for colleges and universities in the US and across the globe. The current e-learning system is abundant with rich resources and easy access that allows learners to engage in independent learning, but it has certain limitations in terms of relevant information sharing and monitored knowledge progression. A major limiting factor is the inadequate analysis of learning engagement and effectiveness and a disjointed assessment process.

Davidovic, Warren and Trichina (2003) in the paper 'Learning benefits of structural example-based adaptive tutoring systems' illustrated and evaluated a generic adaptive tutoring environment, structural example-based adaptive tutoring system (SEATS), based on the theory of cognitive knowledge acquisition. SEATS was evaluated with a recursion tutorial used by 117 students in a 1-hour tutorial session. Results indicated that using adaptation in combination with the structural example-based feature produced an effect on rate and extent of learning significantly greater than when the features were used alone, or when both were absent [3]. Tutoring

has a history as a tool to improve students' academic achievement in the United States (Cohen, Kulik, and Kulik 1982; Wasik and Slavin 1993; Invernizzi 2002) [4] [5] [6]. Ramsden (1992) argues that effective teaching facilitates effective learning by students [7]. E-tutoring applied with Adaptive Remediation Solutions Framework focuses on creating a personalized, customized and timely anchored instructional interplay between the teacher and the learner leading to adequate analysis of learner's engagement and effective and constructive assessment process. E-tutoring can be defined as teaching, support, management and assessment of students on programs of personalized study that involve a significant use of online technologies (TechLearn, 2000) [8].
Researchers have provided guidelines for effective and efficient education. It is suggested that the sound learning theories are incomplete or unrealistic if they do not include a whole person view, integrating both cognitive and affective aspects, implying that no educational program can be successful without due attention to the personal learning needs of individual students (Snow and Farr 1977) [9]. The educators should identify and acknowledge learning differences and make maximum use of the available technology to serve them accordingly (Russell 1977) [10]. Brusilovsky advocates, using adaptive hypermedia to support individual learning. By `adaptive‘, he means to adapt both the content and presentation of the course based on the profile of the learner. (Brusilovsky 2002) [11]. Paolucci addresses the importance of individualization that any strategy should be adaptive and personalized (Paolucci 1998) [12]. Therefore, one of the most formidable tasks for educators is shaping their presentations of core knowledge to meet the needs of individual learners having varied and diverse cognitive and psychological traits (Whitehurst, Powell and Izatt 1998) [13].

In the last 30 years education theory has shifted to advocate a constructivist theory of learning (Ng & Cheung, 2007) where the role of the university professor is 'the guide on the side' rather than the 'sage on the stage' (King, 1993) [14][15]. Collison, Elbaum, Haavind and Tinker (2000) propose that this is also the most appropriate role for leading a virtual learning community. They suggest that the tasks of an online instructor or e-tutor should include; being aware of all postings within discussion forums, encouraging participation and keeping track of the involvement of individual students; keeping the discussion focused; and encouraging higher order thinking [16]. However Cox et al. (2000) suggest that the unique role of the e-tutor requires continual reappraisal in an environment where technology change is constant [17]

Tutoring is a successful system for traditional learning as Prensky (2002) among others points out. Prensky states that tutorial learning is more efficient than learning in traditional classes because of the personal one-on-one interaction between the tutor and the student. And although tutoring in traditional (physical) environments is still an expensive form of learning, Prensky reminds us that the current technology enables us to connect more students with a single tutor at lower costs and over greater distances. (Prensky, 2002) [18]. A similar opinion is shared by Bork, who emphasizes learning over teaching. In his opinion the currently prevailing information transfer educational paradigm, in which the teacher transfers "knowledge" to often passive students should be changed. In his opinion the future lies in the tutorial learning paradigm, in which learning is seen as an active process in which learners play the leading role. This paradigm will focus on learning in smaller groups with the support of a tutor. The key elements of the tutorial learning paradigm are interactivity, individualization, adaptability, creativity, collaboration etc. (Bork, 2000) [19].

E-tutors support e-learners through different roles. Authors have different classifications of roles tutor perform in e-learning environments. An often cited classification made by Berge defines four basic roles of an online tutor: pedagogical, managerial, social and technical (in McPhearson & Nunes, 2004) [20]. In the pedagogical role tutors support the learning process itself by providing instructions, stimulating questions, examples, feedback, motivation etc. to the learners (Teles et al., 2001). The managerial role requires the tutor to perform basic course administration, track student progress and data etc. (Teles et al., 2001) [21]. The tutor's social role includes the efforts to establish a friendly and comfortable environment and a community that stimulates learning, while the technical role requires the tutor to acquaint the students and himself/herself with the ICT that is used for e-learning, and also to provide some technical support to the students (McPhearson & Nunes, 2004) [20]. The ARS framework supports e-tutors/learners to be successful in all the required roles. Teaching-learning interplay happens wherein there is interplay between contextualization and de-contextualization, between constructive conflict and deconstructive conflict, between internal regulation and external regulation and between teacher and learner. Therefore, teaching-learning interplay has been further enhanced because of novel interactive processes that provide multiple learning pathways and e-tutoring is emerging as an effective intervention in this regard. Based on the above indications of Adaptive Remediation Solutions, there is a need to study & analyze the current student retention framework and develop a comprehensive Adaptive Remediation Solutions Framework for Student Success. This new framework has been designed to address the problem of student retention by early identification of students at-risk followed by continuous teaching-learning interventions (differentiated instructions) matched with learning intelligences of students.

II. Approach

The focus of this research is on designing of a framework to meet differentiated learning abilities of learners. The work involves identification of drivers for enhancing the e-tutoring experience by exploring and documenting best practices and key-learning for designing the Adaptive Remediation Solutions Framework. Based on the Framework's findings, a generic e-tutoring instruction on providing a holistic interface with the learner is created and implemented. As a part of the implementation of this model, tutors are trained in the process of training & tutoring for Learning to learn. In the process, tutors are sensitized to customized, personalized and timely interventions for learners leading to improved participation, engagement and attributions in the learning process. The researchers have critically studied & analyzed the Adaptive Remediation Solutions Framework through early signs of learner at-risk, different learning styles, importance of learner's engagement and timely pedagogic interventions to meet differentiated needs of learners. The factors of risk profiling and student advising are leveraged to propose an Adaptive Remediation Solutions Framework for Student Success. The effectiveness of the model is further analyzed and validated by its application to 411 learners spread across four semesters of a leading e-learning institute. Based on this a generic systems view of an internetworked, integrated Adaptive Remediation Solutions Framework has been developed and presented in this research paper.

III. Adaptive Remediation Solutions Framework

This section of the research paper presents two critical components of the Adaptive Remediation Solutions Framework for Student Retention and Performance.

3.1 Risk Profiling

Risk profiling is a necessary step in recognizing the possibility of a learner's non-participation, disengagement and subsequent withdrawal from an assigned e-course. It is an important criterion to evaluate the extent of threat to the teaching-learning process and an early indicator of students at-risk towards designing the necessary remedial intervention. The continuous risk profiling helps in early identification of students at- risk by categorizing students as Red, Amber and Green on the basis of the below mentioned two parameters.

3.1.1 Active Participation & engagement

The best learning occurs when students are engaged in active learning – when they are doing things instead of sitting passively and listening. A classic study by the National Training Board US found that students retained only 5% of the information they received in lecture twenty-four hours later. Retention rates increased to 75-90% when active learning involving peer teaching was used instead of lectures. Other active learning methods (e.g., demonstration and discussion) also resulted in higher retention rates (30% and 50%, respectively). In another study of the effectiveness of lectures (McLeish 1968; cited in Fink 2003), students were tested on their understanding of facts, theory, and application after hearing a lecture that was specially designed to be effective. Despite being able to use their own lecture notes and a printed summary of the lecture, average student recall after the lecture was only 42%. A week later recall had dropped to only 20% [22] [23]. In a recent review of the effectiveness of active learning, Prince (2004) found extensive, widespread support for active learning approaches, especially when activities were designed around important learning outcomes and promoted thoughtful engagement [24]. Many instructors recognize that active learning results in significant improvements in student knowledge retention, conceptual understanding, engagement, and attitudes about learning. According to Vonderwell and Zachariah (2005, p.214), "Learner participation is an essential element for active and engaged learning"[25]. Although student participation is not a direct measure of learning, its necessary in order for a discussion to occur in the first place; and through the discussion, it is more likely that learning takes place (Dennen, 2005) [26]

So, active participation promotes learning in the classroom and is important for receiving the full benefit of class discussions, announcements, and learning materials. If learners do not attend regularly, interact with classmates and class materials, and invest themselves actively in the learning process, they are unlikely to succeed academically. Therefore active participation and engagement is a major aspect of risk profiling and thus needs to be monitored and managed on a regular basis. In order to analyze this correlation, tracking of students is done on the basis of learners engaging in one of the following activities: a) submission of a course assignment, b) participation in a course discussion thread by posting a comment, question, or response related to a course topic, c) submission of an "Ask the Instructor" question in the course management system, or d) submission of a Quiz or Exam. All these activities are tracked by LDA (Last Day of Access) feature of the Learning Management System (LMS). Instructors are encouraged to track student participation and engagement using this feature and to contact learners who appear to be disengaging from the class. This analysis of active participation and engagement of learners in the ARS framework is a useful indicator to profile the learning risk.

3.1.2. Attribution in the classroom

There have been studies in the past to ascertain the correlation between the kind of attributions students make and reasons for making those attributions. One of the most important findings from these studies is that different students make different kind of attributions. Some differences are related to gender, others are related to student's perceptions of ability and few are related to the ways teachers respond to students (Stipek, 1993) [27].A review by Peterson (1990) found that student's negative attributional styles are related to low grades, less help seeking, vaguer goals, poorer use of strategies and lower performance expectations [28]. Best practices of face-to-face tutoring in Socratic mode also apply to online tutoring. However, some students resist the guided discovery learning process. Miller suggests that "it's important to communicate to the student why you're doing it this way and that it won't take long before they get it on their own" (S. Miller, personal communication, April 21, 2001) [29].

Studies focusing on help seeking behavior in particular have reported that many learners do not seek help because doing so provides an explicit low-ability cue to one's peers. The non-help seeking behavior is tracked by the un-attempted assignments. The number of un-attempted assignment is a good indicator of negative attribution. The students with higher number of un-attempted assignments are most likely to dropout in a course. This risk is tracked by the number of un-attempted assignments for a particular course in the LMS and managed by providing strategies for mastering course concepts where comprehension appears to be lacking.

To summarize, the performance of a learner in a course is a reflection of his/her active participation & engagement and attribution in the learning process. The performance of a learner is measured by the grade percentage and calculated basis student performance for graded activities on a weekly basis. In case of a non-graded activity, on completion of the activity, the student is awarded a 100% score. This is an important criteria and truly reflects a student's risk profile. Students with high grades are less likely to be dropped than students with low grades. This metric has been used in the pilot to evaluate performance of learners.

The Fig 1 below shows the effectiveness of Teaching-Learning process by early identification of learners at-risk followed by timely, continuous and multi-tiered Teaching-Learning interventions.

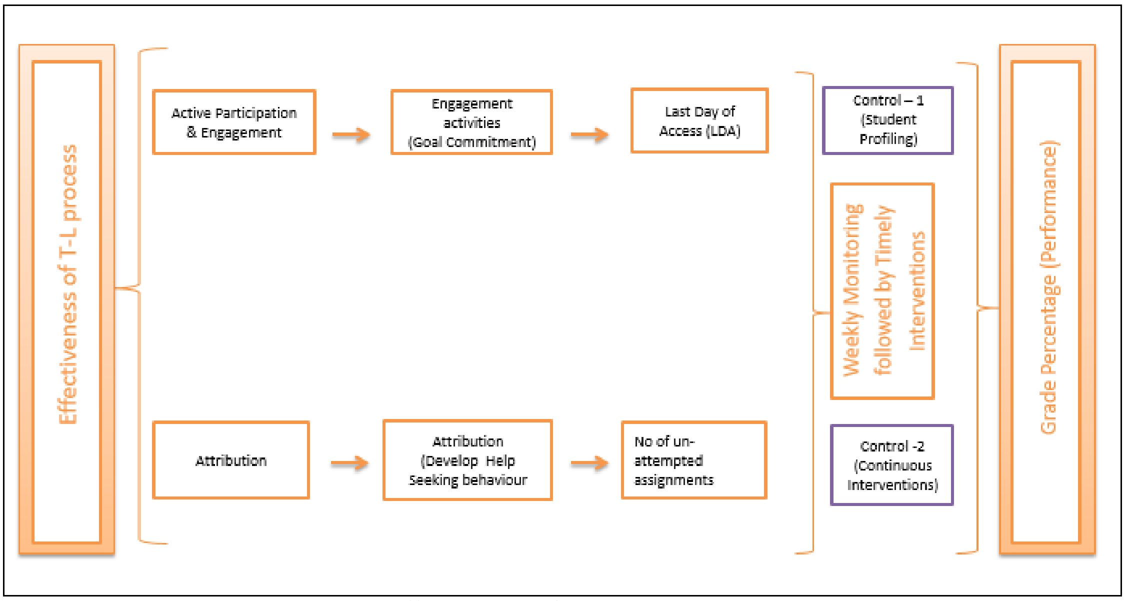

Fig 1. Effectiveness of Teaching-Learning process

The detailed criteria for representing learners as Red, Amber and Green is shown in Table 1 below.

Table 1. Criteria for representing learners as Red, Amber and Green

Risk Profile	Engagement Activities (LDA)	Number of un-attempted assignments (UA)	Current Grade Percentage (CGP)
Red	LDA > 2 weeks	UA > 4	CGP ≤ 64%
Amber	LDA > 1 week	UA ≤3	65% ≤ CGP ≥ 74%
Green	LDA ≤ 1week	UA = 0	CGP≥75%

The Red category students are most likely to drop out or not achieve success in the course. The Amber category students meet minimum standards and have an opportunity to improve and become Green students. The Green students achieve and exceed all standards and need to be motivated to set higher standards for themselves. The above representation helps to monitor a student's progress at intermediate steps because the progress at each intermediate step is closely tied to the final goal.

The technology has been leveraged to monitor student's performance on a weekly basis. The Risk profiling tracker has been developed in Microsoft Excel which is widely used as an effective data analysis tool. This tracker has two sheets in it i.e. a) Input sheet b) Output sheet. The Microsoft Excel 'Macro' functionality has been used to define rules & algorithm that specifies how input data should be mapped to the output sequence. The output sheet classifies students into Red, Amber & Green on each parameter as per the established calculation explained above and calculates the overall status of the student in terms of Red, Amber & Green. If a student is Red in one of the three parameters, his/her overall status becomes Red irrespective of the fact that he might be Amber/Green in rest of the two parameters. Likewise, if a student is Amber in one of the three parameters, his/her overall status becomes Amber even if he/she is Green in rest of the two parameters. A student needs to be Green in all three parameters to secure an overall Green status. This not only makes first level data analysis task less tedious, less repetitive and less error-prone, but also facilitates the process of illustrating information on a real time basis to enable timely interventions (decision making). A sample student profiling output sheet is shown in Table 2 below

Table 2. A sample student profiling output sheet

S No	Student ID/PIN	Last Name	First Name	Current Grade Percentage	Last Day of Access	Un-attempted Assignment	Instructor Name	Current Grade Status	LDA Status	Un-attempted Assignment Status	Overall Status
1	1	Q	a	74%	8/13/2014 13:56	1	z	Green	Green	Amber	Amber
2	2	W	s	34%	8/4/2014 0:07	7	x	Red	Red	Red	Red
3	3	E	d	47%	7/28/2014 22:01	4	c	Red	Green	Red	Red
4	4	R	f	62%	8/5/2014 0:07	1	v	Red	Green	Amber	Red
5	5	T	g	87%	8/11/2014 0:04	2	b	Green	Green	Amber	Amber
6	6	y	h	82%	8/12/2014 22:40	0	n	Green	Amber	Green	Amber
7	7	u	h	63%	8/6/2014 19:38	2	m	Red	Amber	Amber	Red
8	8	i	j	13%	8/4/2014 10:28	8	l	Red	Red	Red	Red
9	9	o	k	91%	8/12/2014 7:29	0	k	Green	Green	Green	Green

3.2 Process Centric Interventions

Process-centric interventions are designed to facilitate the teaching-learning interplay by providing customized and differentiated instructions on the basis of analysis of the learning risk. The key to improving success rate is to monitor progress at an intermediate level since the progress at an intermediate level is tied with the success in the final goal. In the event, the best strategy is to deploy an adaptive remediation program that is personalized to student's needs. As shown in Fig 2, the process centric interventions are broadly categorized in two areas.

3.2.1 Learning Skills

Learning to learn is the ability to pursue and persist in learning, to organise one's own learning, including through effective management of time and information, both individually and in groups. This competence includes awareness of one's learning process and needs, identifying available opportunities, and the ability to overcome obstacles in order to learn successfully. This competence means gaining, processing and assimilating new knowledge and skills as well as seeking and making use of guidance. Learning to learn engages learners to build on prior learning and life experiences in order to use and apply knowledge and skills in a variety of contexts: at home, at work, in education and training. Motivation and confidence are crucial to an individual's competence (European Communities, 2007, p. 8) [30]. As per Fredriksson and Hoskins, one of the basic skills for success in the knowledge society is the ability to learn. With increasingly rapid changes in the work place, in part due to changing technology and as a result of changing societal needs in the context of globalization, citizens must learn to learn in order that they can maintain their full and continued participation in employment and civil society or risk social exclusion. In this context learning to learn is a quintessential tool for lifelong learning and thus education and training needs to provide the learning environment for the development of this competence for all citizens and through different learning environments (formal, non-formal and informal) (Fredriksson and Hoskins, 2007) [31].

There has been a shift of focus in learning to learn from the subject-specific knowledge aspect of today's assessed learning to the diverse cognitive and affective factors that guide learning. These factors not only direct the learning process but they are also reflected in the way in which learning is applied to novel tasks. The focus of education is shifting from "teaching" to "learning" today. Faculty roles are changing from lecturing to being primarily "designers of learning methods and environments" (Barr and Tagg 1995, cited in Fink 2003) [23] [32]. The NRC (2000) recommends that the goal of education shift from an emphasis on comprehensive coverage of subject matter to helping students develop their own intellectual tools and learning strategies. These intellectual tools and learning strategies enable learners to benefit from instructions [33].

Learning to learn skills become more important in the online learning environment. At times, working in the online environment is new for both tutors and students. Miller recommends "trying to encourage the students as much as possible because they often tend to feel quite lost, alone and discouraged. Let them know that the online procedure is new and will get easier" (S. Miller, personal communication, April 21, 2001) [29]. Tutors are trained to develop Learning to learn skills by encouraging and motivating learners to set short-term and long-term study goals (weekly assignments vs. application of concepts), assist in cognitive restructuring and information processing. Learners are encouraged to use Schema Activation, Guided Questioning & Deep learning strategies to encode complex information.

3.2.1.1 Schema Activation

Schema activation refers to various methods designed to activate learners' relevant knowledge prior to a learning activity. The central idea underlying schema activation is that new knowledge always builds on prior knowledge; that is, a foundation of well-understood information will help students comprehend new information and will guide their thinking about the new topic. In summary, schema activation is any teaching procedure that helps students form conceptual bridges between what they already know and what they are to learn. It's done by encouraging learners to describe examples from thier previous experiences, perform experiments, review previous learning and use the context in which the new learning is presented.

3.2.1.2 Guided Qustioning

Asking and answering questions about a text or teacher-presented information can greatly improve comprehension, especially when those questions prompt students to think about and discuss material in specific ways, such as comparing and contrasting, inferring cause and effect, evaluating ideas, explaining and justifying. Research suggests that answering questions while performing a task is more useful than answering questions while learning about a task. This may occur because students fail to integrate information completely or are not fully prepared for inference –type questions until they actually attempt to perform the task. Guided Questioning is applied while responding to learners queries using ATI (Ask the Instructor) feature of the Learning Management System.

3.2.1.3 Deep Processing

The information can be processed in the below mentioned two ways.

- **Deep processing** is centered on meaning. This involves semantic processing, which happens when we encode the meaning of a word and relate it to similar words with similar meaning.
- **Shallow processing** refers to keying on superficial aspects of new material. It takes two forms i.e. structural processing (appearance) & phonemic processing (sound)

As per Savin-Baden and Major, there are both 'surface' and 'deep' approaches to learning (Savin-Baden and Major 2004) [34]. Surface approaches to learning concentrate on memorization (Bloom's lowest level: knowledge). In surface learning, the learner's goal is often to complete required learning tasks by memorizing information needed for assessments. Surface learners mostly focus on facts without integration, they are generally unreflective, and they see learning tasks as external impositions. In contrast, students with deep approaches to learning have an intention to understand. They generally engage in vigorous interaction with content, relate new ideas to old ones, relate concepts to everyday experience, relate evidence to conclusions, and examine the logic of arguments. Deep processing is encouraged by focusing on the semantic base or meaning of the new information so that the information is stored in a semantic memory code and is well-remembered.
These skills are referred as Learning to Learn in the Fig 2 below.

3.2.2 Subject Matter Skills

The subject matter learning involves more than the delivery of standard instructions. The knowledge of the ideas, facts and theories of a subject is one aspect of the subject matter skills whereas understanding & application of the subject is another aspect of it. Whether or not such understandings are explicit goals of instruction, students develop ideas about the subjects they study. Beers (1988) argues that while epistemological issues are rarely made explicit in classrooms, they are implicitly represented in the organization and content of curriculum, in the interaction between teachers and students, and in the nature of classroom activity and discourse [35]. What teachers need to know about the subject matter they teach extends beyond the specific topics of their curriculum. Shulman (1986) argues that "teachers must not only be capable of defining for students the accepted truths in a domain. They must also be able to explain why a particular proposition is deemed warranted, why it is worth knowing, and how it relates to other propositions" (p. 9) [36]. This kind of understanding encompasses an understanding of the intellectual fabric and essence of the subject matter itself. For example, while English teachers need to know about particular authors and their works, about literary genres and styles, they also needs to know about interpretation and criticism (Grossman, in press) [37]. A history teacher needs detailed knowledge about events and people of the past but must also understand what history is: the nature of historical knowledge and what it means to find out or know something about the past. Scheffler (1973) writes that this kind of subject matter understanding "strengthens the teacher's powers and, in so doing, heightens the possibilities of his art" (p. 89) [38].

In this research paper, Subject matter refers to knowledge and comprehension of technical/subject skills. In the ARS framework, these skills are continuously honed for deep learning and better retention and are developed by sharing additional and preparatory content for students to supplement standard instructions, clarifying students' doubts by understanding the context of the difficulty, providing quick resolution through synchronous learning (online chat) and sharing digital resources for quick reference and reinforcement of learning. Rich media, multimodal interplays provided through CT enabled ET in the form of internet, email, online chat, discussion forums, collaborating tools, social networking platforms as shown in Table 3 have been leveraged extensively.

Table 3. Description of CT enabled ET interventions

Intervention	Description
Student Cal Connect (check)	Calling students to understand issues and motivating them to log in and be regular with work
Mentoring e-mails	Sending e-mail asking students to log in (for students not logging into the portal).
Ask-the-Instructor feature	Ask-the-Instructor feature to facilitate 1:1 clarification
Cognitive Hooks	E-mailing students tips and tricks in complex subject areas as a hook to initiate their learning and reinforce concepts
Concept Guide	Sending additional content and preparatory content for students who feel standard instructions are not enough for them
Learning Alerts	Sending alert on upcoming milestone (automated alerts triggered by Learning Management System)
Synchronous Chat	To clarify students doubts by understanding the context in which he/she has difficulty and providing quick resolution in the form of synchronous learning
Asynchronous discussion & collaboration	Discussion forms to encourage peer learning and social learning
Digital resources	Sharing digital resources for quick reference

These skills are referred to as Subject Help in the Fig 2 below.

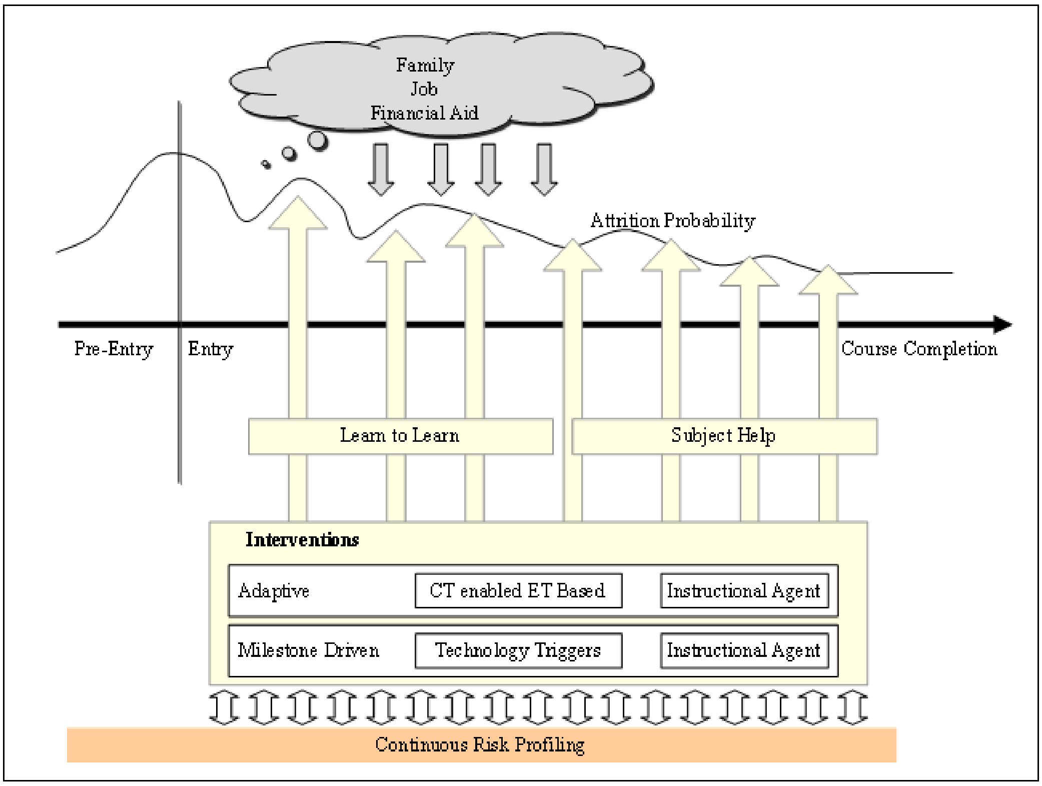

Fig 2. Process centric interventions including learn to learn and subject help

Apart from the above, 'Know your Learner' (KYL) process has been initiated to discover learner's preferred learning style. This is important since learning style greatly affects the learning process, and therefore its outcomes (Hong and Kinshuk 2004) [39]. The underlying idea of a learning style approach is that a learner is more effective when information is presented in a manner that matches his/her preferred methods of acquiring and processing information. Learning styles are defined differently by different researches. For example, Alonso defined learning styles according to cognitive psychology as "personal manners to perceive and process information, and how they interact and respond to educational stimuli" (Alonso 1993) [40], while Keefe defined learning styles as "characteristic cognitive, affective and psychological behaviors that serve as relatively stable indicators of how learners perceive, interact with and respond to the learning environment" (Keefe 1979) [41]. In the ARS framework, this has been introduced in the nascent stage and needs to be further explored and assessed.

Personalized interventions for Red, Amber and Green learners is further illustrated below in Table 4.

Table 4. Personalized interventions for Red, Amber and Green learners

Classification of student	Personalized Interventions
Red	Calling students to understand concerns and motivating them to log in and be regular with work Differentiated Instructions to meet varying needs of learners Sending advising emails asking students to participate in the learning process Sending academic alerts to the resident dean of each school
Amber	Differentiated Instructions to meet varying needs of learners Sending advising email asking learners to participating in the learning process Sending academic alerts to residents dean of each school
Green	Encouraging emails to applaud students on achieving defined milestones Sending additional questions and or supplemental instructions that provide challenge to the high ability group

IV. The Experiment (Pilot)

In order to validate effectiveness of the Adaptive Remediation Solutions (ARS) Framework for Student Success, learners' data was collected from an e-learning course offered by a leading e-learning institute.

1.1 Data Collection and validation

The below mentioned process was followed for data collection and validation

- The learners pass rate data was collected for 4 semesters (Dec-2013, March-2014, June-2014, Sep-2014) from a leading e-learning institute.
- Each semester had multiple sections randomly assigned to e-tutors
- The selection of the e-leanring institute was on the basis of getting an opportunity to create differentiated learning experience for learners.
- The pass rate is percentage of learners successfully completing the course over the total number of learners enrolled for the course. The Pass Rate in this experiment has been collected on the completion of the course and used to determine effectiveness of ARS framework.
- The group A learners were tutored under ARS Framework for student success. It included weekly/periodic learner centric advising and differentiated instructions from instructors.
- The group B learners were provided standard instruction irrespective of learners' learning preference. In other words, the group B was provided with standard instructions where all available learning objects were presented in a default sequence independent of the learners' learning styles
- Group A had 26 learning observations (e-tutoring outcomes) impacting 411 learners whereas group B had 34 learning observations impacting 513 learners in all the four semesters
- E-learning observation (e-tutoring outcome) is the final pass rate of a particular section in a semester.
- The allocation of learners was done by the e-learning institute.
- The colleage mathematics1 course was selected for this experiment The duration of the course is 11 weeks
- The standard/uniform course content was made available for all learning observations

The pass rate completion data for Group A & B for all the semesters is shown below in Table 5

Table 5. Pass rate data for Group A & B

Dec-2013		Mar-2014		Jun-2014		Sep-2014	
Group A	Group B	Group A	Group B	Group A	Group B	Group A	Group B
73%	42%	69%	47%	75%	63%	89%	72%
93%	58%	53%	60%	75%	50%	83%	67%
65%	83%	93%	40%	83%	62%	82%	20%
38%	50%	50%	43%	100%	67%	88%	82%
63%	35%	79%		36%	54%	64%	81%
41%	58%	64%			50%		82%
67%	23%	71%			67%		73%
56%	50%				46%		59%
56%	57%				54%		41%
					38%		67%
					54%		

4.2 Preliminary Analysis

The below mentioned relationships were studies to derive the first impression of the data in the preliminary analysis phase.

- Minimum Pass Rate
- Maximum Pass Rate
- Mean Pass Rate
- Median Pass Rate

The group A&B data is illustrated below in Table 6 & 7 respectively.

Table 6. Group A data

Group A					
Semester	Learning observations	Min Value	Max Value	Mean Value	Median
Sep-14	5	64%	89%	80%	83%
June-14	5	36%	100%	74%	75%
March-14	7	50%	93%	68%	69%
Dec-13	9	38%	93%	61%	63%
(Dec13 to Sep14)	26	36%	100%	71%	70%

Table 7. Group B data

Group B					
Semester	Learning observations	Min Value	Max Value	Mean Value	Median
Sep-14	10	20%	82%	67%	69%
June-14	11	38%	67%	55%	54%
March-14	4	40%	60%	59%	45%
Dec-13	9	23%	83%	50%	50%
(Dec13 to Sep14)	34	20%	83%	58%	55%

4.2.1 Minimum Pass Rate

The minimum value is the lowest number in a data population. The minimum pass rate signifies the lowest pass rate in a particular semester. The minimum pass rate of Group A & B is illustrated in Fig 3 below.

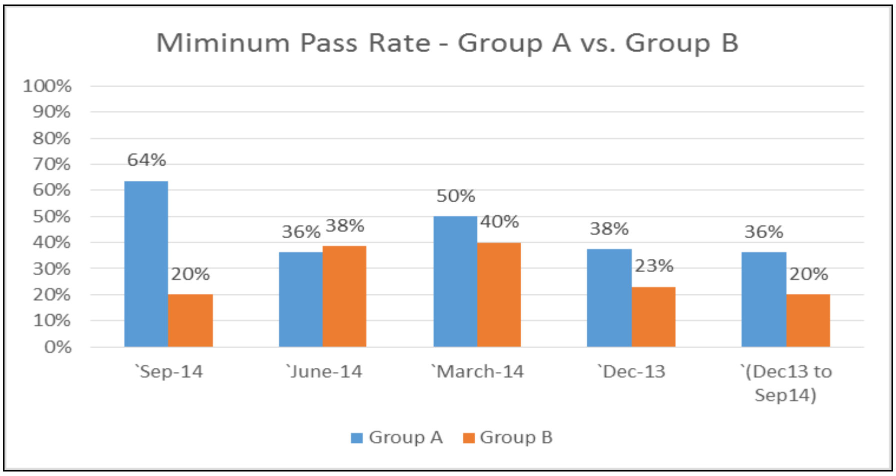

Fig 3. Minimum pass rate for group A & B

Inferences :

- The minimum pass rate for Group A is better than minimum pass rate for Group B for the semester Dec-13, March-14 and Sep-14 by 38%, 20% and 69% respectively
- The minimum pass rate for Group B for the semester June-14 is 6% better than Group A
- The overall minimum pass rate for group A is 45% better than the group B

4.2.2 Maximum Pass Rate

The maximum value is the largest value in a data set. The maximum pass rate signifies the highest pass percetnage of learners in a particular semester. The maximum pass rate of Group A & B is illustrated in Fig 4 below.

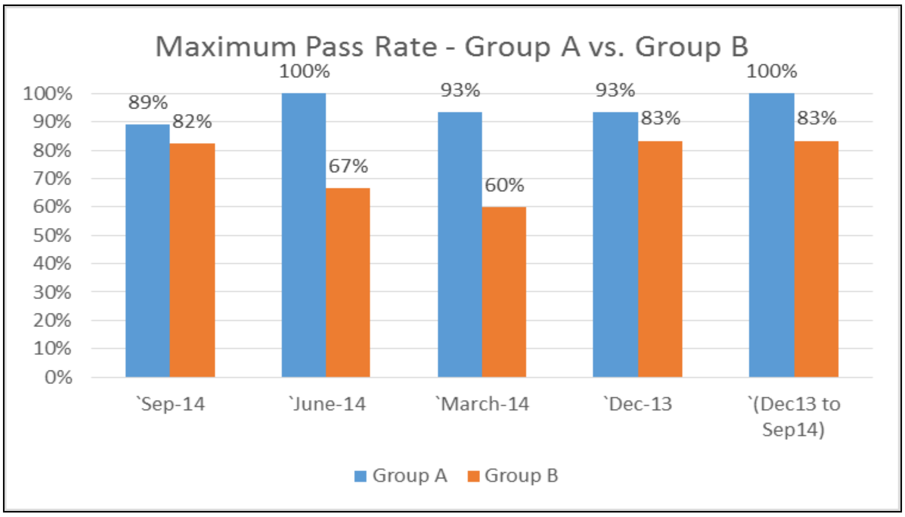

Fig 4. Maximum pass rate for group A & B

Inferences

- The maximum pass rate for Group A is better than maximum pass rate for Group B for the semester Dec-13, March-14, June-14 and Sep-14 by 11%, 36%, 33% and 7% respectively
- The overall maximum pass rate for all the semesters for Group A is 17% better than the group B

4.2.3 Mean Pass Rate

The mean value is the sum of a collection of numbers divided by the count of numbers in the collection. In this experiment, mean pass rate is the percentage of learners successfully completing the course over the total number of learners enrolled in the course. The mean pass rate of Group A & B is illustrated in Fig 5 below.

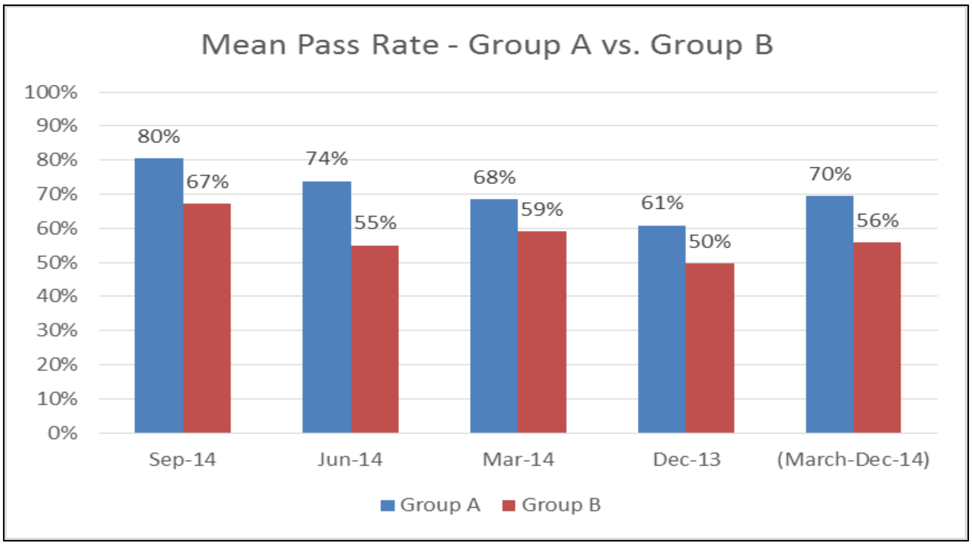

Fig 5. Mean pass rate for group A & B

Inferences

- The mean pass rate for Group A is better than mean pass rate for Group B for the semester Dec-13, March-14, June-14 and Sep-14 by 19%, 14%, 25% and 17% respectively
- The overall mean pass rate for Group A is 20% better than the group B

4.2.4 Median Pass Rate

The median is the numerical value separating the higher half of a data from the lower half. The median pass rate of Group A & B is illustrated in Fig 6 below.

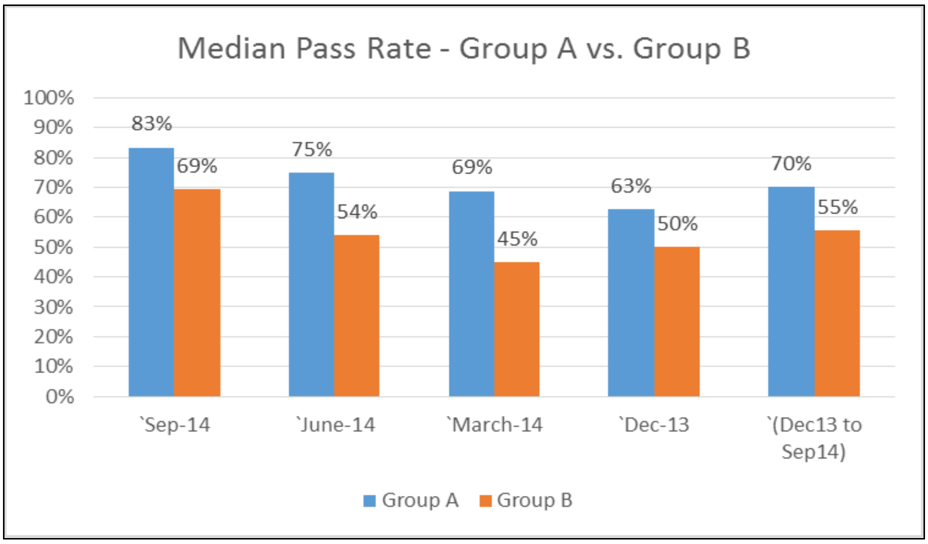

Fig 6. Median pass rate for group A & B

Inferences :

- The median pass rate for Group A is better than median pass rate for Group B for the semester Dec-13, March-14, June-14 and Sep-14 by 20%, 35%, 18% and 17% respectively
- The overall median pass rate for Group A learners is 21% better than the group B learners

All relationship metrics and inferences indicate that group A learners have outperformed group B learners in all the semesters. This indicates that teaching learning process is effective when accompanies with ARS framework.

4.3 Analysis and variance validation

The preliminary inferences were further strengthened and validated by analyzing pass rate outcomes as per Rubrics defined by the e-learning Institute and statistical analysis.

4.3.1 Pass rate outcome as per Rubrics

E-learning institute has provided Rubrics to all e-tutors to ensure grading is consistent and as per the defined parameters. The learner are classified into Novice, Basic, Proficient & Advanced on the basis of their Final Grade at the end of the semester. This is illustrated in Table 8 below.

Table 8. Learners pass rate classification as per Rubrics

Classification	Final Grade
Novice	0-64%
Basic	65-74%
Proficient	75-84%
Advanced	85-100%

While the above mentioned Rubrics was prescribed by e-learning institute to classify learners into Novice, Basic, Proficient & Advanced on the basis of their final grade at the end of the semester, author has used it to classify learning observations into Novice, Basic, Proficient & Advanced on the basis of its pass rate. The table 9 below illustrates all 60 learning observations for Group A & B.

Table 9. Classification of all learning observations as per defined Rubrics

	Novice	Basic	Proficient	Advanced	Total Learning observations
Group	0-64%	65-74%	75-84%	85-100%	
Group A	9	6	6	5	26
Group B	24	6	4	0	34

The number of learning observations are different for group A&B. As a result, percentage of learners in each category was calculated to derive inferences. The percentage classification of all learning observations is illustrated in the Table 9 & Fig 7 below.

Table 10. Percentage classification of all learning observations as per defined Rubrics

	Novice	Basic	Proficient	Advanced	Total Learning observations
Group	0-64%	65-74%	75-84%	85-100%	
Group A	27%	50%	60%	100%	43%
Group B	73%	50%	40%	0%	57%

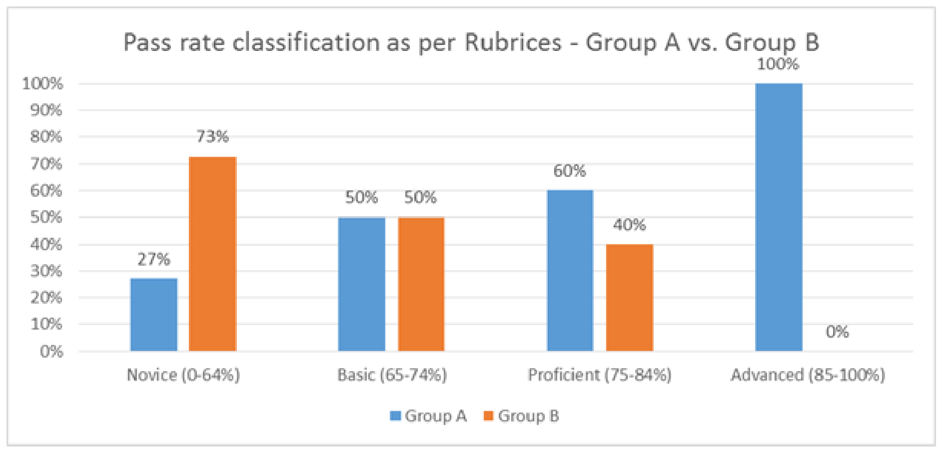

Fig 7. Percentage classification of all learning observations for group A &B

Inferences

- 100% of the Advanced learning observations belong to group A. No observation from group B has qualified for the Advancec category.
- 60% of the Proficient learning observations belong to group A whereas 40% belong to group B. Group A has 50% additional Proficient learning observations as compared to Group B learners.
- Learning observations in the Basic category are 50% each in the group A&B.
- 27% of the Novice obseverations belong to group A whereas 73% belong to group B. The group A has 63% less learning observations in the Novice category as compared to group B

4.2.2 Statistical Analysis

In most comparative studies, the mean is the most important piece of data. But there are also times when the variation is also studied. This is particularly useful in studying the stability of the processes. In statistical literature, F-test is used to compare the variation of two data sets and T-test is used to compare the means of two data sets. In this experiment, both the tests have been used to analyze variation and to determine significance of the mean for group A & B.

4.2.2.1 F-Test

An F-test checks whether or not the two data sets have the same variation. It is also necessary to do an F-test when comparing the means of two samples not coming from a paired experiment. The pass rate data collected for this experiment from group A & B do not qualify for the paired experiment. As with all scientific experiments, we started with formulating two hypothesis along with rules for rejecting the null hypothesis, which are as follows:

- Null Hypothesis: The variation of the two samples coming from group A and group B is the same.
- Alternative Hypothesis: The variation of group A and group B is not equal; they have different standard deviations. In statistics, standard deviation is the measurement of variation. In an F-test it compares the standard deviation of two data sets instead of the mean (which is done in a T-test). Actually, what is being analyzed is the “variance,” which is the square of standard deviation.
- Rules for rejecting the null hypothesis: If P value is less than 0.05, then the variance or the standard deviations of the two sample sets are not equal. It is significantly different.

F-test calculation

`F-Test Two-Sample for Variances’ analysis tool within the Data Analysis tab of MS Excel was used for this calculation.

Table 11. F-Test Two-Sample for Variances

	Group A	Group B
Mean	0.695361	0.557204473
Variance	0.030274	0.024811593
Observations	26	34
df	25	33
F	1.220143	
P(F<=f) one-tail	0.292763	
F Critical one-tail	1.843577	

The P-value is 0.293, which is greater than 0.05. Hence, we cannot reject the null hypothesis and conclude that the variations of the two samples are the same. It means group A and group B pass rate have the same variation. In this case comparison of means is to be done by using the "Two Sample Equal Variance" T-test.

4.2.2.2 T-test

A T-test is used to compare two data sets. The below mentioned requirements have been compiled before conducting T-test on the data collected for this experiment.

- The data is obtained using a random sampling method. The pass rate data for this experiment has been collected for College Mathematics 1 course offered by an e-learning institute. . The Institute has randomly allocated learning opportunities to e-tutors in all the semesters.
- The data is quantitative and has been collected for four semesters i.e. Dec-13, March-14, June-14, Sep-14
- The sample size is 20+ for better experimental accuracy. The pass rate data has got 60 learning observations in both the groups.

  As mentioned in the data collection and validation section, group A learners were tutored under ARS Framework for student success. It included regular advising and differentiated instructions from instructors whereas group B learners were provided standard instruction irrespective of learners' learning preference. In other words, the group B was provided with standard instructions where all available learning objects were presented in a default sequence independent of the learners' learning styles

- Null Hypothesis: There is no effect on the pass rate even if the ARS Framework is applied. In other words, the means of the two groups are the same and the ARS Framework is not effective.
- Alternative Hypothesis: There is a significant difference in the mean. The mean of group A applying ARS Framework is significantly better than group B.
- Rules for Rejecting the Null Hypothesis: If P value is less than 0.05 (95% confidence level of the results), then the difference is significant; otherwise, accept the null hypothesis.

t-Test calculation:

`t-Test : Two-Sample Assuming Equal Variances' analysis tool within the Data Analysis tab of MS Excel was used for this calculation. This is as per the F-test findings.

Table 12. t-Test: Two-Sample Assuming Equal Variances

	Group A	Group B
Mean	0.695361	0.557204473
Variance	0.030274	0.024811593
Observations	26	34
Pooled Variance	0.027166	
Hypothesized Mean Difference	0	
df	58	
t Stat	3.217426	
P(T<=t) one-tail	0.001059	
t Critical one-tail	1.671553	
P(T<=t) two-tail	0.002118	
t Critical two-tail	2.001717	

The P value is 0.002. Since it is less than 0.05, we will reject the null hypothesis and conclude that mean pass rate for group A (applied with ARS framework) is significantly better than mean of group B (standard instructions). In other words, it's established that e-tutoring ARS Framework improves the overall learning experience by identifying the gap and adopting Learning to learn driven remedial interventions with the specific cognitive requirements of the learner traditionally not catered to in a standard (conventional) e-learning environment. This establishes the improvement in the student pass rate by early identification of learners at-risk followed by timely, continuous and multi-tiered teaching-learning interventions.

The results demonstrate that the risk profiling and continuous pedagogic interventions of Adaptive Remediation Solutions Framework help in creating an effective learning environment and thus significantly enhances the average pass rate of learners.

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V. Conclusion

Adaptive Remediation Solutions Framework In The Form Of Student Profiling & Regular Pedagogic Interventions Is Observed To Improve The Overall Learning Experience Of Students. The Framework Supports E-Learning Delivery And Assists To Improve The Student Pass Rate By Creating An Engaging And Conducive Environment For Learners For Steady Progress Towards The Completion Of Course Activities. In Other Words, It Helps In The Academic Integration Of Students Resulting In Higher Academic Performance. This Is

Especially Important For E-Learning Students Who Apparently Don't Get Sufficient Support From Conventional Learning. The ARS Framework Assists In Meeting Specific Cognitive Requirements Of The Learners, By Identifying The Gap And Adopting Learning To Learn Driven Remedial Intervention, Traditionally Not Catered To In A Standard E-Learning Environment. The Effectiveness Of The Model Has Been Analyzed And Validated By Its Application To 411 Learners Spread Across Four Semesters Of A Leading E-Learning Institute. In This Experiment, Learners Have Been Classified Into Two Groups To Study And Analyze The Impact Of ARS Framework Over Standard Instructions. The Group A Learners Have Been Tutored Under ARS Framework For Student Success Whereas The Group B Learners Have Been Provided With Standard Instruction Irrespective Of Their Learning Preference. The Preliminary Analysis Has Been Completed By Studying And Comparing Maximum, Minimum, Mean And Median Pass Rate Of Both The Groups. All Relationship Metrics And Inferences Have Indicated Group A Learner's Outperformance Over Group B Learners. The Comparisons Made In This Study Have Been Tested For Statistical Significance At The .05 Level Using The Student's T Statistic To Ensure That The Differences Are Larger Than Those That Might Be Expected Because Of Sampling Variation. T-Test Has Further Strengthen The Preliminary Inferences And Has Proved That Group A Average Pass Rate Is 20% Better Than The Group B Learners And This Is Not By Chance Or Coincidence. Thus, Students Assisted With Adaptive Remediation Solutions Are More Likely To Succeed Academically Than The Students Who Go Through Standard Instructions. Given The Known Positive Impact, The Researchers Intend A Further Study Of The Impact Of Adaptive Remediation Solutions Framework Along With Differentiated Instructions Is Required To Measure And Quantify Benefits Of The Adaptive Remediation Solutions Framework For Student Success.

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