DESIGNING ADAPTIVE E-LEARNING ENVIRONMENT USING INDIVIDUAL DIFFERENCES

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ABSTRACT: Adaptive educational systems (AESs) aim at delivery of effective education through user modeling techniques. Adaptation effect is provided on the basis of individual differences incorporated into student model. Most of the existing AESs have utilized single source of adaptation predominantly learning preferences or learning styles. The impact of learning style based AESs on learning outcomes is still unclear. This study presented design of adaptive e-learning environment using multiple sources of personalization to improve learning levels of students. The empirical evaluation was conducted in real learning environment using control and experimental groups that's further consisted of subgroups, each representing different combination of parameters. The control subgroups were taught using traditional classroom environment whereas experimental subgroups through adaptive e-learning environment which imparted instruction in accordance to learning needs of learners. The results showed that experimental groups outperformed than control groups in terms of learning improvement.

Keywords: Adaptive educational systems, learning styles, adaptation, personalization.

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INTRODUCTION

Education has been considered globally as one of the vital components for socio-economic advancement. The widely recognized option to reduce drawbacks of traditional learning environment is e-learning approach. (Deborah *et al.*, 2014). The e-learning systems impart knowledge to learners through Information and Communication Technologies (ICT) including radio, satellite, computer, mobile, network, multimedia, and internet (Hamada, 2012; Surjono, 2011). In e-learning environment, the learner's performance is based on the nature of delivered learning content. (Deborah *et al.*, 2014). It is believed that learners are different from each other in terms of their level of prior knowledge, learning styles and competencies. (Nakic, Granic and Glavinic, 2015; Surjono, 2011; Granic and Nakic, 2010; Brusilovsky and Millan, 2007).

The e-learning systems which assess learning needs of each individual to deliver them learning content accordingly are called Adaptive Educational Systems (AESs). AESs mainly include Intelligent Tutoring Systems (ITSs) and Adaptive Educational Hypermedia Systems (AEHSs) which offer learners an individualized, personalized or adaptive learning experience through tailoring content to their characteristics and learning preferences. ITSs provide content adaptivity to learner and did not allow to freely explore the learning domain. On the other hand, AEHSs provide the most pertinent content and navigation paths considering learning needs and preferences (Yarandi *et al*., 2013).

AESs benefit learners in terms of reducing cognitive overload and disorientation specifically in web based learning. Generally such systems have been considered effective in terms of improving learning efficiency, learning outcomes, satisfaction, and motivation. Numerous AESs have been developed which provide adaptivity either based on knowledge or learning styles. The major knowledge based systems are ISIS tutor, SQL tutor, ELM-ART (Brusilovsky, 2004; Brusilovsky and Peylo, 2003).

The learning style based adaptive educational systems include INSPIRE (Papanikolaou *et al*., 2003), learning style based adaptive learning system (Bajraktarevic *et al*., 2003), WHURL-LS (Brown *et al*., 2009) and WELSA (Popescu *et al*., 2010).

Overall the success of LS based AESs is relatively low as their reflection towards improving learning outcomes is still unclear (Ciloglugil and Inceoglu 2012; Akbulut and Cardak 2012). Owing to low impact of AESs on learning it is highly suggested to model combination of learning styles with other effective parameters like Working Memory Capacity (WMC) and prior knowledge to see their impact on learning outcomes (Yavuz and Cardak 2012). Recent studies conducted using learning/cognitive style and prior knowledge and motivation have shown better reflection towards students learning outcomes. (Yang *et al*., 2013; Flores *et al*., 2012).

Learning style can be defined as "a specific way in which an individual learns". It is widely believed that learning style is predictor of quality learning. It is asserted that learner's performance and academic achievement can greatly increase by presenting learning content according to their learning styles (Markovic and Jovanovic, 2012).

The Working Memory (WM) is characterized by small storage capacity to hold information for a shorter period of time. Certainly there are differences among individuals in respect of WM which affects learner's ability to recall and comprehend learning material (Tsianos *et al*., 2010; Tsianos *et al*., 2009; Grimley and Riding, 2009). It has been suggested that combining learning styles and WMC in user model enables system to provide better adaptivity and presents more suitable contents than single sourced adaptive system (Graf *et al*., 2009).

Another significant factor influencing learning is what the learner already knows about the domain of study. Different learners have different levels of knowledge in the subject (Rias and Zaman, 2013; Mampadi *et al*., 2009).

To address the issues found in previous research, present study proposed design of an adaptive e-learning environment based on the combination of learning styles, WMC and prior knowledge to adaptively deliver pedagogical learning contents to diverse learners. This innovative e-learning approach evaluated through control and experimental groups in real learning environment to investigate its impact on the student's learning performance and satisfaction.

MATERIALS AND METHODS

Present study was conducted to investigate the impact of adaptive e-learning approach on student's learning and satisfaction. The approach was based on the combination of different adaptive variables including Entwistle's deep vs. surface learning approach, WMC and prior knowledge.

Content Development: The pedagogical e-content was designed using widely accepted pedagogy called Bloom's taxonomy (Munzenmaier and Rubin, 2013) guided to present learning material at different levels of complexity. At the outset content presented basics of each concept and then evolve to further levels such as understanding, application and then finally move to create level. The evaluation material was designed corresponding to each level of taxonomy to activate cognitive processes for the gradual development of learner's cognition. The evaluation material ensure that learner moved at subsequent level after qualifying the preceding level.

Architecture: The architecture of adaptive e-learning system depicted below in Fig.1. The major components of the architecture were *Domain Model*, *Student Model*, *Adaptive Model* and *personalization parameters.* The parameters were measured using corresponding assessment tools.

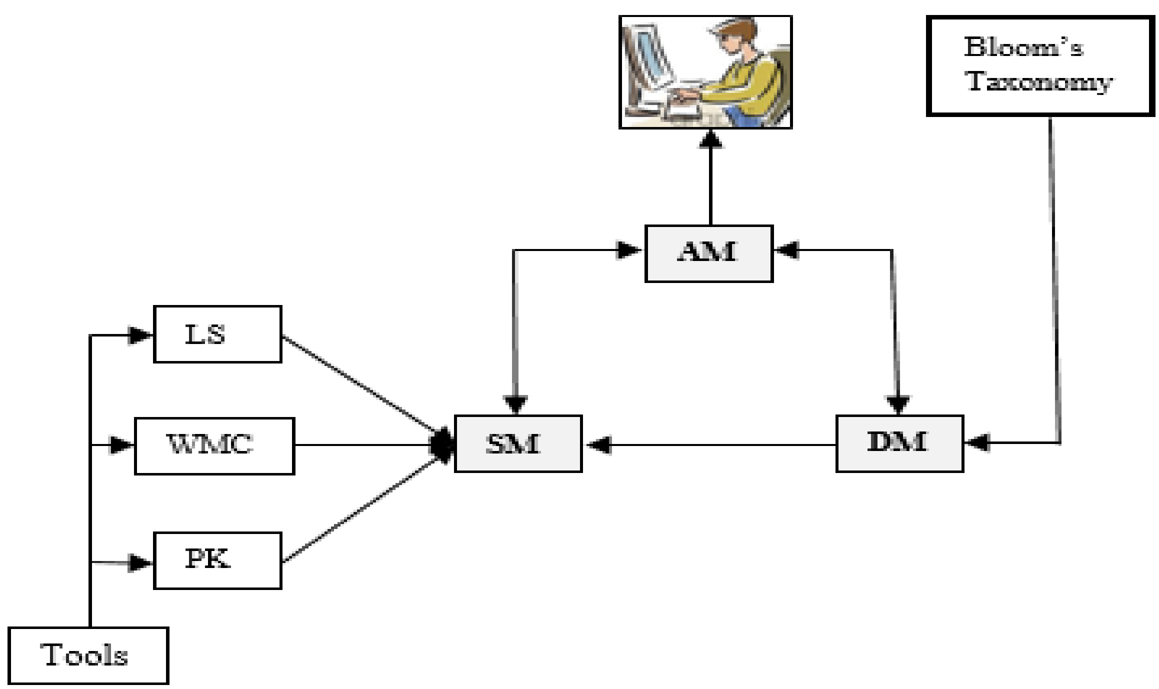

Figure 1: High level architecture of adaptive e-learning environment

Domain model (DM): English grammar was selected as domain knowledge. Each knowledge item was based on the different combination of below mentioned adaptive parameters. The learners with Low PK, Low WMC and Deep LS were presented. Next, learners were presented with comparison/contrast among grammar constructs such as preposition words at, in, on etc. Afterward, learning contents focused on the application of grammar constructs in different contexts, analysis of the usage of grammar constructs, and finally creation of English sentences using learnt concepts. Moreover, in case of *serialist* sub-dimension of Deep-LS the content was presented in sequentially ordered chunks with enough details using illustrations and examples. For *holist* learner the content was offered in the form of overview and summaries without much detail. When the value of PK changed from low to high then content changed respectively from basic to advance knowledge of grammar. Similarly if WMC value was high then the contents were presented without the constraint of amount. If students LS was surface then content changed to foster learner's ability merely to memorize usage of grammar constructs and understanding of differences related to the usage of same construct in different contexts.

Student model (SM):- The SM contained complete information about each student. The model was initially populated using respective assessment tools but later updated according to the changes occurring in the learning behavior of the students. The student model kept the recent information of each student in order to serve them accordingly.

Adaptive model (AM): This model was used to analyze student information and present suitable learning contents from domain repository to cater the learning needs.

Adaptive parameters:

Prior Knowledge (PK) A self-designed tool was used to diagnose student level of knowledge in English grammar to classify them into Low and High PK categories.

Working Memory Capacity (WMC) WMC of each student was measured via WMTB-C a standardized test for ages between 5- 15 years. The students were categorized into Low WMC and High WMC groups. The classification from Low to High in PK as well as WMC could further be broken into sub or medium levels.

Learning Style (LS) Learning style were identified using Entwistle's assessment tool called ASSISST to categorize students into Deep or Surface approach. The deep approach was further classified considering its sub-dimensions namely serialist and holist. The strategic approach was out of the scope of this study as the system mainly intended to support surface learner to make them successful in their study and providing enriched learning environment to deep learner to tape their full potential so ignoring the approach fall in between.

High Level Working of Adaptive e-Learning System: The proposed system initialized the Student Model (SM) to determine the capacity of learners in terms of PK, WMC, and LS prior to start the learning activities. The learner's PK, WMC and LS were acquired from standard tools. The results were stored into SM as an initial value. The content was presented to each learner in accordance to the values of each parameter. The learner begun to learn the concepts and carried out practice activities until he/she took assessment part. The system calculated learner's level of knowledge using tests given in assessment part of contents and modified its stored value in SM respectively. For example, In case level of knowledge was increased then PK value was changed from low to high in order to enable system for the adaptation of advanced learning content. On the other hand if learner's score was below threshold value after repeating the same lesson twice s/he was provided remedial content which presented prerequisite knowledge. However, this change of level (low to high or vice versa) was based on statistical based results and not just one time value.

The system calculated performance of deep and surface learner on practice activities and updated stored value in SM as per student's response. For example, if a deep learner faced difficulty in performing activities designed using Bloom's taxonomy then his/her LS value was changed from Deep to Surface and contents and corresponding activities were given accordingly (Figure. 2). Moreover, the surface learner who were not performed activities successfully, designed using initial levels of Bloom's taxonomy, repeated the lesson. On the other hand, the surface learner who successfully performed at initial level of Bloom's model, were presented content to instill application of acquired knowledge into new context using reinforcement strategies (i.e. hints and polite feedback). On successful performance, in applying learnt concepts, a learner's stored value of LS was change from Surface to Deep for further activities to get into depth of domain knowledge (Figure. 2). The parameter WMC was assumed stable so its initial stored value remained constant throughout.

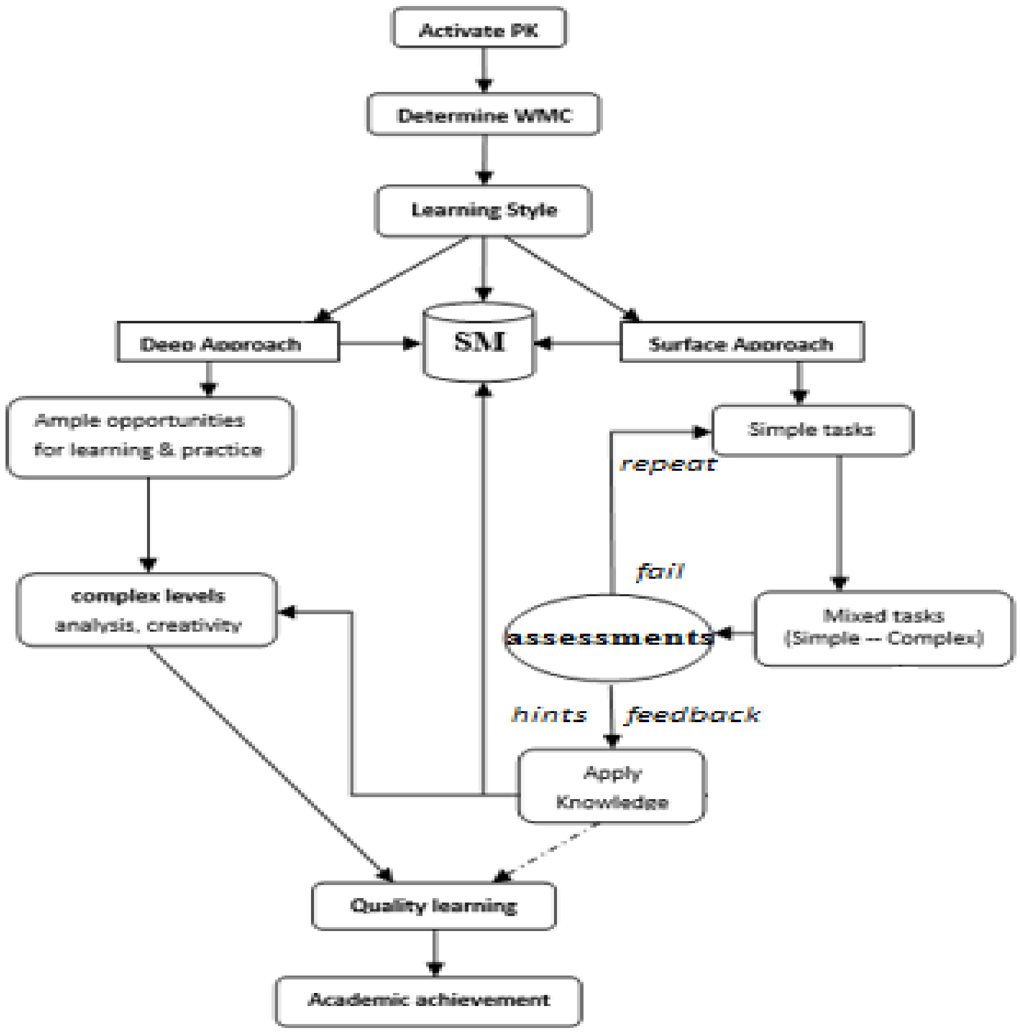

Figure 2: High level working of adaptive e-learning system

Design of Experiment: The experiment was designed to assess the impact of adaptive e-learning system in real settings of local public schools comparatively with traditional learning environment. A sample of around 500 - IX & X grade students of four local public schools was selected randomly and categorized into twelve groups out of possible twenty seven groups (Table 2).

Table 2: Experimental Groups.

Groups	Low-PK	High-PK	Low-WMC	High-WMC	Deep-Serialist	Deep-Holist	Surface
G-1	X		X		X		
G-2	X		X			X	
G-3	X		X				X
G-4	X			X	X		
G-5	X			X		X	
G-6	X			X			X
G-7		X	X		X		
G-8		X	X			X	
G-9		X	X				X
G-10		X		X	X		
G-11				X		X	
G-12				X			X

The groups were formed combining different values of selected adaptive parameters discussed previously.

Each group was consisted of sample of 10 students which was equally divided into experimental and control groups. Both contained all of the above-mentioned twelve subgroups or categories of students. The experimental group was being taught English grammar using adaptive e-content. Each subgroup received distinct version of learning material as already explained. The control group was being offered traditional classroom environment to learn English grammar.

The study was conducted in a local public school using available sample of 30 students of Grade IX. The subjects of sample belonged to different groups. For example, among sample of 30, ten subjects were belonged to G-4 which had low prior knowledge in English verb, high WMC and deep seriailst learning style. Next ten subjects were related to G-5, with low prior knowledge of concept, high WMC and deep-holist learning approach. Rest of the participants fallen in G-5 which had characteristics of low prior knowledge, high WMC and deep holist. Further the participants of each sub-group were equally divided into experimental and control groups.

The learning effectiveness was weighed by objective measures of student learning (test score) and subjective measure (satisfaction). The students of both groups were evaluated using pre-test in which both groups have almost equal marks and that's why were placed into category of low level of prior knowledge.

At the end, a post test was given to sub groups of both controlled and experimental groups on the contents covered during the experiment. The post test consisted of questions to judge the ability of participants in terms of recall and comprehension of learnt material. The post test given to the participants of G-4 and G-5 had an additional part to assess their ability to apply learnt information in new context as they learnt concept through all taxonomic levels. The students learning performance was indicated by differences in test score of experimental and control groups.

RESULTS AND DISCUSSION

Learning performance (Group-4): The results showed that subjects of experimental group-4 has performed better than their counterparts of control group-4 by achieving 24% more score in post test-1 (recall and understanding test) and 37% more score in post test-2 (apply level test). (Figure -3).

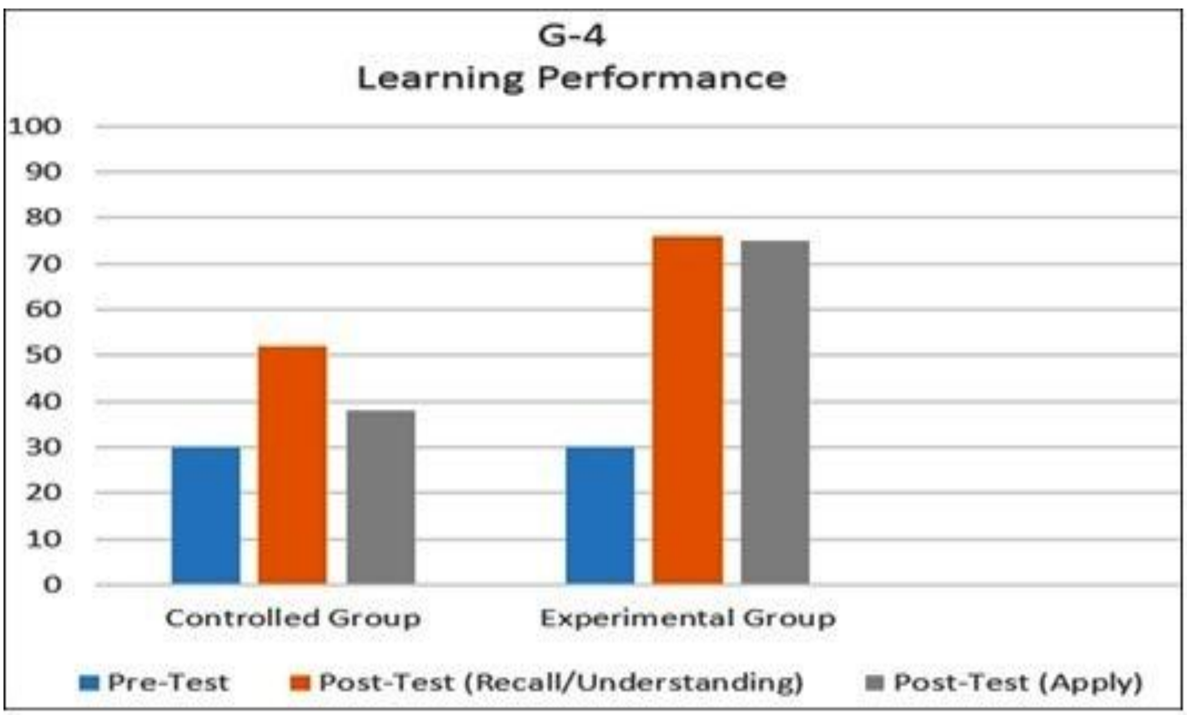

Figure 3: Performance of group-4.

An independent t-test was applied to examine the pre-test as shown in table 3. The results suggested that sub groups G-4, G-5 and G-6 of experimental and control groups did not vary before the experiment. That is, the both groups of learners had statistically equal level of knowledge before taking the concept of course.

Table 3: Descriptive data t-test result of the pre-test score.

	N	Mean	S.D.	*t*
G-4 Experimental group	5	30.00	4.69	.00
Control group	5	30.00	4.74	
G-5 Experimental group	5	30.00	4.69	.00
Control group	5	30.00	4.74	
G-6 Experimental group	5	30.00	4.69	.00
Control group	5	30.00	4.74	

Table 4 and 5 indicates the ANCOVA result of the post test-1 and 2 using pre-test as covariate. It was found that the subjects in the experimental group had considerably better learning performance than their control group counterparts in post test-1 and post test-2 with F = 34.07 and P < .01, F = 123.03 and P < .01 respectively, showing that learning through adaptive e-learning approach is much advantageous for students in comparison to traditional learning environment.

Table 4: Descriptive data and ANCOVA of the post-test-1 score (Group-4)

	N	Mean	S.D.	Std. Error.	F value
Experimental group	5	75.00	7.90	4.11	34.07
Control group	5	51.00	6.04	4.11	

P<.01

Table 5: Descriptive data and ANCOVA of the post-test-2 score (Group-4)

	N	Mean	S.D.	Std. Error.	F value
Experimental group	5	76.00	6.52	3.33	123.03
Control group	5	39.00	3.39	3.33	

P<.01

Learning performance (Group-5): The subjects of experimental group 5 performed better than their fellows placed in control group achieving 23% more score in post test-1 (recall and understanding test) and 34% more score in post test-2 (apply test score) as shown in figure 4.

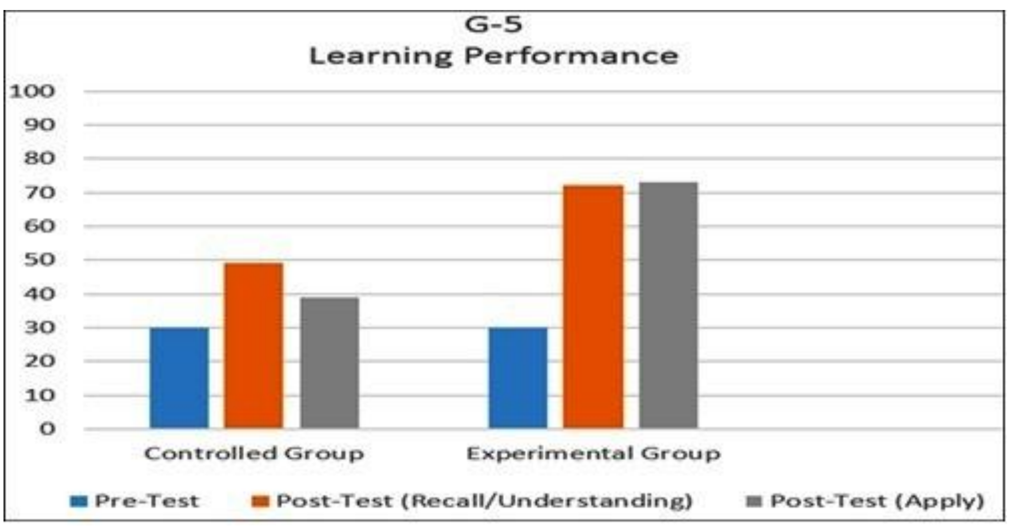

Figure 4: Performance of group-5.

Table 6 and 7 indicates the ANCOVA result of the post test-1 and 2 using pre-test as covariate. It was found that the subjects in the experimental group had considerably better learning performance than their control group counterparts in post test-1 and post test-2 with F = 128 and P < .01, F = 572.76 and P < .01

respectively, showing that learning through adaptive e-learning approach is highly advantageous for students in comparison to traditional learning environment.

Table 8 showing ANCOVA result of the posttest using pre test as covariate. It was revealed that the subjects in the experimental group had considerably better learning performance than their control group counterparts in posttest with F = 292.86 and P < .01 indicating that learning through adaptive e-learning approach is very much useful for students in comparison to traditional learning environment.

Learning performance (Group-6): The learning performance of experimental group-6 is similar to previous group 4 and 5. The participants of experimental group-6 outperformed by achieving 20% more score than control group-6 as shown in figure 5.

Table 6: Descriptive data and ANCOVA of the post-test-1 score (Group-5)

	N	Mean	S.D.	Std. Error.	F value
Experimental group	5	72.00	2.92	2.027	128.77
Control group	5	49.00	3.39	2.027	

P<.01

Table 7: Descriptive data and ANCOVA of the post-test-2 score (Group-5)

	N	Mean	S.D.	Std.Error.	F value
Experimental group	573.00	2.35	1.42	572.76	
Control group	5	39.00	1.87	1.42	

P<.01

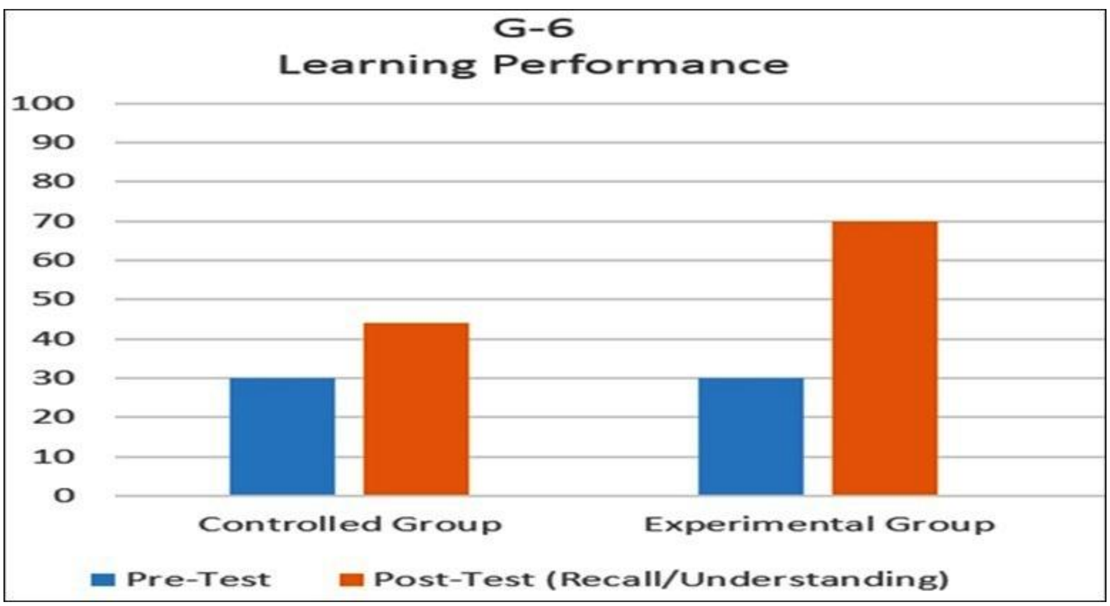

Figure 5: Performance of group-6

Table 8: Descriptive data and ANCOVA of the post-test score (Group-6)

	N	Mean	S.D.	Std.Error.	F value
Experimental group	5	70.00	1.87	1.52	292.86
Control group	5	44.00	2.92	1.52	

P<.01

Moreover, during brief post session interview the students of experimental group showed positive perception towards innovative learning approach.

An important issue related to computers in education has been recognized as an adaptive e-learning. Previously various approaches and systems have been introduced by taking into account students individual characteristics. Majority of the prior research studies considered single parameter to adapt or organize learning contents. Learning style was the most widely accept factor of learners considered in previous research. The learning contents in existing adaptive e-learning systems were not designed considering any pedagogy. In this paper we proposed design of an adaptive learning system which consider multiple aspects of learner to adapt learning content which were designed using sound pedagogical instrument. The experimental results indicated that proposed innovative approach have potential in improving the learning achievement of the students.

The groups investigated during experiment have low prior knowledge, high WMC along with certain learning style. Results from the experiment found that all groups benefited from e-learning approach in terms of understanding and applying learnt knowledge in new context. In terms of prior knowledge the results were consistent to (Flores *et al*., 2012) which revealed that adaptive e-learning approach improve the learning level of students with low prior knowledge. Regarding WMC results were similar to (Tsianos *et al*., 2009) which stated that considering individual differences regarding working memory improve their comprehension level.

In terms of learning style results were consistent to (Yang *et al*., 2013; Bajraktarevic, 2003) which showed that learning style based adaptation improve the learning gain of the students.

An analysis of post session interview data revealed that students were satisfied with adaptive learning approach and they felt that the design of content was much effective in enhancing learning outcomes.

One possible reason behind better performance of experimental groups in terms of understanding and application of learnt concepts in comparison to control group was that the learning in traditional classroom was highly teacher centric. The concepts are taught to the students with minimal student’s interaction. The student’s comprehension about the delivered material is not regularly assessed as well as they have minimal opportunity during class to practice learned material under the supervision of a teacher. In contrast, pedagogical e-contents offered systematic presentation of knowledge in different segments and each knowledge segment is associated with formative assessment material designed from simple to complex fashion. When a student does not understand a particular segment he/she can repeat that specific segment until it is completely understood. This phenomenon thus improves the understanding and long term retention of concepts.

Moreover, the results showed that experimental groups have much greater performance specifically in apply posttest relative to control group. The reason behind such performance was that the participants of experimental group have edge over participants of control group due to the availability of opportunity during learning session to practice material related to the application of learnt concepts. Hence such formative assessment material strengthen their knowledge at application level so that they outperformed in posttest.

Conclusion: Adaptive educational systems provide a lot of benefits to students because they thoroughly address the issue of individual differences. From the experimental results of this study, it can be viewed that the proposed approach is promising so it could be suggested to develop e-learning systems for other domains on the basis of concept proved in this study. On the other hand there were some limitations of the study. First the sample size of experiment was small. Ideally the experiment should be performed with all groups so that differences related to learning performance among experimental groups having diverse characteristics could be investigated but owing to limited access to real learning environment it was not possible. However, in future study we are intended to conduct evaluation using proposed approach with large sample size so that the findings could be inferred to general cases.

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