Augmented Transfer of Knowledge in eLearning Materials based on Associative Relevance

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Abstract—**Studies for enhancement of learning approaches in the field of eLearning have molded beyond frontier. An improved transfer of knowledge can cultivate considerably outstanding knowledge-sharers and better learners as well. In this study, we conducted experiments to assemble samples as data from participants who joined in this research. We investigated the assembled data to confirm our hypothesis that the eLearning materials based on associative relevance had substantially boosted transfer of knowledge process. The analyzed data and produced ingenious specifics evidenced that there were improved transfer of knowledge in eLearning based on associative relevance.**

Index Terms—**Associative relevance, Cognition, eLearning, Transfer of Knowledge.**

I. INTRODUCTION AND BACKGROUND

Research studies on learning approaches have grown exponentially after the integration of learning with information technology. The studies are full of promise and can bring noteworthy advancement among Practitioners, Scholars, Researchers, Teachers, Instructors, Educationalists, Professionals, and other pertinent beneficiaries. A number of literatures have addressed the issue and laid insight over it [1-5].

One of the foremost outcomes for the problem of learning methodologies, which receives widely accepted approval, relies on cognitive impact. As the learning processes stimulate cognitive processes by evolving and persisting it, the study of cognitive effects on transfer of learning and methods to improve the learning processes by means of cognitively developed implements can become a breakthrough in this area. Hence, we study the influential underlying mechanisms of human cognition in eLearning process. Definitely, by improving the influential underlying factors in eLearning materials, we can reinforce the transfer of learning processes as well [6-16].

The eLearning approaches for transfer of learning are the ways of human thinking, perceiving knowledge, and processing information for understanding. Human thinking and reasoning are some of the primary activities that acquire the most basic of motor skills. One of the simplest characteristics of transfer of learning gets illustrations whenever we utter or show, ‘for example’. Transfer comprises the use of symbolic language with analogies and metaphors; the illusory feature of transfer is that when we simply say, ‘like’, ‘similar’, ‘alike’, ‘as’, ‘identical’. Such exemplified interpretations evolve the concept of sameness. The evolution of sameness situates not only for abstract transposition but for associative relevance also, which links an inseparable constituent of it. We can consider the perception of similarity relationships as strongly connected in multiple ways into our brain. This means that our nervous system is a strongly connected mechanism of classification, which is an activity that is dependent on transfer [17-21].

As a result, we can justify that cognitively, there exist a number of associative chains that relate the objects of interests with the notion of ‘sameness’, ‘similarity’, and so on. Undisputedly, we can found these associative chains among the intents and contexts for cognitive discourse and vision respectively. In fact, associative relevance is a notion for the existing inherent underlying mechanism that gets evolve after attention and analogical mapping or higher-level perception cognitively. In fact, associative relevance is a related similarity in which the same relations or likeness hold between different domains or systems [16-27].

The concept of similarity or association has been fundamental to transfer and to reasoning in general. There seems to be a positive correlation between surface similarity and deep important underlying structural similarity or association. Mostly, surface similarity or association is a good indicator of deeper kinds of transfer. The very structure of our brain may have evolved to operate based on feature of similarities in our environment, to generalize, in other words, to transfer. Consequently, we observe that the associatively related objects and their relevance are significant and can bring transfer of learning efficiently [17-27].

We utilize learning approaches based on associative relevance for eLearning materials. In this approach, we intend to transfer the associative contexts of eLearning material to the learners. The contexts have connected via associative chaining. Hence, the memory of learner’s mind could in turn, associate contextual entities. By doing so, human brain can adapt information and retain in memory.

II. PRESENT STUDY

We examine the transfer of knowledge processes for eLearning materials, which has cognitively inseparable underlying mechanism of associative relevance, which evolves during the experimental observations. For the purpose, we follow along and finish the steps of planning experimental setup, participants’ observations, statistical data analysis, and data visualization for interpretation, which are the key steps during the entire study.

Initially, participating students view general eLearning materials to which we have shown in the classrooms with traditional transfer of knowledge approach. We collect the observed data related to this eLearning material based on traditional learning approach from questionnaires of participants as feedback.

Thereafter, we request the participants to view eLearning materials based on associative relevance notion. We cognitively augment these eLearning materials for better adaptive mind. Further, we collect the observed data related to this eLearning material based on associative relevance in terms of questionnaires as feedback as well. Finally, we analyze all collected data for interpretation statistically and carry out the interpretation with the help of statistically existing parameters for such study.

The main objective of this study is to prove that the transfer of knowledge based on associative relevance in eLearning is improved, imperative, clear, and pointed for learning process. We aim in this study that there is significant augmentation in transfer of knowledge based on associative relevance learning approach.

A number of steps need to perform during the study of eLearning materials for better transfer of knowledge. The adjacent flow chart diagram (figure 1) shows these steps in ordered routine. This is a comparative study of two data (the data from traditional transfer of knowledge approach and the data from associative relevance based transfer of knowledge approach) analytically.

III. METHOD

We selected 140 participants from a number of classes randomly, aging from 21 years to 30 years. Further, we assigned these Subjects, the participants to view two sets of ordinary slides as shown below in figure 2 and an augmented slide for each set.

In simplistic manner, the first set of slides (in first row) consisted of three slides related to the topic of 'Types of Computer Networks' and the second set of slides (in second row) consisted of four slides related to the topic of 'Number Systems'. We displayed these general slides, related to computer science course, during active viewing of the participants.

IV. ANALYSIS

There are two phases of analysis for our study. At first, we experimented with the first set of slides and thereafter, the augmented slide for the same set. We assigned this as 'Analysis 1' in our experimentation.

Later, we experimented with the second set of slides and thereafter, the augmented slide for the same second set. We assigned this as 'Analysis 2' in our experimentation.

In the second phase, we analyzed the collected data statistically for details. These analyses directed towards crucial findings after data interpretations.

In this experimental analysis for the set of slides related to 'Types of Computer Networks' (figure 3), at first, we presented to the participants the first set of three slides sequentially. We instructed them with traditional learning approach. In this traditional learning approach, keeping single subtopic for single slide had considered as the easiest and the most efficient way of learning. Therefore, the participants regarded the individual three slides and concluded observations in their questionnaires as their feedbacks.

A. *Analysis I: Study of first set of slides for 'Types of Computer Networks'*

Next, we displayed to the participants the augmented slide (the central slide in figure) based on associative

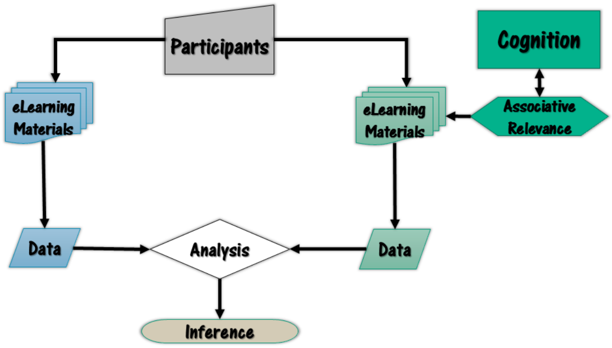

Figure 1. Flow chart of research study

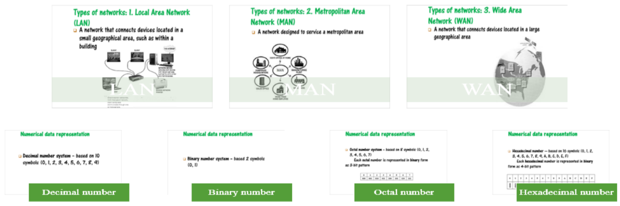

Figure 2. Selected Learning Slides for research study

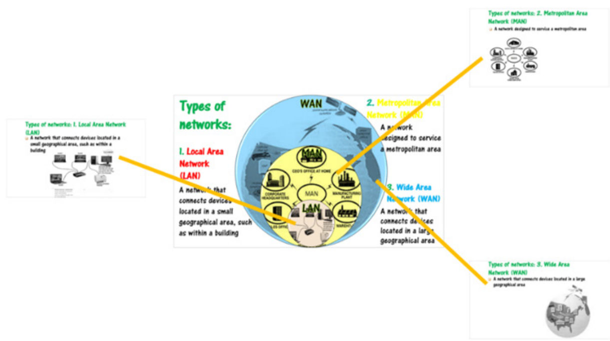

Figure 3. A set of slides and their associative relevance in augmented slide

relevance consideration, i.e., keeping the associated subtopics in relevant unified form in single slide along with relative representation. This slide considered all the aspects of existing associations among the subtopics and put in relevant manner for better adaptation of human minds. We demonstrated the associative chain of relevance in this slide, so that the participants may sense the contextual entities and their associated relations as similarities. Further, we inserted visual impressions in the contextual segments of the slide for recognition of associative relevance that subsisted among various portions within the slide.

However, we collected the data as feedback of participants' responses in the survey.

B. *Analysis II: Study of second set of slides for 'Number Systems'*

In this analysis of slides for 'Number Systems' (in figure 4), at first, we conducted experimentation and recorded the observation as data from participants who looked for the individual four slides consecutively. These were the slides based on the general learning approach, which stated that for the easiest and optimized mode of learning, there should be separate slide for separate topic. This approach makes the learning process easier.

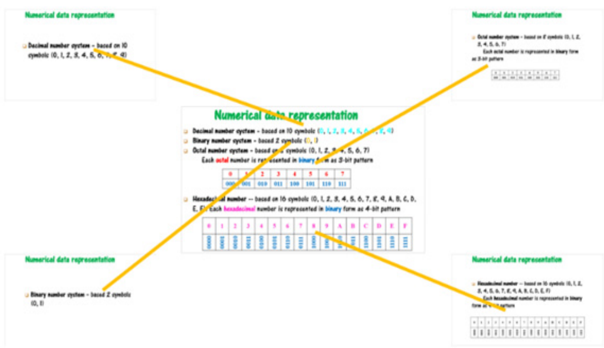

Figure 4. A set of slides and their associative relevance in augmented slide

Afterward, we started experimentation for the augmented slide (the central slide in the figure) based on associative relevance consideration. We cognitively augmented the slide with associative relevance learning approach. This transfer of knowledge based on associative relevance approach enabled the slide to link the associated entities of individual four slides. We put associated entities in relevant manner, so that the participants may sense similarity and their connected articles. Further, we embedded visual effects in the contextual portions of the slide for identification of associative relevance that existed among various pieces of the information within the slide.

However, the participants viewed the slide and gave us feedbacks that we gathered as data for further analysis.

V. STATISTICAL DATA ANALYSIS

Based on gathered data from the participants as feedback, we analyze the data statistically. The plotted chart for the all the observations is show below in figure 5.

However, we are interested in determining whether two populations (the data based on associative relevance learning approach and the data based on traditional learning approach) differ in dispersion. This means that we suppose there is less variability in the data based on associative relevance learning approach than the data based on traditional learning approach. This in turn, leads that the learning approach based on associative relevance is an augmented transfer of knowledge than the learning based on traditional approach.

Moreover, we assume our alternative hypothesis that the data based on associative relevance learning approach are equal or more dispersed than the data based on traditional learning approach, i.e., there is equal or more variability in the data based on associative relevance learning approach than the data based on traditional learning approach.

To test our null hypothesis, we start to analyze the obtained data using F-test based on the sampling distribution of the F-statistic. The shape of F-distribution depends on its degrees of freedom. Further, the collected data comply with the assumptions that are associated with using the F-statistic to test a null hypothesis are (1) the samples are independent, (2) the populations are normally distributed, and (3) the participants have been randomly assigned to the conditions in the experiment. Further, we assign the critical value of F that cuts off the upper α (also known as significance level which is equal to 0.05) region of the sampling distribution [28-31].

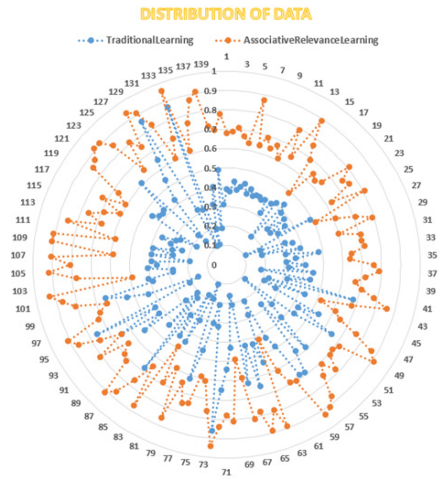

Figure 5. Chart for data distribution in accordance with learning capabilities of participants

We analyze our data for the condition of one-tailed (directional) critical value, i.e. for the critical region in the upper tail of the sampling distribution. This means that we testify our hypotheses as the one-sided hypotheses.

These computations lead towards the following results as mentioned in Table 1. Hereafter, the obtained results are ready for interpretations and subsequent inferences for both learning approaches.

TABLE I.
F-TEST FOR TWO SAMPLES OF BOTH LEARNING APPROACHES

F-Test Two-Sample for Variances		
	Associative Relevance Learning	*Traditional Learning*
Mean	0.739142857	0.386071429
Variance	0.013429476	0.025261434
Observations	140	140
df	139	139
F	0.531619701	
P(F<=f) one-tail	0.000113153	
F Critical one-tail	0.755794274	

As we see from the above-mentioned statistical outcomes, the F-test statistic shows that the obtained F value (F = 0.531619701) lies within the critical F value (F Critical one-tail = 0.755794274) for one-tailed condition. For that reason, we failed to reject the null hypothesis.

Based on F-test statistical analysis, we deduce that the data for associative relevance learning approach are augmented transfer of knowledge mode than the data for traditional learning approach. As a result, we bring about our finding that there is tremendous improvement by transfer of knowledge based on associative relevance learning approach.

VI. CONCLUSION

We wrap up our finding that the transfer of knowledge in eLearning based on associative relevance is more constructive, beneficial, and appropriate for better transfer of knowledge, so that the cognitive minds can clearly adapt the learning naturally.

Further, the augmented transfer of knowledge based on associative relevance can result in better understanding of the eLearning materials. Furthermore, we can extend our vision of transfer of knowledge and bring applicability of this finding to larger frameworks as well.

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