# Instructional Strategy Based on Associative Relevance Improves e-Learning

#### Gufran Ahmad\*

College of Computer Sciences and Information Systems, Jazan University, Jazan, 45142, Saudi Arabia.

\* Corresponding author. Tel.: +966-50-30-82048; email: gufran.researcher@gmail.com Manuscript submitted July 22, 2015; accepted September 25, 2015. doi: 10.17706/ijeeee.2015.5.3.165-172

**Abstract:** Studies in search of improved instructional strategies in e-learning have extended beyond possibilities of speculations. An improved instructional strategy can develop substantially better transfer of learning and better adaptive brains as well. In this study, we experimented to gather samples as data from participants who took part in this investigation. We tested the gathered data to validate our hypothesis that the instructional strategy based on associative relevance had drastically upgraded e-learning. The observed facts and analyzed data established the hypothesis that instructional strategy based on associative relevance improved e-learning.

Key words: Associative relevance, cognition, e-learning, instructional strategy.

#### 1. Introduction and Background

Instructional strategies for e-learning are one of the intensive studies in the area of e-learning. A wide range of optimistic research findings open the doors of opportunities for instructors, teachers, researchers, scholars, educationalists, professionals, and other pertinent beneficiaries. One of the challenges of the very topic is how to design and implement the e-learning instructional strategies. The applicability of the e-learning instructional strategies is widely addressed challenge in e-learning researches [1]-[15].

To settle the problem of e-learning design and implementation, consideration of the cognitive aspect of e-learning is broadly adapted central idea. These cognitive aspects refer to the involvements of cognitively engendered sensation, attention, analogical consideration, and perception processes during the transfer of learning in e-learning. Further, the research investigations reveal the causes and effects of human cognition in e-learning and bring about the solutions to diminish these causes and effects. However, these resolutions are not efficient as these resolutions depend on specific situation and scenario of e-learning process. Nonetheless, utilization of the cognitive aspect in e-learning opens an assortment of applicability for instructional strategy that is indispensable piece of e-learning. Consequently, it becomes obvious that the study of cognitive impact in e-learning is going to lead us towards a path of success. Hence, we study the influential underlying factors of human cognition in e-learning process. Undoubtedly, by improving the influential underlying factors in e-learning materials, we may strengthen the process of learning as well [6]-[17].

Cognitively, human mind and memory play significant role in the transfer of learning. Therefore, the entire span of learning processes during e-learning depends on the coordination of underlying mechanism of continual cognitive processes involving the mind and memory. In addition to these, the learning

processes involve a number of intermediary sub-processes during various stages of the main processing. Within these intermediary sub-processes, there exists an essential and mandatory process, i.e. the process of viewing the objects and assigning relative identities. The human viewing process initiates a series of cognitive functions, including visual attention, perception, analogical thoughts, higher-level perception, cognitive reasoning, and metacognition. These are bound to exist until the end of viewing of objects [6]-[18].

During the learning process of e-learning materials, a human regards the materials and underlying cognitive processes make efforts for efficient retrieval of knowledge or information that are displayed. Further, human mind is working for memory management and permanent storage of the human brain. The process of storage gets involved in after the cognitive process of an establishment of relevant association within the contexts as it makes comparatively better accumulation and retrieval of memory [6]-[17].

The instructional strategies 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. A number of proposed human learning models include the memory as a fundamental component. Models based on associative memories significantly influence our understanding of about learning involving mind and memory [6]-[23].

Associative relevance is evolutionary and cohesive notion that human thoughts of analogy emanate. In the underlying mechanism of human cognition, the human sensory bring about the impression of associative relevance along and after the happening of the phenomena based on analogy. Like analogy, associative relevance is significant in cognitive processes and is key mechanism in concluding creativity, which is also a part of the subject, like e-learning. Further, associative relevance stands for a hardwired or chaining process of contexts or intents based on similarity in which the same relations, sameness, or likeness holds between different domains or systems. In the present e-learning materials, the correlated and coexisted contents have widespread associative relevance by which people understand a content or matter in terms of another, as they are associated in intents or contexts [17]-[23].

We employ instructional strategy based on associative relevance for e-learning materials. In this approach, we intend to transfer the associative contexts of e-learning material to the learners for better understanding of the subject matter. A series of cognitively generated associative chaining is able to connect various contexts within the e-learning material. Hence, the memory of learner's mind could in turn, associate and organize the memory of brain.

By adapting an instructional strategy of learning in accordance with human cognitive phenomena that exist during the learning process, we can improve the learning process. At the same time, the mind can perceive and withstand gigantic amount of knowledge and retain it in memory for longer duration. The e-learning based on associative relevance is proposed instructional strategy that can assist and enhance learning process.

#### 2. Present Study

We investigate the e-learning materials from cognitive perspective, including the underlying mechanism of associative relevance, during viewing of e-learning materials. For the purpose, we follow along and finish steps of planning experimental set up, statistical data analysis, and data visualization for interpretation, which are the key steps during the entire study.

Initially, participating students view traditional e-learning materials that we demonstrate in the classrooms as traditional learning process. Further, we collect the data related to this e-learning material based on traditional instructional strategy from questionnaires of participants as feedback.

Thereafter, the participants view the e-learning materials based on associative relevance. These

e-learning materials consist of cognitively engendered notion of associative relevance. Further, we collect the data related to this e-learning material based on associative relevance as well in terms of questionnaires as feedback. Finally, we analyze all collected data for interpretation statistically. Finally, we carry out the interpretations of the results with the help of statistically existing parameters for such study.

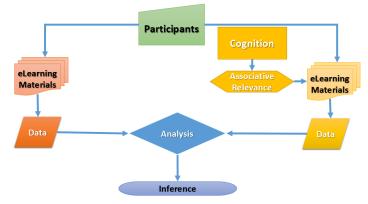


Fig. 1. Flow chart of research study.

As a result, we perform a number of steps for the study of associative relevance in e-learning materials. We further represent these steps in illustrative view as shown in the adjacent flow chart diagram (Fig. 1). This is a comparative study of two datasets (the dataset from traditional instruction based learning strategy and the dataset from associative relevance based learning strategy) analytically. The main objective of this study is to prove the instructional strategy based on associative relevance is improved and imperative for learning process than traditional instructional strategy.

### 3. Method

We selected 140 participants from a number of classes randomly, aging from 21 years to 30 years. Further, we arranged experimental setup for these participants and assigned to view two sets of ordinary slides as shown below (Fig. 2).

In simplistic manner, the first set of slides (in first row) consisted of three slides related to the topic of 'Data vs. Information' and the second set of slides (in second row) consisted of three slides related to the topic of 'Coding Standards'. We put on view these traditional slides, related to computer science course during active viewing of the participants.

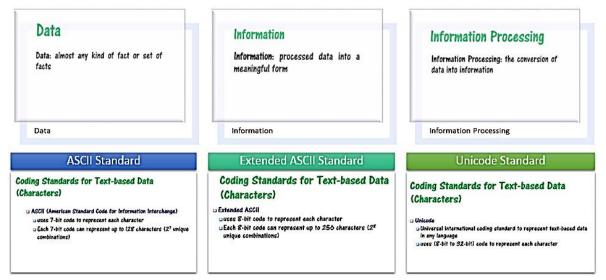
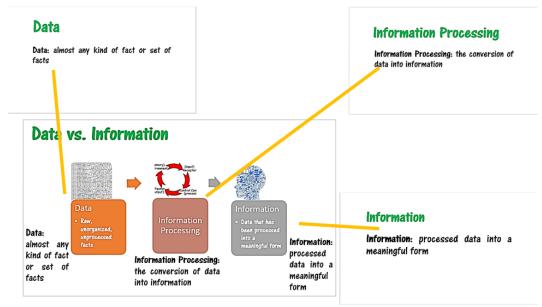


Fig. 2. Selected learning slides for research study.

Furthermore, we demonstrated the restructured slides of the respective sets of slides that we demonstrated earlier in the manner of traditional learning strategy. These restructured slides embedded with the notion of associative relevance, i.e. these reorganized slides were cognitively generated under the influence of relevance in associativity within the slides for the purpose of improvements in transfer of learning within participants.

# 4. Analysis

There were two phases of analysis for our study. At first, we studied the two sets of slides as 'Analysis 1' and 'Analysis 2' along with respective slides based on associative relevance for our experimentations. For all the cases, we recorded the feedbacks of participants in term of questionnaires. Thereafter, we performed detailed data analysis that led to the interpretations and conclusion.



# 4.1. Analysis 1: Study of First Set of Slides for 'Data vs. Information'

Fig. 3. A set of slides and their associative relevance in restructured slide.

In this experimental analysis for the set of slides related to 'Data vs. Information' (Fig. 3), at first, we presented to the participants the first set of three slides sequentially. We instructed them with traditional strategy. The practitioners who followed this traditional learning strategy, i.e. keeping single subtopic for single slide, considered this type of representation as the easiest and the most efficient way of learning. However, the participants regarded the individual three slides and concluded their feedback.

Afterward, the participants regarded the amended slide (the central slide in figure) based on associative relevance consideration, i.e., keeping the associated subtopics in relevant manner in single slide along with relative illustration. This slide considered all the aspects of existing association among the subtopics and put in relevant mode to perceive learning adapted by human minds. We concerned about the human mind and memory during this transfer of learning and did effort to put in elements of cognitive perspective. We collected the data as feedback of participants' responses in the survey.

# 4.2. Analysis 2: Study of Second Set of Slides for 'Coding Standards'

In this analysis of slides for 'Coding Standards' (in Fig. 4), at first, we conducted experimentation and recorded the observation as data from participants who regarded for the individual three slides. This set of slides was an illustration based on the traditional learning strategy that stated that for the easiest and optimized mode of learning, the separate slide for every topic could improve transfer of learning.

Afterward, we continued experimentation for the amended slide (the central slide in the figure) based on associative relevance consideration. This associative relevance notion came in from cognitive perspective and the notion of associative relevance was denoted along with pictorial representations as well. We did our special effort to embed within this slide the underlying mechanism of cognition. Taking as an advantage of associative relevance contexts presented in the slide, we tried to relate the mind to memory that could receive or retrieve information accordingly. We expected that the associated intents in terms of existing contexts in the slide might enhance the capability of learning more efficiently. However, the participants viewed the slide and gave us feedbacks that we gathered as data for further analysis.

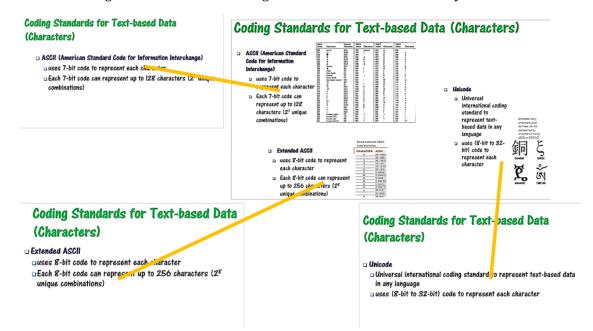


Fig. 4. A set of slides and their associative relevance in restructured slide.

### 5. Statistical Data Analysis

Based on gathered data from the participants as feedbacks, we analyzed the data statistically. Additionally, we plotted the chart for the all the observations (in Fig. 5).

Moreover, we carried out detailed statistical computation for obtained data. Hence, we obtained the following statistical parameters (as in Table 1) for both types of learning strategies, which were essential statistically [24]-[27].

| Traditional Learning    | g Strategy   | Associative Relevance Learning Strategy |              |
|-------------------------|--------------|---|--------------|
| Mean                    | 0.399285714  | Mean                                    | 0.745142857  |
| Standard Error          | 0.015276029  | Standard Error                          | 0.010705094  |
| Median                  | 0.4          | Median                                  | 0.75         |
| Mode                    | 0.43         | Mode                                    | 0.65         |
| Standard Deviation      | 0.180748416  | Standard Deviation                      | 0.126664377  |
| Sample Variance         | 0.03266999   | Sample Variance                         | 0.016043864  |
| Kurtosis                | -0.037523951 | Kurtosis                                | -0.590467092 |
| Skewness                | 0.640746983  | Skewness                                | -0.262888394 |
| Range                   | 0.76         | Range                                   | 0.54         |
| Minimum                 | 0.11         | Minimum                                 | 0.42         |
| Maximum                 | 0.87         | Maximum                                 | 0.96         |
| Sum                     | 55.9         | Sum                                     | 104.32       |
| Count                   | 140          | Count                                   | 140          |
| Confidence Level(95.0%) | 0.030203425  | Confidence Level(95.0%)                 | 0.021165873  |

Table 1. Details of Statistical Analysis for Learning Strategies

In addition, to test our hypothesis, we started to analyze the obtained data using z-test which was very efficient and suitable for the current scenario as the existing data were of large size and there were known sample variances for both samples of traditional learning and associative relevance learning strategies

# [24]-[27].

Initially, we supposed that there was no mean difference hypothetically between the two data series (samples) obtained from associative relevance learning strategy and traditional learning strategy. This was our null hypothesis.

These computations led towards the following results as mentioned in Table 2. Hence, the obtained results were ready for interpretations and subsequent inferences for both learning strategies.

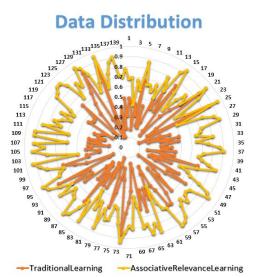


Fig. 5. Chart for data distribution in accordance with learning capabilities of participants.

As we observed from the above mentioned statistical outcomes, the z-test statistic showed that the obtained z-score remained far beyond (nearly 10 to 11 times) the critical z-scores for both one-tail (directional) and two-tail (non-directional) analysis, therefore, we rejected our null hypothesis (there was no hypothesized difference between the means of the two samples).

Based on z-test statistical analysis, we interpreted that the data for associative relevance learning strategy was more notable and increasingly consolidated data than the data for traditional learning strategy. As a result, we accomplished a reasonable amount of support for the improvement of data centered on associative relevance learning strategy.

| z-Test: Two Sample for Means |                                |                      |  |
|------------------------------|--------------------------------|----------------------|--|
|                              | Associative Relevance Learning | Traditional Learning |  |
| Mean                         | 0.745142857                    | 0.399285714          |  |
| Known Variance               | 0.016043864                    | 0.03266999           |  |
| Observations                 | 140                            | 140                  |  |
| Hypothesized Mean Difference | 0                              |                      |  |
| Z                            | 18.54105841                    |                      |  |
| P(Z<=z) one-tail             | 0                              |                      |  |
| z Critical one-tail          | 1.644853627                    |                      |  |
| P(Z<=z) two-tail             | 0                              |                      |  |
| z Critical two-tail          | 1.959963985                    |                      |  |

Table 2. The z-Test for Two Samples of Both Learning Strategies for Means

### 6. Conclusion

We bring to a close with this concluding statement that the e-learning instructional strategy based on associative relevance is more advantageous and beneficial in comparison to the e-learning strategy based on traditional instructions.

Our statistical facts evidence that e-learning based on associative relevance strategy is more cognitively controlled and structured than the learning based on traditional strategy.

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171

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**Gufran Ahmad** has experience in teaching, research, and industrial domains for national and international communities. He is an ardent thinker and passionate knowledge sharer for cultivating intelligence among Scholars and Learners all around the world.

He is dedicating his exertion on data and information visualization, intelligent information processing, cognition, e-learning, predictive modeling, and decision-making, which are some of the energizing and intensive research topics for social, commercial, and

technological advancements of our societies.

Currently, he is a faculty and researcher of College of Computer Sciences and Information Systems, Jazan University. Earlier, he devoted his endeavor as a researcher in The University of Tokyo, Faculty in Al-Falah Engineering College, a lecturer in Institute of Technology, a researcher & teaching assistant in Mie University, Japan, and IT professional in Fintech Compu Systems Limited & Micro Computer Services & Solutions companies.

He holds double post-graduation degrees in computer software & theory from Harbin Engineering University, Peoples' Republic of China, and in Theoretical Physics from Jamia Millia Islamia University, India. In addition, he holds advanced postgraduate diploma in computer applications from Jamia Millia Islamia University, India.

He collaborated and wrote more than four dozens of national and international articles, publications, teaching and technical notes that can demonstrate his writing intents. These creativities had appended as valued assets by organizations and corporates.

Researcher Ahmad has been a committed member of Physics Association, National Computer Software Society, AICIT, and National Literacy Mission. He received numerous awards, including Best Employee of Corporate, Certificate of Merit, Best Author, and Young Researcher. He has been serving as an honorary individual for some of world-renowned organizations to elevate our human societies for furtherance.