Role of a Teacher in e-learning & Face-to-Face Learning Environment

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The main purpose of this study is not to compare online and traditional face-to-face instruction merely to prove which one is better. This paper aims to highlight some of the possible risks and strengths which may help to improve the role of teachers in both methods. The study can be designed using a quantitative and qualitative methodological combination, and focus on the dimensions of "theoretical content", "practical content", "tutor/student interaction" and "design" of the training activity. Teachers in online classrooms primarily need to understand distance education and how it differs from conventional methods. These people are required to be subject matter experts, education designers, social facilitators and teachers in an online environment. The "face" of an e-learning course may not be an actual face, but more the overall look and feel of the design. Classrooms are teacher-driven, whereas an e-learning course is student-driven. Instruction in higher education has developed significantly over the past two decades, influenced by two trends. They are (1) promotion of active learning methods and (2) integration of Web technology in e-learning. Many studies found that active teaching improves students' success, involvement and thinking skills.

Let us consider teacher (t) as source and student (s) as a customer. We establish various parametric impacts on teachers and students and represented in the form of general mathematical model. e-learning is to integrate technologies and new knowledge to allow learners to learn new knowledge anytime and anywhere without constraints of time and space. With the increasing prevalence of e-learning, many cram school operators have released their own instructions based on e-learning methods, including CD or cassette-based distance learning, single-learner online learning, and multi-learner multimedia-assisted instructions. Their primary purposes are to promote e-learning among students. Moreover, effectiveness and satisfaction of learning, instructors, and environments can be compared between E-learning and face-to-face learning. Students who used e-learning method will be more satisfied on learning materials and learning environment compared to traditional face-to-face learning method, using data mining techniques.

Manuscript received July 5, 2011
Manuscript revised July 20, 2011

Key words:
Role of Teacher in online teaching, online learning, e-learning.

1. Introduction

There is an argument that traditional learning is the best way of maintaining a learning process. Other models are always considered to be inferior or less efficient. There is no finding to support this argument, and research shows that e-learning models are at least as good as traditional learning. Although e-learning is still in its infancy, the knowledge acquired by teachers who use online and face-to-face methods can be of great use in improving both types of teaching, which is the reason why researchers nowadays study issues related to these teaching methods. It is not simply a question of retaining traditional teaching methods such as the master class and applying e-learning techniques to gain access to more information. It means, involving the students in the same learning methodology using a different medium. Considerable progress must still be made to enable today's society to take full advantage of the potential of online teaching. On comparing the two methodologies, people may mistakenly regard the two processes as similar when in fact they should be seen as different from the outset. However, it is useful to carry out comparative research which might lead to improvements in each type of learning model.

Teachers can integrate synchronous online discussions with traditional face-to-face instruction, and the results of this study suggested that students were generally satisfied with the blended course format. Examined whether online learners and face-to-face learners are equally satisfied with the quality of their learning, their findings showed that both learning styles scored equally with regard to learning outcomes and satisfaction, despite the fact that each style has decidedly different learning experiences. This study offers insight into the nature of the experience of online learning, and suggests that online course designers focus their attention on particular elements that support the unique experiences of students who select this learning method.

2. Comparing traditional Learning and e-Learning.

The traditional role of a teacher is based on behaviour where the teacher is in control of learning material and how the student learns. This role is challenged in an e-learning classroom as the situation teachers find themselves in is quite different. The principles and responsibilities involved in traditional education are transferable into an e-learning environment. A teacher in an online classroom is faced with a different type of student, one which requires interaction and collaboration with other learners, content and information sources as a result of their existence in the Information Age. These students call for information from around the world, and immediate feedback on their work. They are known as lifelong learners as the skills they acquire means that they are continuously challenging and searching for information.

Teachers in online environments are unable to be assessed in the same way that traditional teachers are. A teacher's presence is evaluated in a conventional classroom, however in terms of e-learning, the teaching presence is considered. Teaching presence refers to "what a teacher does to create a community of inquiry that includes both cognitive and social presence. The three major elements of teaching presence in an online classroom are design, facilitation of discourse and direction of instruction in order to realise meaningful and worthwhile learning outcomes. When comparing learning an identical course in a traditional framework to a computer mediated learning framework, it can be assessed that the latter is more effective and interactive than the earlier one. e-learning includes many components that are familiar from traditional learning, such as: presentation of ideas by the students, group discussions, arguments and many other forms of conveying information and accumulating knowledge. The contents of the course's curriculum might be organized according to subjects and in a serial manner.

3. Recent studies.

According to Tassos A. Mikropoulos, Antonis Natsis, the study conducted [1999 to 2009], in ten-year critical review of empirical research on the educational applications of Virtual Reality (VR). Results show that the majority of the 53 reviewed articles refer to science and mathematics; researchers from social sciences also seem to appreciate the educational value of VR and incorporate their learning goals in Educational Virtual Environments (EVEs). Although VR supports multisensory interaction channels, visual representations predominate. Few are the studies that incorporate intuitive interactivity, indicating a research trend in this direction. Few are the settings that use immersive EVEs reporting positive results on users' attitudes and learning outcomes, indicating that there is a need for further research on the capabilities of such systems. Features of VR that contribute to learning such as first order experiences, natural semantics, size, transduction, reification, autonomy and presence are exploited according to the educational context and content. Presence seems to play an important role in learning and it is a subject needing further and intensive studies. Constructivism seems to be the theoretical model; the majority of the EVEs are based on. The studies present real world, authentic tasks that enable context and content dependent knowledge construction. They also provide multiple representations of reality by representing the natural complexity of the world. Findings show that collaboration and social negotiation are not only limited to the participants of an EVE, however, exist between participants and avatars, offering a new dimension to computer assisted learning.

Let us assume a Gurukula system (G1) in a place (P1) in the Metro City (M1) with teachers (T1) students (S1) in an Educational Institute (I1) situated in the heart of the city and away from the country culture. I1 is attracted by the student (S1) due to knowledgeable teachers (T1) and good placement (P1) Therefore

$$I1 = N1(T1) + MI\ (SI) \quad \text{…………………} \quad (1)$$

Where N1 = Number of the teachers and M1 = Number of the students. The relation between T1 & S1 is very close and ethical value of both is good. As teachers import knowledge through classical methods, students are free to ask the questions face to face which helps measuring learning Quotient (LQ) and spiritual quotient (SQ). That is a good teaching (GT) means

$$GT = LQ + SQ \quad \text{………..…….…………} \quad (2)$$

Equation (2) holds good only when M1 is limited and S1 frequency matches with T1. In Gurukula system, generally experts are dedicated only for teaching and improvement of S1 in 360 degree evaluation. Each student is taken care of by the teachers well. Students are away from the parents. In modern era, it is called International residential school. Now, the question comes 1) Students financial status 2) How much for away from the parents 3) parents punctuality in sending the needs of Gurukula system for their children. 4) Emotional Quotient (EQ) of the students and 5) Relational Quotient (RQ) of the teacher with the students (S1). That is

Ideal students = 1+2+3+4+5 ………. (3)

In the classical way of learning process student will grow in all direction except awareness of the social network system. He will become a knowledgeable person but not practically way behind in the social awareness. In contrast a student who gained knowledge from the networks (e-learning) is more efficient in placement and communication skill is lagging with or without obedient factors.

Emotional quotient is more important in learning with marks. Public awareness, public movements and public behavior are gaining more freedom in e-learning process. It sometime leads to chaos and divergence in the concept of education may occur. The role of the parent is absolutely nil in the case of e-learning even though advance network communication .When we consider the population of the India, only 30% are educated and remaining 70% of population requires more number of resource persons for training. The only way of spreading higher education is through the best practices in technology.

4. Advantages of e-learning over traditional learning

e-learning also includes advantages which are not found in traditional learning, such as: time for digesting the information and responding, enhanced communication among the learners, both as regards quality and as regards urgency, knowledge being acquired and transferred among the learners themselves, the ability to conduct an open discussion, where each learner gets more of an equal standing than in a face-to-face discussion, access to information and to discussion ability, responses may be made around the clock with no restrictions, a higher motivation and involvement in the process on the part of the learners. In traditional learning, the teacher talks more than the student whereas in e-learning the student talks as much or more than the teacher.

Most of the e-learning process takes place in groups or by the individual student. When subject matter comes, the teacher conducts the lessons, however, in e-learning the study is based on various sources of information, including Web data banks and net-experts located by the student. The learning process is tedious in traditional learning, the student learns "what" and not "how”. In e-learning, the student learns "how" and less "what"; the learning includes research study. The student motivation in e-learning is high due to the involvement in matters that are closer to them and to the use of technology.

The e-learning advantages and disadvantages are important to consider when making instructional and learning decisions. Many institutions provide different forms of training and instruction to their teachers or learners. Typically, they provide needed training by sending people to school, holding in-house training classes, or providing manuals and self-study guides. In some situations, it is advantageous for them to use e-learning or other forms of e-learning instead of the traditional training. Other times, it is disadvantageous. As with anything else, there are benefits and limitations, as well as pros and cons. There are many advantages to online and computer-based learning when compared to traditional face-to-face courses and lectures. Successfully completing online or computer-based courses builds self-knowledge and self-confidence and encourages students to take responsibility for their learning. Flexibility to join discussions in the bulletin board threaded discussion areas at any hour, or visit with classmates and instructors remotely in chat rooms.

5. Data mining techniques in e-Learning

Resources in learning environments are authored for the purpose of transferring knowledge to the learner. The growth of learning repositories and the ease of publishing and accessing information has created an environment where finding and making efficient use of the available information can be overwhelming. It is the job of data mining to help the learners digest large amounts of data by lever-aging sophisticated techniques in data analysis, restructuring, and organization. Learning resources are mainly found in textual form; e.g. text documents, Web documents, articles, and papers, among other forms. Due to the unstructured and unrestricted nature of text documents, a special field in data mining was coined the term “text mining”.

It is the field studying the non-trivial extraction of implicit, previously unknown and potentially useful and significant information from text documents. Text mining is generally considered more difficult than traditional data mining. This is attributed to the fact that traditional databases have fixed and known structure, while text documents are unstructured, or, as in the case of Web documents, semi-structured. Thus, text mining involves a series of steps for data pre-processing and modeling in order to condition the data for structured data mining. Text mining can help in many tasks that otherwise would require large manual effort. Common problems solved by text mining include, but not limited to, searching through documents, organizing documents, comparing documents, extracting key information, and summarizing documents. Methods in information retrieval, machine learning, information theory, and probability are employed to solve those problems. Information extraction through text mining deals with finding particular data in text and web documents. The approaches used in this area include document parsing, analysis, and restructuring. This allows for restructuring existing learning material into current standards. Other approaches include identifying and extracting significant semi-structured information, extracting keywords and key phrases from documents using phrase indexing and matching. These methods have high potential in e-learning due to their ability to automatically extract useful information and tag learning objects with certain meta-data extracted from content. Information organization through text mining provides an overview of the topics in a large set of documents without having to read the contents of individual documents. This can be achieved through data clustering and classification techniques. These techniques mainly rely on the analysis of keyword distribution in the documents. They also make use of similarity calculation through word and phrase matching. The end result is a more manageable grouping of document tagged with topics and subjects. While data clustering techniques are mainly used for content organization, it could be used to group learner profiles as well. In this case, we can discover common interest groups of learners by judging the similarity between their profiles. This study focuses on employing machine learning methods in finding relationships between text documents through phrase-based document modeling, similarity calculation, document clustering, and key phrase extraction. In particular, a set of documents is pre-processed through tokenization (identifying whole words and dropping punctuation symbols), removing stop words (very frequent words like ‘a’, ‘and’, ‘the’), and stemming (reducing different forms of a word into a single form). Then a model of the data is built using a graph-based representation of phrases in the documents. Next, pattern analysis is applied to detect similarities between the documents based on shared and significant phrases, followed by clustering the documents to form groups of documents, where each group contains only similar documents sharing the same topic. Finally, the process concludes by extracting key phrases from the clusters and identifying the topic of each cluster.

(A)Phrase-based Document Model:

A process of data modeling is required to convert the input data into a form that is more suitable for processing by the data mining algorithm. In the case of text mining, input data are mainly text documents that do not necessarily obey a regular structure. The challenge is to convert the input space into feature space, where the features of the documents are expected to follow a fixed structure that can be manipulated by a text mining algorithm. The traditional document representation model, as well as the phrase-based model is introduced in this paper.

(B)Vector Space Model:

By far the most common feature model in text mining is the vector space model, originally proposed by Salton et al in 1975 [1–3]. In this model, document features are the words in the document collection, and feature values come from different term weighting schemes. Each document is represented by a vector d, in the term space, such that d = {w1,w2, . . . ,wn}, where wi, i = 1, . . . , n, is the weight of term i in the document. The weight of a term could be simply calculated as the frequency of the term in that document (wi=tfi); i.e. how many times it appeared in the document. A more popular term weighting scheme is TF×IDF (Term Frequency ×Inverse Document Frequency), which takes into account the document frequency of a term (dfi), the number of documents in which the term appears. A typical inverse document frequency (idf) factor of this type is given by log (N/dfi). Thus the TF×IDF weight of a term is wi = tfi × log (N/dfi). In other words, terms that appear more frequently in a certain document but less frequently in other documents are given higher weights in that document, since it has higher correlation with that document than others. On the other hand, terms that appear frequently in all documents are penalized in all documents since they have less discrimination power. To represent every document with the same set of terms, we have to extract all the terms found in the documents and use them as our feature vector. To keep the feature vector dimension reasonable, sometimes only terms with the highest weights in all the documents are chosen as the features. Wong and Fu [4] showed that they could reduce the number of representative terms by choosing only the terms that have sufficient coverage over the document set. Some algorithms [5,4] refrain from using continuous term weights by using a binary feature vector, where each term weight is either 1 or 0, depending on whether it is present in the document or not, respectively.

The simplicity of the model led to its wide adoption in the text mining literature. However, the dependence between the words in the representation is one of its weaknesses. A more informed approach is to capture the phrase structure and word sequences in the document, thus providing context when comparing document features.

(C) Graph Space Model

The model presented here for document representation is called the Document Index Graph (DIG). This model indexes the documents while maintaining the sentence structure in the original documents. This allows us to make use of more informative phrase matching rather than individual words matching. Moreover, DIG also captures the different levels of significance of the original sentences, thus allowing us to make use of sentence significance. Suffix trees are the closest structure to the proposed model, however, they suffer from huge redundancy, gives over 40 references on suffix trees, and Manber and Myers[1] add more recent ones. However, the proposed DIG model is not just an extension or an enhancement of suffix trees; it takes a different perspective of how to match phrases efficiently, without the need for storing redundant information. Phrasal indexing has been widely used in the information retrieval literature [9]. The work presented here takes it a step further toward an efficient way of indexing phrases with emphasis on applying phrase-based similarity as a way of clustering documents accurately. DIG structure overview. The DIG is a directed graph (digraph) G = (V, E) where V: is a set of nodes {v1, v2,… vn}, where each node v represents a unique word in the entire document set; and E: is a set of edges {e1, e2, . . . , em}, such that each edge e is an ordered pair of nodes (vi, vj). Edge (vi, vj) is from vi to vj , and vj is adjacent to vi. There will be an edge from vi to vj if, and only if, the word vj appears successive to the word vi in any document. A set of edges is said to be corresponding to a sentence in a document if they link the nodes corresponding to the sentence in the same order the words appeared in the sentence.

The above definition of the graph suggests that the number of nodes in the graph is the number of unique words in the document set; i.e. the vocabulary of the document set, since each node represents a single word in the whole document set.

Nodes in the graph carry information about the documents they appeared in, along with the sentence path information. Sentence structure is maintained by recording the edge along which each sentence continues. This essentially creates an inverted list of the documents, but with sentence information recorded in the inverted list. Assume a sentence of m words appearing in one document consists of the following word sequence: {v1, v2, . . . , vm}. The sentence is represented in the graph by a path from v1 to vm, such that (v1, v2)(v2, v3), . . . , (vm−1, vm) are edges in the graph. Path information is stored in the vertices along the path to uniquely identify each sentence. Sentences that share sub-phrases will have shared parts of their paths in the graph that correspond to the shared sub phrase.

To better illustrate the graph structure, the following Figure-1 presents a simple example graph that represents three documents. Each document contains a number of sentences with some overlap between the documents.

As seen in the graph below, an edge is created between two nodes only if the words represented by the two nodes appear successive in any document. Thus, sentences map into paths in the graph. Dotted lines represent sentences from document-1, dash-dotted lines represent sentences from document-2, and dashed lines represent sentences from document-3. If a phrase appears more than once in a document, the frequency of the individual words making up the phrase is increased, and the sentence information in the nodes reflects the multiple occurrence of such phrase. As mentioned earlier, matching phrases between documents become a task of finding shared paths in the graph between different documents.

DIG Construction:

The DIG is built incrementally by processing one document at a time. When a new document is introduced, it is scanned in sequential fashion, and the graph is updated with the new sentence information as necessary. New words are added to the graph as necessary and connected with other nodes to reflect the sentence structure. The graph building process becomes less memory demanding when no new words are introduced by a new document (or very few new words are introduced.) At this point the graph becomes more stable, and the only operation needed is to update the sentence structure in the graph to accommodate the new sentences introduced. It is very critical to note that introducing a new document will only require the inspection (or addition) of those words that appear in that document, and not every node in the graph. This is where the efficiency of the model comes from. Along with indexing the sentence structure, the level of significance of each sentence is also recorded in the graph. This allows us to recall such information when we measure the similarity with other documents.

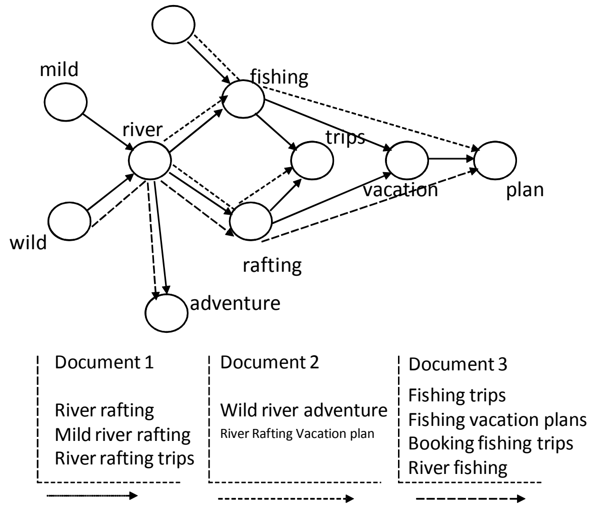
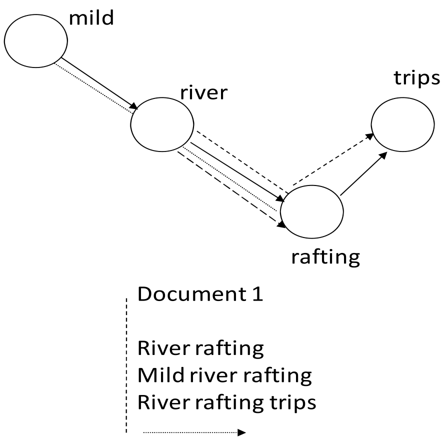
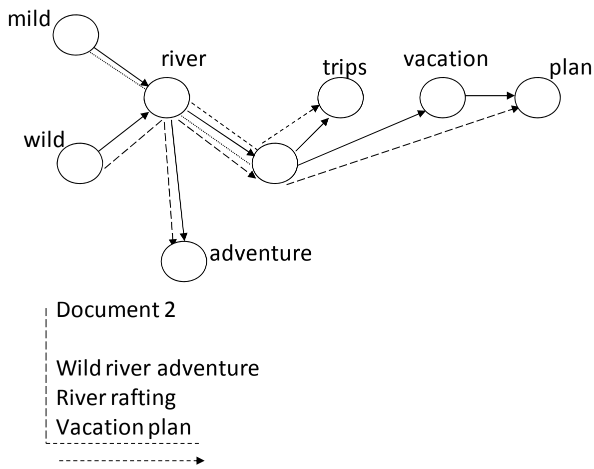


Figure 1: Example of the Document Index Graph

The process of constructing the graph that represents the three documents is illustrated in the following three Figures. Each figure shows the construction of the graph for each document such as document 1, document 2 and document 3.





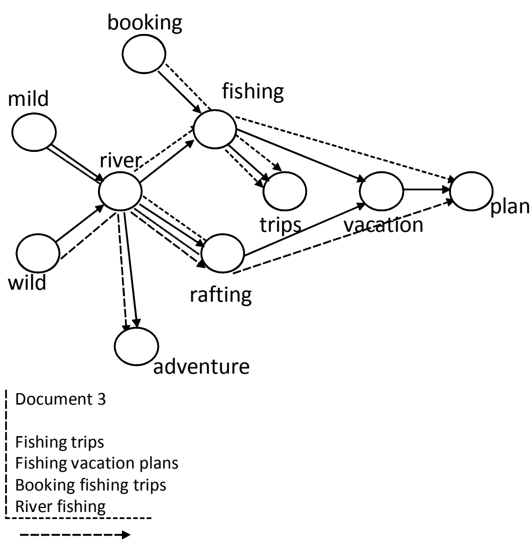


Figure: 2. Incremental Construction of the Document Index Graph.

The emphasis here is on the incremental construction process, where new nodes are added and new edges are created incrementally, upon introducing a new document. It can be defined, now, incremental DIG construction process formally in terms of graph properties. Each document di is mapped to a subgraph that represents this document in a stand-alone manner (an example is the first step in figure 3.) Each sub graph can be viewed as a detached subset of the DIG that represents the corresponding document in terms of the DIG properties: gi = {Vi,Ei}, where Vi is the set of nodes corresponding to the unique words of di, and Ei is the set of edges representing the sentence paths of di.

Cumulative DIG

Let the DIG representation of the documents processed up to document di−1 be Gi−1, and that of the documents processed up to document di be Gi. Computing Gi is done by merging Gi−1 with the subgraph gi:Gi = Gi−1 ∪ gi (1)Gi is said to be the Cumulative DIG of the documents processed up to document di phrase Matching. A list of matching phrases between document di and dj is computed by intersecting the subgraphs of documents, gi and gj, respectively. Let Mij denote such list, then, Mij = gi ∩ gj (2)A list of matching phrases between document di and all previously processed documents is computed by intersecting the document subgraph gi with the cumulative DIG Gi−1. Let Mi denote the such list, then, Mi = gi ∩ Gi−1 (3)Unlike traditional phrase matching techniques that are usually used in information retrieval literature, DIG provides complete information about full phrase matching between every pair of documents. While traditional phrase matching methods are aimed at searching and retrieval of documents that have matching phrases to a specific query, DIG is aimed at providing information about the degree of overlap between every pair of documents. This information will help in determining the degree of similarity between documents. Upon introducing a new document, finding matching phrases from previously seen documents becomes an easy task using DIG. Algorithm 1 describes the process of both incremental graph building and phrase matching. Instead of building document subgraphs and intersecting them with the cumulative DIG, the algorithm incrementally incorporates new documents into DIG while collecting matching phrases from previous documents at the same time. Phrase Matching Using DIG, the procedure starts with a new document to process. Matching phrases from previous documents is done by keeping a list M that holds an entry for every previous document that shares a phrase with the current document di. The following is an algorithm for DIG incremental construction and phrase matching.

Algorithm: DIG incremental construction and phrase matching.

Require: G_{i-1}: cumulative graph up to document d_{i-1} or G_0 if no documents were processed previously

1: $d_i \leftarrow$ Next Document
2: M ← Empty List {M is a list of matching phrases from previous documents}
3: for each sentence s_{ij} in d_i do
4: $v_1 \leftarrow t_{ij1}$ {first word in s_{ij}}
5: if v_1 is not in G_{i-1} then
6: Add v_1 to G_{i-1}
7: end if
8: for each term $t_{ijk} \in s_{ij}$, k =2, ...,l_{ij}, do
9: $v_k \leftarrow t_{ijk}$; $v_{k-1} \leftarrow t_{ij(k-1)}$; $e_k = (v_{k-1}, v_k)$
10: if v_k is not in G_{i-1} then
11: Add v_k to G_{i-1}
12: end if
13: if e_k is an edge in G_{i-1} then
14: Retrieve a list of document entries from v_{k-1} document table that have a sentence on the edge e_k
15: Extend previous matching phrases in M for phrases that continue along edge ek
16: Add new matching phrases to M
17: else
18: Add edge e_k to G_{i-1}
19: end if
20: Update sentence path in nodes v_{k-1} and v_k
21: end for
22: end for
23: $G_i \leftarrow G_{i-1}$
24: Output matching phrases list M

For each sentence (for loop at line 3) we process the words in the sentences sequentially, adding new words (as new nodes) to the graph, and constructing a path in the graph (by adding new edges if necessary) to represent the sentence we are processing. As we continue along the sentence path, we update M by adding new matching phrases and their respective document identifiers, and extending phrase matches from the previous iteration (lines 14 to 16). We first consult the document table of vk−1 for documents that have sentences that continue along the edge ek. Those documents share at least two terms with the current sentence under consideration. We examine the list M for any previous matching phrases (from previous iterations) to extend the current two-term phrase match (on edge ek). This allows the extension of previous matches, and can continue for any-length phrase match. If there are no matching phrases at some point, we just update the respective nodes of the graph to reflect the new sentence path (line 19). After the whole document is processed, M will contain all the matching phrases between the current document and any previous document that shared at least one phrase with the new document. Finally we update Gi to be the current cumulative DIG, and output M as the list of documents with all the necessary information about the matching phrases, which will be used in similarity calculation later.

6. Teacher's role and responsibilities

The most challenging role and responsibility of the online teacher is to provide a creative and interesting learning environment. Teachers use student-oriented Learning Management Systems to oversee their classroom as they are able to continually adjust to societal changes. Teachers base their classroom agendas, which require the teacher to analyse the learner, state the learning objectives, select the methods, media and materials to be used in the classroom, utilise the chosen media and materials, require learner participation, and evaluate and revise the learning material. This model allows careful planning of the learning environment and ensures interaction and collaboration plays a major role in the learning process. In the classroom, it is easy to say, “The instructor didn’t cover that.” When dealing with an e-learning course, all the information is there for the learner, but it is up to the student to learn the material. It is known what information the course contains and from the assessments, it can be known what the student has learned.

In e-learning, the teacher directs the student to the information. The role of the teacher in any learning environment is to “ensure that some type of educational process occurs amongst the learners involved” .In the traditional classroom, the teacher’s role can be seen as that of an instructor imparting knowledge to students as well as advice on “how to do it” refers to the teacher centered style as one in which the responsibility for directing the learning environment is with the instructor. However, the role of the teacher in tertiary institutions “needs to change to match the development and potential of new online environments”. Teaching successfully in an online environment does not come from teachers doing what they have always done In an OLE the teacher’s role becomes that of an educational facilitator, providing guidance and fostering “a sense of community among learners”.

It has been suggested that the online teacher needs to adopt the roles of facilitator and coach combined with moderator and tutor as well as subject matter expert and technician. The teacher in the online environment also needs to assume the role of mentor.

7. Summary & Conclusions

Nevertheless, instructors/teachers satisfaction between these two models didn't show significant difference. As a general conclusion, no important differences were observed in the functions of the teacher in two teaching methods. They are (1) face-to-face and (2) online. Any differences that might exist were usually a consequence of teacher involvement and of the commitment of the institution in programming the learning process. Studies like this may induce online and face-to-face teachers to reflect on their practices, and to become aware of improvements they might make in their role as teachers. The design and structure of the theoretical content of an e-training programme may, on occasions, be more satisfactory and efficacious than those of a face-to-face programme because in face-to-face programmes, the teacher needs to have a previous mental structure of the contents which he/she develops in the course of the theoretical explanation. In the online mode, however, this structure is previously prepared and used as a framework for the online presentation of contents. In face-to-face training, conversely, the explanation of concepts often takes priority over the practice of activities. Online learners, however, may have to cope with an overwhelming amount of practical content, which may even cause them to give up their studies. Interaction between teachers and face-to-face students can be more efficacious than with online students. Visual contact and such contact as an encouraging back-slaps, etc. are useful resources for motivating students. Positively-valued tasks carried out by teachers are identical in both teaching systems, i.e., the facilitating of the teaching/learning process, combining the explanation of theoretical contents with activities, and encouraging interaction.

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