DESIGN OF VIDEO AIDED RETENTION TOOL FOR THE HEALTH CARE PROFESSIONALS IN SELF-DIRECTED VIDEO-BASED LEARNING

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ABSTRACT

Health Care Professionals (HCPs) depend on self-directed learning by watching medical videos. In the traditional video learning system, it is difficult to identify the important videos from the huge data set and to find the essential inside parts of a long video. In addition, it is hard to know learners' preferences inside the video parts, including duration and repetition of watching. If the system could know the attention and retention process of each learner, it could change the way to show the video. Accordingly, this research proposes to design the Video Aided Retention Tool (VART) system for analyzing video content to improve self-directed video-based learning among HCPs. The VART consists of a combination of video tracking, analyzing, and filtering tools, with the integration of domain model, learners' model, and e-teaching strategy model to aid in self-directed learning. The proposed VART will pick important videos on a single topic and put automatic indexes to represent the essential parts of video content. It will also track the learner's ID, content preference, monitor watching duration, and repetition of the content. Using such kind of data, attention, and retention will be determined and filtered reels, recommendations, interactive videos will be provided to the learners.

Keywords: Video Aided Retention Tool (VART), Video-based Learning, Self-directed Learning, Adaptive Learning, Health Care Professionals (HCPs)

INTRODUCTION

Learning from video content received a great response from all kinds of learners since YouTube launched in the year 2005. Following the success story of YouTube, many other video channels, like TED, DTube, Dailymotion, Google Video, Yahoo Video, Vimeo, and some other video-sharing platforms emerged. Very recently, due to the COVID-19 situation, the whole world experienced a new era of communication methods, especially most of the teaching and learning methods moved online with a diverse communication style. Watching video streaming from various video-sharing platforms as well as institutional videos on the web, have become one of the important parts of the teaching and learning process. But determining learning outcomes from video content is difficult especially in self-directed learning. Yuzer, Firat, & Dincer (2016) study suggested that there should be learning analytics tools for educators as well as learners for analyzing learning outcomes from a learner's interaction with every medium of content. In this case, video content again received significant attention from the teaching and learning communities. Most importantly, due to the COVID-19 situation, there has been strong pressure on the Health Care Professionals (HCPs). As a result, they are one step ahead than any other community in the case of online teaching, learning, and communicating with patients, co-workers, and others. Another critical issue for the HCPs is the clinical decision-making at the right time to ensure proper treatment and to save the lives of the patients. So, clinical decision-making is considered as a foundation of effective medical education and a significant criterion of the physicians' competency. HCPs need to deal with different critical situations and make the decision in a complex environment during their daily duties. For this, very often, they rely on self-directed learning by watching medical videos available on the web.

Park & Park (2016) stated that clinical practice-related videos have triggered HCPs' interests and help them to learn major medical subjects. However, the learning process based on only watching the videos may not be effective until learners can remember, reflect, and use it in a real situation (Hasegawa & Dai, 2015). Besides, HCPs have a very tight schedule, but the video resources are enormous and there are several videos on the same topic. However, they want to pick the most important video based on their skills and competency level. In addition, in the case of long videos, generally, multiple topics are included, and it is difficult to pay concentration for a long video. So, it is needed to identify the vital parts of the video because learners may not need to watch the whole video, and that is time-consuming.

Moreover, in the traditional video learning system, it is difficult to determine which part of the video did the learner focus, including the duration and repetition of watching and their expected video contents one after another. In that case, if the system could know the attention and retention process of each learner, it could change the way to show the video. Considering these issues, this research proposed Video Aided Retention Tool (VART) which will track and analyze learner's video watching characteristics that include learner's content preferences, learning process, learning progress, etc. and filter and provide focused contents for effective learning.

However, this paper is an extension of the authors' previous research Video Aided Retention Tool for enhancing decision-making skills among Health Care Professionals (Sagorika & Hasegawa, 2019). In the previous research, the authors discussed the decision-making cultivation cycle among HCPs, VART integration with Moodle, and VART framework. In this research, the researchers introduce the design phase of the domain model, learner's model, and e-teaching strategy model with the integration of VART.

RESEARCH PROBLEMS

Based on the previous research, this study identified several problems that triggered designing VART for HCPs. The core problems include:

1. **Diversified content:** In the field of healthcare and medical learning, there are numerous clinical video contents available on the web. At the same time, there are a variety of video contents available on the same topic in different sources. But HCPs have a hectic schedule, and they want to pick the important videos quickly. So, how to support HCPs to determine the expected video contents from the huge data set is very important.
2. **Content specification:** Many clinical videos have long contents consisting of several topics together. Besides, in long video content, all parts are not equally important for a certain learner. As HCPs do not have enough time to watch the whole video; it is also difficult for them to pay attention to a long video. HCPs want to pick the most critical parts first. If they find the video is essential for them, they can learn profoundly using the whole video. So how to make a summary video from the huge video data, or how to filter essential parts from long video content and represent based on learner's demand is one of the targets for HCPs to support using the video.
3. **Learning behavior:** HCPs have different knowledge levels and learning behaviors. Very often, it is difficult for them to select the right video content based on their competency level and learning progress. However, most of the systems do not have a clear description of providing content based on learner's competency level and learning progress. Furthermore, there is no technique to follow the cognitive behavior of a learner to know his/her learning process and how to assist the learner in that process.

RESEARCH OBJECTIVES

To overcome the above problems, the objectives of this research follows to:

i. find out the mechanism of identifying expected video contents, represent the essential parts inside the videos and filter content based on learner's learning process and progress in the self-directed video-based learning;
ii. illustrate VART functional overview through indexing essential parts, fractioning long videos into specific parts, and matching video content with learner's competency level and way of learning; and
iii. apply the VART technique into the domain model, student model, and e-teaching strategy model to design for video-based learning.

RELATED LITERATURE

Different researchers have emphasized Video-based teaching and learning strategies from different perspectives. Among some important research, Kilinc, Firat, & Yuzer (2017) study examined the usages trends of educational videos in distance learning environments, Jang & Kim (2014) investigated the students' usages and perception of online clinical videos for learning clinical skills; Clifton & Mann (2011) suggested using YouTube for teaching and learning among nurses; Park & Park (2016) remarked anatomy and pathology to be taught with video-assisted technology and, Friedl et al. (2006) and Pape-Koehler et al. (2013)training, and concentration. In recent years, Internet platforms providing surgical content have been established. Used as a surgical training method, the effect of multimedia-based training on practical surgical skills has not yet been evaluated. This study aimed to evaluate the effect of multimedia-based training on surgical performance.\\n\\nMETHODS: A 2 × 2 factorial, randomized controlled trial with a pre- and posttest design was used to test the effect of multimedia-based training in addition to or without practical training on 70 participants in four groups defined by the intervention used: multimedia-based training, practical training, and combination training (multimedia-based training + practical training found the effectiveness of audio-visual contents in surgery education among medical students. In addition, Weeks & Horan, (2013) found that activity and learning based on the video- resources were effective for physiotherapy students in practical examinations and it improved their performance level. Also learning from the video contents for surgical groundwork becomes a very important and regular practice among the specialist doctors in Portugal (Mota et al., 2018)teaching of surgery has remained practically unaltered until now. With the dawn of video-assisted laparoscopy, surgery has faced new technical and learning challenges. Due to technological advances, from Internet access to portable electronic devices, the use of online resources is part of the educational armamentarium. In this respect, videos have already proven to be effective and useful, however the best way to benefit from these tools is still not clearly defined. Aims: To assess the importance of video-based learning, using an electronic questionnaire applied to residents and specialists of different surgical fields. Methods: Importance of video-based learning was assessed in a sample of 141 subjects, using a questionnaire distributed by a GoogleDoc online form. Results: We found that 98.6% of the respondents have already used videos to prepare for surgery. When comparing video sources by formation status, residents were found to use Youtube significantly more often than specialists ($p < 0.001$.

However, the volume of effective research on educational videos used in the e-learning environment is very limited (Kilinc et al., 2017). Besides, it is tough to gather the intuitions of the learners from various video learning practices and logically contribute to the creation of a joint framework for video-based learning (M. N. Giannakos, et al., 2013). The study investigated the usefulness of video analysis by combining learners' interaction information with the video-based courses and how to support instructors with the suitable contents to improve the usage of their courses (M. Giannakos, et al., 2014). Another research proposed a new cross-modal recommendation method based on multi-modal deep learning for the multi-modal video contents depending on learners' preference for video data (Yang, Xie, & Li, 2019).

Very recently, Nazari et al. (2020)the step-by-step group will perceive lower extraneous load during the preparation of the surgical procedure compared to the continuous group. Subsequently, fewer errors will be made in the surgical performance assessment by the step-by-step group, resulting in better surgical performance. DESIGN: In this prospective study, participants were randomly assigned to the step-by-step or continuous video-demonstration. They completed questionnaires regarding perceived cognitive load during preparation (10-point Likert scale found that step-by-step video-based learning results in lower cognitive load and fewer procedural errors than the continuous video-demonstration during the surgical actions among the medical students. Delen, Liew, & Willson (2014)this study investigated the effects of a newly designed enhanced video learning environment, which was designed to support or scaffold students' self-regulated or self-directed learning on students' learning behaviors and outcomes. In addition, correspondence between students' self-regulation strategies in traditional learning environments and observed self-regulated learning behaviors in the enhanced video environment were examined. A cross-sectional experimental research design with systematic random assignment of participants to either the control condition (common video study examined learners' self-directed learning behaviors in online video-based learning using 'common videos' with micro-level functions in the traditional method and 'enhanced videos' included macro-level with the micro-level functions in the experimental method. The study found that an enhanced video learning environment was accepted as a higher instructional tool than the common videos in terms of learners' learning outcomes. So, it is assumed that there needs learner's centered video learning support to fulfill their target in the self-directed video-based learning.

Studies also found that teachers and learners can reflect their own teaching and learning experience with the support of video annotation or video analysis tools (Rich, Hannafin, & Rich, 2010). Some video annotation tools, for example, VideoAnt or EVA, allows users to make a list of comments in the video parts. Another tool called OVA, provide a platform which enables analysis and collaborative discussion on the topics illustrated in the video and allows learners to share comments with each other (Cebrian-de-la-Serna, M; Bartolome-Pina, 2015; Perez-Torregrosa, Diaz-Martin, & Ibanez-Cubillas, 2017). Wang, Lin, Han, & Spector (2020) study used the Tobii X120 remote eye tracker tool to track the students' eye movements to know the watching duration and their attention to the added cues on the short instructional videos. Results found that students had more concentration on the areas focusing on cues in the videos and they performed better with the retention tests and assimilating necessary information.

From the review of existing literature, the researchers revealed that, though several types of research discussed on video-based learning, support systems, and tools, no research has been focused on the essential inside parts with the meaning of video content and providing content based on learners' attention and retention viewpoint along with analyzing video watching history and most watching parts. This research aims to fill this gap.

In addition, usual YouTube and traditional systems use overall watching history and general tags for videos and recommend similar videos. However, they do not analyze and consider deeply inside the video contents and do not consider the learner's learning process and progress point of view. In this case, VART has the potential to find learners' specific interests and unique support for them in the self-directed video learning environment.

PROPOSED METHOD

The main research will follow the five phases of the ADDIE model from the beginning to the end of the task as a framework in analyzing, designing, developing, implementing, and evaluating the VART system in the proposed platform. For the scope of the study in this paper, we have followed the design method based on the analyzed problem from HCPs' video learning characteristics and demand. However in the design method, we have defined the requirements of the system/functions to be developed to resolve the problems. In this design phase, the research has provided the design structure/architecture of the five conceptual models for VART. The models are i) VART overview model ii) domain model, iii) learners' model, iv) e-teaching strategy model, and finally v) integrated VART function model with the domain model, learner's model, and e-teaching strategy model in the LMS.

PROPOSED SOLUTION

Based on the available literature and the statement of problems, this study draws some tentative solutions. Table 1 describes how to address the research problems followed by proposing the VART system.

Table 1. VART problem-solving approach

Problems	Solution Method	Tentative Model	Final Model
Diversified content: Numerous video contents, a variety of contents on the same topic.	Tracking viewing history of previous learners, Analyzing focused part, sequencing video content	Learners' model	
Content specification: Long video, busy schedule, learners' concentration.	Analyzing video content and fraction of content	Automatic indexing in the domain model	VART
Learning behavior: Different learning process and progress among learners.	Analyzing the attention and retention of the learning process	Learners' model & e-teaching strategy model	

The VART is one of the latest tools which can instantly conduct content moderation across a huge amount of data and filter a user's viewing history and preferences very quickly and efficiently to aid in self-directed video-based learning (Sagorika & Hasegawa, 2019). It can also detect the more specific parts inside the videos and put the automatic indexes or tags to represent the contents in a specific and meaningful way.

How VART Works

1. **Investigate of learners' interest:** The research has proposed the VART technique which can pick important videos from the huge data set. The VART analyzes significant attention and retention parts from the learning scenario, learning history from previous learners and pick up the important video sequence from the huge data set or different video sources and provide HCPs as a brief description. If learners feel, they need video contents, they can go through the actual learning resources.
2. **Analyzing content:** Many video service platforms including YouTube, provide viewing history of a certain video. However, only history data is not enough, because HCPs need to know not only about the video but also the essential parts inside the video. Besides, HCPs have different competency levels and learning behaviors too.

   In this case, the VART approach is to combine the domain hierarchy information, previous learner's video watching information, and add indexes, tags, or metadata for videos. The proposed VART can detect the number of the watching history of video content and time of the watching history of the specific part of the video, for example, the part of the watching history from 2 minutes to 5 minutes, etc. So, only such history data may be a popular part of the video, but if we add some indexes, tags, or metadata for inside video contents, learners can find the meaning of video content. For example, this popular part has this kind of content, i.e. from 2-4 minutes, the introduction of COVID-19, 4-10 mins precaution exercise, or something. If we have such indexes for videos, not video files, but tags for each timeline inside videos, users can easily understand the essential parts with the meaning. One of the strong points is the VART function with automatic indexes to detect the more specific parts inside the videos and put automatic indexes or tags to represent the contents in a specific and meaningful way. So, these functions are included in the domain model with the help of VART which we discussed in the Domain model section.

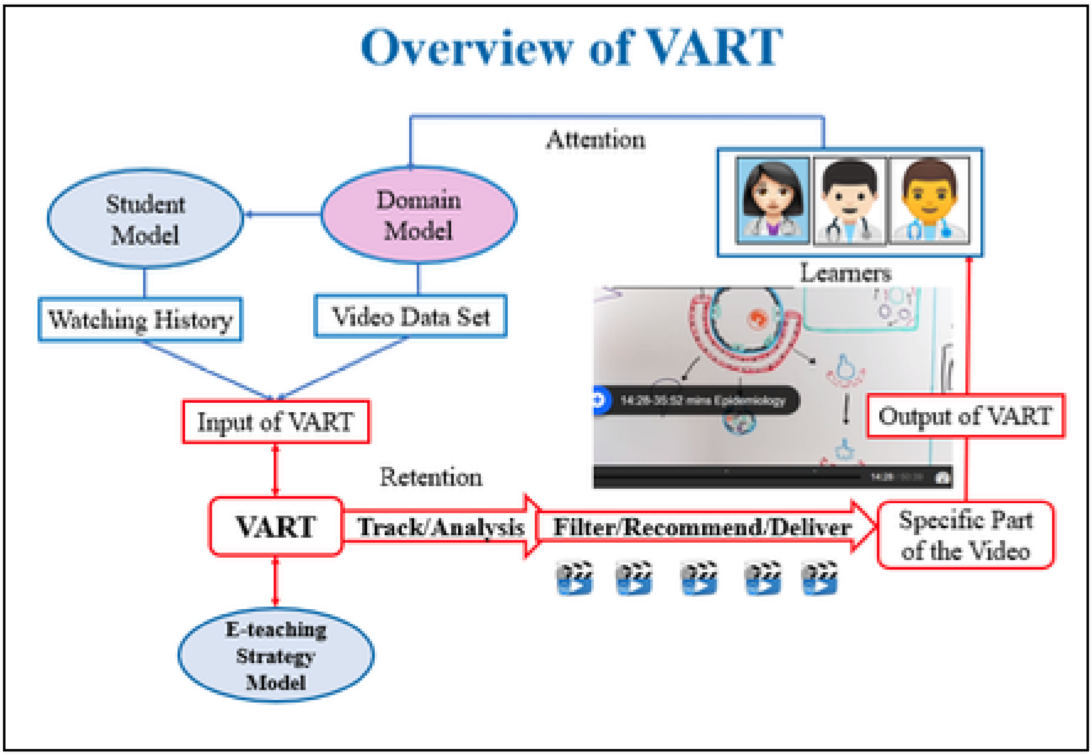


Figure 1. Overview of the VART Model

In figure 1, we have represented the main elements and final output of the VART system. As input data, VART uses video data set and learners' watching history from the domain model and learner's model. After that, it tracks and analyzes videos based on the learner's attention and retention process. In this figure, attention indicates learner's choices or preferred topics or expected parts inside the videos, and retention indicates the remembering process or learning process of a learner. However, after analyzing the input data it filters, recommends, and delivers specific content to the learners considering different strategies. The detailed functions are described in the components of the VART section.

3. **Tracking learner's behavior:** In the proposed platform, the VART will first detect each learner's ID and then track what type of contents they are seeking; this is called attention. At the same time, it will follow the learner's learning duration and repetition of watching, their comments, their weakness, or intentions, which is considered as retention or remembering process. The approach is that, if the system could know the tendency of each learner, someone focuses on the first part of the video, other focus on the middle or, last part, or all of them. Based on such a learning process and progress, the system could change the way to show the video.

Thus, the system can recommend which part is essential using such watching characteristics, attention, and retention process. Accordingly, it can filter contents based on learners' preferences, learning behavior, and competency level, which we consider as learners' models and suggest/provide the expected videos, which we consider as an e-teaching strategy model for this system.

COMPONENTS OF VART

Based on the above discussion, how to create such kind of domain information to the videos and how to analyze the videos and how to provide the support for the learners with the support of VART, these three parts are considered as the main functions for this paper. We explain these primary functions to clarify the design phase of the domain or video model, student model, e-teaching strategy model, and relationship with VART with these three models."

Domain Model

The Domain Model is an organized and structured knowledge of a given course, subject, topic, or problem. In some literature, domain models are also described as domain hierarchy, expert model, knowledge model, target model, etc. (Abdelsalam, 2014). A traditional domain model generally uses the vocabulary of the domain and represents the key concepts of the specific domain and identifies the relationships among all the entities within the scope of the domain. Simply this kind of domain model introduces a visual representation of the contents and their inter-relationship, which helps learners to easily navigate their desired subject, topics or learning objects, etc. (Brown, 2014).

In the proposed domain model, different types of medical courses could be designed and structured based on the learning requirements of the HCPs. In the traditional video domain, video contents are arranged by different subjects, and topics and contents are displayed sequentially one after another. Generally, it focuses on video content management and control. However, in the proposed domain model, it has the traditional features with extended features of VART, which made the video content more specific and learners centered. These features include the content moderation process among a huge amount of data, control inside of the video, provide adaptation with the uses of indexes to identify important parts with meaning, along with the track, analyze, filter, and recommendation attribute based on learner's requirements. Moreover, we use the H5P interactive content plugin integrated with the Moodle to create, modify, rich and interactive video contents in the domain ("H5P," n.d.). However, we have designed a sample domain or content model based on the main course COVID-19, since this is the ongoing emergency topic for the HCPs as well as all the people over the world at this moment. In our proposed system, VART relates to the domain model through Moodle LMS. In the medical and healthcare field there are huge video resources on the web. So, VART first analyzes learning history from previous learners and significant attention and retention part from the learning scenario and picks up the important video sequence from a huge data set and represents the video with a brief description. So before watching the whole video, HCPs can decide whether the video is important or not, and it saves time. The VART also analyzes inside the video contents and identifies important parts in each video and puts automatic indexes or tags so that learners can easily pick up the most important part first. There are some approaches to put automatic indexes inside the video. For example, VART can apply the Natural Language Processing (NLP) to automatically detect the rough contents to get keywords from the slide data used in the videos, and title and subtitle of the video, and can create some basic meta-data for each video part. Another function is if learners make comments for the video, the system can detect such text data as a part of the indexing to provide the meaning of that content. However, figure 1 shows the VART connection with the domain hierarchy and at the bottom level shows how it represents the short description of the video and how it analyzes and represents important parts in single video content. Detail description is given in figure 2, and in images 1 and 2.

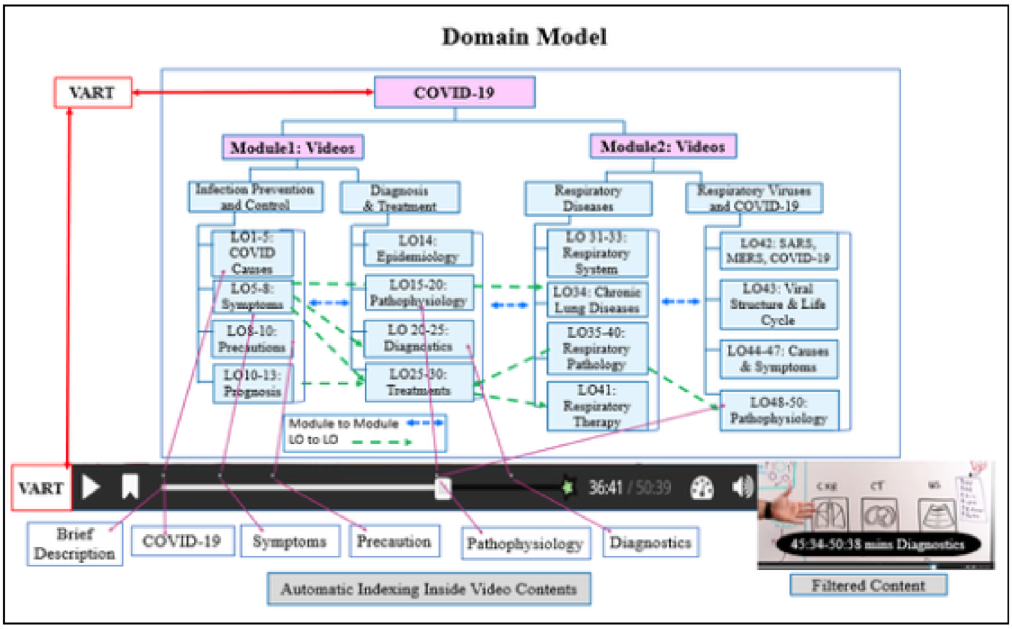


Figure 2. Domain Model

Figure 2 also shows that, in the domain model, there may have different domain hierarchy based on different subjects or topics. However, in the case of self-directed video-based learning, HCPs should have enough flexibility in their learning. They can choose different topics and sub-topics which are known as Learning Objects (LO) from different modules as they wish. For example, any HCP can learn the 'causes' and 'symptoms' of COVID-19 and then move to any module and any topic they like. In the domain hierarchy, contents are inter-related with module to module and LO to LO. The blue arrows show the connection among the module to module, and the green arrow shows the connection among LO to LO. In the VART supported domain model, the video contents summary is provided along with the duration of each fraction. So, learners can easily choose their desired parts for view.

Image 1. Brief description of the video

Image 2. Automatic indexing inside video

Source: *(Nerds, 2020)*

Image 1 shows a brief description of 50 minutes and a 39-second video at the beginning with the essential parts of the video. Image 2 shows the sample automatic indexing representation inside the video with meaning and time duration. So, it is easy for the learners to determine whether the video is important or not and what are the essential topics available inside a long video.

Learners' Model

Modeling users in e-learning is an essential part of designing adaptive e-learning systems. Shyamala, Sunitha, & Aghila (2011) stated that the learner model is used to modify the intersection between system and learners to suit the needs of individual learners. In principle, effective learners' modeling helps to select suitable teaching strategies based on learners' knowledge as well as selecting content relevant to learners' competency. Learners' model serves as a knowledge source in an intelligent system covering different aspects of learners relevant to learners' learning behavior. More specifically, the learners' model represents information on learner's domain knowledge, goals, preferences learning process, learner's progress, and other information about the learners. This information can be obtained from the learner's profile and a pre-assessment questionnaire filled by the learner at the beginning and tracking and analyzing learner's activities in the system.

There are different approaches to designing learners' models in an e-learning system. However, three conventional approaches are an overlay model, stereotypic model, and the perturbation model. The overlay model represents a student's problem-solving approach in a particular domain on a modular basis. Brusilovsky & Millan (2007) stated that the overlay learners model represents learners' model as a subset of the domain/ expert knowledge. Shyamala et al. (2011) described that based on the domain model learners model consists of the value of an assessment module of a particular concept. This value may be binary (0 – does not know or 1 - know) and a categorical variable (low, medium, high).

On the other hand, the stereotypic of learners modeling represents a frequently occurring behavior of learners. In this approach, learners are assessed based on their performance on a predefined stereotype set by academic experts (fixed stereotype), or learners are stereotyped to a default initial setting, and the learning process proceeds to replace individualized settings based on performance data. In the perturbation or buggy approach, the learner model caters to the knowledge possessed by the learner that is not present in the expert domain knowledge (Brusilovsky & Millan, 2007).

Based on the learning style of HCPs, this study designed a learner's model following overlay approaches. Figure 3 illustrates the learners' model of the HCPs.

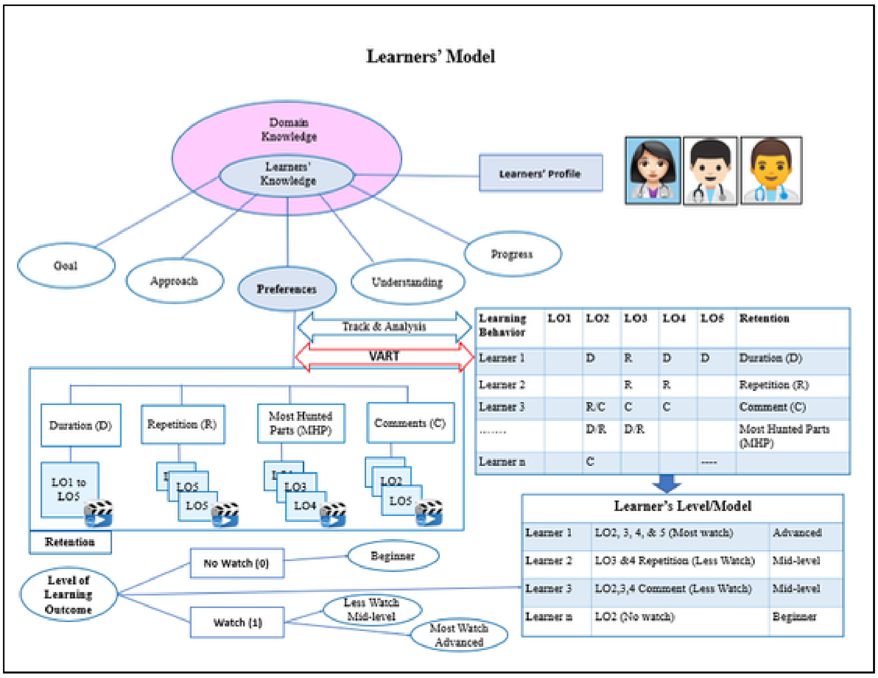
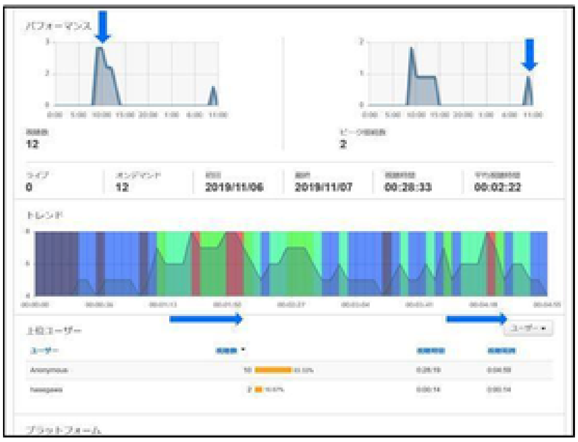


Figure 3. Learners' Model

HCPs have different backgrounds, goals, approaches, preferences, understanding, etc. Based on the preference, HCPs may watch some videos from the domain as retention and system get the learner's model based on watching duration, repetition, most watching parts or comments, etc. This is considered as learner's behavior on the Learning Objects (LO). The learners' model basically indicates the relationship between the domain model and the learner's activities. In figure 2, on the upper table, there are five learning objects, and how learners watch these objects is a retention process. Image 3 and 4 are the visual examples of learners' retention process. This process could be applicable for a certain learner or other learners or groups of learners; for example, 'the watching duration'. One learner may watch LO1 10 minutes, LO2 0 mins, LO3, 0 mins, LO4, 5 minutes something like that. Other learners may watch in a different way. Based on learners' preference system can recommend the next videos.

Besides, the level of learning outcome is determined on whether HCPs watch a particular video or not. If any HCPs do not watch a certain video, VART will identify him/her as a beginner, if someone watches the video, VART system will calculate total number of watching videos, watching duration, repetition, important parts and will identify as a mid-level or advanced learner.

However, image 3 shows the visualization of a single learner's retention history on a five minutes video. The learner watched the video twice. The blue arrows on the top indicate the learner's most hunted parts, repetition of watching and duration of watching, and arrows at the bottom level shows the detail watching fluctuation history of the learner. Image 4 shows the visualization of a group of learner's retention history on a hundred minutes video. The blue arrows indicate the most preferred or most important parts watched by the learners in the video.



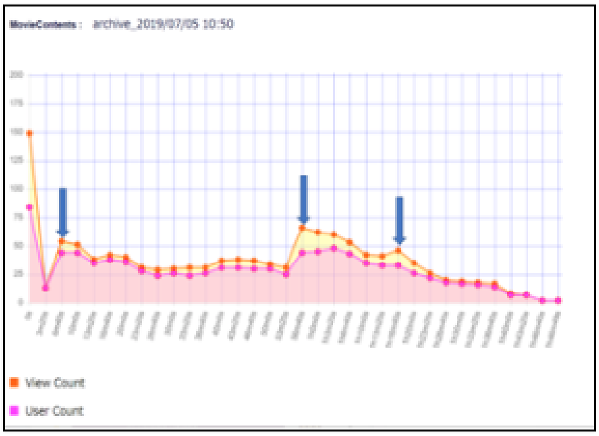


Image 3. Visualization of retention: single viewer **Image 4.** Visualization of retention: group viewers

Source: *("Lecture Archive, JAIST LMS," 2020)*

E-Teaching Strategy Model

The e-teaching strategy model represents the teacher's or instructors' plan on how to represent and teach each topic to the learners in an easy and understandable manner. Different teachers may have different teaching strategies, or teachers can apply different strategies to teach the same concept based on the learner's diverse characteristics and learning needs (El Bachari, Abelwahed, & El Adnani, 2012). In the proposed system, the e-teaching strategy method is determined based on the combination of learners' model and domain model data and depending on the characteristics and learning behavior of the HCPs in the self-directed video-based learning. The VART system will combine HCPs' watching history data including content preferences, watching duration, repetition, most important or most hunted parts, and other information from the learners' model and domain model and decide the proper recommendation. So, the system can propose different strategies combining different parameters; for example, contents preference, and most hunted part, content preference, and watching duration, watching duration and most hunted part, most hunted part and repetition of the video or less watching and no watching, etc. The e-teaching strategy model of VART is illustrated in figure 4.

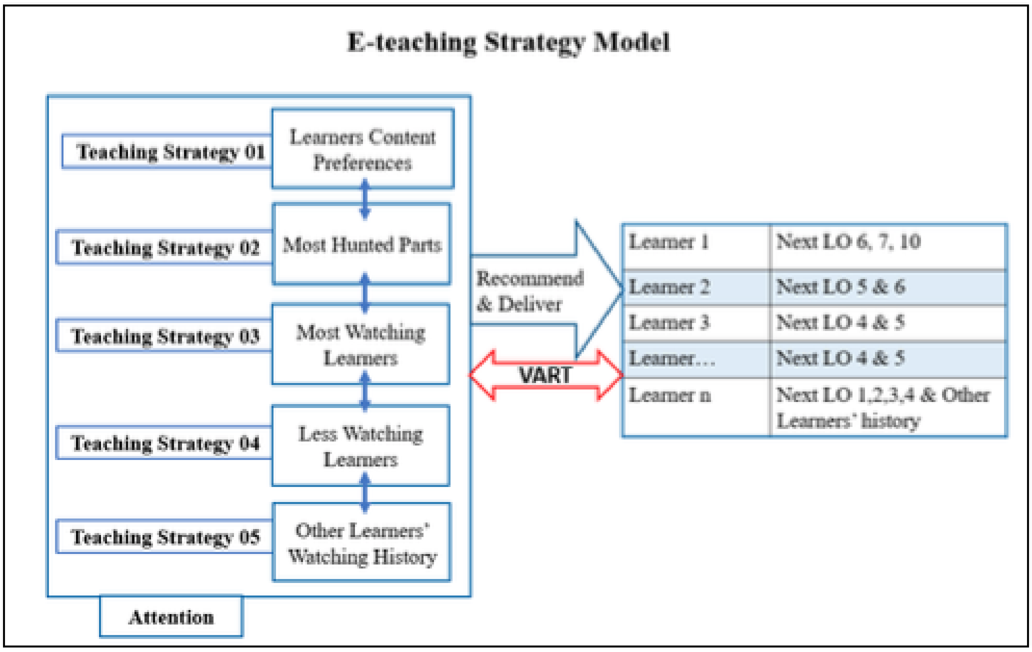


Figure 4. E-teaching Strategy Model

In the e-teaching strategy model, the system will provide mainly five approaches to the recommendation. Figure 4 shows, (i) it will receive learner's content preferences data, (ii) most hunted parts, (iii) most watching learner, and (iv) less watching learner's data. Based on these different characteristics and attention approaches, it will filter or recommend and deliver different content to the different learners depending on their levels. The fourth approach is to use other learners' information. If a similar level of other learners watches a certain part in the video, the system will recommend it. For example, everyone watches LO4, but the certain beginner did not watch LO4, in that case, LO4 should be recommended to that learner. If in case, for some content, there is no other learner's data, in that case, the system can recommend based on learner's preference data. Another example is, if some learners are specialists or advanced learners for COVID-19, they can skip the COVID-19 basic contents. If others watch many times, but if they are specialists, they can skip it.

PROPOSED INTEGRATED VART FUNCTION MODEL

Figure 5 represents the integration of VART functions with different models on the LMS. The VART model has a three layers structure, including the domain model, learners' model, and e-teaching strategy model. With the assistance of VART, the domain model displays the important contents, important parts with the meaning of the videos, and learners watch some videos as retention and system get the learners' model based on the duration or repetition or comments or other information. This is considered the learners' behavior on the learning objects. The VART also assists the e-teaching strategy model to receive and combine data from the learners' model and the domain model and know the learner's attention and retention process. Accordingly, it proposes strategies, using the parameters on learners' model and learning objects. Thus, figure 4 demonstrates that the three models are included inside the VART, and the learning process from LO to the learners is retention, and system filters or recommend the contents add attention. Hence, these functions are major VART functions and are a part of the LMS.

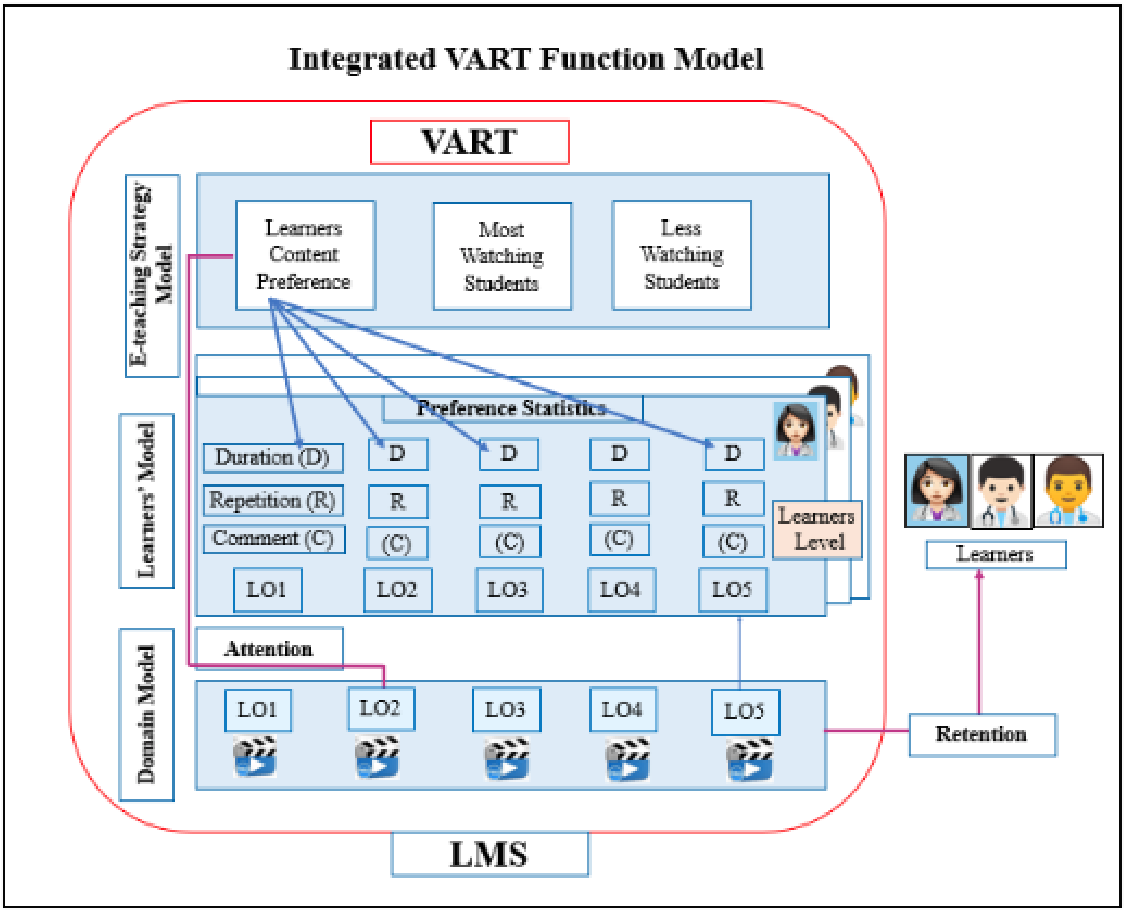


Figure 5. Integrated VART Function Model

CONCLUSION

The learning process, based on simply watching the videos, is too general and cannot fulfill the learning requirements in the modern video-based learning environment. To meet the diverse needs of the HCPs and save their time in video-based learning, they need a learner's centered video watching mechanism. In addition, there are a variety of video contents on the same topic in different sources. Most of the existing web-based video content indexes are equipped with What To Learn (WTL) point of view but not How To Learn (HTL) point of view (Hasegawa, Kashihara, & Toyoda, 2003). Accordingly, this research proposed VART which will track users' video seeking and usage trends and provide appropriate video content. To achieve the scope of this study, we have proposed three models as follows: the domain model integrated with the VART systems will represent the content hierarchy of each video content, show the important videos on a certain topic, and represent the essential parts inside the video with meaningful indexes. As a result, HCPs will be able to find their expected contents within a short time and pick the important parts inside the video quickly. The Learner's model addressed in the VART will represent the retention process of each learner and his/her learning behavior on the learning objects, which will lead to estimate the level of the learner and create the learner's model. The e-teaching strategy model deals with the attention or preferences data from the learners' model and domain model and proposes recommendations for each learner. So, learners' model and e-teaching strategy model will assist learners based on their learning process and progress and provide adaptation in the self-driven video-based learning system. Hence, the VART function includes three models, and, in the retention process, the system makes the learner's model, and in the attention process, learners use the strategy model and the domain model is the base of the system. Finally, VART functions, including all models, are part of LMS.

FUTURE WORK

In this study, the proposed VART model is designed based on the theoretical framework of different conceptual models as well as the learning behavior of HCPs. Now, the research will develop the actual VART framework, including implementation guidelines. In doing so, the researchers will follow the ADDIE model for the actual implementation. The researchers will also customize the Moodle platform for the adoption and implementation of VART. After the successful implementation, the research will collect system-generated output for the evaluation of the proposed model. The finding of the development and implementation phase, along with difficulties faced and other issues, will be presented in the next paper.

In addition, the final model will include more adaptive features so that it could easily incorporate with other video-based teaching and learning systems. For example, the VART model could be used for enhancing disaster survival skills among international students or creating adaptive video-based learning support for delivering content from university lecture archiving systems. In this case, the target learners are different, their way of learning and teaching strategy may have some additional requirement with the common features. So, one of the next targets is to modify the VART system based on such kind of requirements and make it more flexible to support any kind of video-based teaching-learning platform including different types of video-based distance learning systems.

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