Personalized Microlearning Resources Generation and Delivery: A Framework Design

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ABSTRACT

The evolution of digital technologies is leading the world towards the direction of the information explosion. It gradually increases the difficulty for the people to find appropriate content to learn. It has becoming a norm whereby people often use their fragmented spare time for learning. It leads to the motivation to look for a solution to boost up the learning effectiveness. Microlearning serves as a service to generate and deliver microlearning resources to the learners. However, it is also challenging to convey the microlearning resources to each learner based on different learning needs. In this paper, a personalized microlearning framework named "Unique-Learn" is proposed. It possesses the intelligence to identify the real learning needs of a learner based on the contextual information, then conveys the appropriate microlearning videos to the learner from time to time. The proposed implementation plan details how the "Unique-Learn" will be used in a workplace environment for the employee's training and development purpose.

Keywords: personalization, microlearning resources, adult's learning

I INTRODUCTION

Along with technology advancement, people could easily use mobile devices to browse online learning resources for different purposes. Especially for adult learners, they could always look for learning materials that aid in their workplace or self-development during their spare time. The norm that people using their fragmented time to undergo learning leads to the research gap on how the learning effectiveness could be enhanced when the learner's learning duration is fragmented and flexible (Lin et al., 2019). Thus, microlearning comes into plays to adapt to this lifestyle. Sun et al. (2016) also pointed out that short-term learning processes cover the period from a few seconds up to 15 minutes to ensure no information overloaded and retain the learning engagement.

However, the explosive online learning resources gradually lead to the issue whereby a learner may not find appropriate microlearning materials from the Internet since the online learning resources could be represented in various formats. Besides, it is also challenging to personalize the delivery of learning content to each learner due to different learning needs. Lin et al. (2019) conducted a survey on the overall workflow of microlearning services which comprises three main aspects: 1) Segmentation Process; 2) Annotation Process; and 3) Recommendation Process. However, there is lack of a complete personalized microlearning framework that depicts the overall architecture for practical implementation.

Based on the issues mentioned as above, a personalized microlearning framework named "Unique-Learn" is proposed. It aims to generate microlearning resources and deliver them to the learners based on unique learning needs. "Unique-Learn" is designed from the perspective of the microlearning resources providers. The paper's contributions as follows: Firstly, the microlearning resources are generated by identifying "micro-friendly" learning objects from various online resources. Then, the delivery of microlearning resources will be personalized based on learner's data. The overall architecture of "Unique-Learn" is presented for future practical implementation. The activities involved in microlearning resources generation and personalized delivery are described in detail.

To summarize, learning is a life-long process. Especially as adults, they should continue to learn new knowledge or skills to ensure always compatible in this rapidly evolving world. In the past decades, learning activity is usually conducted physically. However, the advancement in technology nowadays has bridged the knowledge and the learners regardless of time-space restrictions. In the year 2020, online learning seems like an inevitable solution to ensure everyone can continue to learn in the Covid-19 pandemic wave. With "Unique-Learn", the learning experience for adult learners is expected to be leveraged. The rest of the paper has been organized as follows: Section II discusses the related works about adult's learning theory, microlearning service, and personalization in the learning domain. The methodology and proposed solution are presented in Section III and IV. Conclusion and next research plan are described in Section V.

II RELATED WORKS

In this section, the learning theory is discussed as the building block of a personalized microlearning framework for adult learners and the general microlearning service workflow is described. A personalized microlearning framework will be proposed to resolve the research challenges in the existing microlearning workflow.

A. Adult's Learning Theory

Before a comprehensive learning ecosystem can be constructed, learning theory is vital to be the building block to support the learning needs. Knowles' Theory of Andragogy is the art and science of adult learning (Pappas, 2013). Based on Knowles's Theory, the characteristics of an adult learner are described as the following points, as stated in (Pappas, 2013):

- **Self-concept**: Adults are self-direct in learning.
- **Experience**: Adults gain experience as they grow.
- **Readiness to learn**: Adults are ready to learn new knowledges.
- **Orientation to learning**: Adults can change their perspectives from procrastination to new learning interest.
- **Motivation to learn**: Adults are motivated to gain new knowledge as they grow.

Based on the adult learners' characteristics, the learners are motivated to learn by internal incentives, such as the self-esteem or the desire to grow. In the current online learning trend, it is a common practice for people to obtain open online resources from the platform like YouTube when they are ready to gain new knowledge.

To summarize, adult learners can be interpreted as individuals which having a clear understanding of their learning objectives, driven by their internal incentives to grow. They will continue to learn based on personal interests and needs. Zhu (2020) has pointed out several use cases about how adults are self-directed in learning. In conjunction with the adult learning theory, microlearning could be the catalyst to boost the overall learning effectiveness in a learning ecosystem.

B. Microlearning

Microlearning refers to the learning mode with small chunks of learning objects within a short-term period (Kovachev et al., 2011). The learning process should cover the period from a few seconds up to 15 minutes to retain the learner's attention and ensure no information overloaded. Generally, the microlearning concept could be imposed to adapt to the norm whereby the learning time of the learners is irregular and fragmented. To support microlearning activities throughout the learning path, Lin et al. (2019) has outlined the microlearning service workflow into three essential phases: 1) Segmentation; 2) Annotation; and 3) Recommendation.

Segmentation process. It is the first step to classify microlearning content from the massive online resources. Short video is the most common among learners (Guo et al., 2014; Anderson et al., 2014). In (Lin et al., 2019), the authors describe two segmentation strategies for videos: the content-based and the user's interaction-based segmentation strategy.

- Content-based: It focuses on the segmentation of the learning object itself, machine learning algorithm such as Optical Character Recognition (OCR) or Automatic Speech Recognition (ASR) is applied to extract the textual metadata. To be specific, study in (Baidya & Goel, 2014) has explained the methodology used to capture the key frames of a learning video and extract the textual information in the scenes using OCR. However, the study also pointed out that sometimes content-based segmentation could be error-prone as some of the texts with artistic fonts are difficult to be recognized.
- User-interaction-based: It focuses on the learner's interaction such as watching behavior to reflect the point of interest and the fitness of learning content. However, the cold start issue is always a challenge to a new learning ecosystem because the involvement of the users is low at the beginning.

Annotation Process. It represents the interpretability of learning objects so that it can be understandable for both machines and humans. For instance, the tag, title, and metadata could be used to annotate the semantic information of a learning object. Generally, annotation strategies can be classified into different types such as:

- Crowd-wisdom-based: It allows the learners to annotate the important points of a learning content (Risko et al., 2013). The annotation result could be used to determine the content fitness and detect off-track learner. However, sometimes the annotation result might not converge as there is no restriction on the tagging strategy.
- Model-based: A trained model with algorithms to annotate the learning objects is depicted in (Dessì et al., 2018). Since a learning object can be presented in various formats, the trained model is required to always be updated on its algorithm from time to time to retain the algorithm's precision.

Recommendation process. It describes how microlearning materials can be conveyed to the learners quickly and precisely. The effectiveness and efficiency of the recommendation process can be verified based on the ability of a recommender system to memorize a learning behavior of a learner and generalize similar finished learning paths for a certain group of learners with similar learning requirements. For examples, the recommendation strategies as follow:

- Ant Colony Optimization (ACO): A finished learning path by certain groups of learners who have similar learning goals and requirements can be reused (Zhao et al., 2016). However, ACO might suffer from the cold start if it is implemented in a new learning ecosystem.
- Transferred Learning: It makes use of the knowledge gained from the other domains to resolve a similar problem in the relevant domain. The missing user-rating values in the target domain can be filled with a similar recommendation decision. Yet, knowledge from other domains might not be appropriate transferred to the learning domain due to the pedagogy issue like prerequisite knowledge (Wu et al., 2015).
- Context-Aware: It utilizes the similarity of contextual information such as location between a learner and his/her friends to define the recommending result. Yet, the generic contexts such as geo-location is not sufficient to personalize the delivery of learning resources precisely because a group of learners with different learning ability may share similar geo-location.

Based on the review done in the three essential parts of the microlearning service, the drawbacks of each strategy have been summarized. First, there is a shortcoming in the segmentation process whereby the approach to segment the learning resources using machine learning techniques may be error-prone, and dependency on the user's interaction to classify the learning resources could suffer from the cold start. Second, the approach to use pre-defined rules to annotate semantic information of learning resources could be labor-intensive. Third, the generic contextual data of the learners is not sufficient to determine a learner's needs. Hence, these shortcomings mentioned above will be resolved in the proposed framework.

C. Personalization in Learning

Personalization in learning advocates that a learner's characteristics influence the way that they engage in learning environments and the outcomes that are obtained (Walkington & Bernacki, 2020). The learning pace, ability, surrounding environment, and behaviors can act as vital contextual information to determine a learner's learning path or goals. The context value can be retrieved from either the user's input or the user's interaction from time to time. Especially for adult learners, they are self-directed to learn and have a clear understanding of the learning objectives. Thus, adult learners' characteristics and behaviors are sufficient to reflect on how they want to personalize their learning process. Table 1 describes the data sources that can be used to personalize learning process, as stated in (Lin et al., 2019).

Table 1. Data Sources for Personalized Learning

Data Source	Utility/Description
User-item rating matrix	Use of user's historical rating.
Content Information	Use of content format and semantic information.
User's interaction	Use of user's behavior to design learning path.
User's profile	Use of user's characteristics such as age and learning interests.
Contextual Information	Use of prerequisite knowledge, time, location, or anything in learning activity for decision making.

From the perspective of the content provider, the work to impose personalized learning is challenging, especially in the aspect of learning resources delivery due to unique learning needs. In the learning domain, contextual information like prerequisite knowledge is more important to determine the personalized recommending result (Wu et al., 2015).

In a nutshell, the learning theory, concepts, and existing challenges have been discussed in this section. Hence, a microlearning framework named "Unique-Learn" is proposed to personalize the microlearning resources generation and delivery. With "Unique-Learn", a hybrid approach will be introduced to classify and annotate the learning resources based on data mining techniques and the user's interaction. Besides, the difficulty to personalize the delivery of learning resources is aimed to be resolved by using specific contextual information such as the learner's prior knowledge instead of generic contexts like age or geo-location. "Unique-Learn" is expected to be implemented in the workplace environment for evaluation.

III METHODOLOGY

In this section, the activities involved in "Unique-Learn" to personalize the microlearning resources generation and delivery will be discussed. The activities can be categorized into three main phases: 1) Segmentation; 2) Annotation; and 3) Recommendation. Meanwhile, the employee training and development related learning content will be used as an example of data input to provide a better understanding of how to implement the "Unique-

Learn" framework. Figure 1 illustrates the activities in sequence for the "Unique-Learn" framework.

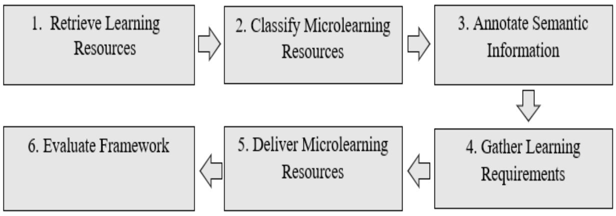

Figure 1. Activities In "Unique-Learn"

1. Phase 1 - Segmentation Process.

For the first activity (Activity 1), the video-based learning resources will be used as the input of the "Unique-Learn" framework since the video is the most common learning object format (Guo et al., 2014; Anderson et al., 2014). YouTube learning videos are used as the source of learning materials as it is a video-centered platform that is able to provide free-to-use learning materials continuously for non-commercial use (Airoldia et al., 2016). The YouTube Data API will be used to obtain a generic list of employee training and development learning videos by querying the results with employee training and development related keywords.

In Activity 2, two strategies are implemented to classify the learning videos from the generic list of videos. First, the content-based strategy is applied. The glossary items defined in (Training Industry, 2020) have been referenced as the representative of different learning content categories. Then, the video's title, tag, and metadata are used to classify the videos into different learning categories. The identification of microlearning videos is depending on the video length. Specifically, learning videos that cover a period from a few seconds up to 15 minutes will be categorized as microlearning resources. Then, the user's interaction strategy is applied. The re-watch rate is used to determine the fitness of the microlearning video. If a video has a low watching rate, it will be eliminated from the list of qualified microlearning videos even though the video length fulfills the micro-learning concept. A hybrid approach is applied to segment the learning videos and improve the overall segmentation process accuracy.

2. Phase 2 – Annotation Process

The annotation of microlearning videos is performed in Activity 3. Besides defining the video's based on its title or metadata, Natural Language Processing (NLP) is used to extract the semantic information from the video's keyframes and audio. So, a model that comprises the algorithms to implement NLP is constructed. Idea from (Dessì et al., 2018) is adopted, which is to use the Speech-to-Text and NLP Tools such as IBM Watson's suite to translate the spoken language in a microlearning video from an audio signal to textual information since the study has demonstrated a mature solution to annotate a learning resource based on keywords and concepts (Lin et al., 2019). Then, the extracted video keywords are mapped to the glossary terms such as *Agile, Compliance Training, and Leadership Development,* which had been defined in Phase I. As a result, all microlearning videos are organized based on its topic and ready to be delivered.

3. Phase 3 – Recommendation Process

Activities 1 to 3 are executed for microlearning resources generation. The next two steps are executed for content delivery. The learner's needs, ability, and prior knowledge are determined in Activity 4. A learner is required to fill up a questionnaire to define some static user's data, such as the topic of interest and profession before they learn. This approach will help to tackle the cold start issue in a new learning ecosystem for the first-time recommending result. The recommending result will be fine-tuned from time to time when the user's interaction increased.

The microlearning videos are delivered to the learners based on the user's contextual information in Activity 5. The Context-Aware Recommendation strategy will be applied. A context-aware predictive model will be constructed based on Random Forest machine learning algorithm. This is because the algorithm provides a high accuracy recommendation result (Dessì et al., 2018). In the model, the default context has been defined as follows: content topic, content publisher, and prior knowledge. The different types of contextual value will be transformed into a numeric value and fed into the machine learning classification technique. From the contextual value, the model predicts the next potential microlearning videos for the learner. The content delivery can be personalized by using the specific contextual information like prior knowledge instead of the generic context, such as similar learning requirements from the other learners.

Activities 1 to 5 are executed sequentially to realize the personalize microlearning resources generation and delivery. The ability of "Unique-Learn" to personalize the generation and delivery of microlearning resources is evaluated in Activity 6. The completeness of the framework is evaluated based on the research motivation and reflected by the learner's satisfaction and learning outcome effectiveness. The proposed framework is designed to provide the learning videos to the learners in micro-formed. Then, the framework should suggest appropriate microlearning videos to the respective learners based on the user's contextual information. Moreover, the complete framework must be able to be applied in a use case.

IV PROPOSED SOLUTION

In this section, the overall architecture and implementation plan of "Unique-Learn" are elaborated. Figure 2 illustrates the overall architecture of "Unique-Learn".

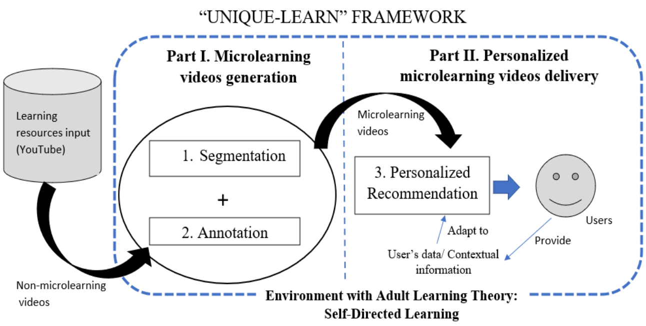

Figure 2. Architecture Of "Unique-Learn".

The architecture of "Unique-Learn" is combined from two parts: Part I is focusing on the classification and interpretation of the learning videos obtained from YouTube to generate the microlearning materials. The output from Part I is the micro-formed YouTube learning videos which serves as the data source for Part II. Part II describes the action to convey different microlearning videos to the learners based on their contextual information such as the topic interest, the learner's favorite content publisher, and the prior knowledge on the certain learning topic. Since the overall "Unique-Learn" framework is built on top of the Self-Directed adult learning theory, the target learners will be mainly adults and we assume that the learners take responsibility for what they want to learn. Specifically, the learner's contextual information clearly defines the learner's needs.

The implementation plan of the "Unique-Learn" framework is presented as follow: First, learning videos will be extracted from YouTube by querying the employee training and development related keywords. The initial set is 500 videos as it is the maximum number of items returned based on YouTube API (Airoldia et al., 2016). Then, the initial set of videos will be segmented and classified into microlearning videos. To annotate the topic represented in the microlearning video, the semantic information from the video will be extracted by using the NLP technique and mapped with the video's tag, metadata, or title. When the user's involvement is sufficient in the learning ecosystem, the user's re-watch rate on microlearning video will be identified to determine the fitness of the content. The criterion to classify and annotate the microlearning video is based on the video length to represent micro-content, the metadata to annotate educational topics, the semantic information from the video content, and the learner's rating to evaluate content fitness.

When the generation of microlearning videos are completed, the appropriate content will be delivered to the learners by using the Context-Aware Recommendation strategy. Since different learners may have different learning needs, the learner's contextual information is essential to predict the next required microlearning video for the learners. In the "Unique-Learn" framework, the default contexts have been defined as follow: content topic, content publisher, and prior knowledge. Given the contextual information, the microlearning videos that are closely matched to the contextual value are identified.

In a nutshell, the overall architecture of "Unique-Learn" is presented and the vital contextual information that describes a learner is identified. Next, we evaluate "Unique-Learn" based on the Kirkpatrick's Learning Evaluation Model (Kirkpatrick & Kirkpatrick, 2006). We perform the Level 1 Evaluation: Reaction to reflect the learner's satisfaction towards the "Unique-Learn". Survey questionnaire is used to evaluate how the learners feel about the learning process through "Unique-Learn". For example, we gather the learners' feedback to assess the ability of "Unique-Learn" to provide appropriate microlearning materials to different learners throughout the learning journey. Then, the Level 2 Evaluation: Learning will be evaluated using the post-learning quizzes to understand the knowledge gained by the learners.

V CONCLUSION

"Unique-Learn" facilitates the adult's learning process in this digitalized era by capturing and managing knowledge with microlearning and personalization concepts. In this paper, the related works on microlearning services and the shortcomings in each process have been discussed. "Unique-Learn" has been proposed as a comprehensive microlearning framework. It possesses the intelligence to identify the real learning needs of a learner, then conveys the appropriate microlearning videos to the learner from time to time. Meanwhile, the overall architecture and essential activities in "Unique-Learn" have been described in detail for future practical implementation. "Unique-Learn" aims to achieve the objectives whereby the learner can obtain microlearning videos and receive learning resources that matched the learning needs. As there is a lack of practical implementation of the personalized microlearning framework, "Unique-Learn" will be implemented in a workplace environment to evaluate the learning outcome effectiveness and the learner's satisfaction to receive appropriate learning resources based on the contextual information. Based on the practical work, the shortcomings, and possible future extensions of "Unique-Learn" can be identified.

ACKNOWLEDGEMENT

This work is supported by funding of Fundamental Research Grant Scheme (FRGS), from the Ministry of Higher Education Malaysia.

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