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Context aware adaptive mobile learning framework for bottom of pyramid people (BOP)

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ABSTRACT

When the learners are truly interested in learning, they learn faster, participate actively, and they pull knowledge. Unlike school education, adult learning mostly occurs with the initiation of the adult learner, and they then pull the relevant knowledge. Vocational education is the master key that opens the door to the economic and social development of a country and it provides an opportunity for Bottom of Pyramid people (BOP) to acquire a sustainable livelihood. Due to many difficulties and commitments of their lives, BOP people are not engaging in a continuous learning process. Since there are many adaptive mobile learning systems available, there is no proper mechanism to achieve the sustainable livelihood of BOP people through vocational education which is tightly coupled with their lifestyle and motivates them to get in learning activities. The context aware adaptive mobile learning framework is an attempt to push vocational knowledge for Bottom of Pyramid (BOP) people, who are not ready to pull knowledge. In this paper, we present mobile learning content design, concept design, system architecture, Adaptivity components, the system implementation and evaluation of the system This system guides BOP people in their vocations through adaptive content delivery mechanisms using mobile technology together with vocational and motivational factors to educate the user in a transparent and non-resistive manner. Social science based models integrated into systems to carry out adaptive delivery of content based on the end user learning behavior, vocation, social and psychological factors.

1. Introduction

Bottom of pyramid (BOP) is the largest and poorest socio-economic group in the world. More than 2.5 billion people in the world, who live on less than $2.50 per day, fall in to the BOP category (London, 2008). BOP people represent 72% of the world's population and the majority of these people live in developing countries in areas like Asia, Africa, Eastern Europe, Latin America and the Caribbean (Confedration of Danish Industries, 2007).

In 2017, Sri Lanka's average Gross Domestic Product (GDP) growth rate was 3.9% (CBSL, 2018). Due to its relatively low GDP per capita, Sri Lanka is currently ranked in the bottom one third of the world. This can be traced back to the issue of poverty, specifically rural poverty. Over 80% of the Sri Lankan population lives in rural areas and this includes 90% of the poor people of the country (NFSL, 2019). A majority of the Sri Lankan population falls into the BOP category. These people are engaged in different trades such as farming, fishing, carpentry etc. The surveys that were conducted with these people, reveal that most of them are engaged in their vocation not because of their talent or interest for the field, but because of poverty or because they inherited the trade from their parents. They engage in their particular trade for the sole purpose of feeding their families, and this lack of psychological investment in their trade leads to many failures and results in very low revenue. Serving people in the BOP and achieving a sustainable livelihood remains a challenge. 'Voices of the Poor' is a study conducted by the World Bank, involving 20,000 poor women and men from 23 countries including Sri Lanka, to explore their perspective regarding poverty, wellbeing and ill-being. This study identified that poor people expect opportunities and not handouts. They are seeking

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opportunities that lead to better livelihoods (Narayan et al., 2000).

As a remedy, education is a key investment in human capital. It is imperative to develop vocational knowledge of the BOP sector in order to make a better contribution towards the economy. As they have passed the age of school education, what is most appropriate is the vocation related education that will empower them in their occupation or vocation. Vocational education enables BOP people to achieve a sustainable livelihood.

Adapting BOP people to a learning process remains a challenge. These people suffer from many economic hardships and they are unable to pay for the education. Another issue is that they live in rural villages that are geographically isolated from cities. They are not ready to obtain a formal education due to transport and economic hardships. They have a fear of entering the educational process. People in the BOP prefer not to engage in any learning processes. They lack interest towards learning and do not have confidence in their ability to learn. Most of them are of the opinion that they are not of an appropriate age for learning, and they are preoccupied with their day-to-day work and their children. These circumstances and hardships do not allow them to pursue an education. The proof of the above factors was evident in our survey (Irugalbandara and Fernando, 2015). We cannot use formal teaching and learning processes to deliver vocational knowledge to these people. One possible solution to this conundrum is the use of technology.

With the exponential growth of mobile technology; the mobile phone has become one of the best ways to reach individuals in the BOP sector. Koole (2009) argued that wireless networked mobile devices can help to shape culturally sensitive learning experience. He further states that, mobile learning offers the learner greater access to relevant information reduces cognitive load and increases access to other people and systems (Koole, 2009).

Since mobile phones are relatively cheap and they are multifunctional tools, interaction by mobile technology among BOP people has significantly improved. "The poorest households are more likely to have access to mobile phones than to toilets or clean water" (WBG, 2016). The number of people who use cell phones is increasing, mostly in the BOP market. The spread of mobile technology also affects the BOP people; they use mobile phones not only as a means of communication but also for computing, entertainment and a wide variety of services (Prahalad, 2004). According to a study on the use of mobile phones by rural poor gender perspectives from selected Asian countries, in Sri Lanka, mobile phone features are used by the rural in Sri Lanka as follows. Among them 85% used mobile phones to make a call and receive a call. Among them around 10% of people used mobile phones only for receiving calls. Only 40% used mobile phones to make, receive calls and send/ receive SMS. The study further revealed that the rural community use mobile phones as an indirect tool to connect with infrastructure and services that are not easily accessible, and the mobile subscription rate per 100 inhabitants is 103.16 (Sylvester, 2016). In reference to these statistics, it is evident that Sri Lanka has acquired a relatively high mobile-cellular penetration. With this immense growth of mobile phone usage among rural communities, we can use mobile phones to deliver learning content for BOP people that lead to national development.

However, simply making content available through m-learning platforms does not motivate them to spend time on learning. Even the use of local languages may fail. However, if the learning process is tightly coupled with their vocation (farming, woodwork, fishing, pottery, and many more) results can be positive. We cannot expect learners' initiation for the learning process. Examining the motivational factors is essential to enable the development of a mobile learning framework, in order to uplift livelihood and empower the vocations of BOP people. We have examined mobile learning adaption of bottom of pyramid people from a motivational perspective. We have employed Keller's ARCS model of motivation theory to motivate BOP people towards the learning process.

2. Methodology

Case studies can be used to understand real life phenomena best, and they are appropriate not only for the exploratory phase of research, but also for the descriptive phase (Yin, 2009). Case studies can be used not only for preliminary studies-they can be used in testing phases as well.

In our research, the case study research method is used in the exploratory and testing phases. The preliminary study explores the lifestyle factors of Bottom of Pyramid (BOP) People in the North Central Province of Sri Lanka in order to uplift their livelihood and to empower their vocations using a Mobile Learning Framework (MLF). Our preliminary study was carried out in Thuruwila, Thimbiriwewa and Yaya, 03 villages in the Anuradhapura district. The primary data was collected using an interviewer administered questionnaire. The study facilitated the identification of lifestyle factors related to their vocations, educational and psychological background, nature of vocations and technology usage. These factors were the main parameters to be considered when designing the MLF. This study provided an insight into the research that will form the path for an MLF (Irugalbandara and Fernando, 2015). It used a case study research method for testing whether scientific theories and models actually work in the real world. This phase testing and deployment again involves interactions with BOP communities in the same villages.

In the System Development phase, we have used an iterative design science research approach. An iterative design science approach emphasizes on iterative construction and evaluation, which ensures validity, reliability, and especially practical feasibility. There are three research cycles in the design science approach: The relevance cycle, rigor cycle and design cycle. The relevance cycle bridges the application environment with the research design. There, it focuses on the contextual environment not only as input or collection of requirements for the research, and also defines how the contextual environment accepts the research design. It evaluates "Does the design artifact improve the environment and how can this improvement be measured?" The rigor cycle connects the design activities with the scientific models and knowledgebase. The design cycle iterates between core design activities and evaluation process (Hevner, 2007). Context aware adaptive mobile learning system for the BOP people is an iterative development, shown in Fig. 1. When the system is designed and developed, it is tested in repeated cycles. Testing is done by involving BOP people. At each iteration, additional features are added to the system and the knowledgebase.

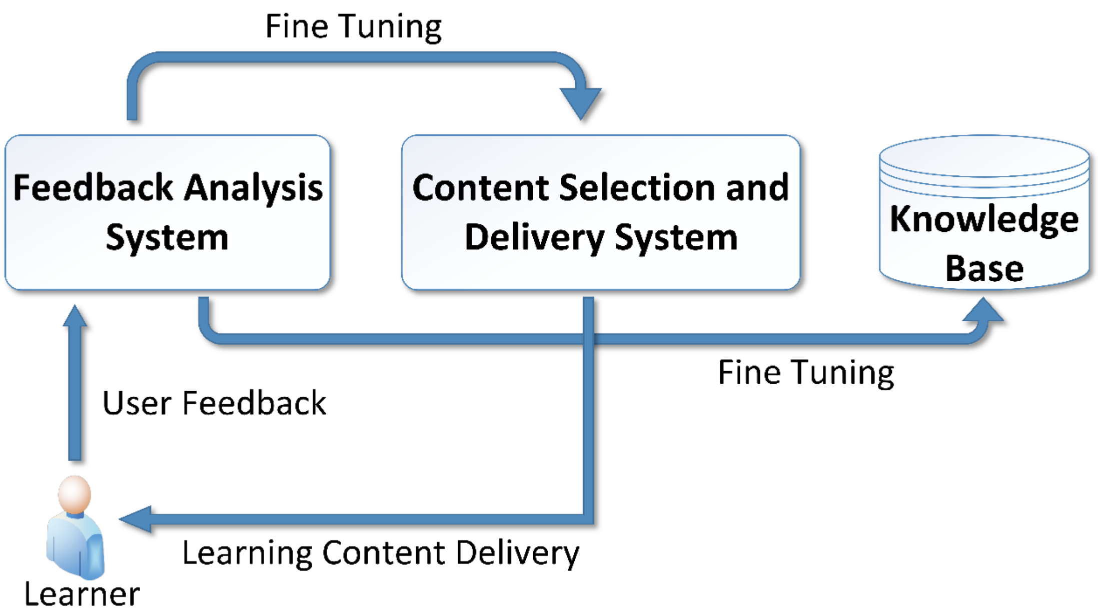


Fig. 1: Design science approach in system development

3. Research background

Adaptivity and personalization in mobile learning system refers to the process of customization of its behavior and functionalities to match the learner's personal needs and characteristics. The system implements the personalization features based on the personal and environmental information of the learner. They are considered as contextual information (Gomez et al., 2014). Context refers to "any information that can be used to characterize the situation of an entity" (Dey, 2001). Identifying the relevant context information for the learning process is a challenge (Gomez et al., 2014).

EduAdapt is an architectural model for the adaptation of learning objects based on the learner's context, surroundings and characteristics of the mobile phone used. They proposed an ontology which consists of inferences and rules named OntoAdapt. It has four main groups of information identify regarding the learner, learning objects, devices and context. EduAdapt suggests learning objects to the learner considering learners' profile and their context information such as location, time and device characteristics. Here to observe the learners, it has used the Learning Management System (LMS). Learners' behaviors have been identified using their LMS activities. In this scenario, to provide adaptive content for all the users, they must interact with the LMS. EduAdapt interacts with the LMS and this interaction allows to the learners, and by using OntoAdapt ontology, determines the most appropriate learning object to send the target learner. Once a learning object is chosen, there are two types of adaptations: Scale and format (Abech et al., 2016).

Tortorella and Graf (2017) introduced an IOS mobile app to deliver adaptive content to school children based on their learning style and the context information. They have used the Felder-Silverman learning style model (FSLSM) to determine the learning style of the learners. In order to consider learning styles, they have used current context of learners to select the appropriate format for each learning content. Various types of sensors in mobile devices were used to gather these data. Relative location of the user is gathered from a proximity sensor of the device, the overall motion of the device gathered from an accelerometer, the amount of ambient light in which the device is located gathered from an ambient light sensor, and the current geographical location of the device gathered from a GPS sensor. By analyzing these sensor data, they recommend the most appropriate format of the content: Audio (mp3), Video (mp4), Presentation (ppt) or Text-based (pdf). This system is supported only for smart devices.

WORBLEARN is a context aware mobile learning system especially developed for work-based learning. Work based learning is a learning process occurring at the work place to enhance knowledge and skills of the workers. This is a real-time learning system and workers are required to pull content when they require certain assistance in their work. WORBLEARN uses three types of contexts, historical context: Profile information of the learner and his learning history (previous interactions with the system), automatic context sensing: Real time physical situations time, noise, luminosity, and manual context: Learning satisfaction. In this scenario, learners have to pull content and the system will provide adaptive content to them (Zhang et al., 2016).

UoLmP is a mobile learning system which is developed for delivering adaptive content and generating adaptive learning activities based on the context information, it uses three types of adaptations: Adaptations to the learning activities, learning content and tools and services. The architecture of UoLmP consists of three parts: 1) Capture/retrieval part, which detects the device capabilities of the learner and current situation properties, 2) Adaptation part, which consists of a filtering mechanism, polymorphic presentation mechanism and executes adaptation mechanisms 3. Delivery/adjustment part, which delivers adaptive learning content to the learners (Gomez et al., 2014).

Al-Hmouz et al. (2011) had presented an adaptive mobile learning framework to adapt learning content to the learners' context. The entire process is designed using seven layers. They have employed four main components for learner modeling. They are 1) Learner Status, which describes learner profile, his learning history and learner knowledge. 2) Situation Status which describes the current situation and general situation which consists of devices, networks, hardware, and software resources. 3) The Knowledge and Shared Properties Status. Assumption of the learners' knowledge of the system: This is to acquire information about the learner and the tools that help learners to involve teamwork. 4). Educational activity status: Electronic information and education content which helps to acquire knowledge. Selection of appropriate content is done using a reasoning engine. Each learning content is available in four formats, video, audio, text and pdf. Based on the learner profile, an adaptive neuro fuzzy inference system selects the most suitable learning content format.

A majority of existing systems have considered only the learners' learning style based on Felder-Silverman learning style model (FSLS). This model classified learners into the following dimensions: Sensing, Visual-verbal, Active-Reflective and Sequential-Global. One of the main purposes of this model is to capture learning style differences among learners (Felder and Spurlin, 2005). This classification should do, by observing the way target learners learn and the way that they interact with any learning platform. In our scenario, we attempt to educate BOP people who do not engage in any learning process or use any learning application. Since they are not learners, at the initial process extracting their learning style according to the Felder-Silverman model is impossible.

We have extracted their learning styles based on their lifestyle factors. In most of these learning systems, learners have to pull content. In our scenario, our target learners are adults and they do not take any actions to initiate the learning process. Their learning style should be tightly coupled with their lifestyle patterns. On the other hand, high performance, multifunctional mobile devices allow acquiring of rich contextual information from their multiple sensors. Since a majority of these people use only featured phones and do not interact with any learning system, we cannot use these high-performance mobile devices to acquire contextual information.

4. Design approach of context aware adaptive mobile learning framework

Context aware adaptive mobile learning framework for BOP people is a complex system which contains a number of components. Layering is one of the best ways to handle the complexity of a system. Separation of each layer increases the simplicity of the system. We have designed the system using layered architecture, which contributes to an increase in flexibility, maintainability and scalability. The most powerful feature of layered architecture is that the components of a specific layer relate to the logic of that layer (Richards, 2015). This feature enhances the simplicity and intelligibility of the system. Each layer performs a specific task in the application. Al-Hmouz et al. (2011) had used seven adaptation layers in his adaptive mobile learning framework, which is designed to adapt learning content to learners' context. In that model he had used Context Acquisition layer, Information Classification Layer, Learner model layer, Information extraction layer, Learner profile representation layer, Reasoning Layer and Interface Layer (Al-Hmouz et al., 2011).

In our system, we have used eight layers, as shown in Fig. 2. They are:

1. Learner context acquisition layer
2. Context processing Layer
3. Learner modeling layer
4. Real time data acquisition layer
5. Learning/Motivational content design layer
6. Adaptive Learning content/format selection layer
7. Content delivery layer
8. Feedback layer.

4.1. Context acquisition layer

"Learning context is the set of circumstances that are relevant when someone needs to learn something" (Figueiredo, 2005). This application is aimed to adapt according to learner's context. It intends to

provide personalized adaptive learning experience based on the context details of learners. Learners' context details are gathered mainly using two methods. These are implicitly and explicitly. Implicit details are the information that we can extract from their devices.

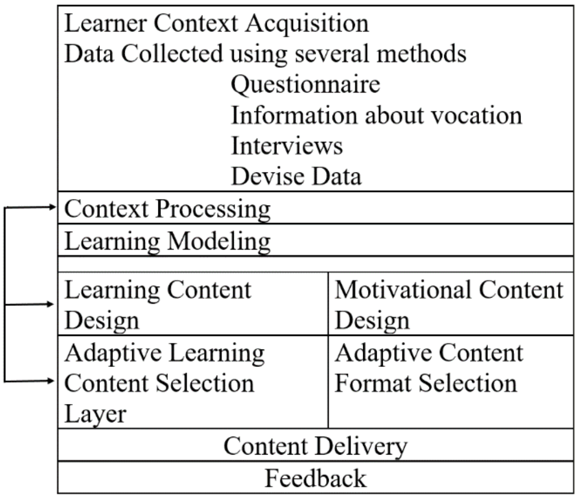


Fig. 2: Layered architecture of adaptive mobile learning system

Mostly smart devices support the extraction of implicit data. They are learner location information, current battery life, bandwidth of the connected network etc. This information only can be extracted from the smart devices which are connected to the network. According to our preliminary study, most of our target learners use featured phones. These devices do not support the extraction of all the above information. We can extract certain information from the service provider with consent from the users. Explicit details are gathered using questionnaires and interviews. These questionnaires are mostly presented to users in an informal manner using their native language.

4.2. Context processing layer

At this layer, useful contextual information is extracted from the data in the context acquisition layer. Learner context classification is shown in Fig. 3. There are two types of context- personnel context and environmental contexts. The concept of context aware is considering two components being aware of personnel context and being aware of environmental context which can affect the vocation.

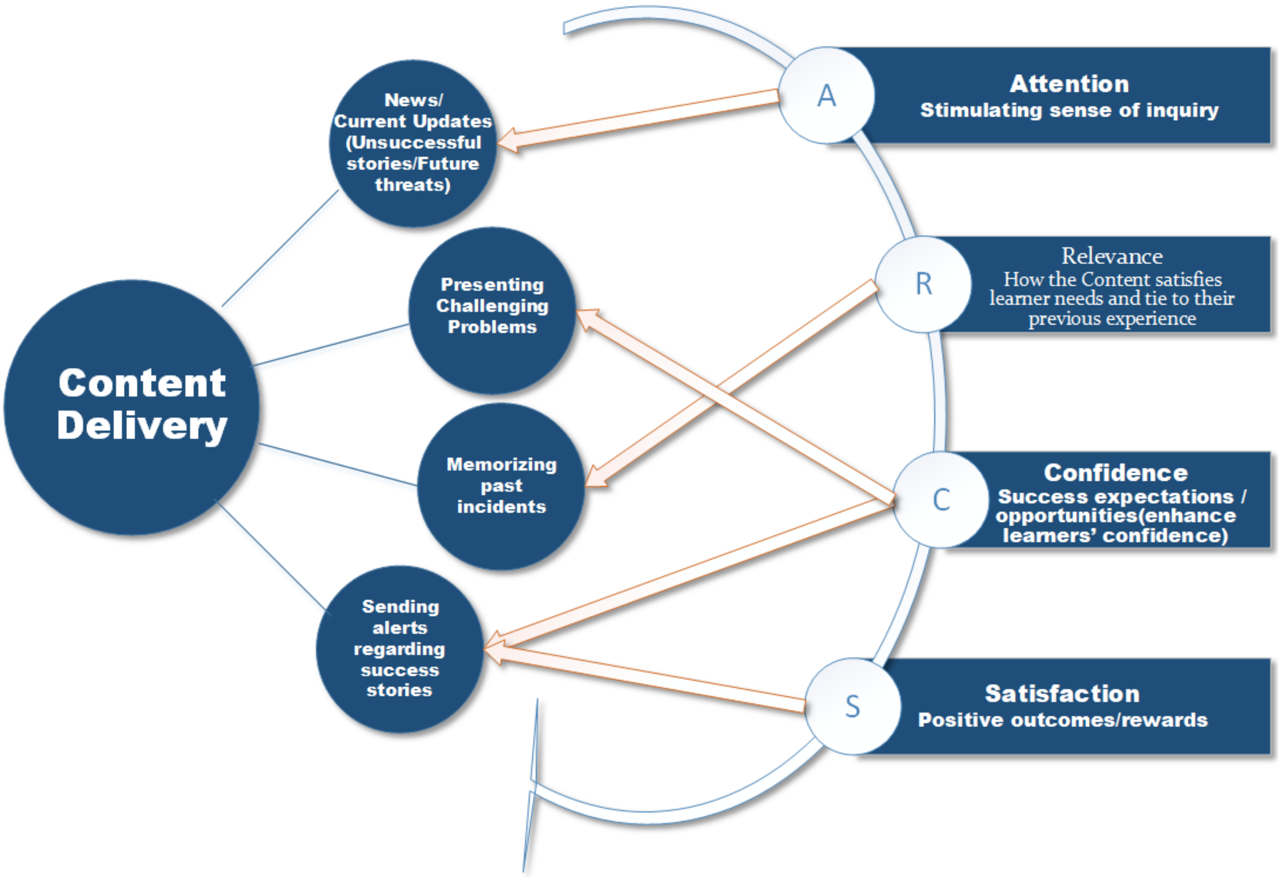


Fig. 3: Employing ARCS model for content design

4.3. Learner modeling/personalization layer

Personalization is a process of changing or designing (something) for a particular person (MerriamWebster, 2019). Personalization in learning is the process of customizing and designing learning content according to the unique needs of the learner. Our target learners are BOP people and they reject traditional leaning. We cannot expect them to pull learning content, therefore it is important to push learning content while attracting them to the learning process. In this endeavor, personalization is very important. Learner modeling leads to a personalized learning environment.

Arghode et al. (2017) explained that learners construct their own knowledge. Since adults bring their day today experiences and their needs to the instructional setting, a constructivist approach is more effective for the adult learning process. The social constructivism theory emphasizes the effect of culture and context when constructing knowledge (Arghode et al., 2017).

System adaptation occurs based on the learner model. The model is the knowledge; information about the learner that is known by the system. If the system has a rich set of information about the learners, their goals, abilities, knowledge, background and interests, it can provide a good personalization service (Sani at el., 2012). Therefore, accuracy personalization is based on the truth and richness of the learner model.

In the learner modeling phase, we have used learner context details which were gathered using implicit and explicit methods.

4.4. Real time data acquisition layer

Adaptive mobile learning framework is designed to deliver adaptive vocational learning content to BOP people. These people are engaged in different vocations such as farming, fishing, carpentry etc. and they are highly influenced by social, economic and weather changes. It is imperative to deliver dynamic content that is adapted for these changes. Real Time Data acquisition layer is to acquire real time data which can affect the vocations; e.g., in paddy cultivation, the influence of weather and climate is high in different phases of crop production. And different types of climatic extremes affect the crop harvest differently. The selection of seed should be done considering the availability of water that season (Iizumi and Ramankutty, 2015).

4.5. Learning/motivational content design layer

This layer presents the design of adaptive learning content. There are two types of content: Learning content and motivational content. In addition to delivering adaptive vocational learning content to BOP people, the system delivers motivational content to motivate them towards the learning process. Each motivational content is linked with one or more learning content, as shown in Fig. 3.

The process of adaptive content design is shown in Fig. 4. In vocational education, the learning content should adapt to the learner's knowledge. Our preliminary study reveals that most BOP people have been educated up to primary level and junior secondary level (grade 8) (Irugalbandara and Fernando, 2015). If the learning content consists of complex words or mathematical calculations, that content may not be understood by the target learners. Learning content has to be designed to align with different levels of knowledge.

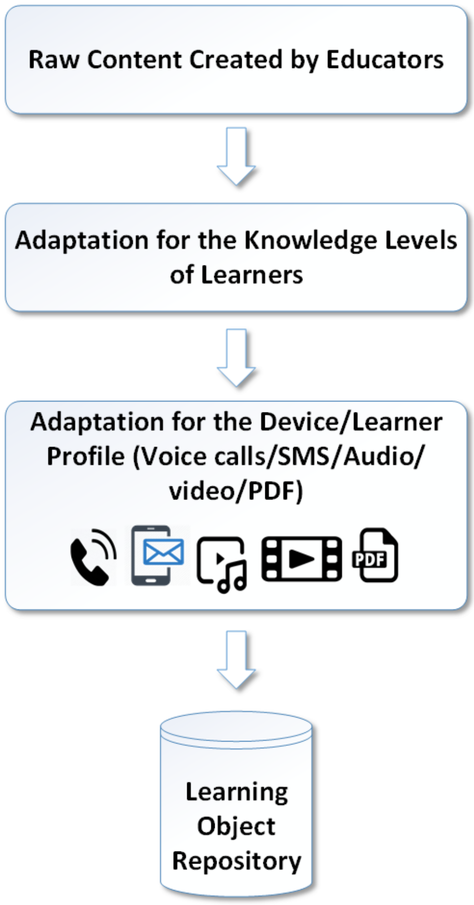


Fig. 4: Learning content design

The final stage of the adaptation is designing the content for multiple delivery modes. The most appropriate content mode is selected considering the learner's preferences, device capabilities, bandwidth of the devices, as determined in the context acquisition layer and real time data acquisition layer. In our system, four main formats are considered. 1) Text messages, which can be sent as a short message service (SMS), 2) Audio, which can be sent as an audio file to smart phone users and as an ordinary telephone call to featured phone users, 3) Video -this is multimedia based learning content which can be sent only to smart phone users, and 4) PDF, where the content is sent as a PDF document and smart phone users can view them using a PDF reader.

4.6. Adaptive content selection layer

Selection of the most appropriate learning content is done by this layer. Learning content selection appears on two occasions: Selection of the content which has to be sent to the learner, and selection of the most appropriate format of the content.

At the content selection stage, there are many steps and the algorithm behind the process is shown in Fig. 5. After selecting the content, it selects the appropriate format of the content. Selection of the appropriate content format is done using a fuzzy inference system (FIS). The process of FIS is formulating the mapping from a set of given input to an output using fuzzy logic. The reasoning engine works on learner data. Since this is a context aware adaptive mobile learning system, extracting the most relevant inputs that can affect the format of learning content is a challenge. A higher number of inputs affect computational complexity. Since this is an iterative design based on the user, the feedback system was fine tuned in many ways. Based on user feedbacks and preliminary studies, we have identified six inputs which can affect the mode or format of the content. They are mobile signal strength, educational level, commitment level, battery life, location, and learner type. In the initial phase of the implementation we took only five inputs and the learner type was not taken, since at the initial phase it is impossible to identify the learning style of each learner. When the learners interact with the system, we are able to use "learner type" as an input.

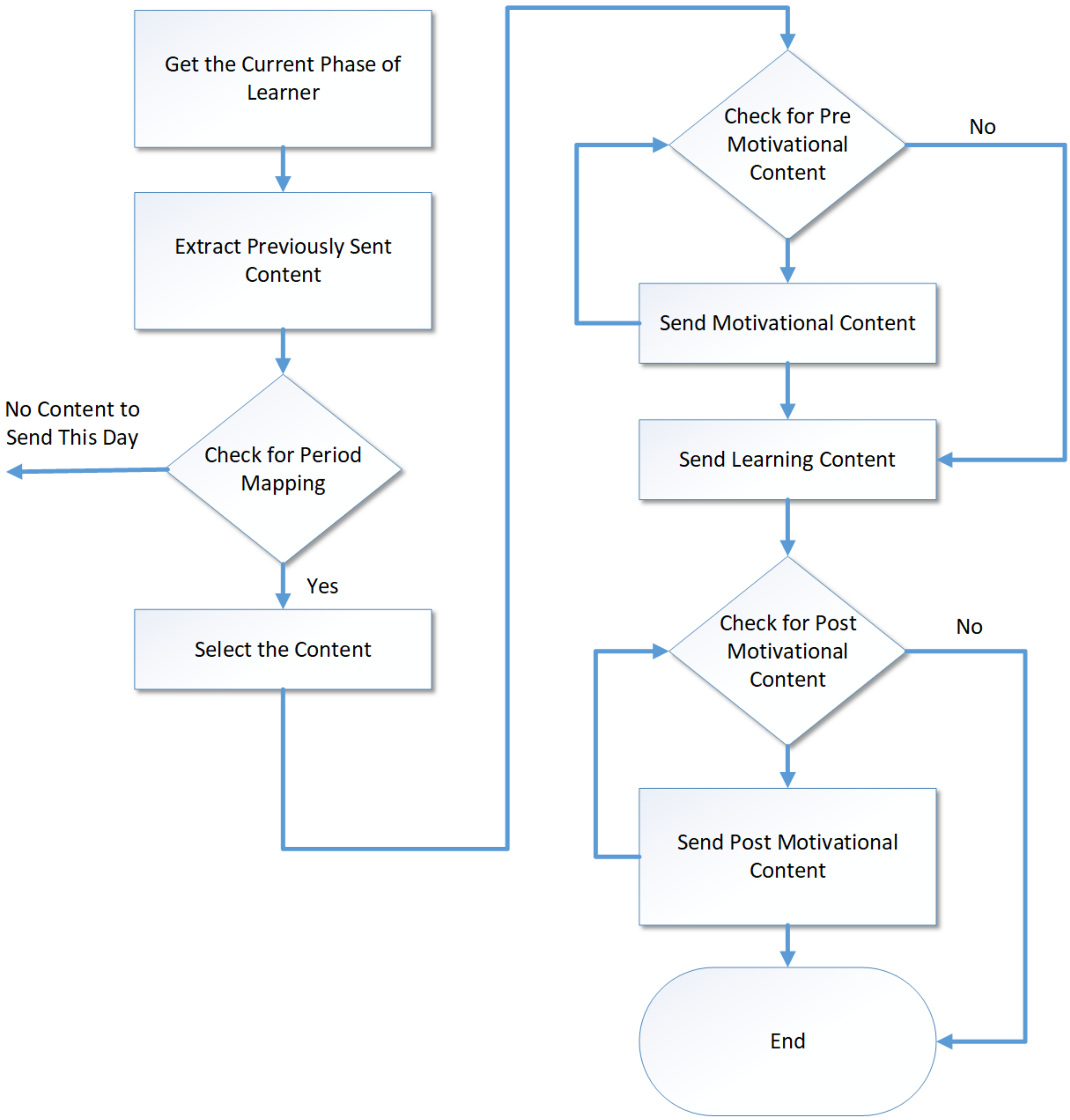


Fig. 5: Learning content selection algorithm

We have used Mamdani type fuzzy inference system with these variables and their membership functions are as follows:

Mobile Signal Strength
- High
- Low
- Medium

Commitment Level
- Ready to commit time and money for educational purposes (High)

• Rejects learning (Low)

Location
• Home
• Paddy field (Working field)
• Outdoors

Educational Level
• Passed the O/L Examination (Good)
• Failed the O/L Examination and have gone to school(Medium)
• Haven't gone to school (Low)

Battery Life
•High
•Medium
•Low

Learner Type
•Visual (prefer to learn using pictures, images, and spatial understanding)
•Auditory (prefer to learn using sound and music)
•Verbal (linguistic): (prefer to learn using words, both in speech and writing)

For these inputs, a set of rules were defined. The sample rules that we have used are as follows:

- IF (Location=outdoor) AND (Network Bandwidth=low) AND (Battery life= low) THEN (content type=text)
- IF (Location=home) AND (Battery life= high) THEN (content type=video)
- IF (Education Level= low) AND (Location=home) AND (Network Bandwidth=high) THEN (content type=video)
- IF (Battery life= high) AND (Network Bandwidth=high) THEN (content type=text)

Finally, the output is labeled as content type. The rule viewer of our FIS is shown in Fig. 6 and the rule editor is shown in Fig. 7.

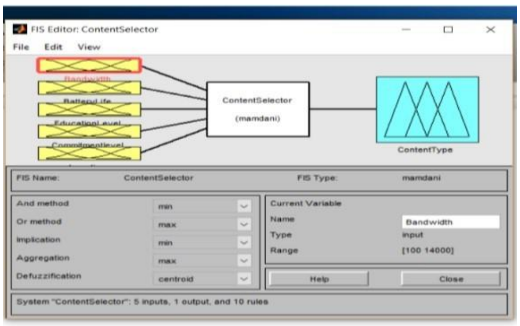


Fig. 6: Rule viewer

4.7. Feedback layer

Users' opinions and their experience regarding the system is very helpful in designing an adaptive mobile learning framework. At the same time, these feedbacks help to update the user profile regularly. We have used the iterative design science approach in system development. As shown in Fig. 2, feedback layer contributes to updating three layers. They are the Learner modeling layer, Learning/Motivational content designing layer and Learning/Motivational content selection layer. The system is iteratively constructed to fit well with the target audience.

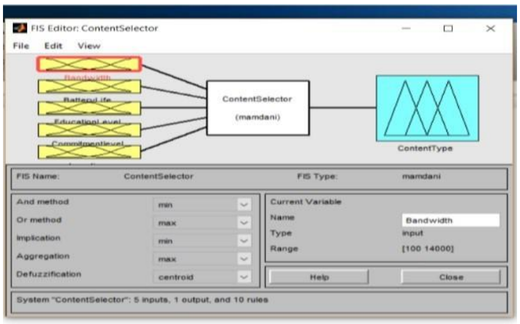


Fig. 7: Rule Editor

5. System implementation

We developed a prototype of the above system. This section describes the system architecture and main components of the proposed framework that have been implemented for creation and subsequent evaluation.

5.1. System architecture

The implementation was done iteratively and finally resulted in the following system architecture shown in Fig. 8. The system consists of several phases. The main phases are described in more detail.

- **Step 1:** Cron jobs are automated job schedulers, which are used to run on servers. They are used when it is required to perform certain tasks periodically (Kuhn et al., 2015). Cron Service allows us to configure regularly scheduled tasks, and we can define times or regular intervals to fire this process. These tasks are automatically triggered by the Cron service. We use Cron job manager to notify two special conditions:

▪ Weather changes
▪ Reaching to the Learning time
▪ Weather changes reporting

Most vocations are tightly bound with the weather; e.g., Farming, fishing etc. If a certain area reports unexpected weather condition, this can affect the vocation. By considering these weather changes, weather specific content is delivered to farmers. Cron Job manager communicates with Open Weather Map API. Open Weather Map is an Application Programming Interface (API) that provides weather data, forecasts, and historical weather data (Openweathermap, 2019). The weather data obtained from the Open Weather Map API are regularly compared with the expected weather conditions. If there is an unexpected

weather change reported, weather details and the affected learner list are sent to the content selection manager.
At the Context Acquisition and Context processing layers, we analyze our target learners' daily routine. By asking several questions we extract their working time, leisure time etc. Finally, we extract the most suitable time to send personalized content to individuals. Cron job manager waits for the learning time, and when it reaches the learner's learning time, the Cron job manager notifies the content selection manager.

- **Step 2:** The task of the content selection manager is selecting the most appropriate content for individuals. After the process, the content selection manager selects the most relevant content for the individuals. The learners can be categorized into two groups according to their mobile phone usage:

- Featured phone users
- Smart phone users

If the learner is a featured phone user (facilitating only voice and text communication), after the content selection process, selected content is sent to the service provider.

- **Step 3:** The content is delivered to learners as a voice call or message through service provider API.
- **Step 4:** For Android application users, it is required to push notifications and learning content to users. Firebase Cloud Messaging (FCM) is a cross-platform messaging solution which enables reliable delivery of messages. Using FCM, we can notify the client that a new notification is available (FCM, 2019). Firebase service manager component in the system prepares notifications for the client.
- **Step 5:** Alerts or notifications of content are sent to FCM platform.
- **Step 6:** Alerts or notifications of content are sent to Android application through FCM service.
- **Step 7:** When the Android application user requests content, the request comes to the learner daemon component.
- **Step 8 / step 9:** The learner daemon component communicates with the fuzzy inference system (FIS) and FIS selects the most appropriate content format for the relevant user.
- **Step 10/ 11/12/13**: The learner daemon component sends a content type message to the Firebase service manager, and it is sent to the Android application through FCM platform.
- **Step 14/15:** Feedback Manager analyzes the feedback from the smart phone user and the featured phone user.
- **Step 16:** After analyzing user feedbacks, useful changes are sent to Content Selection Manager.

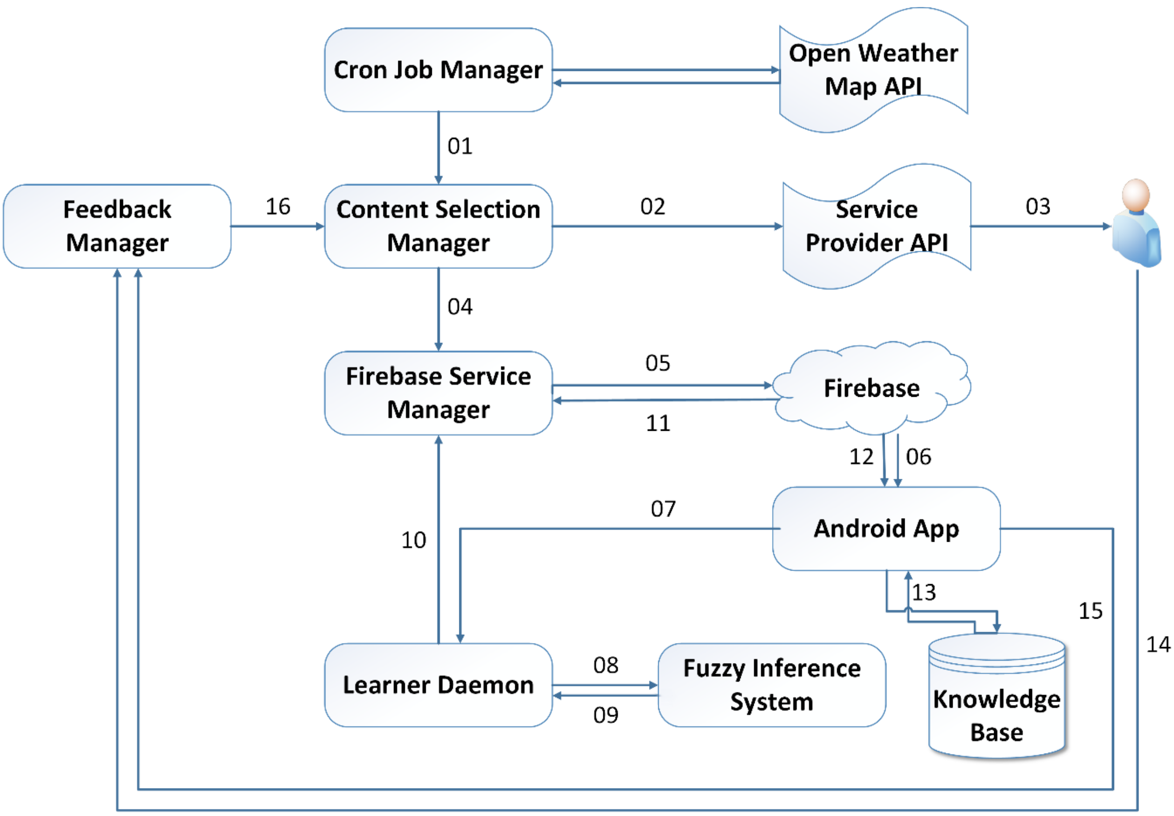


Fig. 8: System architecture

5.2. System components

The system consists of four components, as shown in Fig. 9. They are: Vocational content management system, which is a web-based application, Adaptive mobile learning system, Smart application for smart phone users, and voice and text based Messaging services for featured phone users.

5.2.1. Vocational content management system

Vocational content management system is local language base web portal that enables educators to add/remove content, conduct user feedbacks, view learner details etc. Fig. 10 and Fig. 11 shows two interfaces of vocational learning Content management system.

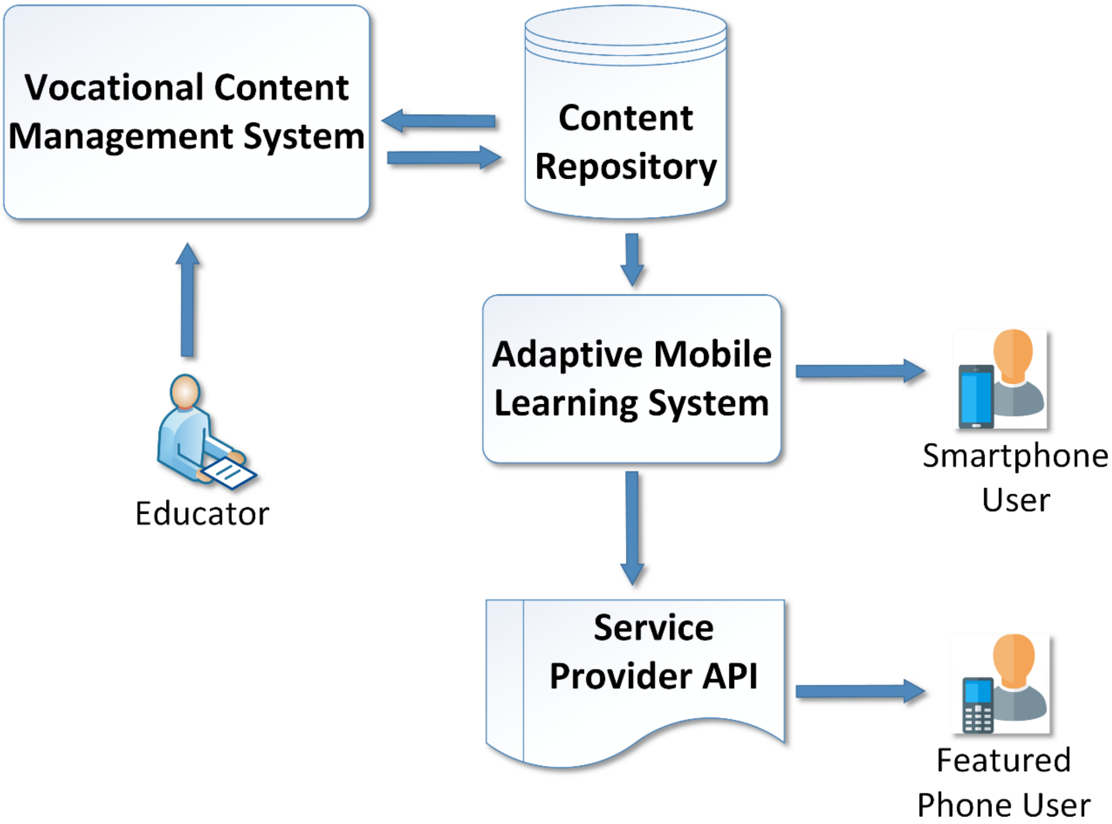


Fig. 9: System components

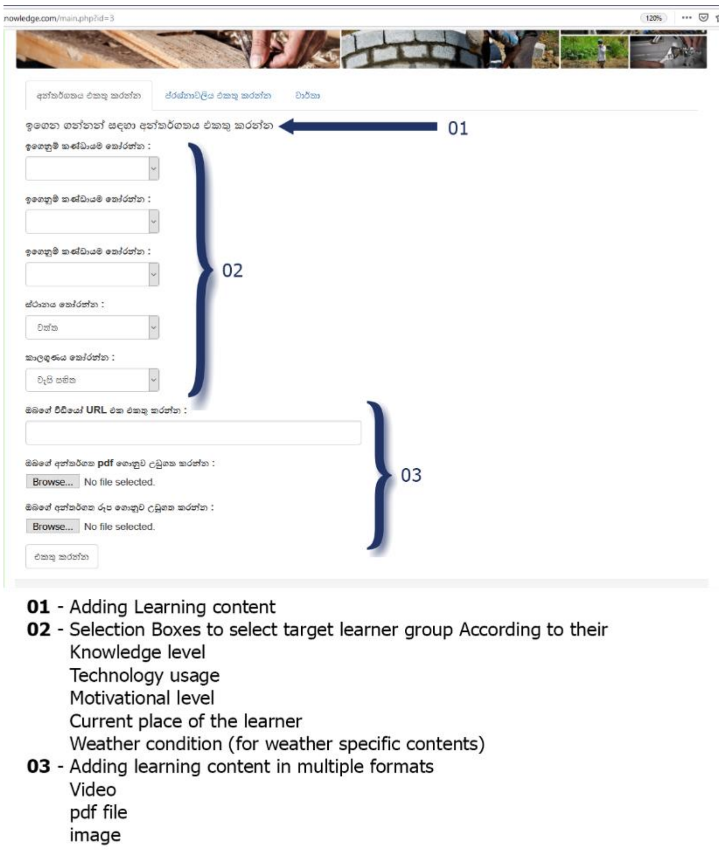
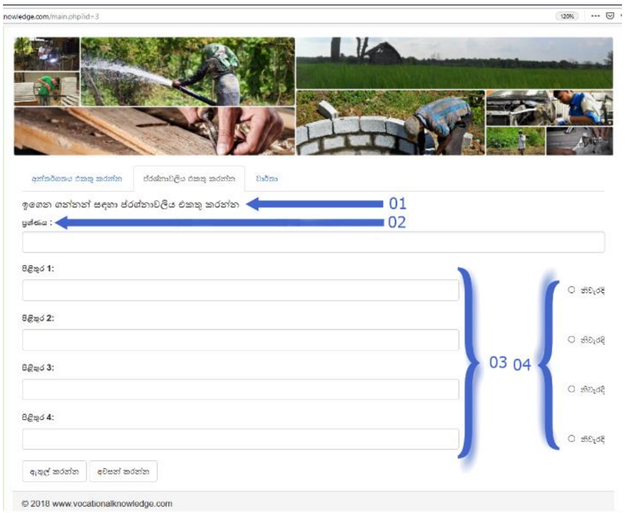


Fig. 10: Adding learning content GUI



01 - Educators' interface for adding questionnaires to model learners according to their knowledge level
02 - Text area to add the question
03 - Text areas to add multiple answers
04 - Radio button to indicate correct answer

Fig. 11: Adding questionnaire GUI

5.2.2. Mobile learning application for smart phone users

For the clients' side, there should be two types of systems running. One is a mobile application for smart phones and tablets with Android operating system. And the other system is to push mobile learning content to featured phone users. All these applications used the native language, which is 'Sinhala' for Sri Lanka. Interfaces of the mobile app are shown in Fig. 12 and Fig. 13 shows two interfaces of the mobile app.

We designed the interfaces of our learning application according to learner information acquired using several questionnaires in the context acquisition layer, and in addition to that it has enabled several sensors in smart devices for collecting contexts.

Fig. 12 shows a learning activity for a farmer and the system identified that the appropriate content format for that individual was video. At the same time, the system allows learners to select any other content format (audio, PDF, etc.). It enables learners to rate their experiences and share their ideas on the same interface.

In Fig. 13, it shows that the system acquired learner data through this interface.

5.2.3. Content delivery for featured phone users

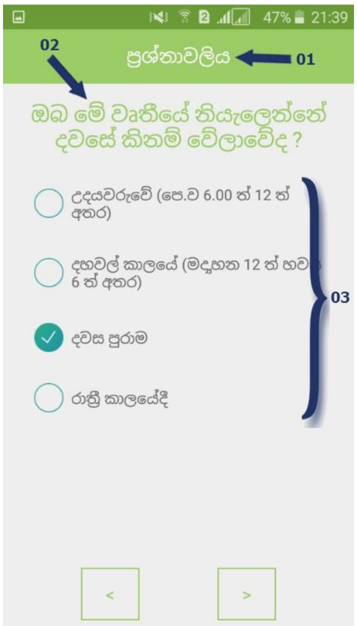
The other application is to push learning content for featured phones using Interactive Voice Responses (IVR). This application requires service provider's API to be executed. At the initial stage of our system, the IVR system may not be successful, since we had to handle rural people who fear technology, or they also may have impersonal feelings. These people have not used many systems and we may not able to get their responses when we directly move towards an IVR system. At the initial stage, instead of using an IVR system executed on a service provider API, we use manual telephone calls and let them listen to the content as an audio call.

01 - Notification
02 - User can select the format of the content (pdf, image, video)
03 - User rating
04 - User Comments

Fig. 12: Adaptive content delivery through mobile app

6. Experiment design

In this section we present the way that we evaluated the system and how it was deployed among BOP community. The study was conducted with 27 paddy farmers in Thuruwila and Thimbiriwewa villages in the Anuradhapura district. According to statistics, nearly 19-23% of paddy produced in Sri Lanka is from Anuradhapura and Polonnaruwa. According to Central Bank records, 90% of people of the district live in rural areas. Thuruwila and Thimbiriwewa are nearby villages (CBSL, 2018).



01 - Questionaire
02 - Question to acquire learner's contexts
03 - Multiple answers for the question

Fig. 13: Acquiring learners' information through the app

Most of the villagers of these villages are paddy farmers. The main objective of this experiment was to measure BOP peoples' perception of a context aware adaptive mobile learning system. In the evaluation phase, we delivered the content of paddy cultivation for 27 farmers in Thuruwila and Thimbiriwewa villages. In our system, we carried out two scenarios based on the mobile devices that the target learners used. Smart phone usage among farmers of these villages is relatively low. Most of them use featured phones which facilitate voice calls and text messages only. We explored this in several villages in our preliminary studies and the results are the same. Smart phone usage among BOP people is relatively low. A total of 27 participants voluntarily participated for this study and among them, 22 farmers used featured phones and the rest used smart phones. Learning contents were adapted for their mobile devices. For the featured phone users, the content was delivered using voice calls and text messages. A mobile application was developed for smart phone users, and content was delivered in many formats such as video, audio and text files. In paddy cultivation, there are two cultivation seasons: "Yala" season and "Maha" season. "Yala" season falls in May to the end of August, and "Maha" season falls in September to March of the following year. In the paddy cultivation process, there are five main phases:

1. Seed selection
2. Land preparation
3. Crop establishment
4. Harvesting
5. Post harvesting.

The experiment was done during "Maha" season. Throughout the season, there were around 40 contents were delivered to 27 farmers.

7. Results and discussion

At the initial phase of the study, an informal questionnaire was given to the participants in order to identify their lifestyle factors, their attitude towards vocational education and learning presence. Results of this preliminary study proved that 83.33% of farmers refused to participate in regular training programs due to time constraints. The elderly population believe that they are not of an appropriate age for learning, and reject learning new things (Irugalbandara and Fernando, 2015). With these constraints, we gradually started the learning process; at the end of each content delivery, small questions were asked to evaluate our adaptation approach. This questionnaire aids to evaluate how the adaptation increases the learner's attraction towards the learning process. We were not able to use a Likert type questionnaire which consists of a set of answers as this attempt was not successful with this population. It was necessary to use an adaptive questionnaire.

These people preferred to talk continuously and in an informal manner. When we asked a direct set of questions, they felt uncomfortable. Based on their long answers, we categorized them in to a five-point Likert scale where 5 denotes, "very satisfied" to "very unsatisfied". The mean value of the learner's attraction towards learning process is 3.05.

There is a positive correlation between adaptive delivery and learner interaction which is 0.67044 (shown in Fig. 14).

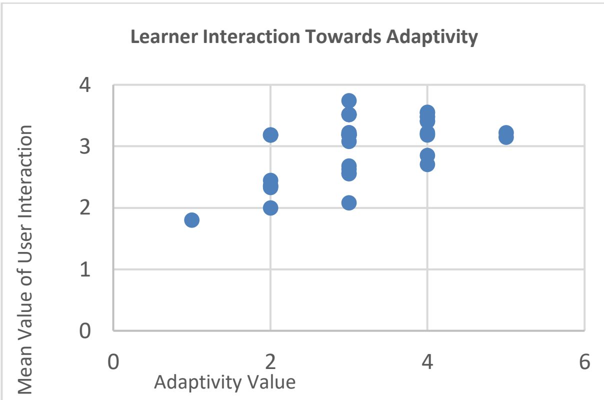


Fig. 14: Learner interaction towards adaptive value of the content

Learner's motivation towards the learning process is measured using a few questions and their interaction with the system. Interaction with the system is measured using: number of views, whether they listen to the content or not (for featured phones), readiness to spend time on learning, whether they ask queries and trying to pull knowledge.

Based on their answers for the feedback questions and their interaction towards the learning process, the motivational factor of individuals towards each learning content is measured. Motivational factor is presented on a five-point Likert scale where 5 denotes, "High" to "Low".

Parallel to content design, we did the motivational design and sent motivational content along with the learning content. Motivational value is given to each learning content considering the number of motivational contents combined with the learning content, and is also presented using a five-point Likert scale where 5 denotes

"High" to "Low". There is a positive correlation between motivational value of the content and learner motivational factor, which is 0.701 as shown in Fig. 15.

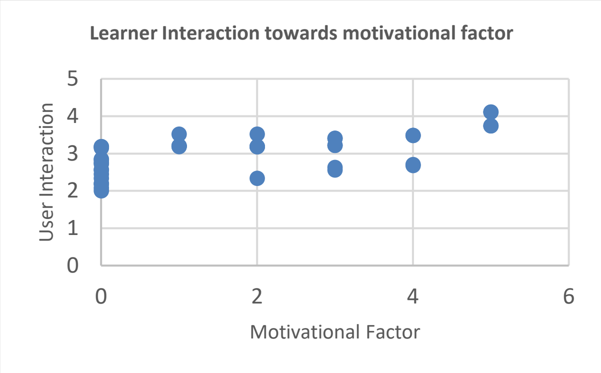


Fig. 15: Learner interaction towards motivational value of the content

The evolution results which are shown in Fig. 14 and Fig. 15 prove that learner interaction is positively correlated with learner interaction and adaptivity value of the content. There are many related works which have been focused on context aware adaptive content delivery for learners who ready to pull the content. There learners are required to enroll for certain learning processes. Here our attempt is to educate BOP people who are struggling with their vocations and not ready to participate any learning process. Most of the prevailing systems deliver the content via mobile apps which runs on multifunctional mobile devices. Here we are highly adaptive for the device and technology capability of our target learners and provide the mostly appropriate content through minimum resources.

8. Conclusion

In this paper we present a context aware adaptive mobile learning framework to deliver vocational knowledge to BOP people. Our preliminary studies revealed that most of these people are engaged in their professions not because of their talent or interest for the field but because of poverty or due to inheritance of the trade from their parents. They engage in their particular trade for the sole purpose of feeding their families, and this lack of psychological investment in their trade leads to many failures and results in very low revenue. Since they work hard, earnings are very low. We strongly believed that the best way to empower their vocations and uplift their livelihood is vocational education. The challenge was that the people in the BOP do not prefer to engage in any learning processes. Most of them are of the opinion that they are not of an appropriate age for learning and they are preoccupied with their day-to-day work and their children.

With these concerns, it was required to implement a specific learning framework, which pushes content while attracting learners to the learning process. The framework we presented here is an integration of a Fuzzy inference system and context aware adaptive learning system and aims to deliver personalized content to learners. On the other hand, one of the main objectives of this is to attract learners to the learning process. We did motivational design employing Keller's ARCS model to motivate the learners.

At the preliminary study, 58% of farmers rejected learning new things, stating that they have enough experience and knowledge. They are also of the idea that they are not of an appropriate age for learning. Forty-two percent (42%) of the farmers preferred learning new things. Although they have several knowledge requirements, some of the farmers refused to participate in regular training programs due to time constraints and these people were not ready to consume their time and money for the learning process (Irugalbandara and Fernando, 2015).

By understanding the attitudes, requirements and concerns of the farmers, we started our learning process. The system always adapted to the BOP community. Since we have used an iterative design science approach, it is tested in repeated cycles. Testing is done by involving BOP people. At each iteration, additional features are added to the system and the knowledgebase. Finally, we could come up with a context aware adaptive mobile learning framework which is highly adopted by BOP community. We could highlight that higher degree of adaptability, which attracts them to the learning process. This adaptation mechanism occurs at the time in which the content is delivered. This makes the content delivery mechanism more dynamic. The adaptation happens considering not only learner's context, profile, learning style and mobile device, but also considers the current weather and social factors which can affect the vocations. Adaptive content selection is done by using adaptation rules.

The BOP community who participated in our study expressed a strong willingness to obtain more content which is offered through this framework, and have high demand for it. We could see a strong difference between the results of our preliminary study and post-test study. The findings show that this demand happens not only because of the highly adaptive mobile learning environment but also the system's motivation mechanism towards the learning process by delivering the motivational content.

Through our system, we could make a positive change in the attitudes of the BOP community. At the post test study, 82% of farmers understood that they have a knowledge requirement. The main and most positive result of our research was observed in the change of this particular attitude.

The BOP community believes that the content sent via this system was helpful for a better harvest. At the initial phase we pushed the content and at the end it seems that learners try to pull the content gradually. They asked queries, requested more content etc. This change leads to a better vocational education environment and it opens the door to economic and social development of a country.

The proposed framework was implemented and tested for a farming community and overall, showed very promising results. In Sri Lanka, the BOP community is involved in many vocations such as fishing, pottery, tailoring etc. It is still required to test our framework with these different vocations and to reinforce our findings.

Compliance with ethical standards

Conflict of interest

The authors declare that they have no conflict of interest.

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