OCIT 2022

Home | Committees ▾ | Papers ▾ | Program ▾ | Attending Conference ▾ | OITS | Past OCIT ▾ | Contact

Technical Co-Sponsorship IEEE Kolkata Section & IEEE Bhubaneswar Subsection

Personalized Instant Messaging UI Design for Elderly

Nurul Sakinah Mohd Heree
Faculty of Computer Science and Information Technology
Universiti Malaysia Sarawak
Kota Samarahan, Sarawak
65155@siswa.unimas.my

Hamimah Ujir
Faculty of Computer Science and Information Technology
Universiti Malaysia Sarawak
Kota Samarahan, Sarawak
uhamimah@unimas.my

Irwandi Hipiny
Faculty of Computer Science and Information Technology
Universiti Malaysia Sarawak
Kota Samarahan, Sarawak
mhihipni@unimas.my

***Abstract*—There is a paucity of studies on the consumption of digital content by elderly people utilising smart devices as well as strategies to get elderly people acquainted with smart gadgets. Usability and familiarity with smart devices for senior persons to utilise and get the most out of smart devices and digital content must be prioritised. A cognitive reaction-based intelligent UI suited for senior persons is proposed in this paper, which is based on the user's cognitive performance and demographics. A cognitive response feedback and demography dataset was built by interviewing a group of elderly in Malaysia. The context of the interview is associated with the unique cognitive keywords that may be anticipated by contextual semantic search. In this paper, two classifiers are used, Support Vector Machine (SVM), and Naïve Bayes (NB), and they are compared in terms of classification performances. The classifiers are validated using k-fold cross-validation (10-folds) using unigram TF-IDF and bigram TF-IDF, and the results were presented using accuracy, precision, recall, and F1 scores. Thus, user interface (UI) pre-sets lists will be matched to the user model based on the dataset classification result and be visualized using a mobile app interface builder.**

Keywords—personalization, user interface design, machine learning classification, elderly

I. INTRODUCTION

User Experience (UX) covers all elements of the user’s contact with the company, its services, products, and overall customer experience [1]. The way a person feels when interacting with a system, such as a website, software, mobile application, or gadget, is referred to as the user experience. Meeting the specific client demands and knowing their behavioural patterns is the most important prerequisite for a successful User Interface (UI). [1] also mention machine learning (ML) enables UI/UX Designers to provide consumers with next-level customization. Personalization based on ML is a more scalable and accurate approach to delivering a unique experience for each user. Rather than segmenting consumers through rule-based customization, it enables us to provide these one-to-one experiences using algorithms, often in the form of product or content suggestions. However, smart device manufacturing businesses are designing mobile layouts just to sell their product, and no one is using this personalization concept in enhancing the elderly quality of life by thinking about what interface will make it easier for them to utilise smart devices [1].

Because of significantly improved health care and quality of life, life expectancy has grown throughout time. Aging index is defined by the United Nations as the fraction of persons 65 years old and older in each community [2]. It is frequently referred to as an ‘Aging Society’ if the aging index is more than 7% or an ‘Aged Society’ if the aging index is greater than 14%. The proportion of Malaysians over the age of 65 was expected to be 7% in 2020. Malaysia is now facing a risk of an aging population, which according to the Department of Statistics Malaysia, might occur as early as 2030.

Mobile services are used by five billion individuals worldwide [3]. Most of these users are young and have sophisticated technological understanding. Those over the age of eighty have mobility and motor issues, while some users have motor problems after fifty years [4].

According to [2], the biggest impediment is a lack of usability, short-term memory, and a fear of technological adoption. As a result, a significant proportion of our society's senior citizens attempt to avoid using cell phones [3]. Several experts feel that the future generations would not be the same as the existing elderly. The children of today are acclimated to the exi`sting system, and it will be normal for them to use a smartphone when they reach retirement age [2]. However, according to [3], they will still be having problems operating the smart device because of their cognitive and motor function. [11] perform a need analysis on UI/UX design for Malaysian seniors when using a mobile banking app. According to [11], the most important feature of a mobile banking application according to senior users is fast loading time followed by s secure verification via one-tap approval method. Therefore, studies to improve the elderly ability to utilize the smart device are needed because it is important to bridge the gap of communication between the elderly present era as most studies to improve elderly quality of life are focused only on health and welfare.

The objective of this paper is to develop an intelligent UI system that adapts to the user's personality type based on cognitive responses and demographic information. In this project, we analyse the cognitive response and demographic details dataset by a group of Malaysian elderly using ML algorithms. We also develop a UI for an instant messaging app based on the dataset user-type define in the classification process using a mobile application builder. Section 2 is about related works which includes data acquisition, personalized system, data preparation and analysis, ML algorithms, and evaluation based on the classification index. Section 3 describes the method used in this paper and section four explains the results. The discussion of the results is elaborated in section 5 and the final section summarizes the findings of this paper.

II. RELATED WORKS

a) Data Acquisition

There are two data acquisition methods which are: using interviews and using cognitive assessment. [5] acquired data for their research using cognitive interviewing because cognitive interviewing is a qualitative procedure. This means that analysis does not rely on a formal statistical analysis of numerical data, but rather on the coding and interpretation of written notes taken during (typically by the interviewer) or after the interview (by either the interviewer or an analyst). [6] used text mining techniques to analyse unstructured data gained from interviews. The data set includes information on paediatric cancer patients' experiences and behaviours in the ward.

According to [1], the sensory and cognitive processes can be measured using several approaches. To assess visual function, various sized and coloured objects and letters are given in their assessment. The auditory function is assessed by delivering auditory impulses to the user via a headset. In their assessment, various games are used to assess cognitive capability. Psychomotor abilities, mood, executive function, attention, and memory are measured with the Tapping Task, Emotional Perception, N-Back Task, Wisconsin Card Sorting Task, and Spatial Span, respectively.

[7] argue that cognitive assessment of senior persons who are illiterate or have a low level of education is particularly challenging since some tasks need a specific amount of schooling. The goal of their study is to perform a thorough analysis of the literature on cognitive assessment tools for diagnosing cognitive diseases like Alzheimer's in elderly people with poor educational attainment. Furthermore, among the 44 assessment tools discovered by [7] for cognitive assessment, were the Memory Alteration Test, the Six-Item Screener, the Persian Test of Elderly for Assessment of Cognition and Executive Function, the Montreal Cognitive Assessment, and the Mini-Mental State Exam. However, only a few of them demonstrated diagnostic accuracy for the diagnosis of MCI and AD in older adults with low levels of education.

The first method of data acquisition is used in this work as we understand that the implementation of a simple cognitive evaluation assessment remains difficult as the need for hard accessible medical tools and the assistance of professional examiner being some of the barriers.

b) Personalized System

Three types of personalized system are discussed in this paper, which are Usability Based, Heuristic Evaluation Based, and Cognitive Reactions Based. Using Cognitive Reaction Based as the personalized system for this research is more suitable as it custom every UI to its user model and cognitive response is one big factor that affecting elderly quality of life.

Cognitive response Based' is defined by [1] as intelligently adjusting UI/UX system for the user-based cluster group based on the user's outline and the contents' characteristics, boosting content usability and user familiarity with the smart device.

According to [1], cognitive reaction-based intelligent UI/UX systems for smart seniors must include three key components. First, a list of factors that influence elderly usability. Next, a collection of characteristics about the material that the consumer is consuming. Finally, a collection of factors that influence senior user familiarity with smart devices and content usability. Intelligent UI/UX systems need three major aspects to allow adaptive UI/UX in the research: a user model, a content model, and a UI/UX model.

The intelligent system of UI/UX comprises details apart from the important cognitive functionality, health and surroundings, knowledge, emotion, and the user model are also one of the important elements. There are two types of features in a user model, static and dynamic features [1]. Age, gender, and degree of education are examples of static traits that are unlikely to change. Dynamic traits, on the other hand, are those that vary more often, such as cognitive capability, mood, and health state. Because the characteristics of a user model change amongst them, the system may be utilized to tailor for everyone. Therefore, it's vital to construct the user model in such a manner that it can distinguish between users.

The attributes of the material being shown to the elderly are referred to as the contents model [1]. It includes everything from fundamental information like title, author, description, and category to more user-friendly features like brightness, subtitles, button size, and loudness. Usability features have an influence on the UI/UX and may be adapted to the user's model.

The UI/UX model describes the components that may alter depending on the user model and content model. The UI/UX components may also be customized to meet the demands of the elderly. The device screen size influences the number of characters shown on a screen, as well as character size and font.

[1] states that to access sensory function, visual and auditory functions are used whereas attention, memory, emotion executive function, and psychomotor competence are used to access cognitive function.

The ability of the eye to sense the existence as well as the shape of an item is referred to as visual function, whereas auditory function is referred to as the ability of the ear to hear noises [7]. Memory is defined as the ability to recall previously learned information in cognitive terms, and it is divided into word, number, phrase, and spatial recall. Attention, according to [7], is the capacity to employ brain resources strategically and switch attention between many activities. The three forms of attention shift. are selective attention, automatization, and attention shift. Executive functions are a set of cognitive skills that include reasoning and logical thinking and are achieved by combining numerous cognitive processes including attention, memory, and recall. To discriminate between positive, stagnant, and negative responses to environmental stimuli, researchers use sentiment and psychomotor competence [7].

The afore mentioned sensory and cognitive processes are measured using several approaches in [1]. A range of sized and coloured items and letters are supplied to measure visual function. Audio impulses are sent through a headset to test the user's auditory function. To test cognitive performance, a variety of games are utilised. In the user model, ML techniques are utilised to quantify and cluster data on quantifiable memory, executive function, attention, sentiment, and psychomotor competence. A recommendation system is an online IT solution that offers consumers with relevant information or services based on their purchasing history or interests [1]. Material is given to the elderly in an ideal UI/UX depending on the qualities of the content and the user's cognitive ability in a cognitive reaction-based system. Because the user will select the material, it is vital to create a tailored system that proposes to seniors the stuff that is most valuable to them.

Therefore, in their experiment, [1] includes a customised content recommendation system for seniors into an intelligent UI/UX system that categorises users based on user behaviour histories such as rating, content purchase, and viewing logs. This is accomplished via the employment of cognitive response-based systems, which not only adapt UI/UX components for each user, but also recommend information or content that is most relevant to that user.

c) Data Preparation and Analysis

Two types of data preparation and analysis are discussed which is using Word Frequency and Pattern and Contextual Semantic Search (CSS) under sentiment analysis text classification. CSS is a clever search algorithm that uses context [10] and it works by taking many messages and a concept (such as Price) as input and filtering out those that are most like the supplied notion. In data mining pipeline and concept of research design in term of methods that are being used, there are three steps in the data preparation: (1) data sampling, (2) data collection, and (3) data pre-processing) [8].

In the data analysis part, there are two steps, unsupervised ML, which is using clustering algorithms, sentiment analysis and thematic qualitative analysis. The score will be normalized to detect the polarity of the interview data as positive, negative, or neutral, then, visual, auditory, psychomotor ability, sentiment, executive function, attention, and memory will be used to annotate the primary cognitive reaction and the cognitive index and scores for each cognitive type will be calculate. That as to why, CSS is used in this research instead of using Word Frequency and Pattern to prepare and analyse the interview data.

d) Machine Learning (ML) Algorithms

There are three ML algorithms that have been discussed in this paper, which are Naïve Bayes (NB) classifier, Support Vector Machine (SVM) algorithms, and Latent Dirichlet Allocation. NB and SVM are chosen to compare and evaluate the results because both algorithms are the most common used in text classification field of study such as [9]

NB is one of the ML algorithms that a lot of researchers have employed to handle sentiment analysis. According to [9], the NB classifier is a supervised ML classifier that handles classification problems using statistical approaches. Cognitive inputs from the elderly will be gathered through interviews and questionnaires, NB classifier is a very simple yet effective classifier, it has two (naïve) assumptions:

- All features are equally important
- All features are independent of one another

The classifier searches for qualities while keeping in mind that all features are distinct from one another. Bayesian classification employs prior probability from the training set to approximate the posterior probability of the class to which a record belongs. The classification model determines how likely a record is to belong to each of the classes. The record's class label is determined by the class with the greatest probability. To extract the features, N-gram models must be utilised. The formula for NB is shown in Equation (1) below:

$$P(C|X) = \frac{P(X|C)P(C)}{P(X)} \quad (1)$$

where,

P(C|X) – posterior

P(X|C) – likelihood

P(X) - predictor prior probability

P(C) – class prior probability

After labelling the dataset, [9] employs the NB classifier. The classification procedure begins with labelling the dataset and then passes through the NB classifier to be categorised. The classification's accuracy is accessed, and the proportion of sentiment is also calculated.

SVM is a well-known supervised learning approach for tackling a variety of classification issues, including text classification and, more recently, question classification. For a two-class learning problem, the primary premise of the SVM is to create a linear decision boundary between two classes that is as far away from the closest training samples inside each class—the support vectors—as possible. Even though numerous forms of SVM have been developed, [9] largely focus on linear SVM in their study on classification based on cognitive level due to its popularity and excellent text categorization.

e) Evaluations

We are using accuracy, precision, recall and F1-score and k-folds cross validation in our experiments to assess the performance of classifiers used in the research. Precision was calculated to quantify predicted of the class that absolutely belong to the class and recall was calculated to quantify the number of class predictions made from the entire dataset. F1 score was calculated to provide a single score that stabilises both precision and recall concerns in one number. [8] analysed their baseline evaluation statistics in their research of emotion analysis on Twitter. These assessment methodologies were employed in two portions of their research: (1) detecting tweet emotions and (2) determining tweet relevancy.

The researchers can calculate precision, recall, and F1-score in the Emotion Tweet Corpus for Classification (ETCC) corpus based on the presence and absence of emotion hashtag in the tweet data, to establish a baseline against which to compare the performance of their classifiers in the tweet emotion detection section. However, according to the assessment findings for the ML classification of tweets on the ETCC corpus showed a variance in performance across all types of emotions.

[8] tested the classifier's performance in detecting emotional tweets in the Emotion Tweet Corpus for Relevance (ETCR) corpus using various score criteria for emotion detection in the tweet relevance section. By adjusting the threshold score for emotion classification, the ideal score for recognising the emotional significance of the tweet may be obtained.

Lower score criteria, as seen in the graph, favoured recall over accuracy. Precision, on the other hand, improved when the criteria were raised. [6] evaluates the outcomes using accuracy, precision, recall, and F1-score. The problems in their evaluation were easily identified because they did not clarify much about the evaluation portion.

In their research on exam classification based on cognitive level, [9] mentions that NB, SVM, and k-NN classifiers were applied to the entire sample-term feature space to evaluate their performance without feature reduction. The experimental findings for each Bloom's Taxonomy cognitive level utilising the NB, SVM, and k-NN techniques as the F1- measure. As indicated, the k-NN technique on macro F1-measure achieved the maximum performance (80.82) of the applications done without the use of any feature reduction method, while the NB classifier achieved the lowest performance (74.95). Because k-NN is a simple non-parametric classifier, testing have demonstrated that it is an effective classifier in short text classification, outperforming other strategies.

III. METHODOLOGY

Through interview and questionnaire responses, cognitive reactions and demographic details are collected from a group of elderly in Malaysia. In the pre-processing stage, to increase data integrity, reliability and efficacy of text mining, the mistakes and contradictions from the dataset are eliminated. The initial stage of text pre-processing is to undergo normalization by converting all words to lowercase, and removing exclamation points, symbols, whitespace, and numerals. To eliminate stop words and stem the data, the dataset was then annotated with positive, negative, and neutral labels. Next, feature extraction was conducted using TF-IDF and N-gram. The dataset undergoes classifications of two ML algorithms, NB and SVM which then will be evaluated. Finally, a personalized UI is developed and visualized based on the instant messaging app interface from the cognitive index result of the elderly dataset. Our methodology consists of two core phases, which are Phase 1 and Phase 2 as shown in Fig. 1 below. Phase 1 is data acquisition and preparation while Phase 2 is the classification phase.

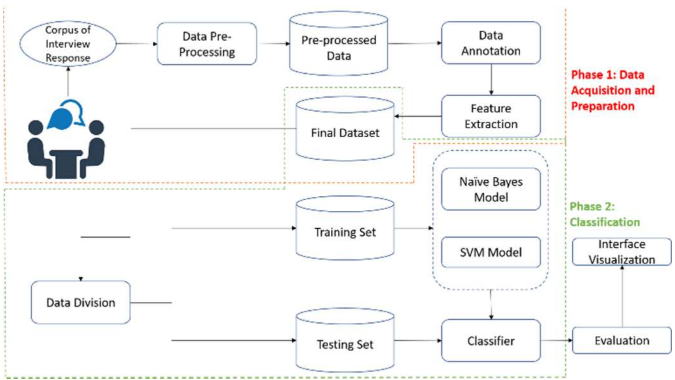

Fig. 1. Project Pipeline Overview

In this paper, a mobile application builder will be used to illustrate the interface visualisation based on the result of the interview's classification data into personalized UI based on the instant messaging app. Different UI design depicts different problem to tackle with the elderly problem. For example, the elderly who has a higher visual score index for their cognitive reaction will be needing a UI that focuses more on visualisation, while the elderly who have a higher memory score index, will be needing a UI that does not require many steps to complete the tasks. Thus, the elderly will be needing their personalized UI for instant messaging apps depending on the cognitive index weightage and importance.

IV. RESULTS

The results of the evaluation for both Multinomial NB (MNB) and SVM classifier in terms accuracy, precision, recall, and F measure for both testing and training set is shown in Table I.

TABLE I. SVM AND MNB CLASSIFIER PERFORMANCE RESULT

	SVM		MNB	
	Training	**Test**	**Training**	**Test**
Accuracy	84.44% +/- 5.21%	85.37 %	89.44% +/- 8.80%	95.12 %
Precision	84.33% +/- 5.09%	85%	100.00% +/- 0.00%	100.00 %
Recall	100.00% +/- 0.00%	100%	87.46% +/- 10.23%	94.12 %
F-Measure	91.43% +/- 3.00%	91.89 %	93.02% +/- 5.85%	96.97 %

Fig. 2 shows the result demonstrated that the SVM classifier has obtained 0.85, which means that 85.37% of the time the interview dataset cognitive attributes were correctly predicted with a test set, while for training data (10-fold CV), the classifier obtained 0.84 which means 84.44% of the time the interview dataset cognitive attributes was correctly predicted.

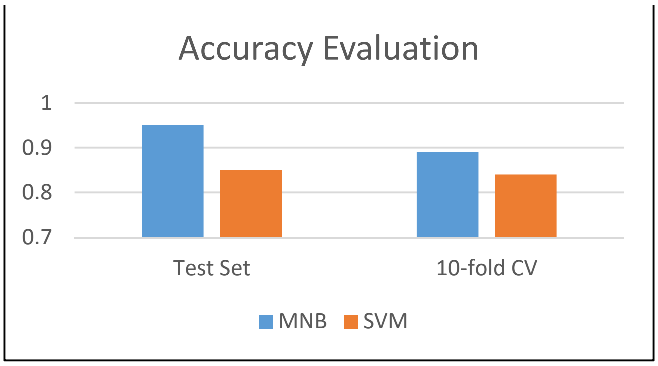

Fig. 2. Accuracy of MNB and SVM Comparison

As for the MNB classifier, however, there are only slightly different as when using the test set, MNB classifies the interview dataset 95.12% correctly, while scores 0.89, which means 89.44% of predicted cognitive attributes of the interview dataset are correct when using 10-fold cross-validation. In conclusion, both SVM and MNB can achieve good predicting results in the text sentiment analysis, especially MNB, as it has the highest score for both test and training set The score for SVM for sets are the same, as the test set size might be equivalent to the average iterations of both training set.

An interface of an instant messaging app that been personalised by the cognitive index score from the classification result based on the group of elderly's collected cognitive response and demographic details had been developed based on WhatsApp Messenger. Table II shows the final value of the cognitive index score of each attribute after the combined dataset undergoes both the classification processes.

TABLE II. COGNITIVE INDEX SCORE FOR EACH ATTRIBUTE AFTER UNDERGOES BOTH CLASSIFICATION PROCESS

Attributes	Value (max: 10)
1. attention (Attention – Cognition Ability)	6.223
2. visual (Visual Acuity – Sensibility)	5.107
3. function (Executive Function – Cognition Ability)	3.981
4. psychomotor (Psychomotor – Cognition Ability)	2.260
5. memory (Memory – Cognition Ability)	1.958
6. audio (Auditory Acuity – Sensibility)	1.929
7. sentiment (Sentiment – Cognition Ability)	0.433

With the new personalized UI of the instant messaging app based on WhatsApp Messenger, a few of the elderly from the Elderly group that undergoes the interview for the dataset beforehand were asked to undergo the same Usability Questionnaire. The purpose of the questionnaire is to collect the elderly's opinions on the UI and functionality of the most used Instant Messaging App in Malaysia, WhatsApp Messenger, and comparison with the proposed personalize the UI based on WhatsApp Messenger based on the group of elderly's interview dataset.

Based on some of the respondent's questionnaire record, it is clear that the group of elderly respondents prefer the personalized UI based on their cognitive function and demographic details more compare to the existing WhatsApp interface that is tailored to all users. This is because they can personalize it based on their needs and make it easier for them to complete the tasks effectively and quickly.

V. DISCUSSION

To conclude, this project aims to develop an intelligent UI system that adapts to the user's personality type based on cognitive response and demographic information. A list of interview responses from a group of elderly in Malaysia has been gathered. The response on instant messaging app perspectives has been crawled using 7 Recognition Response Measurements which include sensibility and cognition ability factors. The dataset then goes through feature selection and is classified using two ML algorithms, MNB and SVM classifier, and the total confidence value of each 7 attributes that had been used to classify the visual dataset, audio, function, memory, attention, sentiment, and psychomotor were counted and sort in descending order.

The analysis showed that elderly interest in smart technology trends has been increasing in recent years based on the interview response as the interview data indicated that the role of mobile phones was to assure the elderly that they could always call somebody when they were in trouble and to not be felt left around in the community. The interview data also indicated that the majority of elderly feel like they were too many functions in most instant messaging apps and the designs of UI are not user-friendly for them to use and adapt to their degrading cognitive and psychomotor functions. It is very concerning since Malaysian is reaching 'Age Society' and elderly familiarities and usability in using smart devices are important to improve their quality of life.

In this paper, two ML algorithms had been compared in predicting the sentiment and classification of interview response dataset from a group of elderly in Malaysia Classification-wise, MNB has the highest score in accuracy compared to SVM for both 10-fold cross-validation and testing sets. This shows that MNB can predict more precise sentiment classification, to predict whether the text is positive, negative, or neutral. The UI for the instant messaging app based on WhatsApp Messenger also has been personalized based on the dataset classification result and the elderly's demographic details.

VI. CONCLUSION

This study provides helpful and an understandable insight on how different elderly levels of cognitive and how a customized interface will help them greatly in consuming digital content as the ML approach is a very reliable approach to predict and solve the human problem in this modern era.

Despite various studies for older persons, there has been little study on strategies to familiarise the active elderly with smart devices and gadgets. Furthermore, because the elderly's capacity to use advanced technology such as smart devices or smartphone is limited, research on smart device UI/UX systems was hardly conducted with the elderly population in mind. To bridge the gap between the old and the current era, everyone is focused on providing outstanding aged care and efficient communication among themselves. Nowadays, the greatest gadget to work on for improved communication and engagement is a smartphone. However, all smartphones are developed following current trends and the trends appeal to the youth. The elderly may see fear or bias as operating on their thinking. This group of people is wary of utilising a smart gadget because of the interface and interaction techniques. To address these concerns, this project presented a personalized UI system design tailored to the needs of the elderly population, especially in Malaysia, and incorporated its interface prototype based on the instant messaging app.

This project proposes a personalised UI system that automatically classifies the elderly by the acquired cognitive response functioning input, and demographic details and optimises UI units based on the classification result. This system also makes use of ML technologies to classify data generated throughout the system. The result of the data classification is used to create an interface based on an instant messaging app to enhance the use of smart devices among the elderly especially in Malaysia as well as their quality of life.

There are limitations of the project whereby the capabilities of text classification in clinical NLP and the lack of Malay language resources. The contribution of this project is comparing two ML algorithms in predicting the factors in Recognition Response Measurements attributes in the elderly's interview dataset.

As for future work, we would like to produce more accurate methods to classify elderly Recognition Response Measurement. In this project, the elderly personalized UI is visualized based on elderly demographic details and responses in the Recognition Response Measurement interview. More ways to improve the recommendation system can be applied by personalising the UI based on content's features or the user's history on smart devices. Because it is the user who already selects the content or function beforehand, creating a custom system that recommends the elderly user to the most used function in their mobile app can be crucial and not time-consuming for the elderly to complete any task.

We also would like to study using text classifiers with more reliable Malaysian native dictionaries. The keywords to feed the classifier can be used for less human intervention if more reliable Malay dictionaries can be obtained from a more reliable and concise source.

ACKNOWLEDGMENT

The authors fully acknowledged Universiti Malaysia Sarawak for the approved fund which makes this important research viable and effective.

REFERENCES

[1] You-Dong Yun, Lee, C., & Lim, H.-S. (2016). Designing an intelligent UI/UX system based on the cognitive response for smart senior. 2016 2nd International Conference on Science in Information Technology (ICSITech). https://doi.org/10.1109/icsitech.2016.7852648

[2] Anam, R., & Abid, A. (2020). Usability study of smart phone messaging for elderly users. International Journal of Advanced Computer Science and Applications, 11(3). https://doi.org/10.14569/ijacsa.2020.0110313 .

[3] M. Pattison, and A. Stedmon. (2006). "Inclusive design and human factors: designing mobile phones for older users". Psychology Journal, vol. 4, no. 3, pp. 267-284.

[4] Al-Razgan, M. S., Al-Khalifa, H. S., & Al-Shahrani, M. D. (2014, June). Heuristics for evaluating the usability of mobile launchers for elderly people. In International Conference of Design, User Experience, and Usability (pp. 415-424). Springer, Cham.

[5] Willis, G. B., & Artino Jr, A. R. (2013). What do our respondents think we're asking? Using cognitive interviewing to improve medical education surveys. Journal of graduate medical education, 5(3), 353-356.

[6] Rasid, N., Nohuddin, P. N., Alias, H., Hamzah, I., & Nordin, A. I. (2017, November). Using data mining strategy in qualitative research. In International Visual Informatics Conference (pp. 100-111). Springer, Cham.

[7] Tavares-Júnior, J. W. L., De Souza, A. C. C., Alves, G. S., Bonfadini, J. D. C., Siqueira-Neto, J. I., & Braga-Neto, P. (2019). Cognitive assessment tools for screening older adults with low levels of education: a critical review. Frontiers in psychiatry, 10, 878.

[8] Xue, J., Chen, J., Hu, R., Chen, C., Zheng, C., Su, Y., & Zhu, T. (2020). Twitter discussions and emotions about the COVID-19 pandemic: Machine learning approach. Journal of medical Internet research, 22(11), e20550.

[9] Abduljabbar, D. A., & Omar, N. (2015). Exam questions classification based on Bloom's taxonomy cognitive level using classifiers combination. Journal of Theoretical and Applied Information Technology, 78(3), 447.

[10] Gupta, S. (2018). Sentiment Analysis: Concept, Analysis and Applications. Medium. https://towardsdatascience.com/sentiment-analysis-concept-analysis-and-applications-6c94d6f58c17

[11] E. Ubam, I. Hipiny and H. Ujir, "User Interface/User Experience (UI/UX) Analysis & Design of Mobile Banking App for Senior Citizens: A Case Study in Sarawak, Malaysia," 2021 International Conference on Electrical Engineering and Informatics (ICEEI), 2021, pp. 1-6, doi: 10.1109/ICEEI52609.2021.9611136.