Acta Scientiarum

http://periodicos.uem.br/ojs
ISSN on-line: 1807-8664
Doi: 10.4025/actascitechnol.v44i1.61112

COMPUTER SCIENCE

Cross-cultural usability evaluation of AI-based adaptive user interface for mobile applications

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ABSTRACT. With the widespread purchase of mobile communication devices and their extensive usage in every aspect of life, allied with global mobility and market penetration – a more culturally universally adaptable interface has become a priority. This pliable interface must conform continuously with the changing abilities of the end user and the person's culture, irrespective of the prevailing ambient culture. The information required to customise this interface must be derived from the user's actual digital footprint and not on their feedback. This treatise presents the usability evaluation results of a culturally inclusive and ubiquitous mobile learning (M-Learning) platform ('Mobile Academy'), with an AI-based adaptive user interface which takes the snapshot of the installed apps on a smartphone as input, predicts the user's cultural affiliation as well as the language preference and thus offer a culturally customised user interface as the output. The proof of concept (PoC) prototype has been developed based on the CIAUI (Culturally Inclusive Adaptive User Interface) framework, using plasticity of user interface techniques. This approach was taken to test the affordability of developing inclusive applications, considering the ever growing large global culturally diverse user base. Usability evaluation was then conducted and the results carefully analysed. The results indicated that the PoC exhibited enhanced cross-cultural usability and affordability of such techniques. The evaluation results of the PoC also advocates in favour of the user's cultural profiling based on the mobile usage data, particularly a single snapshot of installed apps. The research provides direction for future research and application development.

Keywords: Artificial intelligence (AI); CIAUI (culturally inclusive adaptive user interface) framework; cross-cultural inclusivity; digital footprint; plasticity of user interface design; SVM classifiers; usability evaluation.

Received on October 4, 2021.
Accepted on October 25, 2021.

Introduction

Despite the cynics, computational power continues to adhere to Moore's Law (Moore, 1965; Moore, 2006, Burg & Ausubel, 2021). Conversely, the price of computing hardware per CPU performance, network access speeds and cost to access the Internet continue to plummet at an inversely exponential rate. Included within this declining cost is the mobile device purchase cost and internet usage costs globally. With the widespread adoption of smartphones and the Internet of Everything (IoE) (Miraz, Ali, Excell, & Picking, 2018) have led to the utilisation of mobile devices for all kinds of Internet use, including even banking and financial transactions such as spread betting. Such widespread mobile usage offers the potential to widen the international ubiquitousness of teaching and learning, especially using M-Learning. The surfeit adoption of mobile devices, particularly amongst culturally diverse users, significantly contributed in eliminating the digital gap (Miraz, Excell, & Ali, 2017).

Recent literature reviews and ethnographically based surveys by the researchers helped in part with the requirement analysis and identified the need for the development of an AI based adaptive user m-Learning platform for users with cross/multi-cultural affiliations. This treatise is believed to be unique in this regard of addressing the needs of cross-national, cross-cultural and multi-national users along with the application of the AI-based adaptive user interface m-learning prototype.

The usability evaluation plan was necessarily detailed, which generated a comprehensive result helping in the evaluation of the SVM classifiers' performance and cross-device assessment.

The main aims of the research were:

. to identify the arising problems from the mobile learning prototype app requirements and then to find the corresponding solutions;

. to evaluate the effectiveness of inclusivity, usability and effectiveness of the interface.

Being a prototype, the app naturally had limitations which meant that testing for robustness was not a primary goal, these were all explained.

The following sections explains the rationale of selecting the mobile learning to be developed, its characteristics, the development platform and the limitations of the app.

To evaluate the cultural inclusiveness and usability of the m-learning prototype, namely the ‘Mobile Academy’ (Miraz, Khan, Bhuiyan, & Excell, 2014; Miraz, Ali, Excell, & Khan, 2021) evaluation study plans, experimental tasks for the users and questionnaires to capture the users’ feedback were all developed. This paper provides a brief description of the evaluation process, including some general information, mainly regarding the participants, the environment and procedure.

In addition, the results of the research are analysed in this paper, presenting the primary findings of the evaluation studies to test the usability and inclusiveness, focusing on cross-cultural aspects of the prototype.

Finally, a critical analysis of the whole research project has been presented.

Related works

Exploiting the big data generated by the smart devices and from the social media, prediction of the user interface and traits via data mining, have all become an emergent trend. (Chittaranjan, Blom, & Gatica-Perez, 2011; LiKamWa, Liu, Lane, & Zhong, 2013; Pan, Aharony, & Pentland, 2011; Yan, Chu, Ganesan, Kansal, & Liu, 2012; Parate, Böhmer, Chu, Ganesan, & Marlin, 2013; Xu, et al., 2013).

The correlation between the users’ personality traits (deduced from self-report surveys) and behavioural characteristics (by eight months of smartphone usage data analysis) have all been investigated by Chittaranjan et al. (2011). They have adopted data mining as well as machine learning methods utilising users’ usages of SMS, apps, call logs etc., to examine the Big-Five personality traits introduced by McCrae & John (1992) in 1992, e.g. viz. agreeableness, conscientiousness, extraversion, neuroticism and openness to experience. This pioneering research achieved an accuracy of 75.9%.

In a similar research, to study the impact of the personality traits of the users, particularly on social networking services [SNS] usages, Uesugi (2011) adopted the Five-factor model. The principal purpose of the study was to undertake a systematic investigation, utilising the Big Five model, in order to determine the correlation between the users’ personality traits and the SNS use. To be precise, to substantiate whether the users’ personality traits had any significant impact on the users’ adoption trends of and perceptions towards the SNS usage. According to the results of their research, three out of the five factors, i.e. agreeableness(A), conscientiousness(C) and extroversion(E), had statistically significant impact on different type of SNS services.

In another study, Vaidhya, Shrestha, Sainju, Khaniya, & Shakya (2017) adopted the Big Five personality traits model, together with machine learning algorithms, particularly SVM and *k*-nearest neighbours (KNN), to analyse the statuses of the Facebook users in order to enumerate their personality trait score, using a scale between one to five.

Segalin, Perina, Cristani, and Vinciarelli (2016) demonstrated another futuristic application of the Big Five model. This was by the application of the model on the user generated galleries of favourite pictures on Flickr. The Flickr platform lets the users tag the pictures they like as ‘favorite’. By eliciting the low-level features from the pictures, Segalin et al. (2016) mapped them to the numeric score representative of both the self-assessed attributed Big-Five Traits. This was manifested by adopting an approach based on computational aesthetics, proficient to predict the Flickr users’ personality traits. A sample size of larger than 60,000 photos, which were tagged as ‘favorite’ by 300 Flickr users, where used in this study. The results demonstrated positive outcomes – in accordance with personality computing, achieving an effective correlation of 0.68 between the actual and the predicted personality traits.

LiKamWa et al. (2013) designed and developed an app for the iPhone platform, namely MoodScope, which acts like a ‘sensor’ to infer the mental state of the app users by exploring and analysing their communication history and app usage patterns. Even-though the initial performance of the app/study was limited to 66% accuracy, through personalised training for a duration of over two months, the performance steadily reached an accuracy of 93%. However, the study results are limited by its sample size and geographic location. The study was conducted amongst only 32 participants from China and the USA.

A number of different researchers, e.g. Shepard, Rahmati, Tossell, Zhong, and Kortum (2010) and Böhmer, Hecht, Schöning, Krüger, and Bauer (2011), investigated the dependency of app usage on different contextual variables such as the time and day of use, location etc. As demonstrated in (Yan et al., 2012; Parate et al., 2013; Xu, et al., 2013), these assorted contextual variables can also act as indicator and can be used to predict the users' future app usage. In fact, it is also possible to infer the demographic data of the users' by studying the browsing log obtained from both the client side (Goel, Hofman, & Sirer, 2012) as well as the server side (Hu, Zeng, Li, Niu, & Chen, 2007).

Kosinski, Stillwell, and Graepel (2013) demonstrated that by analysing Facebook likes, combined with different demographic data including psychometric test scores, users' psycho-demographic profiles can be inferred. The psycho-demographic profiles include a wide range of excessively sensitive attributes such as the ethnic background, age group, gender, religious beliefs, political views, drug addiction, parental separation and sexual orientation etc. The study was undertaken with a very large sample size of 58,000 participants.

Another similar study was conducted by Volkova, Bachrach, and Durme (2016), analysing Twitter data obtained from the profiles of more than 4,000 users. The study inferred different personality traits of the Twitter users such as gender, age, educational background, political stance et cetera, by applying training models to analyse the correlation between the interests and perceived psycho-demographic attributes of the users. Rather than directly using the twitted texts, they considered and examined the other accounts followed by the participating users. This approach was designed considering the postulation that the users as a matter of fact are embedded in their social network platforms, such as Twitter.

Hassanein, Hussein, Rady, and Gharib (2018) conducted another similar study for inferring personality traits by applying text semantic analysis on SNS data, particularly those obtained from status updates of Facebook. Their study adopted various semantic based measures on the different representations of the user texts, such as status updates, with an accuracy of as high as 64%.

A slightly different approach (i.e. visual analytics) was adopted by Brown et al. (2014) to infer the performance of users and predict a number of different personality traits by administering machine learning algorithms on the interaction data of the users. The users were required to conduct visual search related tasks, for this experiment. Depending on the encoding schemes used and the machine learning algorithms applied, the accuracy rate achieved in successfully inferring the user performance was found to range between 62% and 83%. It should also be noted that the performance measured was formulated into a binary output, i.e. slow or first, in accomplishing the assigned tasks. However, their study was not only limited to predicting the users' performance, rather by utilising the same techniques, it was possible to predict several other aspects of the personality traits of the users, such as the locus of control, extraversion and neuroticism.

Aktivia, Djatna, and Nurhadryani (2014) utilised the user preferences and needs inferred through the analysis of the personality traits, in order to enrich the visual usability of the mobile applications by dynamically customising the interface.

A user behaviour analysed modified adaptive user interface (AUI) was reported by Rathnayake et al. (2019) for supplementing common software platforms. Their research showed the requirement for a generic software infrastructure for AUI by conducting studies on customised web interfaces using machine learning. Using the AdaBoost classifier, their AUI generator achieved 100% accuracy for UI components.

Based on 100,000 smart phone users' app lists, Zhao (Zhao et al., 2017; Zhao et al., 2019; Zhao et al., 2022), conducted research to elicit their traits and user attributes. An attribute-specific representation generation for the user characteristic was the first approach taken (Zhao et al., 2017) which was then expanded to build up a relationship between the app list and the attribute. Achieving an average equal error rate of 16.4%.

Boolean matrix factorisation (BMF) (Zhao et al., 2022) was used to develop the inherent and complex app and user relationship. The approach undertaken was to split 30,000 users into three sets of 10,000 users with their corresponding installed app lists. For each set, the user's attributes, semantic tagging and general grouping were determined using both unsupervised and supervised learning.

Based on 106,672 Chinese Android users (broken down into three income bands and four age ranges), an empirical study was undertaken (Zhao et al., 2019) to perform a detailed statistical analysis to see the intrinsic trends and relationships between the user and the app duration of usage, frequency of usage, functionalities utilised and the user's biometrics including financial status. The overall accuracy results obtained were: 83.29% (gender); 71.43% (income segments) and 69.94% (age bands).

The consensus from the literature review to date shows that personality traits can be proficiently inferred from analysing user installed apps, behaviour and the user's digital footprint. User data based AUI using machine learning have all been reported by capturing instances of installed apps for the input in order to provide the CIAUI (Miraz, Excell, & Ali, 2021) – as presented by our novel framework prototype concept.

Our work is complementary of those by Kosinski et al. (2013), being grounded on Seneviratne et al. (2014), however, differing in several novel ways. Seneviratne et al. (2014) propounded the identification of 'the users' preferred country (for culture-orientation purposes) by using a list of app ratings by country, published by the Appbrain website' (Seneviratne et al., 2014). Nevertheless, the list of countries only looked at 27 countries which also happened to be all outside our project area. The study was also restricted to one country and did not consider multi-cultural, multi-national individuals nor their roaming requirements. Our work is not restricted in such ways, being extended to cover the user's cultural background, country choices and preferential country grouping, for example Semitic countries are usually described as 'Arab'. Though it should be noted that further studies are necessary to distinguish the many non-Arabic people such as the Berbers or Imazighen. To reiterate, based on our detailed study of the literature to date, the proposed CIAUI Framework is still strongly believed by us to be novel and a timely and pertinent contribution.

Materials and methods: the CIAUI framework and the prototype

This current research work is based on the CIAUI Framework, as shown in Figure 1, to extend m-learning and other interrelated mobile applications. The CIAUI Framework integrates universal design concepts to cater for culturally diverse users. It was a serendipitous outcome of our project in developing, completely analysing and fully defining the AI based adaptive interface app, the 'Mobile Academy'. The Mobile Academy used the concept of plasticity of UI design techniques for culturally inclusive design to satisfy successfully cross-cultural usability. The validation, parameters and examples of developing further mobile applications including the suggested future research direction to be undertaken are all given here. A review of the principles of culturally inclusive design are also presented.

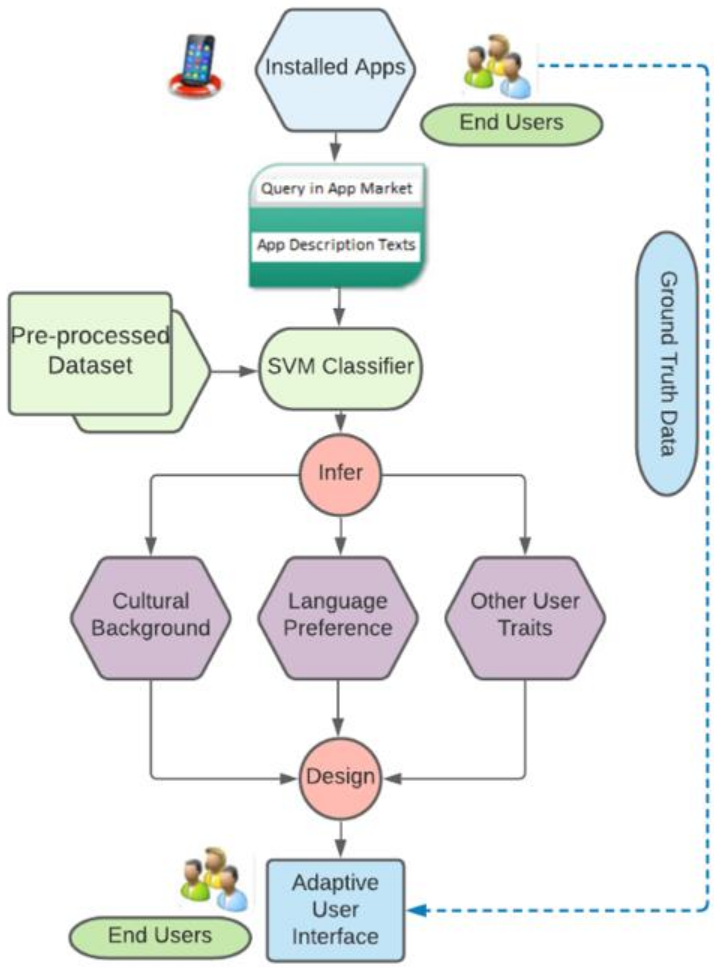

Figure 1. The CIAUI Framework.

The principle aim of the research was achieved, that is, the derivation and development of a framework for the culture-independent universal design for mobile learning through plasticity (Miraz, Excell, & Ali, 2021) of user interface design techniques. More specifically the delivery of the m-learning prototype being the 'CIAUI (Culturally Inclusive Adaptive User Interface) Framework' for future culturally diverse mobile application users.

Moore's Law (Moore, 1965; Moore, 2006) is still being followed along with the surfeit of smartphones and utilisation of Internet of Things (Miraz et al., 2015; Miraz et al., 2018). The sophistication of the chip technologies and the variety of devices have all contributed to the offering of ever more sophisticated m-learning dynamic user interfaces. This is also closely linked to and helped by the lowering of cost of the trio offering (internet access, mobile device hardware and CPU processing power) helping mass access.

The right juncture in time is now to provide culturally specific user interfaces that can be adaptive to the user's needs specifically for m-learning platforms.

The significant objective of the paper, which had been met, was to provide a working demonstration of the CIAUI Framework that satisfied the broad scope for cross-cultural usability.

By reviewing the results from the user surveys as well evaluating the initial version (Miraz, Khan, Bhuiyan, & Excell, 2014; Miraz, Ali, Excell, & Khan, 2021) of the Mobile Academy (m-learning prototype) the proposed Framework was created. The prototype then went through subsequent revision adopting the approach undertaken to create the initial framework. Then the advanced machine learning based Mobile Academy (Miraz, et al., 2014; Miraz, Ali, Excell, & Khan, 2021) was used as a benchmark for the framework. Thus, the Mobile Academy's parameters were used as the foundation of the framework. The revised advanced version of this Mobile Academy (Miraz, Ali, Excell, & Khan, 2021) was then adopted as the framework-based app upon which further research and development was underpinned. Our studies showed the feasibility of machine learning based adaptive UI application could now be developed using the advanced framework.

The framework output comprised adaptive language display and the associated interfaces to render and display the output. This dealt with the culture specific image control, colour palette and character display direction. The framework is expected to behave properly with any other culturally relevant input parameters (snapshots of installed apps and other collected mobile data). App description texts may be obtained by querying the markets which are then fed to the SVM (Cortes & Vapnik, 1995) classifiers along with filtered pre-processed datasets by data mining (Miraz, Ali, Excell, & Khan, 2021). From these inputs the mobile system infers the cultural background of the user (i.e. language preference and associated qualities) to offer the personalised adaptive UI utilising plasticity of UI design techniques. The performance of the system is monitored and verified by the SVM classifiers fed by the ground truth data. The functionality of the framework it should be noted does not require the ground truth data itself.

The basic framework, which is scalable, was intended for the creation of cross-cultural usable m-learning mobile apps. The framework may also be extended to serve global users, the details of which are presented in this research.

As the main aim of the paper is to present the evaluation results, only a basic introduction to the prototype has been included. For technical details of the prototype, please refer to the Mobile Academy (Miraz et al., 2014; Miraz, Ali, Excell, & Khan, 2021) prototype, which is a ubiquitous mobile learning platform developed using Android. The app was developed as a proof of concept (PoC) to examine the viability of an affordable culture-independent inclusive interface for mobile application development, focusing on mobile learning. A combination of plasticity of user interface design techniques (Miraz, Ali, & Excell, 2021; Miraz, Excell, & Ali, 2021; Miraz, Excell, Ali, & Khan, 2021) as well as artificial intelligence (AI) features such as SVM (Support Vector Machine) classifiers (Cortes & Vapnik, 1995) were used. The prototype takes the list of installed apps as input to infer the language preference and cultural affiliation of the users and then offer an adapted interface customised for those traits. The prediction is based on the training parameters set for the SVM classifiers. Figure 2 displays a snapshot of the developed app.

The prototype developed thus facilitates the customisation of the user interface, making the required language preference and cultural affiliation prediction based on the snapshot of the apps installed in the respective devices. The assessments of the SVM classifiers (machine learning techniques) were evaluated by their recall and precision statistics using data (ground truth) from 253 culturally diverse users.

Figure 2. OAuth (Gmail) based login page, the colour of the adaptive interface is associated with the inferred culture of Arabian Countries and Pakistan; Arabic is the predicted preferred language (Miraz, Ali, Excell, & Khan, 2021)(Miraz, Ali, Excell, & Khan, 2021).

Compared against the ground truth data of 253 users from widely diverse users, the current research makes evident that the cultural background of the users can indeed be accurately predicted with a precision rate of 88% and the language of preference can be inferred with as high as 100% precision rate using only the snapshot of the installed apps. The prototype developed is not only limited to offering an interface based on cultural preferences but can be further extended to infer various other personality traits, such as the: gender, age and many more. This technique can also be utilised for recommender systems (Corallo, Lorenzo, & Solazzo, 2006), micro-targeted advertising and other similar projects, without the need for either user profiling nor logged in for a prolonged period – but only by observing and tracking the user activities. Even, if it holds the promise to be analogously used with other tracking systems, thus eliminating the cold-start problem. This is where it is very difficult to build a precise profile, until the necessary amount of data has been collected by observation over some extended minimum period of time.

Evaluation

The usability evaluation, presented in this section, was conducted following the methods and techniques established by Rubin and Chisnell in their famous book entitled '*Handbook of Usability Testing: How to Plan, Design, and Conduct Effective Tests*' (Rubin, Chisnell, & Spool, 2008). As suggested by them, the overall evaluation process includes experiments, hypothesis testing, and both dependent and independent variables were used for the purpose of statistical analyses, participant selection, analysing and reporting results and derivation of directions for future study. The following sub-sections detail the evaluation process in more detail.

The study plan

To evaluate the prototype for its usability (Miraz, Ali, & Excell, 2013; Rogers, Sharp, & Preece, 2012; Kortum, 2008; Shneiderman & Plaisant, 2009), especially cross-cultural inclusiveness (Miraz, Excell, & Ali, 2016; Miraz, Ali, & Excell, 2016; Ali & Miraz, 2015; Miraz, Ali, & Excell, 2018; Miraz, Excell, & Ali, 2016; Miraz, Ali, & Excell, 2016; Ali & Miraz, 2015; Miraz, Ali, & Excell, 2018), users from a wide range of culturally divergent backgrounds were selected as pilot users to test the prototype for learning purposes. They had to install the app on their Android devices with inclusive permissions to access their lists of installed apps. Prior to that, an introduction regarding the aims of the research as well as tasks to be performed was given so that the participants knew exactly what they had to do to help complete the research. The users were also provided with information on association of colours, image control and text flow whether right-to-left or vertically and other association relevant to the cultural background. Upon installation of the prototype, the users were asked to use the application with the loaded interface. The users were also requested to customise the prototype using the default interface if the system was successfully able to infer their cultural background and offer an adaptive interface. If the users were offered the default interface instead, they were requested to customise the app using the interface relevant to their culture. This has thus helped the users to compare both of the options. Finally, the users were asked to complete the survey questionnaire using the app to provide their feedback and the responses were then collected.

Further details about the recruitment of the participants are included in section 4.3 of this paper. Analysis of the responses using statistical tools and the results found are discussed in section 5.

Objectives of the study

The evaluation study was planned to collect baseline data about the overall usability, inclusive design and effectiveness, focusing on the cross-cultural aspects, of the prototype. The objectives of the studies were:

- To assess the overall usability of the CIAUI (Culturally Inclusive Adaptive User Interface) for different types of users performing the tasks;
- To assess the cross-cultural inclusiveness of the prototype;
- To collect ground truth data to assess the performance of the SVM classifiers and finally
- To verify and, if necessary, iterate the framework.

Criteria for and recruitment of participants

All the participants in this study were adult volunteers aged between 18 and 80 years old, of both genders. The participants were from a wide cultural background from all over the world who could speak English but not as their first language. However, for the scale of our research, the recruitment of participants was limited to: the Arabian countries, Bangladesh, Canada, China, Great Britain, India, Ireland, Malaysia, Pakistan, Portugal, Spain, Turkey and the United States of America.

As it is a very important criterion to recruit participants from a wide range of varieties, the recruitment process invited participants from different age groups, genders and cultural backgrounds. A total of 142 participants who met the required criteria including also a wide variety of language proficiencies, thus contributed to this part of the research.

The questionnaire

Upon completion of the tasks, a questionnaire was used to collect the participants' responses. The questionnaire was in digital format, as part of the prototype application. The contents of the questionnaire have been modified and adopted from two distinct usability questionnaires - recognised by Gary Perlman (1997, 2009) and by Jakob Neilsen (1993, 1999).

The questionnaire was designed in bilingual format: English was the common language. The first languages of participants were also used, especially Arabic, Bangla (Bengali), Hindi and Urdu.

Results

The outcome data was tabulated and analysed, collected in the form of a user feedback, to help answer the key questions listed in the objectives of the study section, including derivation of the findings and recommendations for future work.

In addition to investigating the cultural inclusiveness of the prototype, the general usability attributes were also evaluated for conformance to the universal usability characteristics. This was also to make sure that the focus on cross-cultural usability did not deviate the prototype from the general pervasive usability aspects such as layout, ease of use, learnability, satisfaction of use, etc. The following sub-sections present a brief summary of the findings.

However, the results related to the prototype evaluation are presented below.

Performance evaluation of SVM classifiers

Grounded on the value of information gain (Yang & Pedersen, 1997), the performances of the SVM classifiers were evaluated using the two traditional measures used in scoring: precision and recall metrics, as suggested by Russell and Norvig (2003).

Precision, also known as the Positive Predictive Value, is the measure of the ratio of items in the result set that are truly relevant to the total number of retrieved items in the set. It can be calculated using the following formula:

$$Precision = (|\{Relevant\ Items\} \cap \{Retrieved\ Items\}|\ )/|\ \{Retrieved\ Items\}|$$

Recall, also known as Sensitivity, is the measure of the ratio of all the relevant items in the collection that are in the retrieved item set to all the relevant items. It can be calculated using the following formula:

$$Recall = (|\{Relevant\ Items\} \cap \{Retrieved\ Items\}|\ )/|\ \{Relevant\ Items\}|$$

Both precision and recall are traditionally expressed in percentage and often used together to measure relevance. However, a system may trade off precision against recall. A high precision algorithm returns more relevant terms, whilst a high recall algorithm returns most of the relevant terms.

For identification of the preferred language, a 100% precision was achieved with 23% recall. For cultural background, 88% precision was achieved with 22% recall. However, these results may vary, based on the number of installed apps used for the evaluation process. The precision was found to increase and the recall decrease with the increase of installed apps as observed in our experimental experience. Intuitively, the accuracy of the result also depends on the number of installed apps matching a user trait. With the increase of the number, the chances of the user actually possessing that particular trait also increase.

Cross-cultural usability of the prototype

The overall usability of the prototype was evaluated, with special focus on the cross-cultural aspects. Certain specific questions were used to evaluate the users' responses for assessing cross-cultural inclusiveness of the prototype. Analysing the responses to two such questions, as shown in Table 1, considering the phrase 'To Some Extent' as a positive response, over 90% of the users' cultural background was actually correctly inferred by the system. As discussed in section 2, the success rate in predicting the cultural background or any other user traits using the developed system depends on the number of user applications actually installed in the mobile device. In fact, in most cases of failure to infer the culture correctly, the numbers of applications related to the cultural background were fewer than those of the default or neutral applications. It should be noted that the failure rate was less than 10%. This actually went down over time as more and more apps were installed by the user. Thus, having an increasing number of user applications over time actually helped to increase the accuracy of determination of the appropriate cultural user interface to be provided to the user.

Table 1. Prediction of cultural background and language.

Variable/Responses	Yes	To Some Extent	No
Cultural Background Accuracy	86.6%	3.5%	9.9%
Language Preference Accuracy	99.3%	0.7%	0.0%

Responses to the remaining three questions related to cross-cultural usability were collected using a ranking from 1-10 where 1 represented 'Most Unlikely' and 10 represented 'Strongly Likely'. As stated in Table 2, the mean value of liking the concept of culturally inclusive adaptive user interface (CIAUI) is 9.72, over 73% of users strongly believing that using this technique in other mobile or desktop apps to be used by culturally diverse users would enable them to use the information system more effectively, with a mean value of 9.69.

However, to confirm whether this sample is actually representative of the normal population, for the overall satisfaction level of the cross-cultural aspects of usability, the following null (H_0) and alternative hypothesis (H_a) were considered:

H_0: The Mobile Academy prototype application could not add any user satisfaction related to cross-cultural usability of the application;

H_a: The Mobile Academy prototype application provided an increased user satisfaction related to cross-cultural usability of the application.

To test these hypotheses, a One-Sample T-Test using IBM® SPSS® (Statistical Package for the Social Sciences)[1] Statistics was applied, using the responses providing satisfaction index, where anyone who achieves a score of 5.0 (from the range of one to ten), is considered to have 'normal' levels of satisfaction. Lower scores indicate less satisfaction and higher scores indicate greater satisfaction. To know whether this sample is representative of the normal population (i.e., do they score statistically significantly differently from 5.0), the One-Sample T-Test is required. For applying the One-Sample T-Test on the dataset, it must satisfy these four assumptions, as cited from Lund and Lund (2013):

Table 2. Analysis of the cross-cultural aspects of culturally inclusive adaptive user interface (CIAUI).

Variable/Responses	Mean Value	Standard Deviation
Preference of the CIAUI	9.72	0.58
Extended use of CIAUI	9.69	0.59
Cross-cultural usability satisfaction Satisfaction	9.63	0.80

1 "Assumption #1: The dependent variable should be measured at the interval or ration level (i.e., continuous)

2 Assumption #2: The data are independent (i.e., not correlated/related)

3 Assumption #3: There should be no significant outliers (Outliers are data points within your data that do not follow the usual pattern) and

4 Assumption #4: The dependent variable should be approximately normally distributed".

The data collected for the 'Cross-cultural Usability Satisfaction' are independent and was measured on a ten (1-10) level Likert[2] scale: this satisfies the first two assumptions of the One-Sample T-Test. Boxplots were used to check whether there were any significant outliers. As no such outliers were found, the data also meets assumption three. Because of having a reasonably sufficient sample size of 142 participants - the data is considered to be normal and hence no normality test such as the Shapiro-Wilk[3] was conducted. As all four assumptions are met, the One-Sample T-Test was conducted using the SPSS Statistics version 22 (IBM United Kingdom Limited, 2013) programme that produces the following output:

As displayed in Table 3, the mean cross-cultural usability satisfaction score (9.63 ±0.803) was higher than the population's 'normal' satisfaction score of 5.0.

From Table 4, we can conclude that the cross-cultural usability satisfaction score (9.63 ±0.803) was higher than the normal satisfaction score of 5.0, a statistically significant difference of 4.634 (95% CI, 4.50 to 4.77), $t(141) = 68.75$, $p < 0.0005$. Note that the SPSS literature clarifies the following: "SPSS Statistics state that the "Sig. (2-tailed)" value is "0.000", this actually means that $p < 0.0005$. It does not mean that the significance level is actually zero" (Lund & Lund, 2013).

There was a statistically significant difference between means ($p < 0.0005$) and, therefore, we can reject the null hypothesis and accept the alternative hypothesis. Thus, we can summarise that the prototype application brought great satisfaction among the users in terms of cross-cultural usability.

Table 3. One-sample statistics (cross-cultural usability satisfaction.

	N	Mean	Std. Deviation	Std. Error Mean
Overall, I am satisfied with the cross-cultural usability of the app	142	9.63	0.803	0.067

Table 4. One-sample statistics (cross-cultural usability satisfaction).

	Test Value = 5					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Overall, I am satisfied with the cross-cultural usability of the app	68.75	141	0.000	4.634	4.50	4.77

[1] https://www.ibm.com/products/spss-statistics

[2] https://www.britannica.com/topic/Likert-Scale

[3] https://www.itl.nist.gov/div898/handbook/prc/section2/prc213.htm

Colour, graphics and readability

Graphics (including colour) and readability of the prototype were studied and the data, collected using a Likert scale of ten, was analysed as reproduced in Table 5. The lowest achieved mean value of 7.67, with a standard deviation of 1.74, belongs to the attractiveness of colour. This is because the individual choice of colour may not always be in line with the colour of cultural significance. Other attributes, as shown in the table, scored high mean values ranging from 9.44 to 9.47. In fact, both of the readability questions (for text on the screen and for font readability, attractiveness and size) scored exactly the same mean value (9.47) and standard deviation (0.64).

Table 5. Analysis of graphics and readability.

Variable/Responses	Mean Value	Standard Deviation
Attractiveness of Colour	7.67	1.74
Size of Elements	9.44	0.66
Text Readability	9.47	0.64
Font Size and Readability	9.47	0.64

Navigation and layout

The responses for the questions related to navigation and layout were also gathered using a Likert scale of ten (from one to ten) and the mean value and standard deviation were also calculated. The results presented in Table 6 show that the prototype achieved high usability scores in terms of navigation and layout, with mean values ranging from 8.42 to 9.67.

Table 6. Responses relevant to navigation and layout of mobile academy.

Variable/Responses	Mean Value	Standard Deviation
Screen Navigation	9.53	0.60
Understanding the Layout	9.40	0.68
Home Screen Navigation	9.67	0.54
Logical Sequence of Screen Elements	9.42	0.64
Design and Layout preference	8.42	1.41

Ease of use

Similar to other usability attributes, as mentioned in the previous sections, the ease of use of the prototype were also studied, collecting user responses using the Likert scale of ten. The collected data were then analysed as shown in Table 7.

The data collected as responses for both of the questions, as shown in the table, scored very high mean values ranging from 9.56 to 9.57, indicating that the prototype was very easy and simple to use and it performed the required tasks.

Table 7. Analysis of base of use.

Variable/Responses	Mean Value	Standard Deviation
Simplicity to Use	9.56	0.62
Ease of Performing the Stipulated Tasks	9.57	0.59

Learnability

The learnability of the prototype was also evaluated. Participants were asked to provide a Likert scale based feedback about the overall learnability of the system. The mean value and standard deviation of the participants' feedback are collected in Table 8. The table shows that the users have agreed that the CIAUI system was, overall, very effective.

Table 8. Analysis of ease use.

Variable/Responses	Mean Value	Standard Deviation
Information Organisation	9.56	0.62
Learnability	9.57	0.59

Finally, like other usability attributes, the user satisfaction of the CIAUI system has been evaluated and analysed. The mean value and standard deviation of the participants' feedback are presented in Table 9. The table shows that the users have indeed agreed that a CIAUI system is overall, satisfactory.

Table 9. Analysis of ease of use.

Variable/Responses	Mean Value	Standard Deviation
Simplicity to Use	9.56	0.62
Ease of Performing the Stipulated Tasks	9.57	0.59

Satisfaction

However, to know whether this sample is representative of the normal population (i.e., whether they score statistically significantly differently from 5.0), analytical statistics were used, applying a similar methodology to that given in Section 4.1 (Cross-cultural Usability), with the following null and alternative hypothesis for the overall satisfaction level of the usability of the prototype:

H_0: The Mobile Academy prototype application could not add any user satisfaction in terms of overall usability of the application.

H_a: The Mobile Academy prototype application provided an increased user satisfaction in terms of overall usability of the application.

Table 10, which displays the mean overall satisfaction score (9.32 ±0.72), was higher than the population 'normal' satisfaction score of 5.0. Studying Table 11, we can conclude that the overall satisfaction score (9.32 ±0.72) was higher than the normal satisfaction score of 5.0, a statistically significant difference of 4.32 (95% CI, 4.20 to 4.44), $t(141) = 71.62$, $p < 0.0005$. Note again that "SPSS Statistics state that the "Sig. (2-tailed)" value is "0.000", this actually means that $p < 0.0005$. It does not mean that the significance level is actually zero" (Lund & Lund, 2013)(Lund & Lund, 2013).

There was a statistically significant difference between means ($p < 0.0005$) and, therefore, the null hypothesis can be rejected and the alternative hypothesis accepted. Thus, it can be summarised that the prototype application brought great satisfaction among the users in terms of the overall usability.

Table 10. One-sample statistics (cross-cultural usability satisfaction).

	N	Mean	Std. Deviation	Std. Error Mean
Overall, I am satisfied with this app.	142	9.32	0.718	0.060

Table 11. One sample statistics (cross-cultural usability satisfaction).

	Test Value = 5					
Overall, I am satisfied with this app.	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
	71.62	141	0.000	4.317	4.20	4.44

Customisation option

A customisation option was provided so that users could proactively personalise the interface in the seldom case the user did not like the interface adaptively offered. This could be for instance, due to an association with the user's cultural background, or if the inferred cultural background and/or preferred language prediction were incorrect. This also facilitated the comparison between the default and inferred interfaces. Like the usability attributes, the participants were also asked to provide their feedback on the inclusion of the customisation option on a Likert scale based feedback about the satisfaction level. The mean value and standard deviation of the feedback are produced in Table 12. Analysis of the results indicated that most of the users were very happy with the inclusion of this customisation option.

Table 12. Analysis of the customization options.

Variable/Responses	Mean Value	Standard Deviation
Satisfaction with Customization Options	9.57	0.59

Qualitative feedback

The participants were also asked to provide some qualitative feedback. This was by listing the negative and positive aspects of the prototype, based on their experience of using the system. In fact, only a few users recorded their responses. From these responses, it was deduced that the adaptive nature to provide the culturally inclusive interface was the most positive aspect of the application. Whereas the most negative aspects included the initial start-up time of the application. This negative aspect, as observed by the users, has been taken into consideration for future investigation. This may be eliminated, by offloading the associated tasks to the cloud. The processing power of mobile devices are limited, thus offering the adaptive interface based on inferring the users' traits may take a longer time. However, cloud computing has made accelerated advances recently (Ali & Miraz, 2013; Ali & Miraz, 2014). Its elasticity of resource allocation aspect, especially in terms of processing power, may easily be used for this purpose. Based on the analysis and results attained through this research, several future projects could be initiated and commenced, involving adaptive interfaces and cross-cultural usability.

Conclusion

This paper has briefly introduced the 'Mobile Academy' prototype that was developed as a POC. However, the main focus of the paper was in analysing the results of the usability evaluation study conducted, specifically focusing on the cross-cultural aspects.

The evaluation study, the centre phase of any user centred design (UCD) (Norman & Drape, 1986) (Norman & Drape, 1986) based system design, is considered as an important practice to achieve inclusiveness and usability goals of any interface. In parallel to general usability attributes, the main focus of the research was to achieve cross-cultural inclusiveness using plasticity of user interface techniques. The results of the evaluation study, including the hypothesis tests, indicate significant accomplishment in this regard.

Various parameters of usability were considered for the usability tests, such as: graphics and readability; ease of use; learnability; satisfaction and culturally inclusiveness. In addition to the descriptive statistics as well as inferential statistics (Dowdy, Wearden, & Chilko, 2014) were used where deemed necessary. The descriptive statistics indicates that the prototype has highly enhanced the user experience by providing improved usability. The hypothesis tests, as part of the inferential statistical analyses, proves that, the prototype achieved a high level of satisfaction in terms of offering an enhanced cultural inclusiveness. Results of the 't tests', also indicates that the sample is representative.

The qualitative feedback from the users were also sought to investigate the positive and negative aspects of the prototype. The responses received reveals that the adaptive nature of the prototype, which was achieved by a combination of AI features such as SVM classifiers and plasticity of user interface design techniques, to provide the culturally inclusive interface was the most positive aspect. The initial start-up time of the application was identified as the most negative aspect. Future research is planned to offload the tasks associated with the prediction of the preferred language and cultural affiliation to the cloud using cloud computing techniques.

Finally, it can be concluded that the research reported in this paper has achieved its aims of investigating the usability, inclusive design factors and effectiveness of offering a culturally adaptive user interface. The main finding of this research is the framework of developing a culturally inclusive adaptive user interface, called 'the CIAUI framework' (Miraz, Excell, & Ali, 2021).

Acknowledgements

The authors would like to acknowledge the support received from Xiamen University Malaysia as well as Wrexham Glyndŵr University, UK.

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