# INTEGRATED WEBSITE USABILITY EVALUATION MODEL USING FUZZY ANALYTICAL HIERARCHY PROCESS AND ARTIFICIAL NEURAL NETWORK


## ABSTRACT

Numerous websites in this contemporary time have been plagued with many usability issues which have hitherto made the websites not effective and efficient for users while searching for information. Consequently, different website usability evaluation models have been proposed to help in evaluating websites. However, most existing models are rather too ambiguous and not easy to use. Also, selecting and ranking websites based on usability with respect to numerous criteria have become a very important decision-making process among users. Additionally, there is no existing machine leaning model developed to classify websites usability based on user's rating due to lack of usability ratings data. This thesis therefore proposes a new integrated usability evaluation model using Fuzzy Analytical Hierarchy Process (FAHP) with Artificial Neural Network (ANN). Five criteria of Speed ($S_{pd}$), Navigation ($N_{av}$), Ease-of-use ($E_{ou}$), Content ($C_{on}$) and Aesthetic ($A_{es}$) obtained through factor extraction out of initial seven criteria proposed are used in the study. Six Nigerian universities websites with good webometrics ranking are used as alternatives. These are University of Ibadan (UI), Covenant University (CU), Obafemi Awolowo University (OAU), University of Nigeria Nsukka (UNN), University of Lagos (UNILAG) and Ahmadu Bello University (ABU) websites. Two sets of usability data were collected via google forms from 233 and 169 participants. Results from FAHP indicates that UI website has the highest global priority weight and hence is ranked as number one. This is followed by CU, OAU, UNILAG, UNN and ABU websites respectively. Also, final criteria weights obtained are 0.321$S_{pd}$, 0.208$N_{av}$, 0.197$E_{ou}$, 0.166$C_{on}$ and 0.108$A_{es}$ respectively. This implies that the first and most important criteria to website users is speed. Weights obtained from FAHP model were preprocessed and used to train six machine learning algorithms which are Artificial Neural network (ANN), Random Forest (RF), Decision Tree (J48), Simple Logistic regression (SLOG), Bayesian Network (BaNET) and Logistic Model Tree (LMT). Results show that ANN has the best overall performance with accuracy ($A_{cc}$) of 93.36% while RF, LMT, SLOG, J48 and BaNET have 90.12% $A_{cc}$, 88.09% $A_{cc}$, 88.18%$A_{cc}$, 88.18% $A_{cc}$ and 83.63% $A_{cc}$ respectively. The FAHP model is further integrated with ANN to classify the user's websites usability ratings. The ANN structure is 5-3-1 with logsig and trainbr as activation and transfer functions respectively. The best performance was obtained at learning rate ($l$) of 0.8, momentum ($m$) of 0.9 and threshold value($h$) of 0.59. Further results obtained shows a precision ($P_{re}$), recall ($R_{ec}$) and F-measure ($F_{me}$) values of 98.44%$P_{re}$ and 95.45%$R_{ec}$ and 0.96$F_{me}$ respectively. It is recommended that this integrated model, which can be used for users' websites usability evaluation, ranking and prediction be adopted by IT practitioners and web developers.

# CHAPTER ONE

## 1.0 INTRODUCTION

### 1.1 Background to the Study

The internet is nowadays a major source of information through the use of websites, and as a consequence, websites generally have been serving as information gateway to different types of organisations (Dingli and Cassar, 2014; Esmeria and Seva, 2017; Monzer, 2015; Sun *et al.*, 2017). Nowadays, websites offer an easy means of searching and retrieving information about any kind of organisation. Basically in this information technology era, the first impression users of websites have about organisation is virtually based on the look of its website (Ismailova and Kimsanova, 2017). According to the Internet World Statistics (Internet World Stats, 2020) population of internet users in the world is now over 4.5 billion from 360 million in 2000 with 58.81% penetration rate. Following a similar rate, in Nigerian internet users' population have grown from two hundred thousand (200,000) in the year 2000 to over one hundred and twenty-three million (123,000,000) as at June, 2020 with 61.4.7% penetration rate. All these point to the fact that accessing different types of website is inevitable and a must task for these billions of different users in today's information technology driven world.

Consequently, websites have become an essential tool for many organisation because of its wide reach, broad acceptance and general capability to share information. Till date millions of websites have been created and developed and there exist every kind of websites varying from easy to difficult-to-use (Dominic *et al.*, 2013; Rajapaksha and Fernando, 2016). In addition to this, vital roles are being played by the web in the diverse domains of business, education, industry, agriculture, health and entertainment among others. Hence, the degree of website usability and quality coupled with its development has been a major concern to usability researchers (Almahamid *et al.*, 2016; Djordj *et al.*, 2013; Manzoor *et al.*, 2012; Mvungi and Tossy, 2015)

Different genre of websites exists and each is suitable for a particular audience or purpose. Among these are academic websites for educational institutions like universities, polytechnics, colleges and specialized institutions. Other genre includes e-commerce websites, hotel and tourism websites, airline websites, e-government websites, banking websites, political party websites and many others. For academic institutions, their websites are meant to provide information to a wide range of users which include prospective and enrolled students, staff, parents, institutional ranking bodies as well as other categories of users. These websites not only serves as a platform for the stakeholders to exchange information, they also serve as communication tools and help to shape its image (Mentes and Turan, 2012 ; Abdallah and Jaleel, 2015; Galovicova *et al.*, 2016).

Today, millions of people are searching for information on university websites annually. These includes, prospective students looking for schools on potential courses available, subject experts, fees information among other vital information (Affandy *et al.*, 2017; Alahmadi and Drew, 2016; Jati *et al.*, 2018) Enrolled students search for course information, lecture location, materials and times, account access, results updates, schools' calendars, fees payment, news update, teacher's information. Prospective applicants may search for job prospect, vacancies, available facilities, research output, funded projects, sample thesis and project. The main underlining issue is that users should find what they are searching for easily and the content should be easy to understand (Sarsarabi and Sarsarabi, 2015).

In Nigeria, there is increasing competition among the universities especially with respect to web visibility ranking. At present, there are a total of 172 (one hundred and seventy two) universities comprising forty four (44) Federal universities, forty nine two (49) States universities and seventy nine (79) private universities respectively as released by National University Commission (NUC, 2021) In the latest webometric ranking of higher institutions, there is no university in Nigeria among the top one thousand (1000), while twenty six universities are in the category of top five thousand (5000), fifty six (56) appear in the top ten thousand (10, 000), while the rest are in the rank of between ten thousand (10000) and twenty three thousand (23, 000) out of the total of twenty three thousand, three hundred and sixty eight (23,368) institutions worldwide that were included (Cybermetrics Labs, 2020). Nevertheless, while this statistic is not encouraging, there is still greater web presence among Nigerian universities than what was obtained in the past. It is therefore necessary to see how this can improve over time.

Having a good web presence will make potential users to know about the school and this will in turn attract many more visitors to the school websites. As a result, all universities therefore will strive as much as possible to have a user-friendly website which are both functional and usable. Due to increased competition, universities seek to attract the best of all students, faculty and research grants. Hence, there is dire need to increase the web visibility of each university websites (Kargar, 2012; Okello-Obura, 2015; Peker *et al.*, 2016). To achieve this, there have been several attempts in rebranding and redesigning of websites by various universities administration. All these are with the aim of making their websites accessible, usable and have positive impact on users. Hence, the need to improve on the usability and quality of these websites so as to prevent users from being frustrated in this information age. Also, in this competitive era, if users cannot find what they are looking for, they will simply turn to competitor's websites. This necessitates the need for a good usability (Manzoor *et al.*, 2019).

In this information age, users of any websites are mostly concerned with two major issues – finding the information being sought with ease and finding it in a timely fashion. To achieve this, a high level of usability which is one of the important criteria in measuring website quality is required (Aziz and Adzhar, 2015; Roy *et al.*, 2016). According to International Standard Organisation, ISO 9241-11, usability can be defined as "the extent to which a product, service or system can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use". It is further defined as the effectiveness, efficiency, and satisfaction with which specified users achieve specified goals in particular environments (Speicher, 2015).

From websites context, usability is seen as an important attribute of quality which describes how easy it is for users to navigate through the website. It can be viewed as the extent to which a goal can be achieved by users successfully by learning and using websites. As earlier stated, a functioning website is needed by every organisation for easy information dissemination to the public. In this context, university websites as specialized genre of websites are supposed to be given adequate attention in terms of usability due to numerous services to its users worldwide (Yerlikaya and Durdu, 2017). However, many existing websites have been discovered over the years to have usability problems (Arasid *et al.*, 2018; Stoimenova and Christozov, 2013). This has consequently led to the growing interest by researchers to develop users' models to measure and evaluate website usability so as to fully discover its inherent problems. In further response to this, there have been increasing attention in website usability evaluation model research in the field of Human Computer Interaction (HCI) (Leung *et al.*, 2016; Nagpal *et al.*, 2016b; Presley and Fellows, 2013) . In HCI, usability of interfaces is being considered a factor of growing importance in application development, especially in web-based application. According to Peker *et al.* (2016), usability of websites is one of the popular subjects in the HCI literature which focuses on the interaction between people and Information & Communication Technologies (ICTs). Several research efforts have shown that usability is one of the most important issues in ICTs (Affandy *et al.,* 2017; Das and Patil, 2014; Mvungi and Tossy, 2015; Nagpal *et al.*, 2016a; Niazi *et al.*, 2020). Till date, one of the challenges faced by HCI researchers is how best to measure or evaluate website usability.

As a result of this, several researchers have proposed different models for website usability evaluation. Most of these models are based on inspection methods and formal experimental test which are generally known as the traditional approach (Affandy *et al.*, 2017; Hussain and Kadhim, 2014; Ismailova and Kimsanova, 2017; Majrashi and Hamilton, 2015; Nagpal *et al.*, 2016b; Subair and Aleisa, 2016). However, in usability there are several criteria involved and determining which one contributes more to usability and at the same time ranking the alternative websites based on the criteria is a complex decision-making process. This therefore requires the formulation of websites usability problem by using a Multi-Criteria Decision Making (MCDM) approach. Website evaluation hence, belongs to MCDM field which involves making a preference decision, such as evaluation or selection over the available alternatives using a set of criteria. In MCDM several alternatives are usually involved, among which the decision-makers (DMs) have to give weights to each criterion (Jain *et al.*, 2016; Özkan *et al.*, 2020)

Also, with the advent of machine learning, attempt to use machine learning techniques in usability evaluation research have achieved little or no success (Boza *et al.*, 2014; Korvald *et al.*, 2014; Nayebi, 2015; Oztekin *et al.*, 2013; Sagar and Saha, 2017) This approach involves using different machine learning algorithms like Neural network, support vectors machine, decision tree, linear regression and the likes to generate and model users usability data. This can then be used for prediction and consequently give a better insight into usability data. This has however suffered several limitations partly because of the nature of data that is required for machine learning training and the low performance output of the machine learning algorithms used in the models (Korvald *et al.*, 2014; Sagar and Saha, 2017; Taj *et al.*, 2019).

Therefore, to handle the dual problems highlighted above with a view to getting better insight into usability data from users' perspective and further help in usability users rating prediction, the need arises to integrate machine learning techniques with MCDM approach. This combined data-based and expert-user based approach is the main focus and contribution of this thesis. This research therefore is based on integrating an MCDM approach based on fuzzy Analytical Hierarchical Processing (AHP) with Artificial Neural Network (ANN). This integrated approach handle both the subjective and objective aspect of usability evaluation thereby eliminating biases exhibited by human being during evaluation. More so, appropriate ranking of websites performance based on usability as well as better user website usability rating is also achieved.

## 1.2 Statement of the Problem

Usability is a key factor in the quality and success of a website. This is because the ease, comfort , distraction or difficulty that users experienced with websites determines their success or failure

(Hasan, 2013; Hasan and Morris, 2017; Quiñones and Rusu, 2017). Most times, a number of users experience frustration due to the fact that the information been sought for on the websites are not readily available or requires great efforts to access simply due to usability and accessibility problems in websites (Jano *et al.*, 2015; Manzoor *et al.*, 2019; Sagar and Saha, 2017). At present there are many usability issues with most academic websites and the major challenge is to know the appropriate usability issues to tackle in order to ensure better usability. If a website does not meet user expectations with an appropriate level of usability, it will lead to increase in website failure rate. As a result, users' ratings about the website will be poor (Esmeria and Seva, 2017; Nagpal *et al.*, 2016a; Yerlikaya and Durdu, 2017). Though attempts have been made by researchers to identify different criteria of website usability in the academic field, there is yet to be a widely acceptable model (Kaur *et al.*, 2016a; Quiñones and Rusu, 2017; Subair and Aleisa, 2016)

More so, most studies focused more on website quality criteria but only a few focused-on website usability especially in academic domain and such are not adequate considering its relative importance. Also, providing a machine learning model for website usability evaluation especially for academic websites is also a great challenge to researchers in the field of HCI. Most of the existing usability evaluation models have been using the traditional approaches and do not really solve the usability issues (Dingli and Cassar, 2014; Hasan, 2013; Jano *et al.*, 2015; Subair, 2014). Furthermore, classifying website usability based on users rating is non- existence and this is very important with the advent of data mining. This implies that, there is no existing model that can aid in classifying and predicting user rating based on website usability so as to know the class a particular website belongs based on some criteria or parameters. So, the need arises to develop better models which are clear, simple, easy to use and can in in users' website usability prediction with good performance.

## 1.3 Aim and Objectives of the Study

The aim of the study is to develop an Integrated Fuzzy AHP and ANN Model for Website Usability Evaluation. The aim will be achieved through the following objectives.

I. To identify and formulate a hierarchy of criteria for academic websites usability evaluation.

II. To develop a fuzzy AHP model based on the criteria identified above to determine and measure the weight of the usability criteria.

III. To carry out comparison evaluation on the data obtained from model (ii) above using different machine learning algorithms.

IV. To integrate the model with Artificial Neural Network for users' website usability rating classification.

V. To evaluate the performance of the integrated model using standard machine learning performance evaluation metrics.

## 1.4 Significance of the Study

The website of a university gives the first impression about the school, it is therefore very essential for each university to create a usable, visually attractive and appropriate web presence (Ismailova and Kimsanova, 2017). Poor usability often means poor user interaction and hence reduced user acceptance and satisfaction. Due to neglect of usability issues, a lot of time, efforts and money are being wasted from time to time on redesigning academic websites in many educational institutions. The intention to continue or quit browsing a website depends on the first impression with the website A website that is acceptable will be judged by users within a minute and if they are not satisfied with the content, the websites will be discarded (Ulutaş, 2019) . This may force some potential students and faculty to abandon the websites if the required information is not readily available. This study will be of immense benefits to users of academic websites, the management as well as web designers of various academic institutions.

Users will find it very easy to retrieve required information effectively, efficiently and satisfactorily while reducing cognitive load. The management of the institution will also benefit by spending less money, efforts and time on rebranding and redesigning websites on regular basis. Web designers on the other hand will be able to know which area(s) of the websites need improvement and attention so as to improve the usability. Therefore, knowing the important criteria that influence usability is very important as it will help the stake holders to pay attention to factor(s) with the highest weight and then identify the best way to improve it (Roy *et al.*, 2014).

## 1.5 Scope and Limitation of the study

This research covers only the usability aspect of websites which is a very important component of website quality. The data collected covers users' interaction with six identified university websites with good webometric presence. Users testing used are both the moderated and unmoderated which include also laboratory test conducted during the different phases of the study. The class of the ANN is a binary class based on user's evaluation. The target audience of the study are enrolled students; both undergraduates and postgraduates.

This study only takes into consideration the usability aspects of human computer interface; in this case university websites. Though the study can be extended to other genre of websites but the target users are mostly users of academic websites. Also, the last phase study is limited to laboratory setting where the users' activities with the websites in use can be easily observed for authentic and adequate data collection. The choice of machine learning algorithms used in performance evaluation is limited to those with high accuracy.

# CHAPTER TWO

## 2.0 LITERATURE REVIEW

### 2.1 Introduction to Web Usability

Usability as a quality factor can be applied to a variety of products, services and systems which include software applications and websites It is derived from the term user friendly (Esmeria and Seva, 2017)). Typically, it is a measurement of ease of use and efficiency of users in the course of performing tasks during product usage. Usability is a wide area and has been distinctly defined by diverse scholars. According to the recent definition given by international standard organisation (ISO, 2018) usability is "the extent to which a ***product, service or system*** can be used by specified users to achieve a specified goals with effectiveness, efficiency, and satisfaction in a specified context of use". From the definition, service and system have been added in contrast to the old decade long definition which has only product in the definition (ISO, 1998).

In a web-based system context, usability is viewed as the perceived ability to understand the systems structure easily, or as ease of using website with simplicity and ability to locate items with speed and accuracy. It also involves been able to navigate the website with ease , and able control users' movement within the system (Paz and Pow-Sang, 2014; Guinalı *et al.*, 2006) . A more formal definition is given by Institute of Electrical and Electronics Engineers (IEEE) as "the ease with which a user can learn to operate, prepare inputs for, and interpret outputs of a system or component" (IEEE, 1990). Another important definition of usability which is oriented toward software application is given by ISO/IEC 9126-1 in which usability is defined as the "the capability of a software product to be understood, learned, and liked by the user, when it is used under specified conditions" (ISO, 2001). Even the ISO/IEC 25010 (2011) a quality model which has been used to replace ISO 9126-1 standard , offers same definition given by ISO 9241-11 by defining usability based on definition given by ISO (1998) .

However, looking at usability from the context of usability engineering, usability is viewed in terms of ease-of-learning, user satisfaction and ease-of-use of computer system quality (Rosson and Caroll, 2002). From the view point of Ergonomics or human factor engineering, usability is described as the ability of users to carry out his tasks effectively, efficiently and satisfactorily as enabled by the capacity offered by the system (Freire *et al.*, 2012). Lastly according to Nielsen (2012), a world renowned web usability expert, usability is one of the quality features that measures how easy users can use a user interface In summary, the main aim of usability is to ensure efficient, effective and ease of navigation of websites by different types of users who aim to perform different task.

### 2.1.1 Attributes of usability

There are many attributes which usability consist of and most usability models emphasize the importance of usability as it relates to four core characteristic (ISO, 2018; Joo *et al.*, 2011). These are:

**Effectiveness:** This is a measure of how accurate and complete tasks are being performed by users while using a particular website (Seffah *et al.*, 2006)

**Efficiency:** This relates to performance level of users while using a specific website (Joo *et al.*, 2011).

**Learnability:** This relates to the ability of users to learn or understand the workings of a particular system (Simon *et al.*, 2017).

**User Satisfaction:** This is the subjective assessment  users have for a particular website regarding how beneficial and easy it is to use it  (Bakaev *et al.*, 2017)

In the same manner five usability attributes were identified by Nielsen (2012 ) which are;

**Efficiency:** This refers to expended resources which enables users' goals to be achieved in relation to its accuracy and completeness.

**Satisfaction:** It is defined as freedom from uneasiness, and having a optimistic attitudes towards product usage.

**Learnability:** This entails the ease of learning a system to aid users in getting task done on the system.

**Memorability:** This is ability to remember the system easily after being returned to it after some periods of abandonment. It is to avoid repeating to learn the system again.

**Errors:** This provides a very low error rate for the system. This is to only give room for few errors in the course of using the system and being able to recover easily from the system if errors are made. It ensures avoidance of catastrophic errors.

In general, several design goals are inherent in usability. These include ease-of-learning, ease-of-use, easy-of remembering, easy-of -understanding and ease-of-information.

### 2.1.2. Website usability models

Usability is one of the important quality factors in user interface design. This quality has attracted many researchers and hence different usability models have been proposed in literature for different product, services and systems. Some of the existing models found in literature are discussed as follows. The  ISO/IEC 9126 standard model, defined usability by five factors; understandability, learnability, operability, attractiveness and usability compliance (Botella *et al.*, 2004). ISO 9241-11 standard model characterized usability based on efficiency, effectiveness and satisfaction of product, services and systems (Abran *et al.*, 2003; Speicher, 2015). Nielsen in his model proposed that usability is to be measured based on effectiveness, efficiency, satisfaction, and learnability (Nielsen, 2012).

In the 2QCV3Q model, Mich *et al.*(2003) formulated a conceptual model that consists of seven dimensions to evaluate the quality of a website was proposed to evaluate quality of a website based on who-what-why-when-where- how and feasibility (with what means and devices). The model defines accessibility, navigability and understandability as usability factors. McCall's model (also known as McCall's triangle of quality) is one of the software evaluations models which defines usability as product operation (basic functionalities), product revision (ability to change), product transition (ability to adopt new environment). Usability was defined under product operation and it comprises operability, training and communicativeness. Furthermore, a high-level usability factors was defined in the new usability measurement model (UMM) as accessibility, understandability, learnability, operability, attractiveness, and navigability, which are all defined in previous models, but not in one model (Shawgi and Noureldien, 2015) .

Other usability models include Quality in use integrated (QUIM) model which defined usability in terms of efficiency, effectiveness, productivity, satisfaction, learnability, safety, trustfulness, ,accessibility, universality and usefulness (Seffah *et al.*, 2006). Web Usability Evaluation Model (WUEM) proposed by Manzoor and Hussain (2012) comprises web design, page design, accessibility and Navigation as its usability attributes. The enhanced usability model (EUM) comprises effectiveness, efficiency, satisfaction, learnability and security as criteria to measure usability (Abran *et al.*, 2003). Table 2.1 shows the model in a tabular form for easy representation.

In addition to these, there are still some other factors on which usability depends as viewed by other authors (Manzoor and Hussain, 2012; Seffah *et al.*, 2006; Shawgi and Noureldien, 2015, Mehrotra *et al.*,2017).

**Table 2.1: Web usability evaluation models**

| Usability factor | McCall | ISO 9126-11 | ISO 9241-11 | Nielsen | 2QCV3Q | UMM | WUEM | QUIM | EUM |
|---|---|---|---|---|---|---|---|---|---|
| Understandability | | ✓ | | | ✓ | ✓ | | | |
| Learnability | | ✓ | | ✓ | | ✓ | | ✓ | ✓ |
| Operability/functionality | ✓ | ✓ | | | | ✓ | | | |
| Attractiveness | | ✓ | | | | ✓ | | | |
| Usability compliance | | ✓ | | | | | | | |
| Training | ✓ | | | | | | | | |
| Communicativeness | ✓ | | | | | | | | |
| Accessibility / readability | | | | | ✓ | ✓ | ✓ | ✓ | |
| Navigability | | | | ✓ | ✓ | ✓ | ✓ | | |
| consistency | | | | | | | | | |
| comment | | | | | | | | | |
| Web design | | | | | | | ✓ | | |
| Page design | | | | | | | ✓ | | |
| Security/privacy | | | | | | | | ✓ | ✓ |
| organisation | | | | | | | | | |
| efficiency | | | ✓ | ✓ | | | | ✓ | ✓ |
| effectiveness | | | ✓ | ✓ | | | | ✓ | ✓ |
| productivity | | | | | | | | ✓ | |
| satisfaction | | | ✓ | ✓ | | | | ✓ | ✓ |
| universality | | | | | | | | ✓ | |

## 2.2 Website Usability Evaluation

Usability Evaluation (UE) entails the usability assessment of a product so as to recognise the embedded usability problems and consequently the usability measures. The evaluation is usually conducted to enhance improvement in product usability or to ascertain the extent to which the usability objectives have been met. For any software, usability evaluation is made up of several methodologies that can be used to measure system's User Interface (UI) usability. Also, identification of distinct specific problems is possible via this evaluation methods (Nagpal *et al.*, 2017; Paz and Pow-Sang, 2014).

In order to carry out UE, different UEM have been proposed and are classified differently by researchers (Fernandez *et al.*, 2011; Insfran and Fernández, 2008; Kaur *et al.*, 2016b; Madan and Dubey, 2012; Nagpal *et al.*, 2017; Paz and Pow-Sang, 2014). UEM is composed of a series of well-defined activities used in collecting usability data to know how the particular properties of software contribute to the achieve specific goals (Fernandez *et al.*, 2011; Paz and Pow-Sang, 2014). Author like Nielsen (2012) categorized UEMs into four basic groups as automatic, empirical, formal and informal methods. Automatic methods entail computing usability measures by running a user interface specification through special software. In empirical method, usability is assessed by testing the interface with real users or experts. Formal methods allow usability measures to be calculated by exact models and formulas while informal method involves obtaining usability measures based on rules of thumb.

UEMs are also classified broadly into inspection and empirical methods (Fernandez *et al.*, 2011). Empirical methods in this case are based on capturing and analysing usage data from real end-users, by completing a predefined set of tasks while the tester (human or specific software) records the outcomes of their work. On the other hand, in inspection methods, expert evaluators or designers are involved in the evaluation. They are based on reviewing the usability aspects of Web artefacts, which are commonly user interfaces, with regard to their conformance with a set of guidelines.

However, due to advancement in technology and computing field, a recent classification of UEM are given as been divided into majorly six categories based on Evaluator, User, Tool, Model, Multi Criteria Decision Making (MCDM) and Soft Computing (Nagpal *et al.*, 2017). Some of these methods are discussed below.

### 2.2.1 Empirical usability evaluation methods

Empirical evaluation methods can be grouped into user study and system inspection methods. User study methods can further be grouped into surveys, focus groups, usability testing and contextual inquiry. While system inspection methods are expert review, heuristic evaluation cognitive walkthroughs (Kaur *et al.*,2016a; Subair, 2014).

#### 2.2.1.1 Usability testing

This involves giving representative of end users a set of tasks to complete while using the product software. It is conducted under specific set-up so as to identify usability problems. This UEM can also be referred to as user testing, usability test and usability study(Paz and Pow-Sang, 2016). It can be done through various methods. In **Cognitive walkthrough,** the test is planned to evaluate how the interface give supports to first-time or new users in the course of learning how to complete a task. The design of the user interface is evaluated for its comfort of experimental learning based on mental learning and usage (Husin *et al.*, 2012). **Laboratory testing** involves that the user and tester are located in the same place, such that the tester can watch the how the tasks are performed by the user with adequate note taking so as to report back to the development team and other interested parties (Granić *et al.*, 2011). In **Remote usability testing,** the locations of the user and the tester are in different. It can be directed through webinar with the moderator watching the user use the interface (Alghamdi *et al.*, 2013) . Lastly **Think aloud testing** is a situation whereby the user while executing the tasks gives remarks to verbalise their thought or the reason they are performing a certain activity (Goh *et al.*, 2013)

In all these, users are engaged in the test and data can be collected before, during and after the test which will then be analysed by the tester.

#### 2.2.1.2 Expert or inspection based evaluation method

This involves the use of expert to test an interface based on some sets of design guidelines. It may be heuristic evaluation, pluralistic walkthrough (Granić and Ćukušić, 2011). In *heuristic evaluation*, usability is evaluated by the experts and they identify the problem in the user interface based on compliance with well-defined usability principles known as “heuristics” (Quiñones and Rusu, 2017). *Pluralistic Walkthrough* involves inspection of the interface by the group of evaluators which includes users, designers and evaluators (usability experts). This is to perform the set of tasks for presenting the new idea about the interface. It is known as group inspection method (Husin *et al.*, 2012).

#### 2.2.1.3 Tool based evaluation method

In this method, software tools are deployed to evaluate the usability of an interface instead of employing users or experts (Adepoju and Shehu, 2014; Ahmi and Mohamad, 2016). It may involve the use of automated tools which checks whether certain set of usability interface standard. HTML codes are verified to check for compliance. Some of these stools include ClickHeat, Webpage analyser, Google analytics, web page optimisation, OpenHallway, Achecker, WebAIM, TAW (Ahmi and Mohamad, 2016; Ismail and Kuppusamy, 2018; Nagpal *et al.*, 2017)

#### 2.2.1.4 Soft computing methods

In soft computing approach, there is replacement of traditional approach with soft computing methods like Fuzzy logic, neural computing, Genetic Algorithm and probabilistic reasoning without the solution being affected. Soft computing is simply a collection of methodologies that aim to exploit the tolerance for imprecision, uncertainty, and partial truth to achieve tractability, robustness, and low solution cost (Iraji, 2013; Nagpal *et al.*, 2017; Rekik and Kallel, 2013). The main components of soft computing approach are; Fuzzy Logic, Probabilistic Reasoning, Neural Computing and Genetic Algorithms

## 2.3 Multi-Criteria Decision Making

Multiple Criteria Decision Making (MCDM) or Multiple Criteria Decision Analysis (MCDA) as a field originates from Operations Research (OR). Operation Research offers a diversity of numerical tools and approaches that aid the Decision Maker (DM) to make rational decisions. As a field of knowledge, it focuses on carrying out a complete examination of a certain decision situation, constructing its scientific explanation (mathematical model). Furthermore, an optimal solution is found by using suitable computer-based, numerical, systematic methods and tools to the decision problem tackled (Zyoud and Fuchs-hanusch, 2017). MCDM usually involves making decisions in the presence of multiple but usually conflicting criteria. The fundamental problem is how to evaluate a set of alternatives in terms of a number of criteria (Zavadskas *et al.*, 2014).

Similar to Operation Research, MCDM attempts to equip the decision maker with a set of tools and methods that help him or her to solve complex decision problems. At the same time, MCDM as opposed to Operation Research focuses its efforts on solving MCDM problems, that is such complex decision situations in which several – often contradictory – points of view must be taken into account (Alabool *et al.*, 2018; Tolga, 2018).

Basically, MCDM primary aim is at making preference decision (e.g., evaluation, prioritization, and selection) over the available alternatives that are characterized by multiple, usually conflicting, criteria. In essence, MCDM provides DM different tools, methods and algorithms that enable him/her to advance in solving a given multiple criteria decision problems. MCDM uses knowledge from many fields, including mathematics, behavioral decision theory, economics, computer technology, software engineering and information systems (Behzadian *et al.*, 2012). MCDM is designed in such a way that using a predefined set of attributes, a group of solutions are analyzed and an optimal alternative is selected. (Rani and Sakthivel, 2015)

According to Zare *et al.*(2016), the MCDM process is made of four key stages which are as following. First, intelligence stage which aim to clarify decision goals by means of defining the problem. Second is the design stage and at this phase the decision problem is formulated through MCDM model. Furthermore, determination of criteria and alternative sets is determined at this stage. Third phase is choice stages, where evaluation of the criteria selected MCDM method is done. Also, recommendation is made about the suitable solution to the decision problem. Lastly, implementation stage which is the implementation phase of the cycle.

Figure 2.1 shows the process of MCDM approach according to its four main phases.

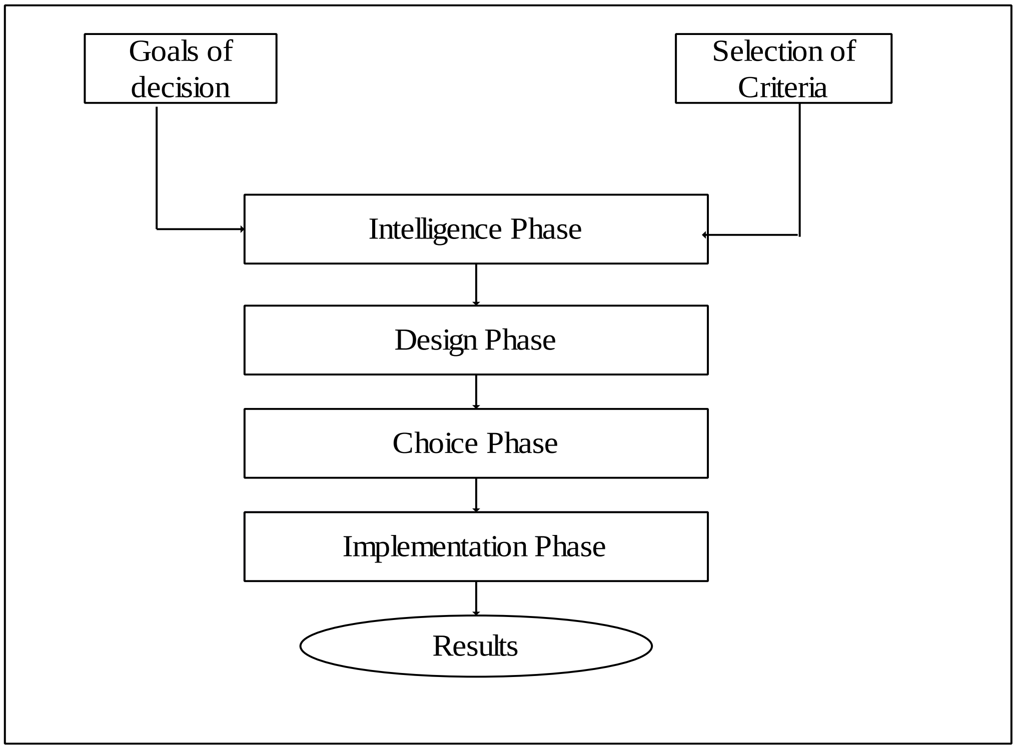



**Figure 2.1: MCDM phases (Zare *et al.*, 2016)**

## 2.3.1 Classification of MCDM methods

There are various distinct approaches covered by MCDM methods. These methods can be generally grouped into two categories: discrete MCDM or discrete MADM (Multi-attribute Decision Making) and continuous MODM (Multi-Objective Decision Making) methods (Mosavi, 2014). The basic classification of MCDM is shown in Figure 2.2. There is a presence of multiple conflicting objectives or criteria with each having different unit of measurement. Hence, MCDM focusses on means of assessing real-world situations which is dependent on qualitative or quantitative criteria in the presence of certain or uncertain or risky environments so as to find a appropriate course of action choice, strategy or policy among several available options (Raju *et al.*, 2006)

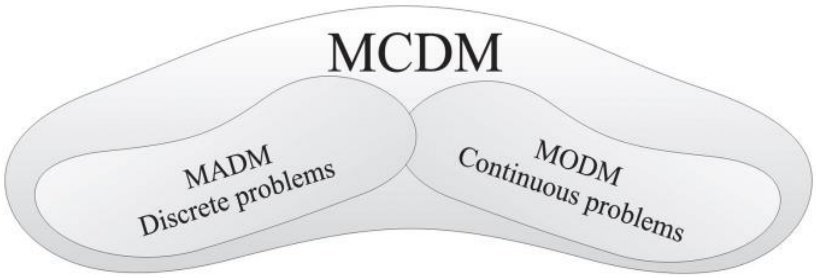



**Figure 2.2: MCDM classification** (Zavadskas *et al.*, 2014)

Diverse familiar MCDM methods are available for the alternative analysis and prioritization purposes. These MCDM techniques according to Zavadskas *et al.*(2014) differ in difficulty and possible explanations. The strength, weaknesses and privileges of each MCDM varies depending on the application area.

Some of the most important and widely used MCDM techniques are; Analytical Hierarchy Process (AHP), Et Choix Traduisant la Réalité or Elimination and Choice Translating Reality (Elimination and choice expressing reality) (ELECTRE), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Analytical Network Processing (ANP), Decision Making Trial and Evaluation Laboratory (DEMATEL), Preference Ranking Organization METHod for Enrichment Evaluations (PROMETHEE), Multi-Attribute Utility Theory (MAUT), Vlse Kriterijumska Optimizacija I Kompromisno Resenje (VIKOR) . Some of these methods are briefly discussed in the subsequent sections with greater emphasis on AHP.

#### 2.3.1.1 Analytical hierarchy process (AHP)

AHP method proposed in 1988 by Thomas Saaty is a comprehensive framework designed to be applied to certain, uncertain, rational and irrational multiple criteria decision problems (Kabassi *et al.*, 2020) . It serves the evaluation, ranking and criteria selection, which results in optimized and predicted decisions. The basic principle of AHP involves studying complex problems as a large system, then analysing the number of factors in the system. Various interrelated factors are then distinctly arranged to form an orderly hierarchy. Thereafter an objective evaluation of the factors in every hierarchy is calculated with the weight of every factor (Weight is equal to importance) being worked out. The approach is people-oriented and it involves comparing the factors one by one with the aim of finding out the individual psychological perception and difference of the users. Therefore the results are more objective and effective (Guimei and Taowei, 2012).

Basically, AHP is expressed by a unidirectional hierarchy, which shows the relationship between goals and criteria levels. This hierarchy is decomposed into several levels, in which the highest level represents decision goals and the lower level respective decision criteria. Sub-criterion elements are constructed under each relevant criterion (Zare *et al.*, 2016). Figure 2.3 shows the hierarchical model of AHP. AHP algorithm is basically composed of two steps.: determination of the relative weights of the decision criteria and determination of the relative ranking (priorities) of the alternatives.

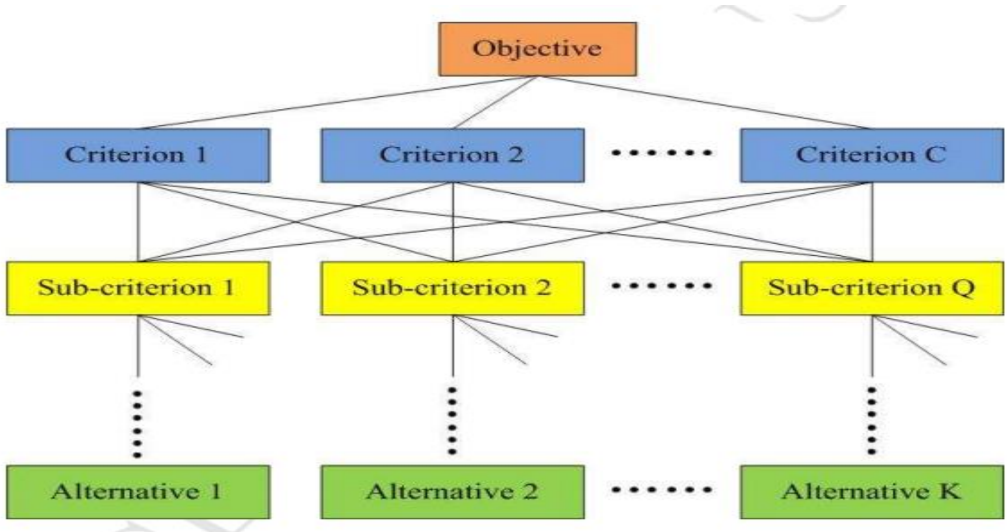



**Figure 2.3: Hierarchical Model of AHP (Presley and Fellows, 2013)**

AHP is widely used in the literature as a result of its simplicity in defining MCDM problem and the diverse calculation steps imposed by the method. In general., AHP can be defined in seven stages (Zyoud and Fuchs-hanusch, 2017). These are described in the following steps below and shown in Figure 2.4.

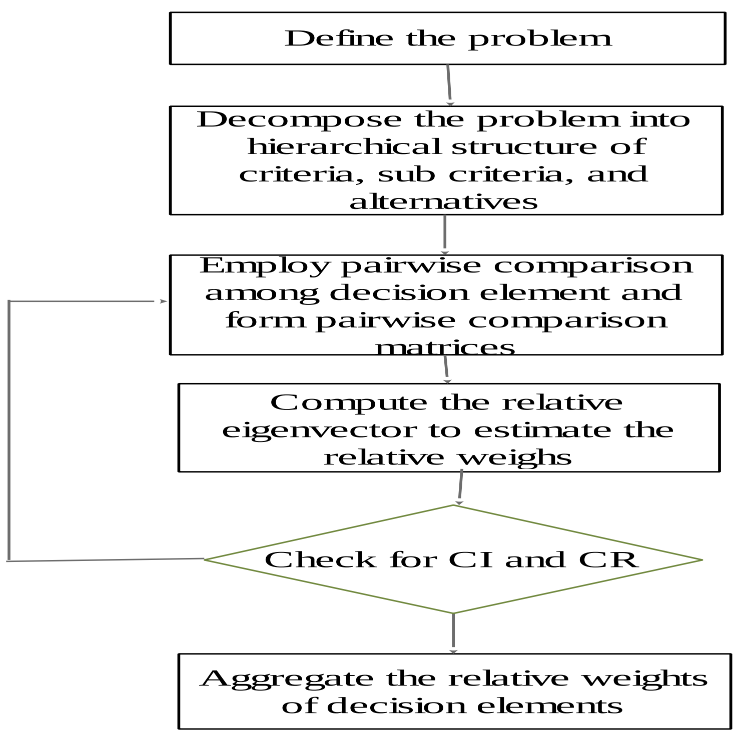



**Figure 2.4: Analytical Hierarchy Process steps**

#### 2.3.1.2 Technique for order of preference by similarity to ideal solution (TOPSIS)

TOPSIS was first introduced by Hwang and Yoon in 1980 (Pohekar and Ramachandran, 2004). It involves sorting alternatives according to their distance from the positive and negative ideal solutions. The Positive Ideal Solution (PIS) represents the point with maximal and minimal attainable values for benefits and costs criteria. Conversely, the Negative Ideal Solution (NIS) maximizes the cost criteria while minimizing the benefit criteria. In TOPSIS, the alternative farthest from NIS and closest to PIS achieves first rank (Amini and Rezaeenour, 2016; Efe, 2016). In TOPSIS attribute information are fully used and cardinal ranking of alternatives are provided. Also, independence of attribute preference is not necessary. For this technique to be applied, the attribute values must be numeric, monotonically increasing or decreasing, and have commensurable units.

#### 2.3.1.3 Elimination and choice expressing reality (ELECTRE)

The origin of ELECTRE method goes back to 1968 and was developed by Bernard Roy and his colleagues. ELECTRE is capable of handling discrete criteria of both quantitative and qualitative in order to provide a complete order of alternatives (Govindan and Jepsen, 2015). ELECTRE refers to a category of preference aggregation based methods which are applied to pairwise comparisons of alternatives (Diaby *et al.*, 2013). They are known as outranking approaches because they intend to help determine whether one option is at least as good as (i.e. outranks) another.

It has three purposes; to aggregate heterogeneous criteria which are not commonly considered in one common scale, to avoid compensation behavior, and to account for preference differences, which results in the introduction of thresholds. ELECTRE is made up of four elementary binary relations which are : indifference, preference, weak preference and incomparability (Zer *et al.*, 2019; Govindan and Jepsen, 2015). Similar to TOPSIS, the weights of the criteria are obtained as the main input. However, instead of using tabular data directly, the algorithm only needs them for comparison purposes.

#### 2.3.1.4 Analytic network process (ANP)

One of the extensions of AHP method is ANP and it is also its complementary method. It was introduced and further developed by Saaty (Ergu *et al.*, 2014). ANP is a distinct type of AHP, where network shape is used to model the decision problem. In AHP, the framework is represented by uni-directional hierarchical structure, while in ANP, there is allowance for interrelationships among decision levels and attributes which are complex. There exists interconnection between goals and objectives in ANP. The method can handle decision problems that cannot be structured hierarchically, and there is lack of inner-independent and outer-independent assumptions. There is provision for feedback connections and loops in ANP which is used to illustrate interdependence. (Chen and Qiao, 2015; Rekik, Kallel and Alimi, 2016; Tavanaa *et al.*, 2017)

#### 2.3.1.5 Decision making trial and evaluation laboratory (DEMATEL)

The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method originated from the Geneva Research Centre, Battelle Memorial Institute between 1972 and 1976 through the science and human affairs program. In DEMATEL relationship between the causes and effects of criteria is converted into an intelligible structural model of the system. This allows for confirmation of interdependence among the variables/attributes (Kabak and Burmaoğlu, 2013) . There has been successful application of DEMATEL method in many fields. For example, it is been used to analyse complex scientific, political and economic problems (Liang *et al.*, 2017; Sheng-li *et al.*, 2018). It is practical and useful in visualization of the structure of complicated causal relationships using matrices or digraphs. The matrices or digraphs represent a appropriate relation among system elements, where the strength of influence is given by a number. Hence, the DEMATEL method have the capacity to build an intelligible structural model through conversion of the relationship between the causes and effects of criteria (Zare *et al.*, 2016)

### 2.4. Fuzzy System

Fuzzy set involves the use of linguistic variables to give a description of fuzzy terms which is consequently mapped to a numerical variable. The numerical variable falls within two valued sets of Boolean logic which now replace these two values by the unit interval in the decision-making process. In fuzzy set, there exist intermediate value within each membership which is referred to the degree of affiliation of a member of the set (Fernández-pérez *et al.*, 2018; Shrivastava, 2019). In general, element of value 0 is outside the set, element with value 1 is completely inside the set while element with value between 0 and 1 is a partially inside.

Let X be the universe discourse, X- { $X_1$, $X_2$, $X_3$,., Xn } Ă is a fuzzy set of X that represent a set of order couples.

$$\{(X_1,\ \mu_{\breve{A}}(X_1)),\ (X_1,\mu_{\breve{A}}(X_1)),\ldots\ (X_1,\mu_{\breve{A}}(X_1))\}\qquad \mu_{\breve{A}}:X \longrightarrow [0,1] \qquad (2.1)$$

is the function of membership grade "membership function of Ă and $\mu_{\breve{A}}(X_1)$ stands for the membership degree of $X_1$ in Ă

A fuzzy number represents a fuzzy subset in the universe of discourse that is both convex and normal. Triangular Fuzzy Number, Trapezoidal Fuzzy Number, and Bell-shaped fuzzy number are types of membership function. However, among the various types of membership function, this study makes use of a triangular fuzzy number which is defined below.

In the fuzzy AHP, fuzzy numbers are used to express the entries of the pairwise comparison matrices. A function $\mu : R \rightarrow [0, 1]$ is a *fuzzy number* iff there exists an $X_0$ such that $\mu(X_0) = 1$ and all the upper level sets of $\mu$ are convex, i.e. the set $\{ X \in R | \mu(X) \geq \alpha \}$ is convex for all $0 < \alpha \leq 1$.

Triangular Fuzzy Numbers (TFNs) are described by three real numbers, expressed as (l, m, u). The parameters l, m and u indicate the smallest possible value, the most promising value and the largest possible value, respectively that describe a fuzzy event. Their membership functions are described as

$$\mu\left(\frac{x}{\tilde{M}}\right) = \begin{cases} 0, & x < l \\ \dfrac{(x-l)}{(m-l)}, & l \leq x \leq m \\ \dfrac{(u-x)}{(u-m)}, & m \leq x \leq u \\ 0, & x > u \end{cases}$$

Figure 2.5 shows the description of crisp and fuzzy sets

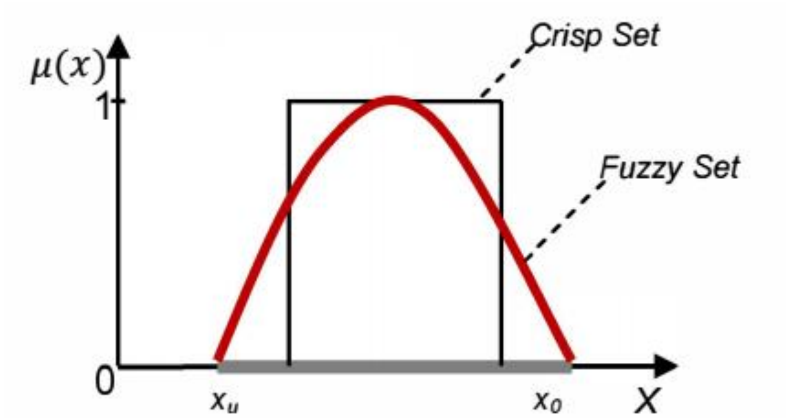


**Figure 2.5. Crisp and Fuzzy Set (Rekik et al, 2016)**

Saaty's AHP has become old and has some shortcomings like its limitation to mainly being used for applications with mostly crisp decision. There are also problems of creation of how to handle scale of judgment that are not balanced, inability to put into consideration the uncertainty connected with the mapping of human decision to a number, the imprecise ranking in AHP method and ability of the personal judgment, choice and preference of decision-makers have great influence on the AHP results. These shortcomings necessitate the need to combine fuzzy logic with AHP thus resulting in fuzzy AHP which is described in the next section.

### 2.4.1 Fuzzy analytical hierarchy process

AHP based on multi criteria evaluation is suitable for website usability, since usability is characterized by various factors (Nagpal *et al.,* 2015a). However, the human perception to those criteria contains vagueness and the perceptional judgment depends on person to person, usually uncertain with the data. So the fuzzy based evaluation is needed to address such problem (Lamichhane and Meesad, 2011)

In the initial AHP method proposed by Saaty (2008), a nine-point scale is used for pairwise comparisons for each level with respect to the goal of the best alternative selection. The scale is shown in Table 2.2 which is a variant of Saaty scale.

**Table 2.2. A variant of Saaty scale**

| Intensity of importance | Definition | Explanation |
|---|---|---|
| 1 | Equal importance | Two activities contribute equally to the objective |
| 3 | Weak importance of one over another | Experience and judgment slightly favour one activity over another |
| 5 | Essential or strong importance | Experience and judgment strongly favour one activity over another |
| 7 | Demonstrated or very strongly importance | An activity is strongly favoured and its dominance demonstrated in practice |
| 9 | Absolute or extremely importance | The evidence favouring one activity over another is of the highest possible order of affirmation |
| 2,4,6,8 | Intermediate values between the two adjacent judgment | When compromise is needed |

As a result of the imprecision and vagueness on decision makers judgments, the use of crisp pairwise comparison in the initial AHP looks inadequate and too vague to describe the judgment of decision makers' correctly. This leads to the introduction of fuzzy logic into the AHP pairwise comparison to recompense for this deficit in AHP. Hence, the method is referred to as fuzzy AHP. The main idea of fuzzy set theory is that there is a degree of membership in a fuzzy set defined by a membership function of each element. This is commonly ranged within the unit interval [0,1]. A fuzzy set, elements with different degree of membership are available. There are three common types of fuzzy membership functions which are: monotonic, triangular, and trapezoidal. Since, the fuzzy set is a convex function, the trapezoidal function or triangular function approaches the convex function well. The Saaty scale is re constructed to accept fuzzy values in contrast to the traditional crisp values used in AHP. With this a wider range of options is available for decision maker in decision making. A triangular Saaty scale is shown in Table 2.3.

**Table 2.3: Membership functions of fuzzy numbers**

| Fuzzy number | Definition | Membership function | Reciprocal scale |
|---|---|---|---|
| $\bar{1}$ | Equally important | (1,1,2) | (1/2.1,1,) |
| $\bar{3}$ | Moderately important | (2,3,4) | (1/4,1/3,1/2) |
| $\bar{5}$ | Strongly important | (4,5,6) | (1/6,1/5,1/4) |
| $\bar{7}$ | very strongly important | (6,7,8) | (1/8,1/7,1/6) |
| $\bar{9}$ | Extremley important | (8,9,10) | (1/10,1/9,1/8) |
| $\bar{2}, \bar{4}, \bar{6}, \bar{8}$ | Intermediate values | | |

In both AHP and Fuzzy AHP, the choice of linguistic terms is dependent on the problem at hand. So, adjectives like important, relevant, preferable, better etc. can be used to capture the data needed.

Various variant of fuzzy AHP available in literature are discussed as follows.

#### 2.4.1.1 Van Laarhoven and Pedrycz's fuzzy priority approach

Van Laarhoven and Pedrycz in 1983 proposed a fuzzy methodology to choose among different alternatives under inconsistent criteria which is a fuzzy version of Saaty Thomas model AHP method (Rekik *et al.*, 2016). Lootsma's logarithmic least-squares method is used in this method to derive fuzzy weights and fuzzy performance scores through AHP operations using triangular fuzzy numbers. The steps involve are outlines as follows:

Step 1. Construct the MCDM and obtain n+1 fuzzy reciprocal matrix that takes the following form as shown in equation 2.3.

$$\widetilde{A} = \begin{bmatrix} (1,1,1) & \begin{matrix}\widetilde{a}_{121}\\ \widetilde{a}_{122}\\ \vdots \\ \widetilde{a}_{12P_{12}}\end{matrix} & \cdots & \begin{matrix}\widetilde{a}_{1n1}\\ \widetilde{a}_{1n2}\\ \vdots \\ \widetilde{a}_{1nP_{1n}}\end{matrix} \\ \begin{matrix}\widetilde{a}_{211}\\ \widetilde{a}_{212}\\ \vdots \\ \widetilde{a}_{21P_{21}}\end{matrix} & (1,1,1) & \cdots & \begin{matrix}\widetilde{a}_{2n1}\\ \widetilde{a}_{2n2}\\ \vdots \\ \widetilde{a}_{2nP_{2n}}\end{matrix} \\ \vdots & \vdots & \ddots & \vdots \\ \begin{matrix}\widetilde{a}_{n11}\\ \widetilde{a}_{n12}\\ \vdots \\ \widetilde{a}_{n1P_{n1}}\end{matrix} & \begin{matrix}\widetilde{a}_{n21}\\ \widetilde{a}_{n22}\\ \vdots \\ \widetilde{a}_{n2P_{n2}}\end{matrix} & \cdots & (1,1,1) \end{bmatrix} \tag{2.3}$$

Where $\tilde{a}_{ij}P_{ij}$ are fuzzy ratios which are estimated by several decision makers. $P_{ij}$ may be 0 if no decision maker gives comparison ratios or when the value is more than 1 when many decision makers expresses comparison ratios.

Step 2. If $Z_i=(l_i,m_i,u_i)$ , then solve the linear equations in equation (2.4)

$$l_i\left(\sum_{\substack{j=1\\ j\neq i}}^{n} P_{ij}\right) - \sum_{\substack{j=1\\ j\neq 1}}^{n} P_{ij}u_j = \sum_{\substack{j=1\\ j\neq 1}}^{n}\sum_{k=1}^{P_{ij}}\left(\ln l_{ijk}\right), \quad \forall \mathrm{i} \tag{2.4}$$

$$m_i\left(\sum_{\substack{j=1\\ j\neq i}}^{n} P_{ij}\right) - \sum_{\substack{j=1\\ j\neq i}}^{n} P_{ij}m_j = \sum_{\substack{j=1\\ j\neq i}}^{n}\sum^{P_{ij}}\left(\ln m_{ijk}\right), \quad \forall \mathrm{i} \tag{2.5}$$

$$u_i\left(\sum_{\substack{j=1\\ j\neq i}}^{n} P_{ij}\right) - \sum_{\substack{j=1\\ j\neq i}}^{n} P_{ij}l_j = \sum_{\substack{j=1\\ j\neq i}}^{n}\sum^{P_{ij}}\left(\ln u_{ijk}\right), \quad \forall \mathrm{i} \tag{2.6}$$

As ln ($l_{ijk}$) and ln($u_{ijk}$) are lower and upper values of ln($a_{ijk}$ ) = -1 ln($a_{ijk}$), the following must hold true (equation 2.3)

$$\ln(l_{ijk}) + \ln(l_{ijk}) = \ln(l_{ijk}) + \ln(l_{ijk}) = 0, \ \forall i, j, k \tag{2.7}$$

Thus equations (2.4) and (2.6) are linearly independent. The same is true for equation (2.5)

Generally, a given a solution for equations (2.4, (2.5) (2.6) as

$$z_i = (l_i + t_1, \ m_i + t_2, \ u_i + t_1) \ \ \forall i \tag{2.8}$$

where $t_1$, and $t_2$ can be chosen randomly.

Step 3. With the use of logarithmic operations on the right sides of the equations above, then the fuzzy weight in Equation (2.9) is obtained:

$$w_i = \left(\lambda_1 \exp(l_i), \lambda_2 \exp(m_i), \lambda_3 \exp(u_i)\right) \tag{2.9}$$

Where.

$$\lambda_1 = \left[\sum_{i=1}^{n} \exp(u_i)\right]^{-1} \quad \lambda_2 = \left[\sum_{i=1}^{n} \exp(m_i)\right]^{-1} \quad \lambda_3 = \left[\sum_{i=1}^{n} \exp(l_i)\right]^{-1}$$

the performance score $r_{ij}$ can be determined by equation (2.9)

Step 4. Steps 1-3 can be repeated many times until all reciprocal matrices are solved. The fuzzy utility for alternative $A_i$ is calculated as

$$u_i = \sum_{j=1}^{n} w_j r_{ij} \tag{2.10}$$

#### 2.4.1.2 Buckley fuzzy priority method

This is proposed by Buckley in 1985 based on geometric mean method and it can also be used to extend the AHP in a situation where linguistic variables are involved. Buckley also extended Saaty's AHP method by incorporating fuzzy comparison ratios $a_{ij}$ . This method was formulated so as to solve the problems discovered in Van Laarhoven and Pedrycz's methods which are:

inability of the obtained linear equations not always have a unique solution. and insistence on obtaining triangular fuzzy numbers for the weights.(Çelik and Cansu, 2017)

Buckley's approach is performed by using the following steps:

Step 1. Get decision maker and formulate the comparison matrix A whose elements are $\bar{t}_{ij}$ $=(a_{ij}, b_{ij}, c_{ij}, d_{ij})$ , where all i and j are trapezoidal fuzzy numbers.

Step 2. Calculate the fuzzy weights $w_i$ as follows by first find the geometric mean for each row as:

(2.11) $$\tilde{z}_i = \left[\prod_{j=1}^{n} \tilde{t}_{ij}\right]^{1/n}, \text{ for all } i$$

The fuzzy weigh $w_i$ is given as

$$w_i = \tilde{z}_i \oplus \left[\sum_{j=1}^{n} \tilde{z}_j\right]^{-1}. \tag{2.12}$$

The fuzzy weight is derived as follows: Given left and right leg of $\bar{t}_{ij}$ as

$$f_i(\alpha) = \left[\prod_{j=1}^{n} \left(\left(b_{ij} - a_{ij}\right)\alpha + a_{ij}\right)\right]^{1/n}, \quad \alpha \in [0,1] \tag{2.13}$$

$$g_i(\alpha) = \left[\prod_{j=1}^{n} \left(\left(c_{ij} - d_{ij}\right)\alpha + b_{ij}\right)\right]^{1/n}, \quad \alpha \in [0,1]. \tag{2.14}$$

Also let,

$$a_i = \left[ \prod_{j=1}^{n} \tilde{t}_{ij} \right]^{1/n} \tag{2.15}$$

and

$$a = \sum_{i=1}^{m} a_i \ . \tag{2.16}$$

Similarly, bi and b, $c_i$ and c, and $d_i$ and d defined thus. The fuzzy weight $w_i$ is determined as:

(2.17)

Repeat $w_i = \left( \frac{a_i}{a}, \frac{b_i}{b}, \frac{c_i}{c}, \frac{d_i}{d} \right), \ \forall i$ this step for all fuzzy performance scores

Step 3. Aggregate the fuzzy weights and fuzzy performance scores. The fuzzy utilities Ui, $\forall_i$, are obtained based on

$$U_i = \sum_{j=1}^{n} w_j r_{ij}, \quad \forall i. \tag{2.18}$$

#### 2.4.1.3 Chang extent analysis method

This method was proposed by Chang in 1992 and has been used widely to get crisp weights from a fuzzy comparison matrix. The extent analysis is performed when every criteria or alternative has been evaluated by linguistic. It is formulated as follows.

Let X = $\{x_1, x_2 \ldots, x_n\}$ be an object set and U = $\{u_1, u_2, \ldots, u_m\}$, be a goal set. Each object is taken and extent analysis for each goal, $g_i$ , is performed then respectively.

m extent analysis values for each object can be obtained, with the following signs:

$M^1_{gi}, M^1_{gi}, \ldots M^m_{gi}$ $\qquad$ i=1, 2, …, n

Where all the $M_{gi}^{j}$ (j=1, 2, …, m) are TFNs

The steps are as given as follows

Step 1. The value of fuzzy synthetic extent with respect to ith object is defined as

$$S_i = \sum_{j=1}^{m} M_{gi}^{j} \otimes \left[ \sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} \tag{2.19}$$

To obtain $\sum_{j=i}^{m} M_{gi}^{j}$ perform the fuzzy addition of m extent analysis

values for a particular matrix such that

$$\sum_{j=1}^{m} M_{gi}^{j} = \left( \sum_{j=1}^{m} l_i , \sum_{j=1}^{m} m_i , \sum_{j=1}^{m} u_i \right) \tag{2.20}$$

and to obtain $\left[\sum_{i=1}^{n} \sum_{i=1}^{m} M_{gi}^{j}\right]^{-1}$ perform the fuzzy addition operation of

$M_{gi}^{j}(j=1,2,...,m)$ values such that

$$\sum_{i=1}^{n} \sum_{j=1}^{m} = \left( \sum_{i=1}^{n} l_i , \sum_{i=1}^{n} m_i , \sum_{i=1}^{n} u_i \right) \tag{2.21}$$

and then compute the inverse of the vector in Equation 2.16 such that

$$\left[ \sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} = \left( \frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i} \right) \tag{2.22}$$

Step 2. The degree of possibility of $M_2 = \{l_2, m_2, u_2) \geq M_1 = \{l_2, m_2, u_2)$ is defined as

$$V(M_2 \geq M_1) = \sup_{y>x} [min(\mu_{M1}(x), \mu_{M2}(y))] \tag{2.23}$$

and can be equivalently expressed as follows:

$$V(M_2 \geq M_1) = hgt(M_1 \cap M_2) = \mu_{M2}(d) = \begin{cases} 1, & \text{if } m_2 \geq m_1 \\ 0, & \text{if } l_1 \geq u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & \text{otherwise} \end{cases} \quad (2.24)$$

where d is the ordinate of highest intersection point D between $\mu_{M1}$ and $\mu_{M2}$ (see figure 2.5)

To compare $M_1$ and $M_2$ , the values of both $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$ are needed

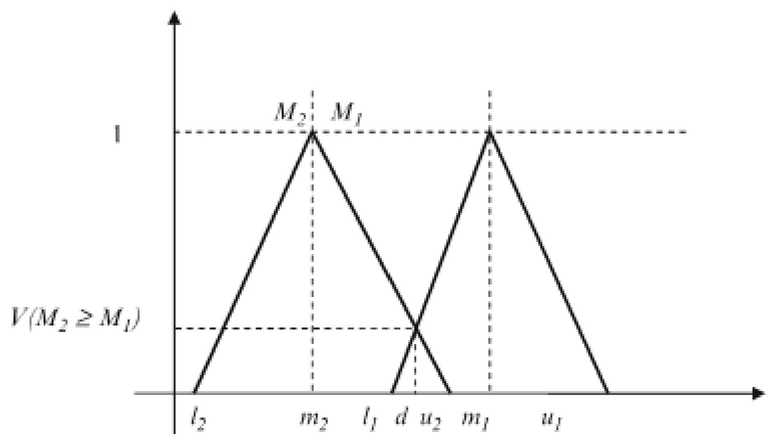



**Figure 2.6 The intersection between M1 and M2 (Demirel *et al.*, 2008)**

Step 3. The degree of possibility for a convex fuzzy number to be greater than k convex fuzzy numbers $M_i$ = ( I = 1,2,…,k) can be defined by:

$V(M \geq M_1, M_2, \ldots, M_k) = V[(M \geq M_1)$ and $(M \geq M_2)$ and …and $(M \geq M_k)]$ (2.25)

$= \min V(M \geq M_i)$, i=1,2,...,k

Assume that

$$d'(A_i) = \min V(S_i \geq S_k) \qquad (2.26)$$

For k=1,2,…,n; k≠1, then the weight is given by

$$W' = \left(d'(A_1), d'(A_2'), \ldots, d'(A_n)\right)^T \tag{2.27}$$

where $A_i$ (i=1,2, …, n) are n element

Step 4. Via normalization, the normalized weight vectors are

$$W = \left(d(A_1), d(A_2), \ldots, d(A_n)\right)^T \tag{2.28}$$

Where W is a non fuzzy number

### 2.4.1.4 Chang's entropy-based fuzzy AHP

The Shannon entropy was developed in 1996 and is applicable only to probability measures and it assumes the following form in evidence theory.

$$H(m) = -\sum_{j=1}^{n} m(\{x\}) \log_2 m(\{x\}). \tag{2.29}$$

This function, which forms the basis of classic information theory, measures the average uncertainty associated with the prediction of outcomes in a random experiment. Its range is

$[0, \log_2|X|]$

Clearly, H(m)=0

Where m({x})=1 for some $x \in X$;  H(m)=log2|X|  where m defines the uniform probabilities distribution on X (i.e., m({x})=1/|X|, $\forall x \in X$)

Cheng's evaluation model can be described as given below:

Step 1. Construct a hierarchy structure for any problem.

Step 2. Build membership function of judgment criteria.

Step 3. Compute the performance score.

Step 4. Utilize fuzzy AHP method and entropy concepts to calculate aggregate weights.

To assemble the total fuzzy judgement matrix Ã , multiply the fuzzy subjective weight vector $\breve{w}$ with the corresponding column of fuzzy judgement matrix $\breve{X}$ . Thus,

$$\widetilde{A} = \begin{bmatrix} \widetilde{w}_1 \otimes \widetilde{x}_{11} & \widetilde{w}_2 \otimes \widetilde{x}_{12} & \cdots & \widetilde{w}_n \otimes \widetilde{x}_{1n} \\ \widetilde{w}_1 \otimes \widetilde{x}_{21} & \widetilde{w}_2 \otimes \widetilde{x}_{22} & \cdots & \widetilde{w}_n \otimes \widetilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{w}_1 \otimes \widetilde{x}_{n1} & \widetilde{w}_2 \otimes \widetilde{x}_{n2} & \cdots & \widetilde{w}_n \otimes \widetilde{x}_{nn} \end{bmatrix}. \tag{2.30}$$

Then obtain fuzzy number multiplications and additions using the interval arithmetic and $\alpha$ cuts are made as shown in Equation 2.31

$$\widetilde{A}_\alpha = \begin{bmatrix} [a_{11l}^\alpha, a_{11u}^\alpha] & \cdots & [a_{1nl}^\alpha, a_{1nu}^\alpha] \\ \vdots & \ddots & \vdots \\ [a_{n1l}^\alpha, a_{n1u}^\alpha] & \cdots & [a_{nn1}^\alpha, a_{nnu}^\alpha] \end{bmatrix} \tag{2.31}$$

Where $a_{ijl}^\alpha = w_{il}^\alpha x_{ijl}^\alpha, a_{iju}^\alpha = w_{iu}^\alpha x_{iju}^\alpha$, for $0 < \alpha \leq 1$ and all $i, j$.

Next is to estimate the degree of satisfaction of the judgment Â . When $\alpha$ is fixed, the index of optimism $\lambda$ by the degree of the optimism of a decision maker is set. A larger $\lambda$ indicates a higher degree of optimism. $\lambda$ is a linear convex combination explained as:

$$\hat{a}_{ij}^\alpha = (1-\lambda) a_{ijl}^\alpha + \lambda a_{iju}^\alpha, \ \ \forall \lambda \in [0, 1]. \tag{2.32}$$

Thus,

$$\hat{A} = \begin{bmatrix} \hat{a}_{11}^\alpha & \hat{a}_{12}^\alpha & \cdots & \hat{a}_{1n}^\alpha \\ \hat{a}_{21}^\alpha & \hat{a}_{22}^\alpha & \cdots & \hat{a}_{2n}^\alpha \\ \vdots & \vdots & \ddots & \vdots \\ \hat{a}_{n1}^\alpha & \hat{a}_{n2}^\alpha & \cdots & \hat{a}_{nn}^\alpha \end{bmatrix} \tag{2.33}$$

Where Ã is a precise judgement matrix.

The entropy is first computed by using the relative frequency of Equation 2.34 and the entropy formula of Equation 2.35, i.e.,

$$\begin{bmatrix} \frac{a_{11}}{s_1} & \frac{a_{12}}{s_1} & \cdots & \frac{a_{1n}}{s_1} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{a_{n1}}{s_n} & \frac{a_{n2}}{s_n} & \cdots & \frac{a_{nn}}{s_n} \end{bmatrix} = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ f_{n1} & f_{n2} & \cdots & f_{nn} \end{bmatrix} \tag{2.34}$$

Where,

$$s_k = \sum_{j=1}^{n} a_{kj} \ .$$

Equation 2.31 can be used to calculate the entropy, i.e.

$$\begin{aligned} H_1 &= -\sum_{j=1}^{n} (f_{1j}) \log_2 (f_{1j}) \\ H_2 &= -\sum_{j=1}^{n} (f_{2j}) \log_2 (f_{2j}) \\ &\vdots \\ H_n &= -\sum_{j=1}^{n} (f_{nj}) \log_2 (f_{nj}) \end{aligned} \tag{2.35}$$

Where $H_i$ is the entropy value

The entropy weights can be determined by using Equation 2.36

$$H_i = \frac{H_i}{\sum_{j=1}^{n} H_j}, \quad i = 1, 2, \ldots, n \tag{2.36}$$

## 2.5 Data Mining Algorithms and Classification Models

Data mining is the process whereby valuable patterns and trends are being discovered in large data sets. It basically involves the extracting previously unknown, hidden and possibly beneficial information from data. This can be done either automatically or semi- automatically from a large quantity of data. It entails problems solving through analysis of data already present in databases

(Kurilovas, 2018; Parimala and Porkodi, 2018). It can be done by using three approaches: supervised, unsupervised and reinforcement learning.

Supervised learning approach involves giving the computer example inputs and their anticipated results with the aim of learning the general mapping rule of inputs to outputs. In this scenario, a function that maps input to output is learnt and given some example of input-output pairs (Abisoye, 2018; Amancio *et al.*, 2014)

In this instance, there is a label on each data point in the training set. The learning algorithms then analyse the training data and derive a function that can return the corresponding output for a given input. The end point of the task resolution is when the resulting function can generalise data points that are new and not in the training set, otherwise there is overfitting of the function. Examples are classification, regression and association mining.

In unsupervised learning approach, the learning rules are not be given. Rather the algorithms simply search out structure in its input. An unsupervised learning involved an agent learning a pattern in an unlabeled dataset. For example, a clustering algorithm has the ability to automatically figure out the internal structure of a set of inputs without any form of feedback. Hidden Markov Model (HMM), association rule mining and blind source separation (BSS) are other approaches of unsupervised learning (Rendleman *et al.*, 2019).

In reinforcement learning approach, there is interaction between computer program and dynamic setting within which it should perform a precise goal. Feedback is provided in terms of rewards and punishments because it navigates its drawback area. The difference between reinforcement learning and supervised and unsupervised learning is that it is a learning style in which an agent learns an optimal policy for sequential decision-making through interaction with its environment in a trial and error fashion (Jain *et al.*, 2017).

The classification defined in this section is shown in Figure 2.7.

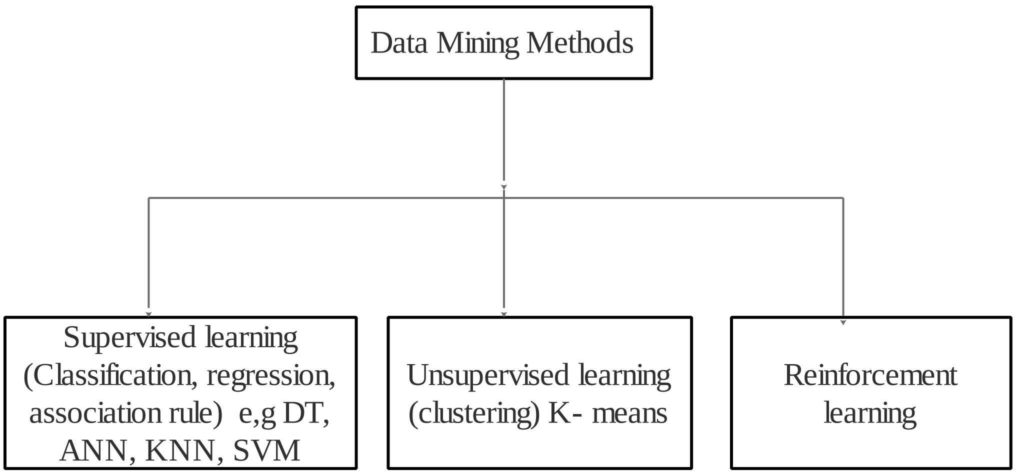



**Figure 2.7: Data mining methods**

Classification is one popular well-known methods in data mining. It is a form of data analysis method been used for the purpose of extracting models in order to describe important classes or allows for future data trend predictions. It is a supervised version of machine learning as described earlier. This method is used to determine a model that best distinguishes and labels the classes and concepts of data. Also, it is used to identify to which class a new or anonymous instance belongs.

It also falls under the predictive method which is aimed to predict a class for all the cases of information. Though, various classification problems exist but one of the common and simplest classification problems is binary classification. In this circumstance, the feature or target variable has two possible values whereas multiclass targets have more than two values. This approach has

been widely applied in many fields like engineering, management, medicine, agriculture, banking and many others (Bhardwaj and Siddhu, 2013; Camargo *et al.*, 2019; Doulah, 2019; Otunaiya and Muhammad, 2019; Shakil *et al.*, 2015)
In this study, one of the objectives is the classification problem to identify to which class (SATISFIED (TRUE): Positive usability rating and UNSATISFIED (FALSE): Negative usability rating) a new instance of a website belongs.

Classifiers are used to carry out classification tasks and they are grouped into different categories, like those that are based on probability like Naive Bayes and Bayesian Classifier; on functions like Artificial Neural Network (ANN), regression, Support Vector Machine; and trees based like decision tree (e.g. J48), repTree, random forest (Amin and Habib, 2015; Gulzar *et al.*, 2018; Ramesh *et al.*, 2017). Various implementation of these algorithms is available in many software which can be used to carry out machine learning tasks like Waikato Environment for Knowledge Analysis (WEKA), Python, R, MATLAB among others.

In this thesis, the main classifier used is Multi-Layer Perceptron (MLP which is a type of ANN. Its performance is compared with random forest, Bayesian Classifier, decision tree (J4), random forest and linear logistic regression. The next section gives an overview of these selected classifiers.

### 2.5.1 Artificial Neural Network (ANN)

Artificial Neural network is viewed as a computing system that mimic the workings of human brain, It is composed up of a number of simple processing elements that are highly interconnected and process information through their dynamic state response to external inputs (Nagpal *et al.*, 2017). ANN involves modelling of human intuition through simulation of the physical process upon which intuition is based. This involves simulation of the adaptive biological learning process. ANN can learn continuously through experience despite obvious changes in the problem environment (Moon *et al.*, 2015; Rahman *et al.*, 2019, Amin and Habib, 2015; Patil and Sherekar, 2013)

ANNs can be supervised and unsupervised In supervised learning, a set of example pairs (x, y), x ε X, y ε Y is inputted. The aim is to find a function *f in* the allowed class of functions that matches the examples. In other words, the aim is intended to how the mapping may be implied by the data and the cost function is related to the mismatch between the referred mapping and the data. So, the learning process is independent. In the unsupervised ANNs, no external evaluator is required and there is independence. The patterns, input data features and the relation for the input data over the output are discovered by the network. Figure 2.8 shows the structure of ANN with input layer, hidden layers and output layer.

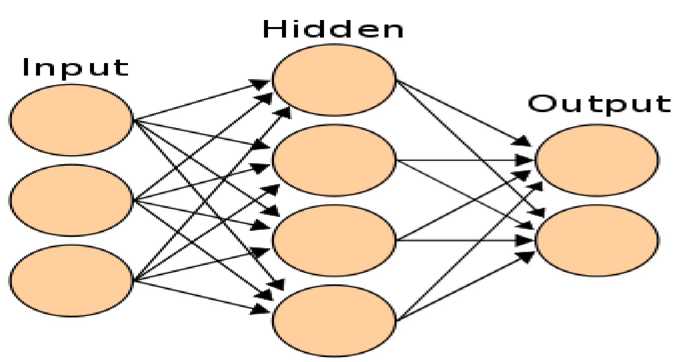



**Figure 2.8: Artificial Neural Network Structure (Patil and Sherekar, 2013)**

There are inputs, a processor, and outputs. The inputs form the **input layer**, the **middle layer(s)** which performs the processing is called the **hidden layer(s)**, and the **output(s)** forms the output layer.

The neurons are defined as a central processing unit similar to biological neuron structure, where mathematical operations are performed in order produce one output from a set of inputs. The output of a neuron is a function of the sum of the input weights and the bias. Operations are performed by each neuron which can lead to activation provided the total amount of signal received exceeds an activation threshold. Figure 2.9 shows ANN activation function.

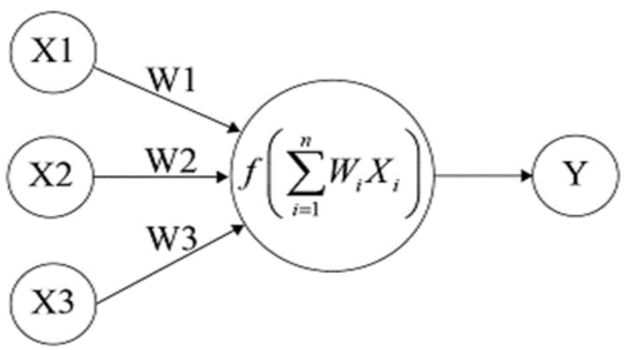



**Figure 2.9 . Activation function**

#### 2.5.1.1 ANN Weights and Biases

ANN has weights which are very important factor used for conversion of input into desired output. Much like linear regression slope, where a weight and input are multiplied and added up to generate the output. Weights are seen as numerical parameters which determine how strongly each of the neurons affects the other.

For example in a typical neuron, if the inputs are given as $X_1$, $X_2$, and $X_3$ , then the expected synaptic weights to be applied to them are denoted as $W_1$ , $W_2$ , and $W_3$, .

Output is given as

$$y = f(x) = \sum x_i w_i \qquad (2.37).$$

where *i* is the number of inputs.

Matrix multiplication is needed to compute the weighted sum. On the other hand, bias is similar to the intercept used in a linear equation. It is needed as an additional parameter to adjust output in conjunction with the weighted sum of the neuron inputs. which is used to adjust the output along with the weighted sum of the inputs to the neuron.

The neuron processing is thus denoted as

$$output = sum(weights * inputs) + bias \qquad (2.38)$$

A function known as **activation function** (next section) is applied on this output. The input of the next layer is the output of the neurons in the previous layer, as shown in Figure 2.9

#### 2.5.1.2 ANN activation functions

Activation functions handles the processing abstraction in neural network. This is a mathematical function which changes the input to an output, and thereafter adds the magic of neural network processing. If there is no presence of activation functions, ANN will simply operate like linear functions, where the output is directly proportional to input as given in the example below:

$$y = 2x + 1 \qquad (2.39)$$

$$y = f(x) \qquad (2.40).$$

This is a polynomial of one degree, a straight line and without any curve. However, in neural networks, problems that are solved are nonlinear and complex in nature. To achieve the nonlinearity, the activation functions are used.

Nonlinear functions are high degree polynomial functions, for example:

$$y = x^2 \tag{2.41}$$

$$y = \sin(x) \tag{2.42}$$

This gives a curved graph and consequently add the complexity factor. The nonlinearity property and ability to function as universal function approximator is given to ANN by activation function. The activation function must be robust, differential, not cause gradients to vanish, simple, fast in processing and not zero centered.

The *sigmoid* which is logistic model is the most used activation function, but also have some shortcomings. These include, time consuming computation and complexity, vanishing of gradients and disallowing signals not to pass through the neurons at some point of time, slow in convergence and not zero centered (Bakaev *et al.*, 2017; Moon *et al.*, 2015)

#### 2.5.1.3 Epoch

Epoch refers to each iteration or a pass which an ANN undergoes to provide the network with an input and update the network's weights. In a feed-forward and backpropagation network, it is a full run and used to update weights. It is also one full read through of the entire dataset. In a typically ANN, tens of thousands of epochs are necessary at times to train the neural network efficiently. The learning rate (*l*) refers to the amount that weights are updated as controlled by a configuration parameter. In other words, the complete pass back and forth is called a **training cycle** or **epoch**. The updated weights and biases are used in the next cycle. The training is being done recursively until the error is very minimal (Fashoto *et al.*, 2016; Moon *et al.*, 2015).

Table 2.4 shows a step by step operations in ANN training:

**Table 2. 4 ANN Operational steps**

*1. Take the input as a matrix.*
*2. Initialize the weights and biases with random values. This is one time and we will keep updating these with the error propagation process.*
*3. Repeat the steps 4 to 9 for each training pattern (presented in random order), until the error is minimized.*
*4. Apply the inputs to the network.*
*5. Calculate the output for every neuron from the input layer, through the hidden layer(s), to the output layer.*
*6. Calculate the error at the outputs: actual minus predicted.*
*7. Use the output error to compute error signals for previous layers. The partial derivative of the activation function is used to compute the error signals*
*8. Use the error signals to compute weight adjustments*
*9. Apply the weight adjustments.*

Steps 4 and 5 are forward propagation and steps 6 through 9 are backpropagation.

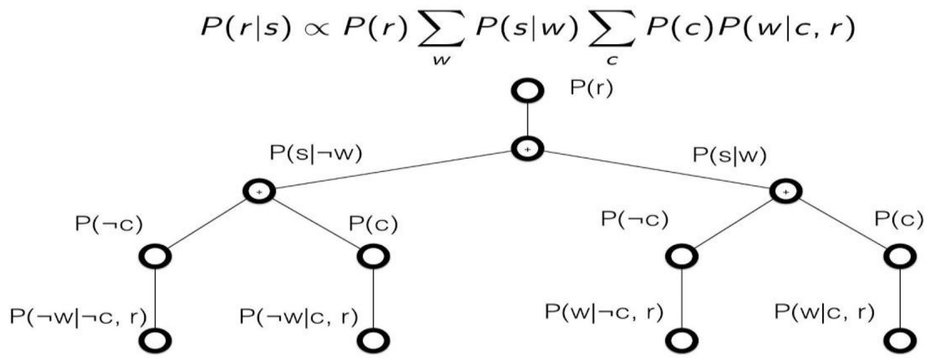
### *2.5.2* Bayesian Classifiers

The Bayesian network which is also known as the belief network, is a form of probabilistic graphical model where knowledge is represented concerning a set of random variables (Begum and Unal, 2019). In this model, each node is in form of a graph which represents a random variable. The edges of the graph between the variables represent the conditional dependencies. To compute conditional dependencies, statistical probabilistic theories and computation are done. It is a statistically based alternative which has well founded theoretical way to represent probability distributions succinctly and comprehensibly in a graphical manner.

They are made up of network of nodes, one for each attribute and , connected by directed edges in way that no cycles exists such as in *directed acyclic graph*. (Parimala and Porkodi, 2018). The structure is shown in Figure 2. 10

It involves the application of Bayes Rule to compute the posterior from the prior and the likelihood, because the latter two is generally easier to be calculated from a probability model.

**Figure 2.10 Bayesian Network (Brownlee, 2019)**




Bayes theorem is stated as follows

$$P(M|D) = \frac{P(D|M)P(M)}{P(D)} \tag{2.43}$$

Also,

$$P(D,M) = P(M)P(M|D) = P(M)P(D|M) \quad (2.44).$$

Where, $P(D)$ is the probability of $D$, $P(D|M)$ is the conditional probability of $D$ given $M$ and $P(D, M)$ is the joint probability of $D$ and $M$.

Equation 2.43 is read as "the probability of the model given the data $P(M|D)$ is the probability of the data given the model ($P(D|M)$) times the prior probability of the model $P(M)$ divided by the probability of the data ($P(D)$)"

A Bayes net is an augmented directed acyclic graph which is represented by a V which is set of vertex set V and E a set of directed edge. Loops are not allowed., and each vertex v ∈ V represents a random variable. Two variables $v_i$ and $v_j$ may still correlated even if they are not connected. Each variable $v_i$ is conditionally independent of all non-descendants, given its parents. The steps in building a Bayes Net are shown in Table 2.5

**Table 2.5 Steps to Build Bayes Net**

*1 Choose a set of relevant variables.*
*2 Choose an ordering for them.*
*3 Assume the variables are $X_1$, $X_2$, …, Xn (where X1 is the first, Xi is the ith).*
*for i = 1 to n:*
*Add the Xi vertex to the network*
*Set P arent(Xi) to be a minimal subset of X1, . . . , Xi−1, such that we have conditional independence of Xi and all other members of X1, . . . , Xi−1 given Parents(Xi)*
*Define the probability table of P(Xi = k | Assignments of Parent(Xi)).*

Some of the parameters needed to set up a Bayesian Network include the following :

An estimator to find the conditional probability table and a search algorithm to search and learn the network structures. Typically, the search algorithm needs the initial network to learn the structure, a markov blanket classifier to make sure all the nodes present in the network are part of the node in the markov blanket, and ensure markov blanket correction is applied to learn the network structure, the maximum number of parents a node has, order of nodes which can be defined randomly or alternatively the use of the dataset order and the score type which is used as indicator to assess the quality of a network structure (Nayebi, 2015)

### 2.5.3 Decision Tree Algorithms

The decision tree algorithm is one of the most interpretable and simplest machine learning algorithms. It is a tree like structure algorithm which is based on supervised technique. It is viewed as a white box machine learning algorithm and is comparable to the decision-making process exhibited by man. In comparison to some other machine learning models, it is very simple and slightly underperform but can be used to provide helpful visual explanations for its results (Ahishakiye and Niyonzima, 2017; Amin and Habib, 2015;. Kaur and Chhabra, 2014). Despite its simplicity and interpretability, there is susceptibility to noisy data in decision tree algorithm. For instance, if some attributes with same values from two instances of data are provided, different classification results will occur and is prone to overfitting. It is a frequently used algorithm because it is easy to implement, has low cost and is reliable.

The roots consist of decision nodes, branches, and leaves. J48 Decision tree also known as C4.5 is an extension of the ID3 algorithm. A decision tree builds its classification (or regression) models by imitating a tree structure. This involves breaking down a data set progressively into smaller subsets while at the same time an associated decision tree is incrementally developed. The final result s of decision tree are decision nodes and leaf nodes. A decision node has two or more branches while the leaf node represents a classification or decision. The root node is the topmost decision node in a tree, which corresponds to the best predictor. The DT algorithm is shown in Table 2.6

**Table 2.6: Decision Tree Algorithm**

***Input:*** *a sample T = (**x**, y), number of random features k, a leaf size limit lsize*
***Output:*** *Tree, a trained decision tree Initialize Tree, fnum as a total number of features, tnum as a predefined number of thresholds*
***function*** *trainDT(T, k)*
  ***if*** *sizeof(T) <= lsize* ***then***
    *label ← indexof( max in histogram(T) )*
  ***else***
    *fraction ← random(k from fnum)*
    *thresholds ← random(tnum)*
    *(f, t) ← max of split function in fraction and thresholds*
    *(leftT, rightT) ← split(T, f , t)*
    *add left child ← trainDT(leftT, k)*
    *add right child ← trainDT(rightT, k)*
  ***end if***
***end function***

### 2.5.4 Simple Logistic Regression

Simple Logistic regression is also used in binary classification through learning of the model. It is a form of a generalized linear model because the outcome constantly depends on sum of the inputs and parameters. In other words, the output cannot depend on the product (or quotient, etc.) of its parameters. Logistic regression is a form of predictive analysis as in all other regression analysis

(Chen *et al.*, 2017; Trigila *et al.*, 2015). Logistic regression is used to describe data and to explain the relationship between one dependent binary variable and one or more nominal, ordinal, interval or ratio-level independent variables.

Quantitatively, the relationship between the occurrence and it's the dependency on several variables can be expressed as below:

$$p = 1 / (1 + e^{-z}) \text{ or } p = e^{z} / (1 + e^{z}). \qquad (2.45)$$

*P* is an event occurring probability and *e* is the natural logarithm. The probability varies from 0 to 1 on an S-shaped curve and, z is the linear combination. It follows that logistic regression which involves fitting the data to an equation of the form

$$z = \beta_0 + \beta_1 X_1 + \beta 2 X_2 + \cdot \cdot \cdot + \beta_n X_n. \qquad (2.46)$$

While $\beta_0$ is the model intercept, $\beta_i$ ($i$ = 0, 1, 2, ..., $n$) represents the slope coefficients of the logistic regression model, and $X_i$ ($i$ = 0, 1, 2, ..., $n$) are independent variables (Saro *et al.*, 2016) This will be written as

$$p = \frac{1}{1+e^{-(\beta_o + \beta X)}} \qquad (2.47)$$

the Logistic Regression uses a more complex cost function, this cost function can be defined as the '**Sigmoid function**' or also known as the 'logistic function' instead of a linear function This function predicted values to probabilities as well maps any real value into another value between 0 and 1. It is to map predictions to probabilities.

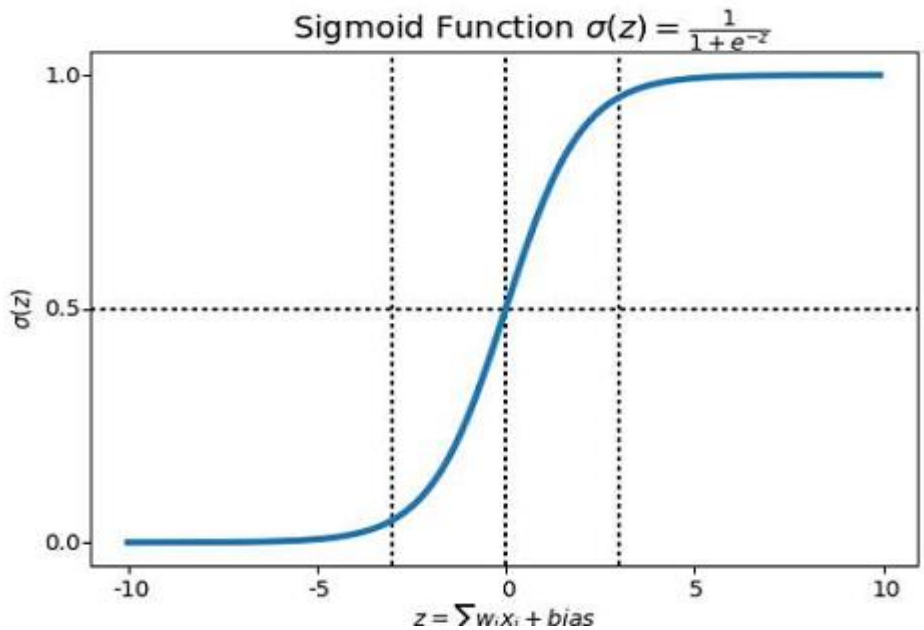



**Figure 2.11 Sigmoid function graph (Yang, 2019)**

### 2.5.5 Logistic Model Tree (LMT)

Logistic Model tree is a form of associated supervised learning algorithm that combines logistic regression and decision tree learning to be used in classification model. This is a model type that is made up of a tree like structure containing a set of inner nodes and leaves or terminal nodes. It combines the C4.5 algorithm which is at the nodes with logistic regression function been used at the leaves. Pruning of the tree is done by using a CART algorithm and cross-validation is used to find a number of LogitBoost iterations to prevent training data overfitting (Colkesen and Kavzoglu, 2016; Parimala and Porkodi, 2018).

To find the posterior probability in a leaf node , linear logistic regression with the equation below is used.

$$P(N|x) = \exp(L_i(x)) / \sum_{i=1}^{n} \exp(L_i(x)) \tag{2.48}$$

where the posterior probability is given as P(N|x) in a leaf node of N number of classes in the input vector x and Li (x) is the least-square fits given by the following equation:

$$L_i(x) = \sum_{i=1}^{n} \alpha_i x_i + \alpha_o = 0 \quad (2.49)$$

where n is the number of influencing factors, αo, αi are the coefficients of the component of vector x = xi which represents the influencing factors.

LogitBoost algorithm proposed by Friedman *et al.*, (2000) is shown in Table 2.7 and is been used for building the logistic regression functions at each nodes of the tree

**Table 2. 7 LogitBoost Algorithm**

1. Start with weights $w_{ij} = 1/N, i = 1, \ldots, N, j = 1, \ldots, J, F_j(x) = 0$ and $p_j(x) = 1/J \forall$
2. Repeat for $m = 1, \ldots, M$ :
   (a) Repeat for $j = 1, \ldots, J$ :
      i. Compute working responses and weights in the $j$th class

$$z_{ij} = \frac{y^*_{ij} - p_j(x_i)}{p_j(x_i)(1 - p_j(x_i))}$$

$$w_{ij} = p_j(x_i)(1 - p_j(x_i))$$

      ii. Fit the function $f_{mj}(x)$ by a weighted least-squares regression of $z_{ij}$ to $x_i$ with weights $w_{ij}$
   (b) Set $f_{mj}(x) \leftarrow \frac{J-1}{J}(f_{mj}(x) - \frac{1}{J}\sum_{k=1}^{J} f_{mk}(x)), F_j(x) \leftarrow F_j(x) + f_{mj}(x)$
   (c) Update $p_j(x) = \frac{e^{F_j(x)}}{\sum_{k=1}^{J} e^{F_k(x)}}$
3. Output the classifier $\mathrm{argmax}_j F_j(x)$

### 2.5.6 Random Forest

Random forest which was proposed by Breiman Leo in 2001 is a powerful ensemble-learning method which is used for classification, and regression as well as unsupervised learning (Chen *et al.*, 2017; Parmar *et al.*, 2018). Random Forests operates as an ensemble learning algorithm where the base learners are decision tree classifiers, bagging, and bootstrapping. The algorithm is built on decision trees being used as classifiers. Each tree is trained by bootstrapping, using different samples from the training data. Additionally, each tree is trained using a random subset of the predicting variables. Many decision trees (500–2000) are used and each tree casts a vote with the prediction of the class decided by the majority vote.

Random forests are a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest. Two parameters are needed to train a RF which are the number of tress (ntree) in the forest and the number of randomly selected features/variables used to evaluate at each tree node (mtry). RF also allows adjustment of the voting threshold or cutoff (fraction of trees in the forest needed to vote for a given class), which is used to compute recall, precision and f-score (Petkovic *et al.*, 2018). The procedure for RF is shown in Table 2.8. They are fast, robust, easy to implement, produce highly accurate predictions and can handle a very large number of input variables without overfitting. This method has been widely used in many fields and exhibited good performance (Chen *et al.*, 2017; Eisavi and Homayouni, 2017; Elias *et al.*, 2018; Kalmegh, 2015; Venkatesan and Priya, 2015).

**Table 2.8 Random Forest procedure**

1. For $b = 1$ to $B$:
   (a) Draw a bootstrap sample $\mathbf{Z}^*$ of size $N$ from the training data.
   (b) Grow a random-forest tree $T_b$ to the bootstrapped data, by recursively repeating the following steps for each terminal node of the tree, until the minimum node size $n_{min}$ is reached.
      i. Select $m$ variables at random from the $p$ variables.
      ii. Pick the best variable/split-point among the $m$.
      iii. Split the node into two daughter nodes.
2. Output the ensemble of trees $\{T_b\}_1^B$.

To make a prediction at a new point $x$:

*Regression:* $\hat{f}_{\text{rf}}^B(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x)$.

*Classification:* Let $\hat{C}_b(x)$ be the class prediction of the $b$th random-forest tree. Then $\hat{C}_{\text{rf}}^B(x) = \textit{majority vote}\ \{\hat{C}_b(x)\}_1^B$.

## 2.6 Related Works on MCDM Approach in Website Evaluation

The use of MCDM approach for website evaluation has been on the increase in recent years with different researchers using the technique on different genre of websites (Das and Patil, 2014; Gupta, 2015; Insfran and Fernández, 2008; Nawaz and Clemmensen, 2013; Paz and Pow-Sang, 2014). At present, MCDM is one of the popular website performance measurement tools (Sunny *et al.*, 2017). It is also established that the fields of Engineering and Computer science have the most important part in utilizing MCDM for solving decision problems according to Scopus database (Rekik *et al.*, 2016).

The sections following gives a review of MCDM approaches in website evaluation from both the usability and quality point of view.

### 2.6.1 MCDM approach in website evaluation

As stated in section 2.3, MCDM methods are frequently used to solve real world problems with multiple, conflicting, and incommensurate criteria and/or objectives (Kubler *et al.*, 2016). MCDM involves making of decision by choosing the best alternative in the presence of multiple criteria. This approach is used based on the fact that a lot of factors have been identified by researchers which are both generic and specific in nature for various websites.

The common objective is to help decision makers' deal with complex problems in form of *evaluation, selection and prioritisation* by imposing a disciplined methodology. Website usability evaluation as well as website evaluation quality comes under selection or evaluation process and hence can be solved by using MCDM approach (Kubler *et al.*, 2016). In the way usability is seen as a MCDM problem which gives room for the suitability of usage of MCDM to predict usability (Nagpal *et al.*, 2017)

Various studies that have used the MCDM approach in evaluating different websites are discussed in the next sections as follows.

#### 2.6.1.1 MCDM approach in educational website evaluation

One of the early users of websites are academic institutions (colleges, universities, polytechnics, institutes). In considering the role websites play in academic institutions, some studies have used various MCDM approaches in evaluating both the quality and usability of academic websites. These studies are grouped under university, college or portal websites' evaluation, e-learning websites' evaluation and library websites' evaluation. Some of these studies are discussed as follows.

Nagpal *et al.* (2015b) used fuzzy AHP to rank four India educational institutes on usability. The study criteria were based on Response Time (RT), Ease of use (EOU), Ease of Navigation (EON) and Informative (INF) as criteria. Further study by the same authors combined the use of fuzzy AHP and fuzzy TOPSIS to rank four university websites. An integration of fuzzy AHP and entropy approach was used to determine the usability of six academic websites based on the same four criteria as previously used (Nagpal *et al.*, 2016). It was reported in the result that response time contributed most to academic websites usability by using entropy approach, while ease-of-use contributed most to academic websites usability by using Fuzzy AHP. Büyüközkan *et al.*(2010) evaluated e-learning website using fuzzy axiomatic and fuzzy TOPSIS. The method incorporated requirements which enabled reduction in the size of the problem.

Dominic and Jati (2010) in their study proposed a quality evaluation model based on fuzzy AHP for five university websites in Malaysia. Furthermore, a quality evaluation on five university websites in Malaysia using eleven criteria obtained from automated tools was also carried out by Dominic *et al.*( 2013). The outcome of the research indicated that the selected Malaysia universities were not paying adequate attention to performance and quality criteria. Ranking of Greece universities based on quality by using AHP was also carried out by Kostoglou *et al.*(2014). The study was based on five criteria and simos method was also employed. Results obtained show that coverage/content and web services received the highest weight while objectivity and presentation of research were the least in weight.

Garg and Jain (2017) evaluated e-learning websites using fuzzy AHP for weight selection in their study. Combination of COPRAS (COmplex Proportional ASssessment), VIKOR and WDBA (Weighted Distance Based Approximation) were used for the ranking. Results show that the developed model used in the study was effective and efficient in assessment. Jain *et al.*(2015) carried out an assessment of quality of e-learning websites using TOPSIS. Twenty-one e-learning websites based on seven criteria were used for the study. Usability analysis on a university website was also evaluated by combining AHP and Heuristic evaluation method based on severity of usability problems detected from the website (Delice and Gungor, 2009). Lin (2010) also evaluated course websites using FAHP based on four criteria grouped into sixteen sub- criteria among different independent groups.

#### 2.6.1.2 MCDM approach in e-commerce website evaluation

E-commerce websites are also very important considering its impact on the economy of any given country. Masudin and Saputro (2016) applied fuzzy AHP and fuzzy TOPSIS to carry out usability evaluation on two e-commerce B2C websites. Five criteria of trustworthiness, shopping support, information access efficiency, ease of comprehension and hedonic quality were used. It was further subdivided into fifteen sub- criteria. The results of fuzzy AHP show that security and privacy are the most important criteria, followed by trust, loading time, easy transaction, and e-payment support respectively. The quality of three e-commerce websites in Turkey was examined by using fuzzy AHP and fuzzy VIKOR as stated in a study by Aydin and Kahraman (2012). Five main criteria and twenty sub-criteria were used in the study and the methodology proposed was reported to offer have the advantage of having ability to use both positive and negative fuzzy numbers to evaluate the hierarchy.

Fuzzy AHP was also applied to determine success factor in e-commerce websites in a study conducted by Kong and Liu (2005). It involves five criteria of trust, system quality, content quality, online service and use which were further sub divided into seventeen sub-criteria. The most important criteria were found to be trust and online service, while security and tracking order status were the most critical factors under each of them. Younghwa and Kenneth (2006) in their study aimed at selecting the most preferred website based on website quality factors and their relative importance. The association between website preference and financial performance was as well considered. DeLone and McLean's Information System (IS) success model was extended through the application of AHP on some e-business companies in the study.

Rekik *et al.*(2016) in their study aimed to know the best criteria for the evaluation of e-commerce websites quality using fuzzy ANP based on eight criteria. The study concluded from the results obtained that customers' satisfaction and transaction security are the two most important criteria for a successful e-commerce website. Yi-wen *et al.* (2007) proposed the use of fuzzy AHP approach to evaluate e-commerce websites using four criteria which were further grouped into different sub criteria. The results obtained when compared with AHP method were found to be consistent. In another study, a model for web interface evaluation of e-procurement website was developed by Kabak and Burmaoğlu (2013). Combinations of DEMATEL, ANP and fuzzy set theory were used to develop the model. Ten criteria were used and the results obtained from the study show that standardization, links, reliability and navigability are the most important criteria when evaluating e-Procurement website.

Similarly, shopping websites were evaluated using MCDM by Sun and Lin (2009). Fuzzy TOPSIS method was used to evaluate the competitive advantage of the four shopping websites on twelve criteria. It was discovered based on the results that security and trust are the most important factors needed to improve the competitive advantage of these websites. Vatansever and Akgu (2014) applied fuzzy AHP to measure the service quality of private e-shopping websites in Turkey. Four criteria and twenty-two sub criteria were used. From the analysis of results, vendor specific quality is the most significant factor which affects the quality of the website. This is followed by service quality, system quality and information quality respectively. An exploratory study to determine the usability factors in e-commerce websites was also carried out by Pearson and Pearson (2008). Five criteria of navigation, customization and personalisation, download speed, accessibility and ease of use were used. It was discovered in the findings that, ease-of-use and navigation were two critical components to determine e-commerce website usability.

Yu *et al.*(2011) integrated AHP and fuzzy TOPSIS to rank five e-commerce websites based on nine criteria. The criteria are speed, confidence, appearance, price, abundance, intelligence, security, ease-of-use and trust. Dey *et al.*(2015) developed a hybrid evaluation model that combined the use of AHP and fuzzy TOPSIS. Six major e-shopping websites of India were considered as alternatives and six important criteria factors which influence online shopping the most were taken into consideration. Results obtained from the study indicate that price and quality of product, purchase security, account privacy statement and customer support are five top most influential criteria in online purchasing in Indian market. A fuzzy MCDM approach for evaluating B2C e-commerce websites was also developed by Liang *et al.*(2017). It was developed using single-valued trapezoidal neutrosophic decision making trial and evaluation laboratory (SVTN-DEMATEL). Four criteria of efficiency, fulfillment, system availability and privacy were used to evaluate six e-commerce websites in China. The outcome of the research shows that impact factors affecting e-commerce services were affected by different priority levels and interrelationships.

#### 2.6.1.3 MCDM approach in e-government website evaluation

In e-government websites evaluation, MCDM approaches have also been applied. Byun and Finnie (2011) in their study proposed AHP method in order to assess the usability of e-government websites and ranking of Australian state governments portal. Six main usability criteria and fifty-nine sub-criteria were used. Markaki *et al.*(2010) applied fuzzy AHP to evaluate the quality of e-government websites using five criteria decomposed into seventeen sub criteria. Results obtained indicated that e-service axis is the most important factor which affect the overall quality website of public authority. Other essential criteria include website content and the technical performance. Fuzzy AHP was also applied to carry out usability evaluation on e-government websites from a study conducted by Lamichhane and Meesad (2011). It was based on four criteria and five websites were used as alternatives. Relevance and complete information about the services were found to be the most important sub criteria.

Burmaoglu and Kazancoglu (2012) evaluated e-government websites in Turkey using fuzzy AHP and fuzzy VIKOR. It was based on three criteria of e-democracy, e-service and website design. These were further broken down into different subcriteria. The study concluded by recommending that e-service applications must be developed by different countries. Dominic *et al.*(2011) compared e-government websites in five Asian countries using combination of Linear Weightage Model (LWM), fuzzy AHP, AHP, and a new hybrid model (NHM). The results of the study confirmed that quality and performance criteria were neglected by most Asian e-government websites.

#### 2.6.1.4 MCDM approach in travel website evaluation

Another important genre of websites is travel website. From the study by Kabir and Hasin (2012) important factors for travel agency websites quality based on users' viewpoint perception were examined. The study further explored the use of MADM approaches to evaluate the service quality of travel website. Five criteria grouped into seventeen sub-criteria were used to develop the model. Soleymaninejad *et al.* (2016) evaluated two travel agent websites based in USA using TOPSIS and six criteria were used in the study. Results from the study show that the most important criteria are visibility, findability, functionality and accessibility. Furthermore, Khan and Dominic (2013) evaluated the website quality of four Malaysia airline websites using AHP based on criteria generated from web diagnostic online. The best airline with the most quality website was obtained at the end of the study.

Wen-Hsien *et al.*(2009) developed a model using DEMATEL ANP and VIKOR to evaluate five airline websites in Taiwan. The study concluded that Taiwanese airlines did not utilize full potential of the internet. Also, it was discovered that all the five websites did not performed very well in price negotiation, low price, responsiveness and communication. Studies by Kabir and Sutana (2013) considered the users viewpoint in evaluating the major factors for travel agency websites. Fuzzy TOPSIS was used for the evaluation. Study by Lee *et al.*(2012) proposed a hierarchical MCDM evaluation model based on the fuzzy AHP and the fuzzy TOPSIS methods to evaluate the quality of four travel websites in Taiwan base on five aspects which is further sub-divided into seventeen criteria. Dominic and Jati (2011) and Khan and Dominic (2013) in their studies developed MCDM models to measure the quality of Asian airlines websites via web diagnosis tools by using AHP, FAHP and Linear Weighted Model (LWM). The newly proposed method was found to be effective in measuring airline websites quality.

#### 2.6.1.5 MCDM approach in evaluation of other websites genre

Other websites genre where MCDM approach have been applied are discussed as follows. Zhang *et al.*( 2015) carried out usability evaluation on four ecological park websites using a model that is based on index layer, criterion layer and target layer. Three criteria of topicality, functionality and information elements were selected by using Group AHP. Presley and Fellows (2013) used AHP to evaluate the usability of three financial portals in USA based on five criteria and fourteen sub-criteria. The order of the importance of criteria were ease of use, content, made-for-the-media, emotion and promotion. From the sub-criteria level, the three highest weighted were structure, goals and feedback. Aytuna *et al.*(2012) developed a model based on AHP to evaluate political websites in Turkey using five criteria which are functionality, efficiency, usability, reliability and interactivity. Findings from the study shows that functionality and visibility are main goal of the Turkish political parties' website while interactivity has the lowest weight.

Alptekin *et al.*(2015) proposed the use of fuzzy TOPSIS method to evaluate the quality of five Turkish bookstore websites. Four criteria which were further categorised into fifteen sub categories were used in the evaluation. Mirbargkar and Zadmehr (2015) investigated the quality of three hospital websites quality using ANP and fuzzy TOPSIS. Six major criteria and nineteen sub-criteria were used. Results indicate that information quality criteria are ranked first. This is followed by assurance and the least is responsiveness. Form the sub-criteria, information accuracy and trust were ranked first and second respectively with customerisation ranked last. Tsai *et al.*(2010) used a combination of DEMATEL ANP, VIKOR and Weight Variance Analysis (WVA) to evaluate the quality of seven national park websites in Taiwan. Djordj *et al.*(2013) employed the use of ANP to measure the relative importance of usability factors of a defense ministry portal in Serbia. Three factors which are usability, safety and flexibility were used in the study for the analysis.

Bijan and Salehi (2013) in their study proposed a model to compare the customer satisfaction indices of two e-recruitment website in order to select the most preferred website in a specific context. The model was developed by merging the ANP approach with the America Customer Satisfaction Index (ACSI) for ecommerce. Kaya and Kahraman (2011) developed an assessment methodology for four e-banking websites using an integrated fuzzy AHP-ELECTRE approach. The criteria used are information system (IS) quality, reliability, competence, access, customer services quality, security, ease-of-use and product quality.

Kaya (2010) in his study proposed a methodology for e-business website quality based on multi-attribute approach. The model was involved the use of modified fuzzy TOPSIS approach, where fuzzy AHP procedure was used to determine the weight of the evaluation criteria. Chou and Cheng (2012) developed a hybrid approach combining the fuzzy ANP and fuzzy to evaluate website quality of four Certified Professional Accounting firms in Taiwan. Three criteria were used in the study which were further sub divided into twelve subcriteria. Results obtained show that the richness, understandability, assurance, relevance, and reliability are the top five priorities.

Another important area where MCDM approach have been widely used is in Hotel and Tourism. Akincilar and Dagdeviren (2014) evaluated five-star hotels in Ankara turkey using AHP and PROMETHEE. The quality of e -service of four hotels using Webqual and fuzzy AHP was also carried out by Shahin *et al.*(2014). Three criteria were used in the study and it was discovered that the highest priority is received by information quality followed by usability dimensions and service interaction. In another study fuzzy TOPSIS was used to evaluate and compare the ability and functionality of hotel websites of websites in China based on usability. Four criteria; Navigation, website friendliness (ease of use), language and overall layout which was further subdivided into twenty five sub criteria were used in the study (Qi *et al.*, 2017). Calisir *et al.*(2009) in their study used ANP determined the relative importance of the usability and functionality factors using two online auction and shopping websites as case studies. The findings reveal that users of these websites give higher priority to usability factors than to functionality. More so, navigation and interaction are found to be factors with highest relative importance.

Table 2.9 gives the summary of the various MCDM approaches that have been used in both usability and quality evaluation of websites. Tables 2.10 and 2.11 show the criteria used in by different authors on different genre of websites in website quality and usability evaluation studies respectively,

**Table 2.9: Distribution Based on MCDM approaches**

| Method/Approach | Author(s) |
|---|---|
| AHP | Aytuna *et al.*(2012), Khan and Dominic (2013),Byun and Finnie, (2011), Roy *et al.*(2016),Presley and Fellows (2013),Younghwa and Kenneth (2006), Zhang *et al.*(2015),Delice and Gungor (2009), Guimei and Taowei (2012),Kostoglou *et al.*, (2014), Pathania and Rasool (2017) |
| ANP | Djordj et al (2013) |
| DEMATEL &ANP& Fuzzy | Kabak and Burmaoğlu (2013) |
| Fuzzy AHP | Dominic *et al.* (2011), Yi-wen *et al.*,( 2007), Lin (2010),Markaki, Charilas, and Askounis (2010), Vatansever and Akgu (2014) Shahin *et al.*, (2014), Aydin and Kahraman (2011),Dominic and Jati (2010), Kong and Liu (2005), Nagpal *et al.*, (2015a) |
| AHP &TOPSIS | Soleymaninejad *et al.* (2016) |
| AHP & ELECTRE | Kaya and Kahraman (2011) |
| AHP & PROMETHHE | Akincilar and Dagdeviren (2014) |
| AHP & COPRAS-G | Ecer (2014) |
| Fuzzy TOPSIS | Kabir and Hasin (2012), Alptekin *et al.*(2015) Sun and Lin (2009), Büyüközkan *et al.*,(2010), Qi *et al.*(2017) |
| Fuzzy AHP & TOPSIS | Lee *et al.*(2012), Masudin and Saputro (2016), Kaya (2010), Nagpal *et al.*(2015b) |
| Fuzzy AHP &Fuzzy VIKOR | Burmaoglu and Kazancoglu (2012), Aydin and Kahraman (2012) |
| Fuzzy ANP & FuzzyVIKOR | Chou and Cheng (2012) |
| AHP & PROMETHEE | Bilsel *et al.* (2006) |

| | |
|---|---|
| AHP & FTOPSIS | Yu *et al.*(2011) |
| FAHP &COPRAS &VIKOR& WDBA | Garg and Jain (2017) |
| ANP & Fuzzy TOPSIS | Mirbargkar and Zadmehr (2015),Dey *et al.* (2015) |
| Fuzzy AHP+ENTROPY | Nagpal *et al.*(2016) |
| DEMATEL & ANP & VIKOR | Tsai *et al.* (2010) |
| SVTN-DEMATEL | Liang *et al.*(2017) |
| NS (FUZZY MCDM) | Pearson and Pearson (2008), Law (2007), Castro-Lopez *et al.*, (2017) |
| TrIFMAGDM | Lian *et al.* (2017) |

**Table 2.10: Criteria used in previous Website Quality Evaluation Studies**

**Table 2.10 (CONT): Criteria used in previous Website Quality Evaluation Studies**

**Table 2.11 Criteria used in previous Website Usability Evaluation Studies**

From the literature review and the summary tables in this section, the following observation and gaps are discovered in the literature. There is clearly lack of comprehensive educational website usability criteria. More so, there is dearth and lack of adequate researches on educational website

| Website Type | Author(s) | Criteria number | Criteria used |
|---|---|---|---|
| Education | Nagpal *et al.*(2015a) Nagpal *et al.*(2016b) Nagpal *et al.* (2015b) | 4 | Ease of use, response time, Navigation, informative. |
| | Roy *et al.*(2016) | 5 | Attractiveness, Controllability, Efficiency, Helpfulness, Learnability' |
| | Delice and Gungor (2009) | 3 | Design consideration, operation of website, website user accordance |
| E-government | Lamichhane and Meesad (2011) | 4 | Adequacy of information, Update and interaction, Appearance and outline, navigation |
| | Guimei and Taowei (2012) | 4 | Service, technology, system structure, culture |
| | Byun and Finnie (2011) | 8 | Contents, Page, Navigation, Ease of learning, Interaction, functionality |
| Financial | Presley and Fellows (2013) | 5 | Content, Ease of use, Promotion, Made for the Medium Emotion |
| Ecological park | Zhang *et al.*(2015) | 3 | Topicality, Functionality, Information elements |
| E-commerce | Masudin and Saputro (2016) | 5 | Trustworthiness, shopping support, information access efficiency, ease of apprehension, hedonic quality |
| Hotel | Qi *et al.* (2017) | 3 | Effectiveness, safety, flexibility |
| | Poormostafa, (2014) | | |
| E learning | Büyüközkan, Arsenyan and Ertek (2010) | 7 | Right and Understandable Content, Complete Content, Personalization, Security, Navigation, Interactivity, User Interface |
| | Garg and Jain (2017) | 10 | Functionality, Maintainability, Portability, Reliability, usability Efficiency, Ease of Learning Community, Personalization, System Content, General Factors |
| | Dey, Jana, Gourisaria, | 5 | Website design and usability, product, security, service quality, fulfilment |
| E -shopping | Mohanty and Chatterjee, (2015) | 12 | Efficiency, Practical, Ease of Use, Time-Saving, Communication, Confident, Security, Trust, Familiar, Past Experience, Proficiency, Knowledgeable |
| | Sun and Lin (2009) | | |
| | Nirmala and Uthra (2017) | 5 | Service., Information, website, system, vendor specific |
| | Lian *et al.* (2017) | 4 | Visual appeal, information accuracy and abundance, navigation, convenience and website interaction, |

| | | |
|---|---|---|
| Stanujkic ( 2014) | 6 | Design, Authority, accuracy, adaptability, currency, navigation |

usability evaluation using MCDM approaches. Also, integrated model for website evaluation combining MCDM techniques with artificial intelligent techniques are lacking in the context of website evaluation especially as regards usability and quality Furthermore, researches from students' perspectives; enrolled and prospective are also lacking. There may be variations in the way usability is being viewed by different categories of students, especially enrolled and prospective students.

Only few research focuses on using data mining or artificial intelligent techniques in usability evaluation (Boza *et al.*, 2014; Korvald *et al.*, 2014; Nayebi, 2015; Oztekin *et al.*, 2013; Taj *et al.*, 2019) These studies are inadequate considering the exponential growth of machine learning application in other fields. Also, the methods used in collection of data are mostly automated whereas usability data are better collected when they are generated first hand from the users (Ahmi and Mohamad, 2016; Manzoor *et al.*, 2019). In addition to this, only one study whose focus is on iOS rating used machine learning algorithms for prediction to develop a model with Bayesian network having the highest accuracy of 92% (Nayebi, 2015).It was also observed that research studies on combination of automated tools, usability evaluation approach with integration of MCDM approach is uncommon and where available are very scarce.

Since existing website usability evaluation methods, approaches and models suffer from some of these identified weaknesses, the need therefore arises to come up with a methodology aiming at combination and integration of more methods to compensate for these weaknesses. Integrating two or more methods will provide better usability insight, reveal more usability problems, reduce cognitive overload on the users, aid web designers and improve website quality as a whole. Also, it will make classification of websites usability apparent which will aid in prediction.

# CHAPTER THREE

## 3.0 RESEARCH METHODOLOGY

### 3.1 Research Design

The research design presents the methodology used in achieving the objectives of the study. The procedures followed in achieving this is shown in Figure 3.1 involving different phases as outlined below.

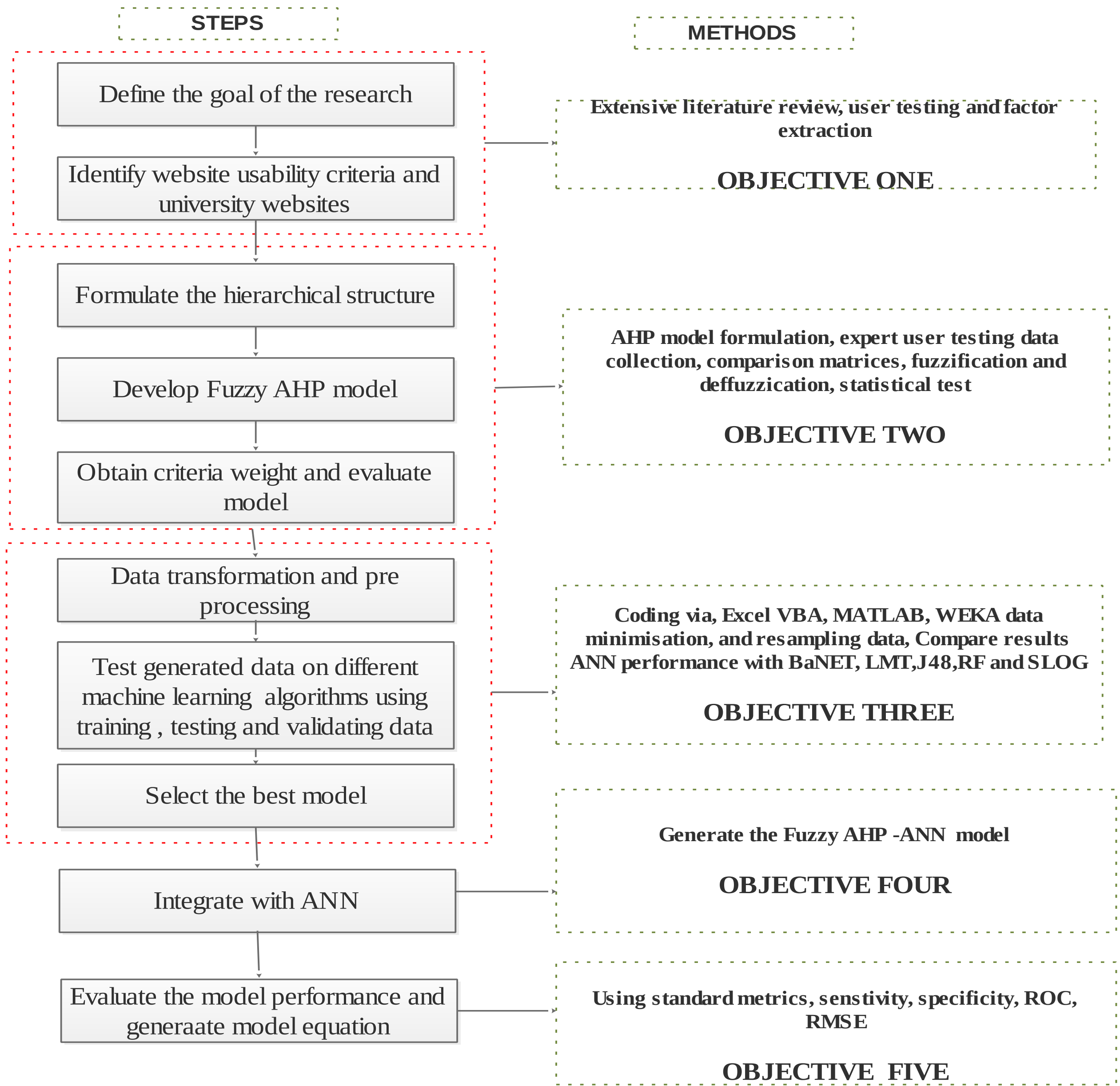



**Figure 3.1 Research Methodology of the Study**

Phase one involves identification of websites usability criteria and development of a website's usability evaluation model, selection of university websites, users testing and task analysis, factor analysis and extraction. Phase two is the development, formulation and validation of Fuzzy AHP model while phase three involves testing the data on different machine learning models. Phase four is integration with ANN which is the best model with highest accuracy and finally phase five involves the integrated model evaluation.

### 3.2 Identification of Website Usability Criteria

This phase involves reviewing of past studies in the research area of usability evaluation with specific focus on academic websites usability evaluation criteria. The procedures followed in this phase is shown in Figure 3.2.

Various electronic sources were employed to do this and they are primarily from the Internet and online academic databases. These sources include EBSCOhost, Science Direct, IEEExplore digital library, Inderscience, ACM digital library, Taylor and Francis and Google Scholar. After the articles have been selected, reviewed and analysed critically, the following website usability criteria were identified.: System quality, information quality, service, coverage and content, web services, technical, aesthetic, completeness, objectivity, load time , response time, page rank, frequency of update, traffic, size, number of items, accessibility error, markup validation, broken link, Ease of use, navigation, informative, attractiveness, controllability, efficiency, helpfulness, learnability', design consideration, operation of website, website user accordance, Accessibility, findability. Content, organisation, readability, effectiveness, design, navigability, satisfaction.

After identification of all criteria listed above, further validation, analysis and synthesis were done which led to renaming, filtering and removal of overlapping or duplicates criteria. At the end of this stage, but only seven criteria which are very relevant and essential to this study were selected and it is sufficient for the model (Saaty and Ozdemir, 2003). These are; Speed, Navigation, Ease of Use, Content, Aesthetic, Accessibility and Security.

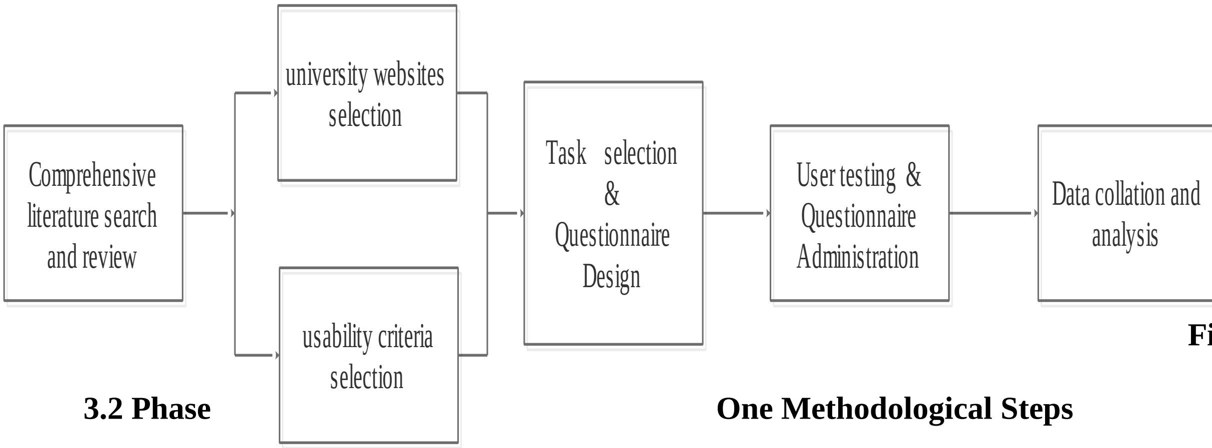



**Figure 3.2 Phase One Methodological Steps**

Speed is the amount of time it takes for the website to render or respond after a request has been made i.e. the load time. Navigation of a website measures the ability to detect and gain possession of appropriate information, menu, reports, options, and elements. Ease of Use refers to the ease at which the user uses and understands the structure, architecture and organization of the website. Content on the other hand refers to the textual, aural and visual information published on the website. Accessibility is the extent to which the website is compatible for use by people with disabilities. Simply put, it is availability of the websites to different categories of users without any form of discrimination. Aesthetics has to with attractiveness and look and feel of the website. This includes the design and color combination used in the website design. Lastly, based on ISO/IEC 9126 security, which is a sub-characteristic is defined a set of software attributes which relates to its ability to prevent unauthorized access, whether accidental or deliberate to programs and data.

### 3.2.1 Selection of university websites

The university websites used for the study are selected based on the most recent webometric ranking web of universities between 2016 and 2018 (Cybermetrics Labs, 2016, 2017, 2018). As a result of this, the sample consist of six Nigerian university websites as of July 2018 ranking. The selection is done to ensure that only top-ranking universities in the country with good web presence are selected for the study. Also, the selection is limited to only six websites to avoid information overloading in the course of carrying out users task on the websites as recommended in previous studies (Dominic *et al.*, 2013; Nagpal *et al.*, 2016a; Yerlikaya and Durdu, 2017) Table 3.1 shows the selected universities in descending order with their respective world ranking while Figures 3.3. to 3.8 shows the home pages of the selected universities websites.

**Table 3.1: Ranking of Selected University Websites on Webometric**

| | University name | URl | Acronym | 2016 ranking | 2017 ranking | 2018 ranking |
|---|---|---|---|---|---|---|
| 1 | University of Ibadan | www.ui.edu.ng | UI | 1st | 1st | 1st |
| 2 | Covenant university | www.covenant.edu.ng | CU | 6th | 2nd | 2nd |
| 3 | Obafemi Awolowo University | www.oauife.edu.ng | OAU | 3rd | 4th | 3rd |
| 4 | University of Nsukka | www.unn.edu.ng | UNN | 7th | 3rd | 4th |
| 5 | University of Lagos | www.unilag.edu.ng | UNILAG | 2nd | 6th | 5th |
| 6 | Ahmadu Bello University | www.abu.edu.ng | ABU | 4th | 7th | 6th |

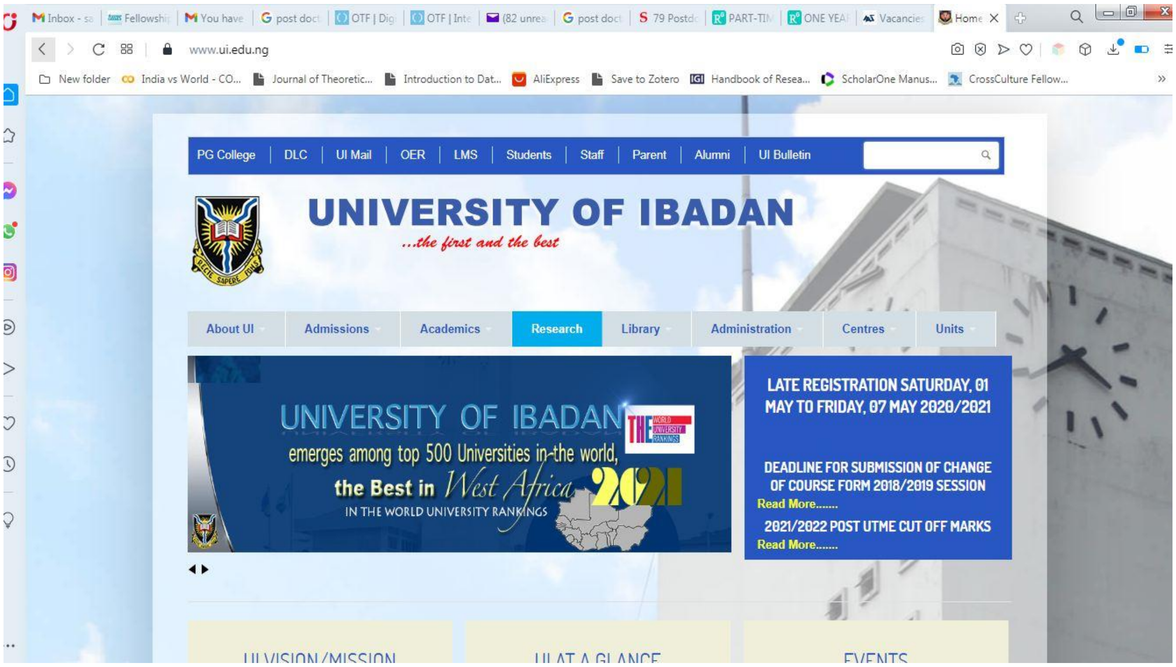



**Figure 3.3 Home page of University of Ibadan website**

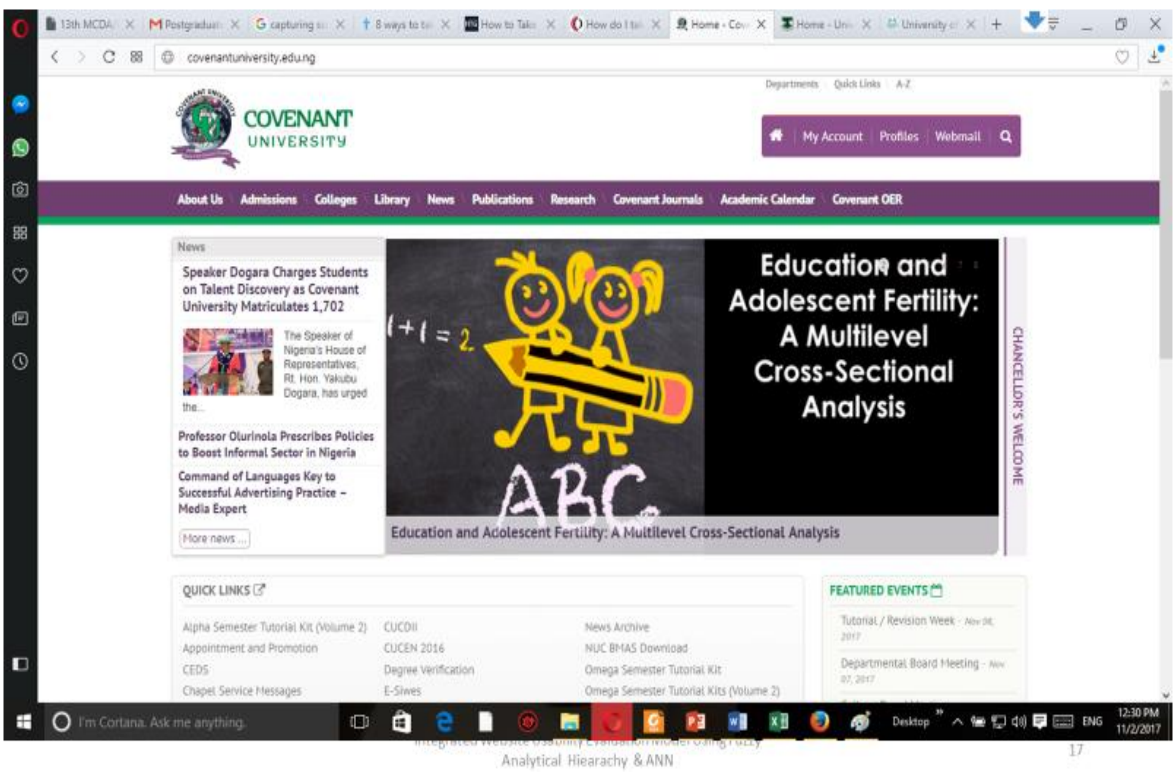



**Figure 3.4 Home page of Covenant university website**

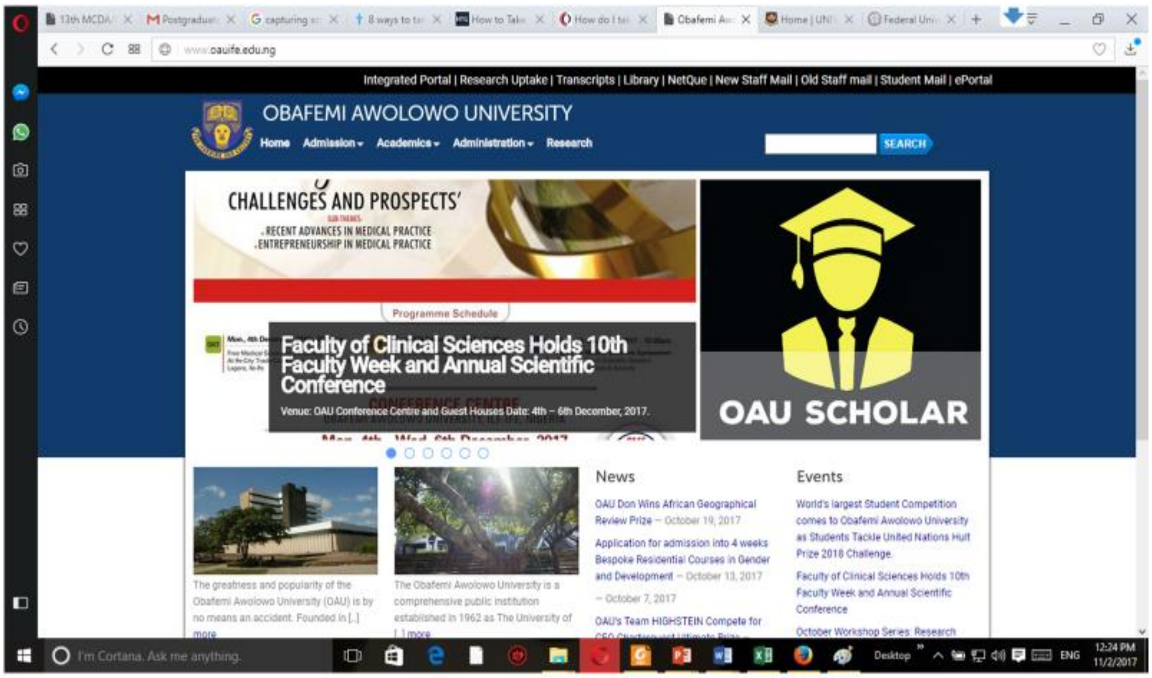





**Figure 3.5 Home page of Obafemi Awolowo university website**

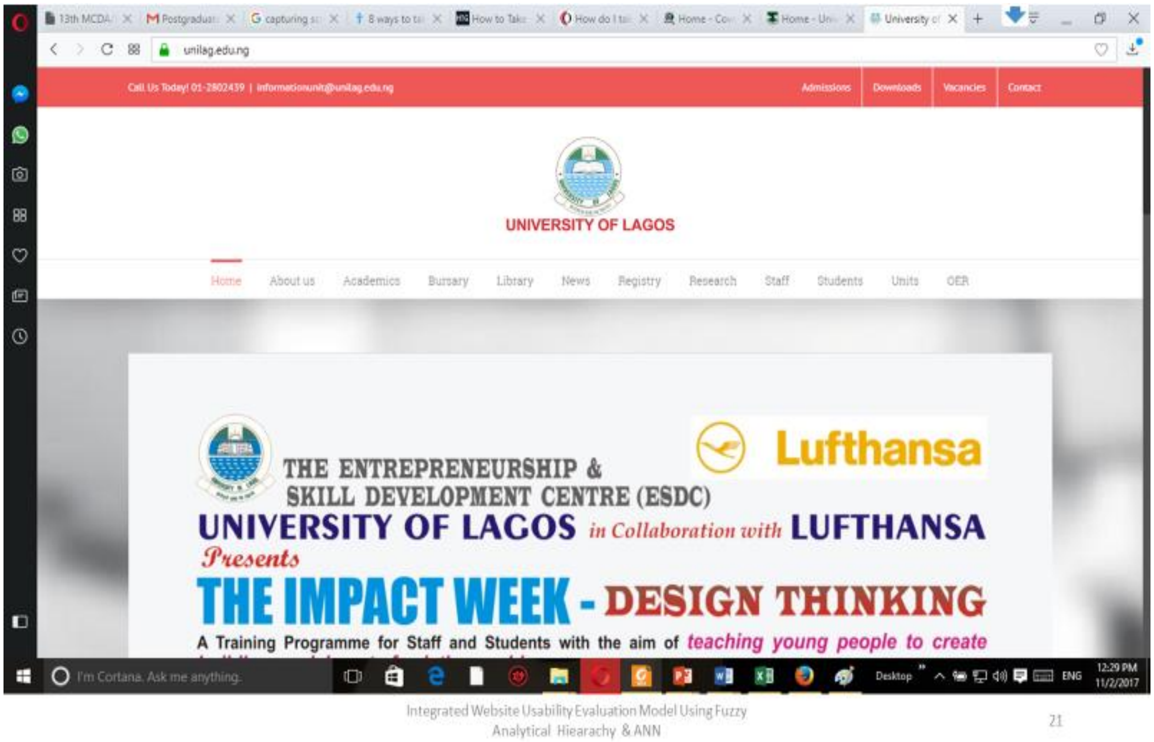



**Figure 3.6 Home page of University of Lagos website**

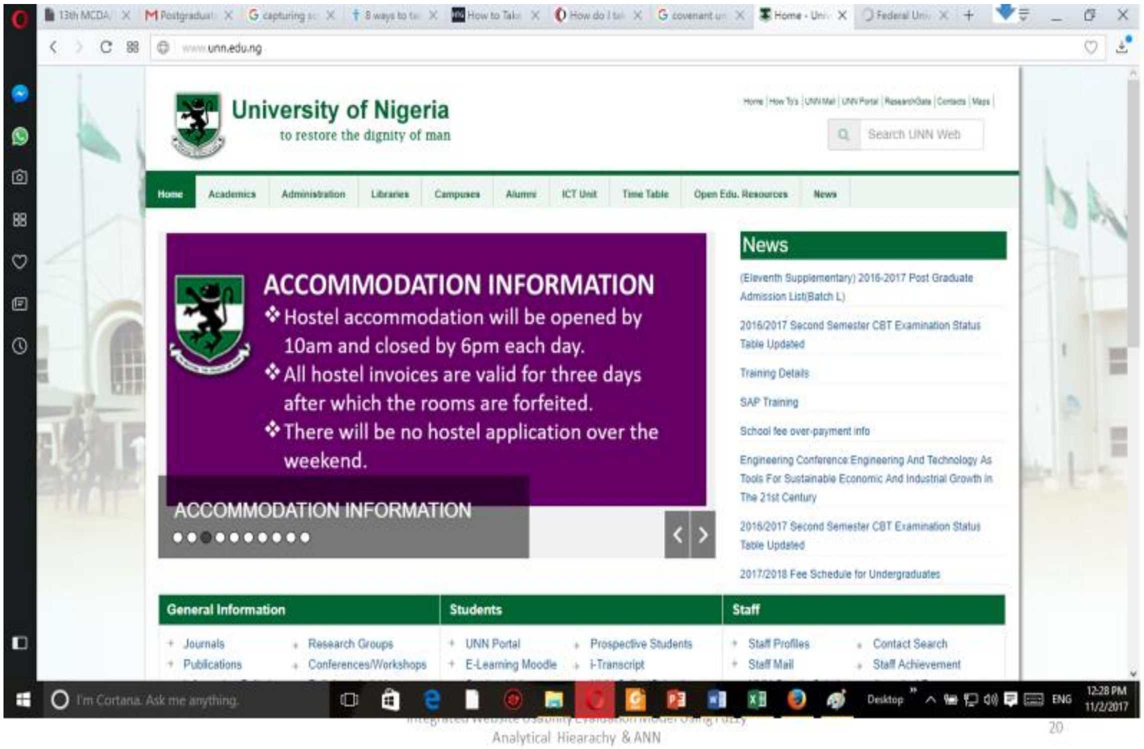



**Figure 3.7 Home page of University of Nigeria website**

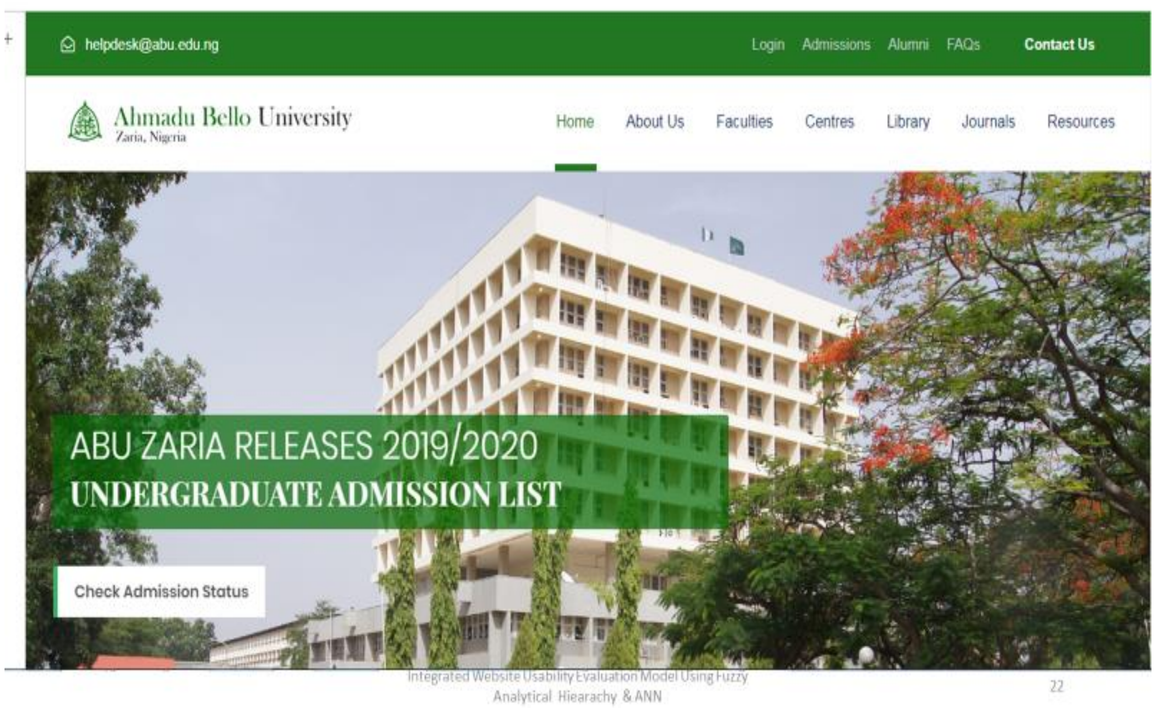



**Figure 3.8 Home page of Ahmadu Bello University website**

### 3.2.2 Questionnaire design

After identifying the criteria to be used, collection of both quantitative and qualitative data follows. This involves the use of survey technique and in this case online questionnaires were used as the data collection tool. These questionnaires were designed and modified based on some previous standardized questionnaires (Aziz and Adzhar, 2015; Cairns, 2013; Sauro and Lewis, 2012) . Two online questionnaires were used in the course of the research. The first questionnaire was used to collect the user data to extract the website usability criteria through exploratory factor analysis for the website usability model while the second questionnaire is used to collect expert users' data for fuzzy AHP model based on pairwise comparison. The data obtained from the second questionnaire is further computed and transformed to be used as the classification data set.

The first questionnaire comprises two sections. Section A collect data about the demography of the participants which include gender, age, department, level, internet level literacy and CGPA. Section B is grouped into seven items according to the numbers of criteria used. The total number of items is twenty-one. Respondents' responses are rated from 1 to 5 based on five-point Likert scale of Strongly Disagree to Strongly Agree. Five-point scale was adopted so as to allow respondents give answer and judge the questions appropriately. Also, five-point scale makes it easier to rate midpoint during analysis. The sample of the first questionnaire is in Appendix A.

After designing the online questionnaire, it was reviewed, edited and reconstructed by three experts who are IT specialist and researchers with vast experience in the field. This was subsequently validated through content validity and reliability. Content validity is done to ensure that the questions measure the content the concept adequately. This was carried out via pilot study to ensure that all the questions are clear and comprehensible for the respondents. The reliability of the evaluation criteria analysis was checked by the IBM SPSS package (Version 23) using Cronbach Alpha (α). A value of α= 0.867 was obtained for all the extracted usability evaluation criteria (Lazar *et al.*, 2017). This value is considered as an acceptable value for the reliability of the usability evaluation criteria.

The outcome of this first phase is to extract the final usability criteria which is subsequently used to construct the hierarchy for fuzzy AHP modeling in the second phase of the study. Also, preliminary results were obtained which give insight into the websites performance based on the criteria in the phase. The diagrammatic schematic structure for this phase is depicted in the Figure 3.9

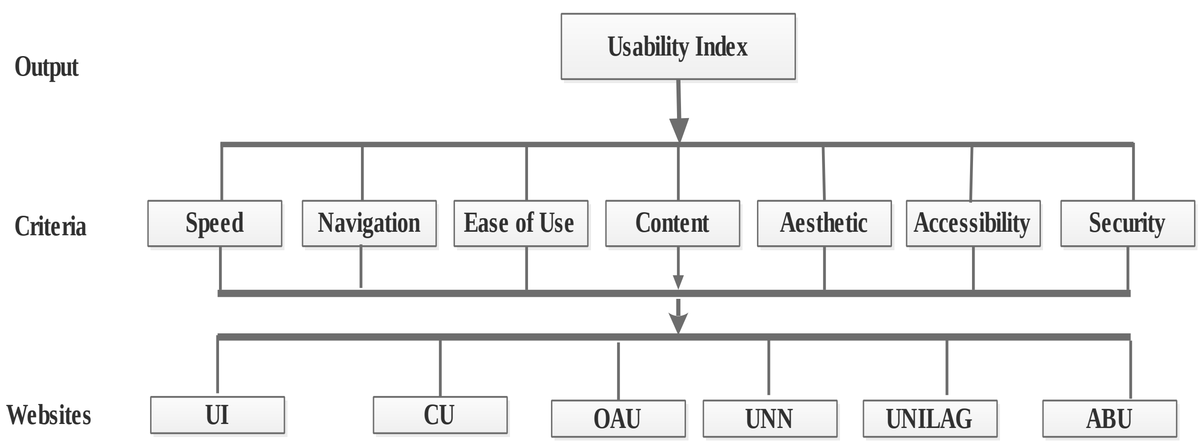



**Figure 3.9**

**Initial Schematic Structure for phase 1**

### 3.2.3 Usability testing task and evaluation

In order to obtain website usability score, there is need for task analysis which involves engaging users to perform some tasks on the selected websites. These tasks are common task users perform on a typical university website. Participants in the study were asked to visit the six university websites and perform tasks on each of them. Six tasks which aim at measuring each of the criteria identified in this first phase of the study were carefully selected. The tasks cover a wide range of activities that are available on university websites. The tasks each of the participants perform on the websites are:

1. To check for the mission and vision of the university
2. Navigate and view a list of all the faculties in the school.
3. Search for the list of all the lecturers in the Electrical engineering department.
4. Search and download he university's academic calendar for the 2017/2018 session,
5. Search for campus news on the university websites.
6. Attempt to register on the university portal.

### 3.2.4 Population and sample of the study

The target population for the study consists of students and staff from the School of Information and Communication Technology at Federal University of Technology Minna. The recommended sample size in this type of study varies among expert as it is dependent on the study. Researchers suggested between five and twenty users (Lazar *et al.*, 2017). For this study, link to the questionnaire were sent to the volunteered and interested participants via social media and email to participate in the study. At present the student population is about 20,000. Convenient and snowball sampling techniques were adopted for the study. The link sent to the interested participants were requested to be subsequently forwarded to other friends and colleagues. In all, a total of 233 and 169 participants who are mostly students responded to the first and second online questionnaires respectively. The data for the phase was collected between June and August 2018 while that of the second phase was collected between June and September, 2019

At the end of the task, users were asked to fill the online form based on their interaction with each website. The responses obtained from the first questionnaire were automatically collected, recorded and collated. These are used to extract the needed criteria which are used in the next stage of the study.

### 3.2.5 Selection of criteria

This involves selection of factors to be used to formulate the Fuzzy AHP model. From the analysis of results obtained in the first phase of the study using exploratory factor analysis, only five criteria satisfied the reliability requirements for the study. They are thereby considered suitable and appropriate for the next phase of the study as affirmed by Saaty and Ozdemir (2003). Details of the analysis done in order to arrive at this number are discussed in section 4.1 of chapter four. Therefore, Speed ($S_{pd}$), Navigation $N_{(av)}$, Ease of Use ($E_{ou}$), Content ($C_{on}$) and Aesthetic ($A_{es}$) criteria were selected for the development of Fuzzy AHP model.

The algorithm for developing the website usability evaluation criteria model in phase is shown in Table 3.2

### 3.3 Development of Fuzzy AHP Model

This phase two involves formulation of Fuzzy AHP model by building the hierarchical structure and comparison matrices. The second online questionnaire was deployed to collect expert users' opinion in order to carry out pairwise comparisons on the criteria as well as on the alternative websites based on each criteria. The users were further given another set of tasks to carry out on the alternative websites. The questionnaire consists of five sections. Section one contains demographic data of the participants which is mainly age and education level. Section two consist of users' task.

**Table 3.2. Website usability evaluation model stages**

*Input: identified criteria*

*Output: extracted criteria*

*Start*

*1. identify and choose criteria from literature*

*2. choose websites and identify user tasks*

*3. design survey instrument*

*4. carry out pilot study*

*5. redesign survey instrument*

*6. send out survey via email, WhatsApp*

*7. users carry out users' task and fill out online questionnaire*

*9. researcher collates and analyse usability data*

*10. compute KMO and Bartlett's test*

*11. if (KMO & Bartlett's test values are acceptable) then*

*12. Compute Cronbach alpha (α) value*

*11 elseif α.>= 0.7 then*

*14. carry out factor analysis*

*15.* *extract criteria*

*15 endif*

*End*

Section three consist of alternatives websites rating, which is subdivided into five sections based on the number of criteria used in the study. Section four contains criteria rating and comparison. The sample questionnaire used for this phase is shown in Appendix B.

The number of pairwise comparison (PC)to be done given n number of criteria is given by

$$\text{Number of pairwise comparison (PC)} = \frac{n[n-1]}{2} \tag{3.1}$$

For the five criteria, 10 pairwise comparisons will be done by each user ((5x4)/2). Also, for the alternatives websites which are six in number, the number of pairwise comparison per criteria is 15 ((6x5)/2). So, in all, 75 (15x5) pairwise comparisons are carried out on the alternative websites altogether. In total there are 85 pairwise comparison altogether for both criteria and alternatives. In summary the total number of pairwise comparison for both criteria and each alternative based on the criteria is given by the formula.

$$\text{Total pairwise comparison (TPC)} = \frac{m[m-1]}{2}.n + \frac{n^2-n}{2} \tag{3.2}$$

For m alternatives and n criteria.

In this case m=6 and n=5, so TPC= 85

Section five contains overall usability rating of each websites and general comments. This involves the use of Likert scale ranging from Not satisfied to Extremely Satisfied. The eight questions in this section collect qualitative data based on user's opinion on the websites in general. Here, the users are required to write comments on their observation based on the interaction with the websites.

Scale based of Saaty and Vargas (2012) was adopted and modified in order to collect the appropriate data for the research. The first scale used to compare the criteria are shown in Table 3.3 while the scale used to compare the alternative websites based on each criteria
is shown in Table 3.4

**Table 3.3: Linguistic variable for Criteria Preference**

| Linguistic value | Question value | Real value | Fuzzy value |
|---|---|---|---|
| Extremely more important | 9 | 9 | (8, 9, 9) |
| Strongly more important | 8 | 7 | (6, 7, 8) |
| Fairly more important | 7 | 5 | (4, 5, 6) |
| slightly more important | 6 | 3 | (2, 3, 4) |
| Equally important | 5 | 1 | (1, 1, 1) |
| Slightly less important | 4 | 1/3 | (1/4, 1/3, 1/2) |
| Fairly less important | 3 | 1/5 | (1/6, 1/5, 1/4) |
| Strongly less important | 2 | 1/7 | (1/8, 1/7, 1/6) |
| Extremely less important | 1 | 1/9 | (1/9, 1/9, 1/8) |

**Table 3.4: Linguistic variable for Alternative Preference**

| Linguistic value | Question value | Real value | Fuzzy value |
|---|---|---|---|
| Extremely preferable | 9 | 9 | (8, 9, 9) |
| Strongly more preferable | 8 | 7 | (6, 7, 8) |
| Fairly more preferable | 7 | 5 | (4, 5, 6) |
| slightly more preferable | 6 | 3 | (2, 3, 4) |
| Equally important | 5 | 1 | (1, 1, 1) |
| Slightly less preferable | 4 | 1/3 | (1/4, 1/3, 1/2) |
| Fairly less preferable | 3 | 1/5 | (1/6, 1/5, 1/4) |
| Strongly less preferable | 2 | 1/7 | (1/8, 1/7, 1/6) |
| Extremely less preferable | 1 | 1/9 | (1/9, 1/9, 1/8) |

As discussed in section 2.4, Fuzzy AHP has the ability to model the decision-making process of human's mind better than the classical AHP. Instead of using a precise number, Fuzzy AHP shows human's preferences by use of a membership function. Therefore, Fuzzy AHP is used for the model development. Steps involved in fuzzy AHP have been clearly described in Section 2.4.1

Collection of data for this phase commenced in May 2019 and was completed in September 2019. To ensure that the users are subjected to the same test condition, SMART laboratory located in the Information Technology Services (ITS) unit of the university which have full internet access with about forty systems was used for part of the study. The hierarchical structure of the fuzzy AHP model for the study is shown in Figure 3.10.

The experimental moderated usability sessions are shown in plate 1 and 2 while the systematic procedures followed in conducting the study is shown in Figure 3.11.

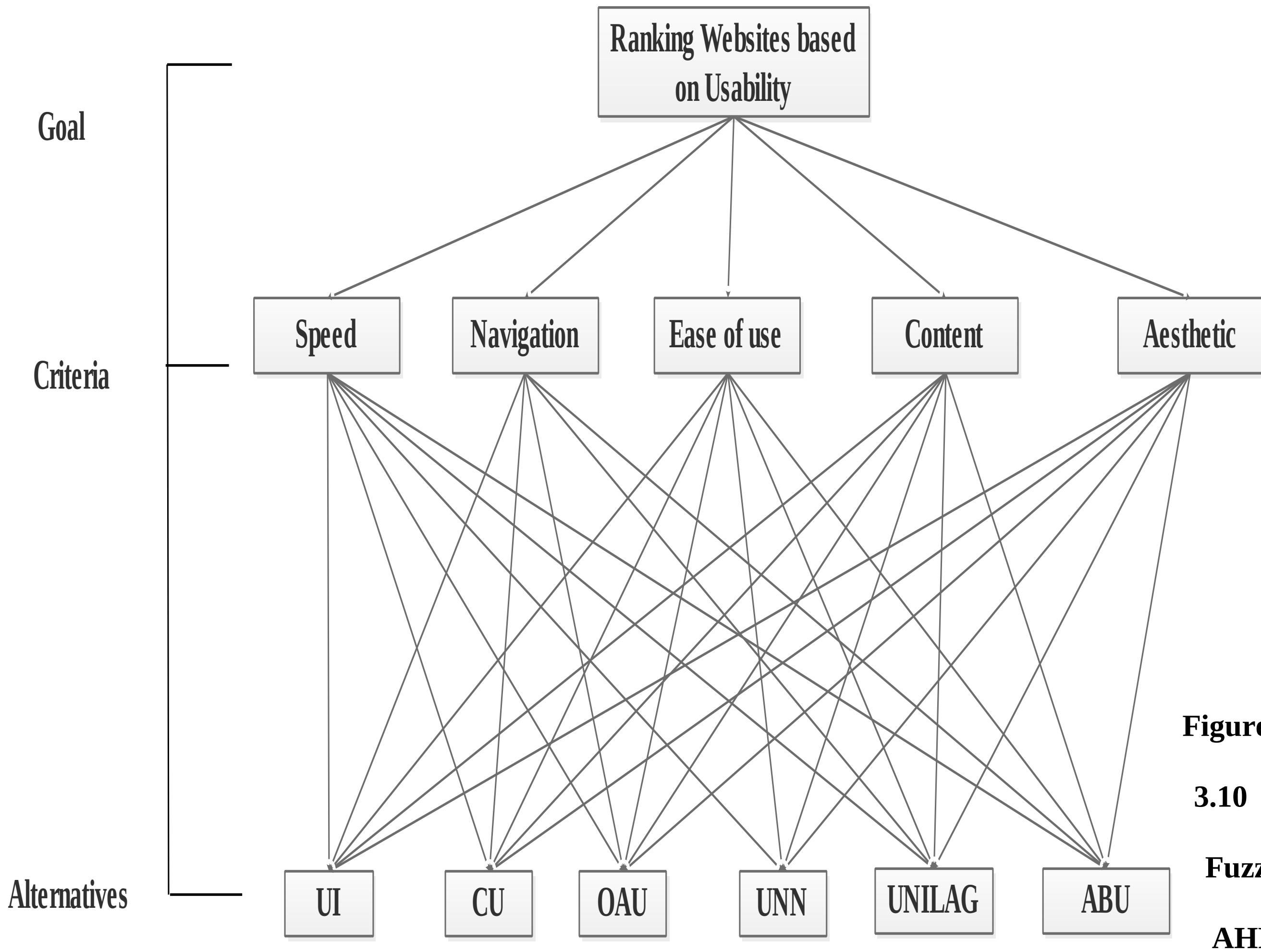



**Figure 3.10 Fuzzy AHP Model**

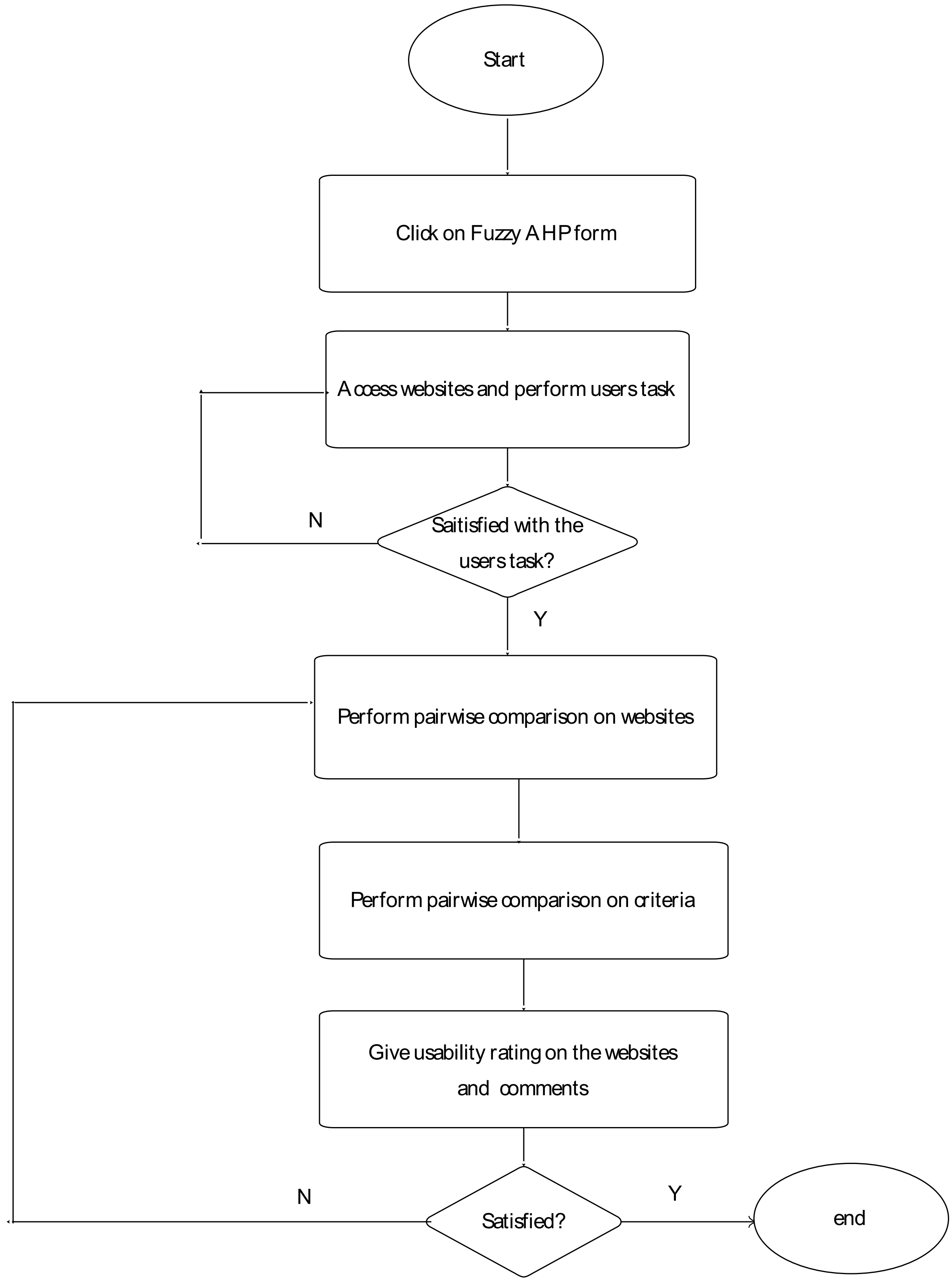



**Figure 3. 11 Phase 2 methodological Procedure**


**Plate 1: User testing session one in university ITS SMART Laboratory**


**Plate 2: User testing session two in university ITS SMART laboratory**

The study uses the modified Buckley Fuzzy AHP (BA) algorithm discussed in section 2.4.1.1 to derive the criteria and alternative weights. This is because Buckley is fast, robust and easy to use compared to others, especially when considering the large number of expert users involved in the study. The commonly used Chang Fuzzy Extent Analysis (FEA), have been found to perform less to other methods (Ahmed and Kilic, 2018). More so, the computationally requirement of BA is less than that of FEA, apart from the fact that FEA sometimes gives zero weight which is not ideal for the study at hand.

### 3.3.1 Data transformation

The raw data collected during the study were transformed in five stages labelled T1, T2, T3, T4

| Original data | T1 | T2 | T3 | T4 | T5 (Final fuzzy value) |
|---|---|---|---|---|---|
| Extremely less preferable | 1 | a | 1/9 | ((1,1,1)/(8,9,9),(1,1,1)/(8,9,9),(1,1,1)/8) | (1/9,1/9,1/8) |
| Strongly less preferable | 2 | b | 1/7 | ((1,1,1)/8,(1,1,1)/(6,7,8),(1,1,1)/6) | (1/8,1/7,1/6) |
| Fairly less preferable | 3 | c | 1/5 | ((1,1,1)/6,(1,1,1)/(4,5,6),(1,1,1)/4) | (1/6,1/5,1/4 |
| Slightly less preferable | 4 | d | 1/3 | ((1,1,1)/4,(1,1,1)/(2,3,4),(1,1,1)/2) | (1/4,1/3,1/2) |
| Equally preferable | 5 | e | 1 | (1,1,1) | (1,1,1) |
| Slightly more preferable | 6 | f | 3 | (2,3,4) | (2,3,4) |
| Fairly more preferable | 7 | g | 5 | (4,5,6) | (4,5,6) |
| Strongly more preferable | 8 | h | 7 | (6,7,8) | (6,7,8) |
| Extremely more preferable | 9 | i | 9 | (8,9,9) | (8,9,9) |

and T5 using Excel VBA code into a form suitable for use in AHP and Fuzzy AHP computation as shown in Table 3.5and Table 3.6. While Table 3.5 shows transformation stages for website alternative, Table 3.6 shows for usability criteria. Subsequently, the values of AHP as well as Fuzzy AHP was computed via programming using Excel VBA template and MATLAB due to large volume of the dataset. This gives the comparison matrices of each user evaluator and the corresponding weight of each criteria and alternatives based on each criterion was computed. In overall, the aggregation of the whole weight by criteria and alternative was done using geometric mean.

**Table 3.5: Stages of Data Transformation for websites alternatives**

| Original data | T1 | T2 | T3 | T4 | T5 (Final fuzzy value) |
|---|---|---|---|---|---|
| Extremely less important | 1 | a | 1/9 | ((1,1,1)/(8,9,9),(1,1,1)/(8,9,9),(1,1,1)/8) | (1/9,1/9,1/8) |
| Strongly less important | 2 | b | 1/7 | ((1,1,1)/8,(1,1,1)/(6,7,8),(1,1,1)/6) | (1/8,1/7,1/6) |
| Fairly less important | 3 | c | 1/5 | ((1,1,1)/6,(1,1,1)/(4,5,6),(1,1,1)/4) | (1/6,1/5,1/4 |
| Slightly less important | 4 | d | 1/3 | ((1,1,1)/4,(1,1,1)/(2,3,4),(1,1,1)/2) | (1/4,1/3,1/2) |
| Equally important | 5 | e | 1 | (1,1,1) | (1,1,1) |
| Slightly more important | 6 | f | 3 | (2,3,4) | (2,3,4) |
| Fairly more important | 7 | g | 5 | (4,5,6) | (4,5,6) |
| Strongly more important | 8 | h | 7 | (6,7,8) | (6,7,8) |
| Extremely more important | 9 | i | 9 | (8,9,9) | (8,9,9) |

**Table 3.6: Stages of Data Transformation for usability criteria**

The procedure is described as follows: The original data collected from the users are in form of T1 where 1 implies extremely less preferable, 2 implies strongly less preferable, 3 fairly less preferable, while 4, 5,6,7,8 and 9 implies slightly more preferable, equally preferable, slightly less preferable, fairly less preferable, strongly less preferable and extremely less preferable respectively.

This is transformed to stage T2 by assigning a to 1, b to 2, c to 3, d to 4, e to 5, f to 6, g to 7, h to 8 and i to 9 respectively. This is further transformed to stage T3 where a is assigned the value if 1/9, b the value of 1/7, c value 1/5, d value 1/3 while e,f,g,h,i are assigned the values of 1,3,5,7,9 respectively. This is further transformed into stage T4 and finally T5 as shown in Table 3.4 and 3.5. The same procedure is used for transforming both the criteria and alternative websites data.

### 3.3.2 Triangular fuzzy numbers (tfns) and fuzzy AHP

AHP is a widely used multi-criteria decision analysis technique that decomposes the decision problem in a hierarchical structure and derives priorities from the value judgment of individual or a group in decision making (Hanine *et al.*, 2016). Due to observed vagueness and uncertainty as regards the judgments made by decision makers, crisp pairwise comparison in the conventional AHP seems unsatisfactory and too inaccurate to capture the decision makers' judgments appropriately. Therefore, fuzzy logic is introduced into the pairwise comparison of the AHP to compensate for this deficiency in the conventional AHP, and the technique is called fuzzy AHP.

The central idea of fuzzy set theory is that there is a membership function where an element has a degree of membership in the fuzzy set. Membership function is commonly used in the range within the unit interval [0, 1]. A fuzzy set contains elements that have different degrees of membership in it.

In this study Triangular fuzzy numbers (TFNs) is used. This is because TFNs are more suitable in this study due to its computational simplicity and usefulness in promoting presentation and information processing in a fuzzy environment. Also, it has been successfully applied in various applications Tang 2009 cited in (Taha and Rostam, 2012).

The TFNs used in the pair-wise comparison are defined by three real numbers expressed as a triple ($l$, $m$, $u$) where $l \leq m \leq u$ for describing a fuzzy event. The parameters $l$, $m$ and $u$ indicate the smallest possible (lowest) value, the most promising (middle) value and the largest possible (upper) value respectively that describe a fuzzy event. The characteristics and membership function of the triangular fuzzy number are shown in Figure 3. 12

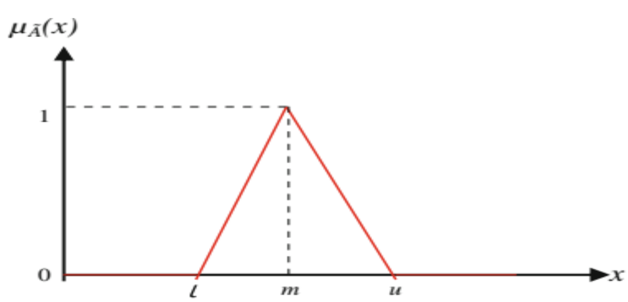



**Figure 3.12 Membership function of Triangular fuzzy number**

Mathematically, this is represented as:

$$\mu\left(\frac{x}{\tilde{M}}\right) = \begin{cases} 0, & x < l \\ \dfrac{(x-l)}{(m-l)}, & l \le x \le m \\ \dfrac{(u-x)}{(u-m)}, & m \le x \le u \\ 0, & x > u \end{cases} \tag{3.3}$$

Figure 3.13 shows the linguistic variable description of the importance of each criteria used of the research

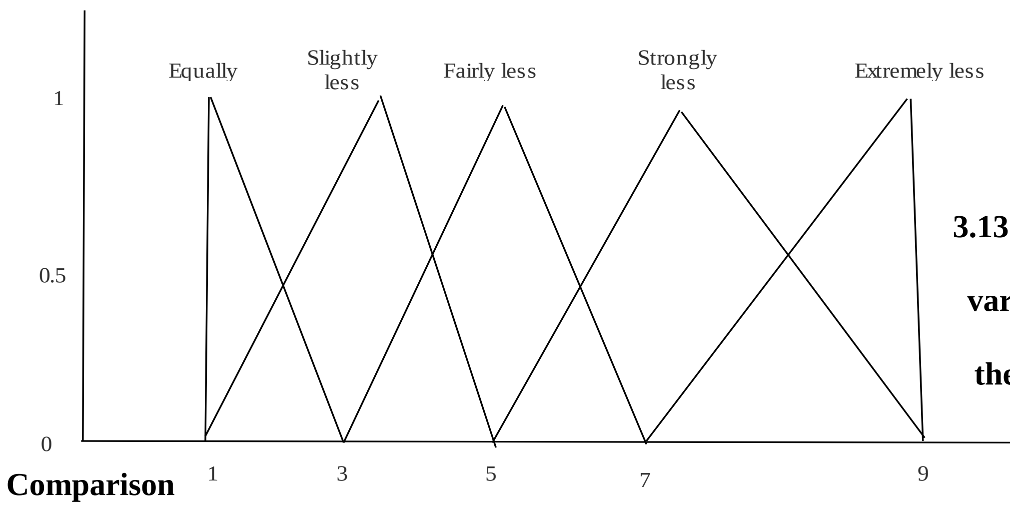



**Figure 3.13 Linguistic variables for the Criteria**

The operations on TFNs can be addition, multiplication, and inverse. Suppose $M_1$and $M_2$ are TFNs where $M_1 = (l_1, m_1, u1)$ and $M_2 = (l_2, m_2, u_2)$, then

Addition: $M1 \oplus M2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2)$ (3.4)

Multiplication: $M1 \otimes M2 = (l_1 \cdot l_2, m_1 \cdot m_2, u_1 \cdot u_2)$ (3.5)

Inverse: $M_1^{-1} = (l_1, m_1, u_1)^{-1} \approx (1/u_1, 1/m_1, 1/l_1)$ (3.6)

In the fuzzy AHP, fuzzy numbers are used to express the entries of the pairwise comparison matrices.

### 3.3.3 Pairwise comparison matrix

The second stage involves determination of relative weights of the criteria as well as the priority weight of the alternative's websites based on each criteria at similar level in the hierarchy. A pairwise comparison matrix (PCM) is built for the criteria and alternative preferences according to the scale used for the study.

Generally, a pairwise comparison matrix reflects the preference of the decision maker when comparing two objects with respect to an evaluation criterion.

A set of evaluation criteria is defined as Given $C_i$ as the ith criterion for i = 1 . . . n, the set of evaluation criteria is defined as

$$C=\{C_{1,}\ C_{2,}\ \dots, C_n\} \qquad (3.7)$$

For this study C= $\{Speed, Navigation, Easeof\ Use, Content, Aesthetic\}$

To construct the fuzzy judgment matrix $\tilde{A}=\{\tilde{a}_{ij}\}$ of n criteria or alternatives via pair-wise comparison, the TFNs are used as follows.

Let $P_{n\times n}$ be a practical pairwise comparison matrix. Then the matrix is positive (i.e. $P_{ij} > 0$ for all i, j 1, . . . n).

Let Ã represents a n *x n* pair-wise comparison matrix. The fuzzy pairwise comparison matrix $A\ \tilde{a}_{ij}$ = [$\hat{\imath}j$] is constructed as

$$\tilde{A} = (\tilde{a}_{ij})_{n\times n} = \begin{bmatrix} (1,1,1) & (l_{12,}\ m_{12,}\ u_{12}) & \cdots & (l_{1n,} m_{1n,}\ u_{1n}) \\ (l_{21,} m_{21,} u_{21}) & (1,1,1,) & \dots & (l_{2n,} m_{2n}\ u_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & & \vdots \\ (l_{n1,} m_{n1,} u_{n1}) & (l_{n2,} m_{n2,}\ u_{n2}) & \dots & (1,1,1,) \end{bmatrix} \qquad (3.8)$$

In general,

$$\left(l_{nm,} m_{nm,} u_{nm}\right) = \frac{1}{\left(l_{mn,}\, m_{mn,}\;\, u_{mn}\right)} = \left(\; u_{mn\,,}{}^{-1}\;\; m_{mn,}{}^{-1}\;\; l_{mn,}{}^{-1}\right) \quad (3.9)$$

Where $ij$ stands for the triangular fuzzy degree of the alternative (criterion) $x_i$ over $x_{ij}$. $l_{ij}$ and $u_{ij}$ represent the lower and upper bounds of the triangular fuzzy number $\tilde{a}_{ij}$ respectively and $m_{ij}$ is the middle value. $l_{ij}$, $m_{ij}$ and $u_{ij}$ are non-negative real numbers with $l_{ij} \le m_{ij} \le u_{ij}$ and $l_{ij}\, u_{ji} = m_{ij}\, m_{ji} = u_{ij}\, l_{ji} = 1$.

### 3.3.4 Computation of the criteria local weight

Based on the PCM constructed in Section 3.3.3, the non-fuzzy values that represent the relative preference or weight of one criterion over others are needed. This study uses the Buckley (2001) method as earlier discussed with the following steps Based on the PCM .**Step 1:** The fuzzy geometric mean value $\check{r}_i$ for each criterion $i$ is computed as

$$\check{r}_i = (\tilde{a}_{i1} \times \tilde{a}_{i2} \times \tilde{a}_{i3} \times \ldots \times \tilde{a}_{in})^{1/n} \quad (3.10)$$

This is derived from the formula

$$\check{r}_i = \left[\prod_{j=1}^{n} \tilde{a}\right]^{1/n}, i = 1,2, \ldots m \quad (3.11)$$

**Step 2:** The fuzzy weight $\tilde{\omega}_i$ $i$ for each criterion $i$ is calculated as

$$\tilde{\omega}_i = \check{r}_i \times (\check{r}_1 + \check{r}_2 + \ldots + \check{r}_n)^{-1} \quad (3.12)$$

where $\check{r}_k = \left(l_{k,} m_{k,} u_k\right)$ and $(\check{r}_k)^{-1} = \left(1/u_{k,} 1/m_{k,} 1/l_k\right)$ (3.13)

**Step 3:** The fuzzy weights $w_i=( l_i, m_i, u)$ are defuzzified by any defuzzification method; here the CoA, (Centre of Area) method is used as follows:

$$\tilde{\omega}_i = ( l_i + m_i + u_i)/3 \qquad (3.14)$$

**Step 4:** After obtaining crisp weights normalization process is implemented

The algorithm for fuzzy AHP is shown in Table 3.7 and Table 3.8

**Table 3.7: Fuzzy AHP Algorithm for Criteria Weight Computation**

*Input: users data obtained from online questionnaire*
*Output: Initial Criteria weight*

```
1   Begin
2   WHILE i< 170 do where i= number of users
3       Supply the input data
4       Prepare the numeric pairwise comparison matrix
5       Convert to Fuzzy pairwise comparison matrix
6       Compute the fuzzy geometric mean value of each row
7       Add all the fuzzy Geometric mean values computed in 6 above
8       Find the reciprocal of the fuzzy geometric mean computed above
9       Multiply each fuzzy geometric mean value obtained in 6 with reciprocal of fuzzy
        geometric mean obtained in 8 to get the weight
10      Obtain the weight of each criteria in fuzzy form
11      Defuzzify to obtain crisp weight value using centre of area (COA)
12      IF sum of weight obtained in step 9 < 1.0
13          Normalise the weight by dividing each weight by total
14      ELSE
15  ENDWHILE
16  End
```

**Table 3.8: Fuzzy AHP Algorithm for Alternative Weight Computation**

*Input: expert users data obtained from questionnaire*
*Output: Initial Alternative weight with respect to each criteria*

```
1   Begin
2   WHILE i< 170 do where i= number of users
3       Supply the input data
4       Prepare the numeric pairwise comparison matrix
5       Convert to Fuzzy pairwise comparison matrix
```

```
6        Compute the fuzzy geometric mean value of each row
7        Add all the fuzzy Geometric mean values computed in 6 above
8        Find the reciprocal of the fuzzy geometric mean computed above
9        Multiply each fuzzy geometric mean value obtained in 6 with reciprocal of fuzzy
         geometric mean obtained in 8 to get the weight
10       Obtain the weight of each criteria
11       Defuzzify to obtain crisp weight value using centre of area (COA)
12       IF sum of weight obtained in 9 < 1.0
13           Normalise the weight by dividing each weight by total
14     ELSE
15   ENDWHILE
16 End
```

### 3.3.5 Computation of the priority weight and weight aggregation

The final step in this phase is to compute the global priority weight for the alternative so as to obtain the alternative websites ranking. In order to get this accomplished, aggregation of all the weight obtained per users from the previous steps was done. Geometric metric is used because it gives better result than average.

It is represented in the algorithm in Table 3.9.

**Table 3.9 Fuzzy AHP Algorithm for Overall Priority Alternative Weights**

*Input: weights obtained from table 3.6*
*Output: Final Priority weight (ranking) of the alternative*

```
1   BEGIN
2     Compute the geometric mean of the weight obtained for each criterion which gives (1 x 5) matrix
3     Compute the geometric mean of the weight obtained for the criteria which gives (5 x 6) matrix
4     Compute the matrix multiplication of 2 and 3 above to give ((1 x 6) matrix
5     IF the sum of columns <> 1 then
6         Normalise the weight by dividing each weight by its total weight
7     ELSE
8   END
```

## 3.4. Data Preprocessing

To develop the model, data obtained from the previous phases has to undergo different preprocessing stages This is to ensure that data for training and testing in the classification model is in suitable format and free form noise and outliers. This process is described below.

### 3.4.1.1 Data cleansing

This involves the removal of abnormal and error prone data. They are otherwise known as outliers. They are points which vary widely from other data in the data set. At this phase they are discarded. However, because of the nature of data generated from Fuzzy AHP, there are only few outliers which arose in the process of computation. Also, there are no missing data present as all the fields necessary for the analysis are made compulsory (required) while filling the online questionnaire.

### 3.4.1.2 Data normalization

Data normalization or otherwise known as feature scaling is the procedure done to ensure that the ranges within the data set is minimal and compact. Though the input data have ranges from 0 to 1, they are further minimized using MinMax minimization method. This ensures the neutralization of scale difference among the criteria used. Also feature normalization makes gradient descend converges much faster than without it.

The formula used is given as follows

$$MinMax=(X--min)/max-min \tag{3.15}$$

Where x is the original data value while MinMax is the normalized data value.

The output ensures that the data is wells called.

Th sample data is shown in Appendix C

#### 3.4.1.3 Data transformation

To use the data, it has to be converted into a form that is understandable by the software use in the coding and analysis. The data is first converted to comma separated value (CSV) file and later to Attribute relation file format (ARTF) format which is the required data format.

#### 3.4.1.4 Data reduction

Due to the imbalance nature of the of the data, reduction of the majority class was done so as to ensure that the classification accuracy of the testing data is improved. This is also to ensure overfitting of data is avoided and prevent accuracy paradox which tends to give false performance accuracy by the classifiers.

Originally 1014 instances of the data were obtained but after preprocessing stages only 732 instances were used in the study. This is made up of 481 positive classes (satisfied) and 251 negative classes (not satisfied).

## 3.5 Comparison of Machine Learning Algorithms

The first evaluation involves comparing the results obtained from all the machine learning model and thereafter the best model is chosen for integration. These machine learning algorithms have been discussed in section 2.5.1.1 to 2.5.1.6. They are ANN, Bayes Net, Decision Tree, Simple logistic regression, Logistic Model tree and Random forest. The choice of these is based on the results obtained in the course of training the data as well as categorization into function, tree and probabilistic based machine algorithms.

The procedure for testing the data on different classification algorithms is shown in Figure 3.14

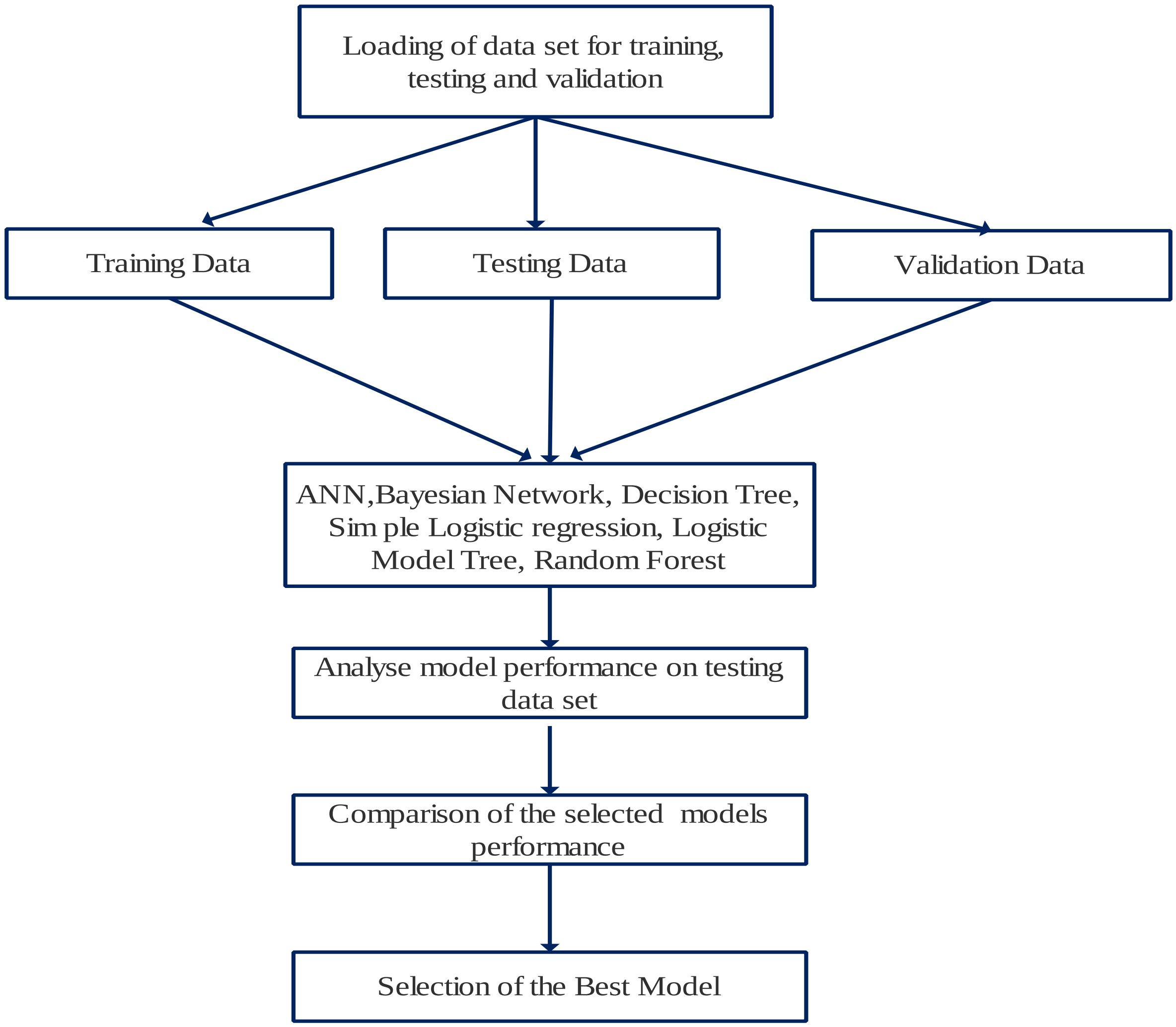



**Figure 3.14 Classification algorithms performance evaluation**

Each are tested based on accuracy, precision, recall, specificity and RMSE performance metrics. They were run using WEKA software which has a standard inbuilt ML algorithm using the dataset partitioned into 70%, 15% and 15% for training, testing and validation. Results obtained were compared with that of ANN as discussed in Section 3.4. The various machine learning algorithm have been described in Section 2.5.

## 3.6. Integration with Artificial Neural Network

The fourth phase involves development of the classification model based on usability using ANN. The ANN type used is Multi-Layer Perceptron (MLP) neural network, which is very good in handling classification problem. A classification problem arises when an object needs to be allocated into a predefined group or class based on a number of observed attributes associated to that object. This has been extensively discussed in section 2.5.1

### 3.6.1 Multi-Layer perceptron neural network

A Multi-layer feed forward neural network (MLP) which is used neural network to develop the model due to its widely usage. The MLP receives its input from the values obtained through priority weights of the criteria in fuzzy AHP model. This input signal to each neuron and the corresponding weights are multiplied and the results is summed up and passes through a transfer function. These neurons are grouped together to form a layer which is sigmoid transfer function which is described and it is described as

$$f(x) = \frac{1}{1 + e^{-x}} \tag{3.16}$$

If the result of the summation is over a certain threshold, the neuron output will be activated otherwise not.

$$y_i = f(\sum_{j=1}^{n} w_j x_j + w_0) \tag{3.17}$$

In this study, the structure of *MLP* model used is 5x3x1 architecture which is made of five input nodes (which are weight derived from the fuzzy AHP model) , 3 neurons in the hidden layer and one output layer which is a binary class. The structure is shown in Figure 3.15 and the parameters are described as follows.

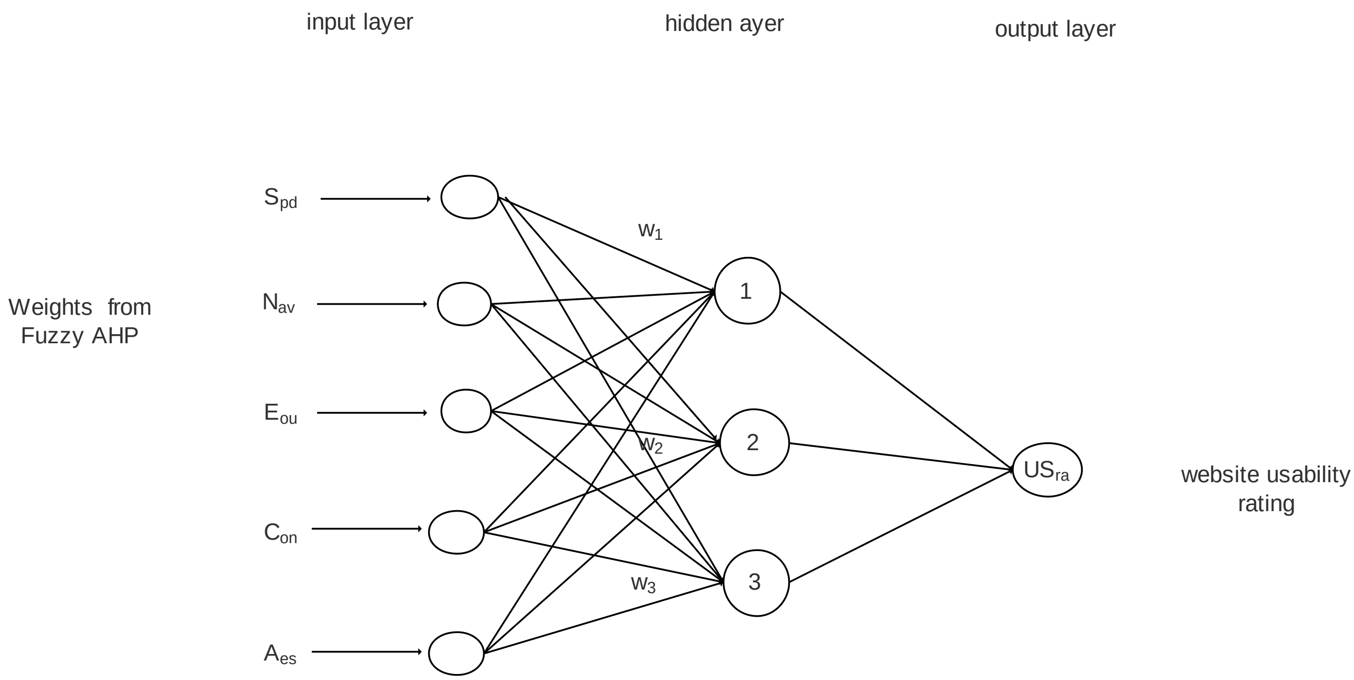



**Figure 3.15 ANN model Architecture**

i The inputs are from the from weights obtained from fuzzy AHP results which are Speed ($S_{pd}$), Navigation ($N_{av}$), Ease of Use ($E_{ou}$), Content ($C_{on}$), Aesthetic ($A_{es}$).

ii. The output which is also known as the target variable is the usability rating ($US_{ra}$). It is a binary class which is depicted as follows:

$$US_{ra}(x) = \begin{cases} 0, & x < 0.5 \\ 1, & x \geq 0.5 \end{cases}$$

Where 1 is satisfied (positive user rating) and 0 is not satisfied (negative user rating).

iii. w represents the weight of the MLP

iv e represents the error which signify is the difference between the target of the network node and the output *i.* *l* the learning rate is the amount that weight is updated

ii. *m* stand for the momentum which is applied to the weights during updating

iii. *h* is the number of hidden layers

In order to get the best result from the network, different parameters like *h*, *l*, *m* are being adjusted several times until the best result is achieved.

The ANN can be represented mathematically as given in Equation 3.18 (Norgaard *et al.*, 2000; Al-Hiary *et al.*, 2008):

$$\begin{aligned} \hat{y}_i &= g_i[\Phi, \theta] \\ &= F_i\left[\sum_{j=1}^{n_h} W_{i,j} f_j\left(\sum_{l=1}^{n_\Phi} w_{j,l}\Phi_l + w_{j,0}\right) + W_{i,0}\right] \end{aligned} \quad (3.18)$$

Where the output signal is represented by ŷi and $g_i$ is the function realised by the neural network while the parameter vector is specified by θ specifies and it contains all the adjustable parameters of the network (weights $W_{j,0}$ and biases $W_{i,j}$ and h nodes in the hidden layer). MLP training is done by using the backpropagation (BP) learning algorithm and it entails adjusting the network weights such that the objective criteria is minimized (i.e. minimize the error difference between the network output $\hat{y}_i$ and the input Φ).

The ANN achieves a good match when the Mean Square Error (MSE) is minimized (See Equation 3.17)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3.19}$$

In this network the data flows forward to the output continuously without any feedback.

There are three steps in solving an ANN problem which are: training, generalization and implementation.

Training is a method that network learns to classify present pattern from input data set. The network is presented with training examples, which comprises a design of events for the input units together with the anticipated pattern of activities for the target (output) units. For this purpose, each ANN uses a set of training rules that describe training method.

In generalization also known as testing the network is evaluated to know its ability to extract a feasible solution with inputs which are unknown to network and are not trained to network. Determination is then made on how closely the actual output of the network matches the predicted output in new circumstances. During the process of learning, there is adjustment in values of interconnection weights so that the network produces a better approximation of the targeted output. In this study, training was done by using 70% (512) instances of the dataset while 15% (110) instances each were used for testing and validation respectively.

### 3.6.2 Thresholding Algorithm

In order to get the optimum and most accurate results, threshold values which gives the best results are used repeatedly on the training data. This is to ensure that a global maximum is arrived at. In this research the threshold value that give the highest accuracy with a corresponding high-performance metric on Area Under Curve (AUC) value is chosen. This is to ensure that the model is not just learning randomly due to the nature of dataset used for the study. So, the thresholding algorithm carried out best trade-off search of the threshold optimal parameters in terms of accuracy, sensitivity, specificity, precision, false negative rate and false positive rate. The algorithm for the thresholding is shown in Table 3.10. To get the threshold value parameters of *l, m and h* were adjusted as well as the activation function. Values of *l* and *m* ranges from 0 to 1 while *h* can take any value, but the recommended values are 2, 3,4 5, and 10.

In this study values of h are chosen at random as 2,3,4,5 and 10 and it was found out that *h* at values 3 perform best. However, range values of threshold is from initial value of 0.52 to 0.85 at 0.01 step size was used in this research work because all the local and global maxima concentrated within this region. With the step size as low as 0.01, all the possible optimum threshold values were explored and refined out of the dataset.

**Table 3.10: Thresholding Algorithm**

*Input: Websites usability training dataset*
*Output: Thresholds* Values*(population), Accuracy,*

1. *Begin*
2. *Supply the usability data features*
3. *Preprocess the data by using the MinMax normalization method*
4. *Split the data into Training, Testing and Validation Usability datasets in ratio 70:15:15*
5. *Set the hidden layer (h) value to 2, 3 or 5*
6. *Set l to 0.8 and m to 0.9*
7. ***While** Threshold_ Val >= 0.52 Step 0.005 Do*
8.     ***While** Accuracy Instances<= No_of _Runs*
9.         *Perform ANN Training*
10.         *Get Error and Performance Computation*
11.         *Get Optimum Accuracy Valu**e***
12.     ***End While***
13.   *Tabulate Threshold_Val, Accuracy, Ave-accuracy, standard- dev.*
14. ***End While** Threshold_Val=0.75*
15. *End*

### 3.6 Model Implementation

The implementation of the model is done using different software like  Excel VBA, SPSS, MATLAB  and WEKA.to carry diffeent computation at each stage of the work.

### 3.7 Model Performance Evaluation

The performance evaluation carried out at different stages of the work are stated as follows.

#### 3.7.1 Fuzzy AHP model performance analysis evaluation

Validity of fuzzy AHP model can be evaluated through two different approaches (Salimi and Rezaei, 2015). The first approach involves using the consistency index (CI) as described in section 2.3. The second approach involves comparison of fuzzy AHP with the results obtained from the conventional AHP. The nearer the two results are, the greater the model validity degree. This is the method that is used in this study due to the large numbers of expert users involved in the study. Also, the data collection approach used in the study favours the latter approach.

Non-parametric Wilcoxon Signed Rank Test is employed to observe the differences in median between the obtained results at different levels.  That is, it examines the median difference of results obtained from both AHP and Fuzzy AHP. The α value obtained from the table will indicate wheeler there is or there is no significant difference between the two models.

#### 3.7.2 Machine learning algorithm performance analysis evaluation

To evaluate a classification or prediction model, the predicted value is compared with the actual value during the testing phase.  Various performance metrics can be used to check the model performance depending on the state of the target variable. In binary classification problem, the predicted variable and the actual variable can be grouped into any of the four states as shown in Table 3.11

**Table 3.11: Performance Table**

| Predicted | Actual |
|---|---|
| Predicted=TRUE | Actual =TRUE |
| Predicted=TRUE | Actual =FALSE |
| Predicted=FALSE | Actual =TRUE |
| Predicted=FALSE | Actual =FALSE |

The model is accurate whenever the predicted and actual values are the same. A 100 percent accuracy occurs when if all predicted and actual values are same (either all *TRUE* or all *FALSE*). There is a bit of occurrence of errors since neural networks are approximation models, so all four possible states can occur as shown in Table 3.11

The performance metrics are discussed as follows:

#### 3.7.2.1 Confusion matrix

This involves plotting of classification results in a $n \times n$ matrix (2x2) in case of binary classification). This matrix is called the confusion matrix, which is simply a table that used in describing classification model performance on a set of test data for which the true values are known as shown in Table 3.12. Different performance evaluation metrics are derivable from the confusion matrix.

**Table 3.12: Confusion Matrix**

| | Predicted Values | | |
|---|---|---|---|
| Actual Values | | TRUE | FALSE |
| | TRUE | **TP** | **FN** |
| | FALSE | **FP** | **TN** |

The following terminologies and metrics are defined for the model:

**True Positives** (**TP**): This involves all cases where the predicted and actual are both *TRUE* (good accuracy).

**True Negative** (**TN**): This involves all cases when predicted is *FALSE* and the actual is also *FALSE* (good accuracy).

**False Positive** (**FP**): This is a case when the predicted value is positive (*TRUE*), but the actual value is negative (FALSE). This is also called **type 1 error**.

**False Negative** (**FN**): When the predicted value is as *FALSE*, but the actual value is *TRUE*. This is also called **type 2 error**.

**True Positive Rate** (**TPR**). This is also known as sensitivity, recall or hit rate. It measures the number of true positives that were identified out of all the positives cases:

$$TPR/recall = \frac{TP}{P} = \frac{TP}{TP+FN} \qquad (3.20)$$

Ideally, the model is better if we have this closer to one.

**True Negative Rate** (**TNR**) also known as specificity is the ratio of true negatives and total number of negatives we have predicted:

$$TNR = \frac{TN}{N} = \frac{TN}{TN+FP} \qquad (3.21)$$

**Accuracy:** This is a measurement of how good the performance of a model is. For a performing model, the value is expected to be closer to 1. Accuracy is the ratio of true predictions and all the total predictions: Accuracy is a great measure but only when there is symmetric datasets where values of false positive and false negatives are almost same (balanced). The formula is given as:

$$Accuracy = \frac{TP+TN}{P+N} = \frac{TN}{TP+TN+FP+FN} \qquad (3.22)$$

**Precision** is given as the number of selected items that are relevant. That is, how many instances of the predicted classes are actually predicted correctly. The equation is:

$$Precision = \frac{TP}{TP+FP} \qquad (3.23)$$

The closer precision is to one, the more accurate the model.

**F-score:** F-score, or F1-score, is another way of measuring accuracy. It is the weighted average of Precision and Recall. Technically, it is the harmonic mean of precision and recall. It conveys the balance between the precision and the recall. F1 is usually more useful than accuracy, especially if there is an uneven class distribution.

$$\text{F score} = \frac{2(precsion * Recall)}{precision + recall} \qquad (3.24)$$

#### 3.7.2.2 Receiver Operating Characteristic curve

A Receiver Operating Characteristic (ROC) curve is a graphical visual illustrating binary classifier system with predictive ability. ROC curve is a performance measurement for classification problem at various thresholds settings. It tells how a model is capable of distinguishing between classes. The ROC curve is obtained via plotting a graph of the TPR against the False Positive Rate (FPR) at various threshold settings. This means plotting Sensitivity against (1 - Specificity). A typical ROC curve bends toward the y axis and curve upward. It is measured by Area of Curve (AUC). The nearer the value of AUC to 1 show that the model is has a good measure of separability. A poor model has AUC near to the 0 which means it has worst measure of separability and is reciprocating the result. AUC value of 0. 5 implies that the model has no class separation capacity.

**Root Mean Square Error (RMSE):** The RMSE is a quadratic scoring rule which is used to measure the error average magnitude It is the difference between predicted and real values which are each squared and then averaged over the sample. The square root of the average is then taken. Since the errors are squared before they are averaged, the RMSE gives a relatively high weight to large errors.

Mathematically, it is the stated as follow:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \ (predicted - actual)^2}{N}} \qquad (3.\ 25)$$

The best performing model in terms of the metrics is chosen as the integrated model in this a case ANN. This is evaluated using various metrics and thereafter the model equation is obtained.

# CHAPTER FOUR

## 4.0 RESULTS AND DISCUSSION

This chapter present the results of the study which involves the use and integration of Fuzzy AHP to examine a set of criteria for evaluating usability of websites. A look at previous studies using fuzzy AHP in other academic fields gives no strict rules as regards the sample size (Alroobaea and Mayhew, 2014). For example, Lin (2010) study involved 25 undergraduate students to attend the experiment on course website effectiveness; A total of 150 students were involved in the study to determine the usability of four academics websites (Nagpal *et al.*, 2016b). The same is applicable in other studies (Chen and Qiao, 2015; Crystal, 2011) In carrying out the first phase of the survey, a total of 237 users participated in the study while only 233 responses were found to be properly filled upon examination of the data and hence were used for the analysis.

## 4.1 Data Analysis

The result of the initial analysis performed during the first stage of the research are presented in this section. The demographic data of the participants in the study is shown in Table 4.1. It shows the sex, internet experience and age of participants used for the study

**Table 4.1 Demographic data of the participants**

| Item | Option | Value |
|---|---|---|
| Sex | Male | 148 |
| | Female | 85 |
| Age | Below 16 | 2 |
| | 16-20 | 23 |
| | 20-25 | 165 |
| | 26 and above | 44 |
| Internet experience | Expert | 103 |
| | Intermediate | 121 |
| | Novice | 9 |

More male participants responded to the online questionnaire than their female counterpart and most of the participants are within the age bracket of 21-25 years. This is partly because most of the participants are undergraduates and the school used is a male dominated institution.

### 4.1.1 Criteria extraction

In order to ensure that the final criteria to be used are carefully selected, exploratory factor analysis is first used to extract relevant criteria out of the identified criteria proposed to use in the study. This is to ensure that the study is appropriate, reliable and the results obtained are statistically significant and relevant. The first step involves checking for the sample adequacy of the collected data. To check this, Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was conducted and the value of 0.855 was obtained as shown in Table 4.2. The interpretation of different values of KMO is shown is Table 4.3 as given by Kalutara (2013).

**Table 4.2: KMO and Bartlett's Test**

| **KMO and Bartlett's Test** | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .855 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 1467.850 |
| | df | 210 |
| | Sig. | 0.000 |

**Table 4.3 KMO Acceptability Values interpretation**

| KMO value | Interpretation |
|---|---|
| 0.5-0.69 | mediocre |
| 0.7-0.79 | good |
| 0.8-0.9 | great |
| above 0.9 | superb |

The value (0.855) is acceptable as it shows it is adequate. A KMO values closer to 1 shows that correlation patterns are relatively compact and hence factor analysis will yield distinct and reliable factors (Hutcheson and Sofroniou, 1999; Kalutara, 2013).

The next step is Bartlett's test of sphericity. This is to examine whether the correlation matrix (CM) resembles an identity matrix. If the CM was an identity matrix then it there exists perfect independency of all the variable from one another (all correlation coefficients are zero). If the value given by the Bartlett's test is less than 0.5, then it is highly proper to continue factor analysis. From Table 4.2 The value of Bartlett's test of sphericity test is 0.000 which is less than 0.05. From this result, the variables are orthogonal i.e. not correlated. So, the value is acceptable and it is appropriate to run factor analysis.

### 4.1.2 Extraction and rotation of factor with interpretation

Extraction of factors encompasses defining the smallest number of factors that can be used to best represent the interrelations among the set of variables. Rotation on the other hand is to improve how the factors are interpreted. In rotation, there is maximization of the loading of each variable on one of the factors been extracted whilst the loading on all other factors are minimized. Two of the ways these can be achieved is through the use of eigen value and scree plot. In this study, oblimin rotation approach which is a variance of oblique rotational is used. The result of this with communalities output are in Appendix D.

Furthermore, to know the number of factors to extract scree plot graph is used for the analysis. The graph helps to determine the numbers of factors to retain which will subsequently be used as criteria in the study. The key point of note is where the curve starts to flatten. Figure 4.1 is the scree plot which depicts the graph of Eigen value versus. Component number two-dimensionally obtained during the data analysis. The point of variation is initially noticed at component number four but there is another drop after

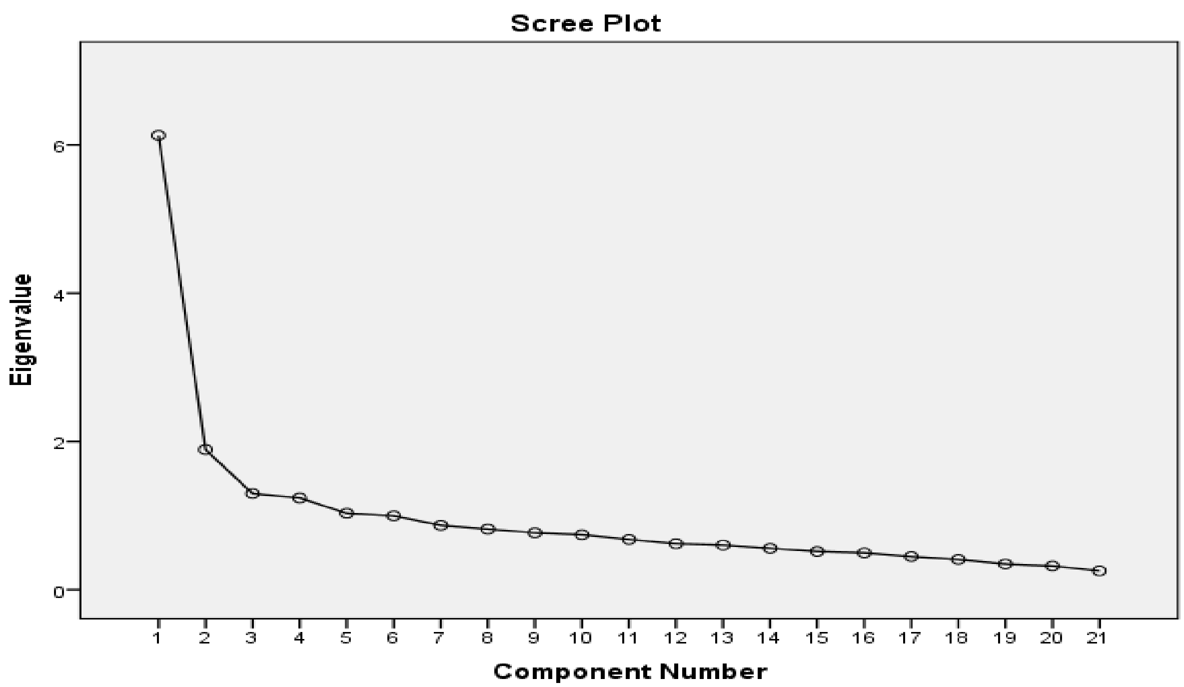



**Figure 4.1 Scree Plot**

component number five. It is observed then that the curve begins to flatten between component number 5 and 6. It is noted also that factor 6 onwards have an eigenvalue of less than 1, so only five factors have been retained. Eigenvalue simply is the number of factors that have been extracted but whose sum should be equal to number of items which are subjected to factor analysis.

At the end of the analysis, out of the total of seven criteria initially proposed only five which were extracted through factor analysis discussed are used in the next stage of Fuzzy AHP modelling. This is in within the range of recommended minimum and maximum number of criteria to be used in MCDM which is given as plus or minus 7 so as to avoid cognitive overload on the users in the course of doing comparison (Saaty and Ozdemir, 2003). The number of criteria used therefore valid.

#### 4.1.3 Reliability analysis of the derived criteria

Cronbach's α is a measure of internal reliability of the questions items which is a reflection of how well the items in a set are positively correlated to one another (Lazar *et al.*, 2017). The cut-off points and correlated reliabilities value of 0.70 is the most acceptable level, However, it is confirmed in literature that the alpha value of 0.60is still acceptable (Sekaran and Bougie, 2016). The Cronbach's alpha is used to calculate the reliability of each factor with respect to the items (variables) of which the scale is comprised.

Reliability test was performed for each scale (criterion) and the results are shown in Table 4.4 for criteria 1-5. Five criteria have results that are 0.6 and above, which is the acceptable cut-off point for reliability. The other two criteria, accessibility and security have values of 0.3 and 0.5 respectively, hence they were excluded from the study. Since all the remaining the five criteria have acceptable reliability; hence the data used to derive factors can be regarded as consistent. Table 4.5 shows the various interoperations for Cronbach alpha values.

**Table 4.4 Cronbach Alpha value of the criteria**

| No | Criteria name | Number of Items | Cronbach alpha (α) value |
|---|---|---|---|
| 1 | Speed | 3 | 0.6 |
| 2 | Navigation | 4 | 0.7 |
| 3 | Ease of Use | 3 | 0.7 |
| 4 | Content | 3 | 0.7 |
| 5 | Aesthetic | 3 | 0.8 |
| 6 | Accessibility | 3 | 0.3 |
| 7 | Security | 2 | 0.5 |

The acceptable range of Cronbach alpha and its interpretation are shown in Table 4.5. The values obtained in the study for different criteria used are therefore valid.

**Table 4.5 Cronbach alpha value interpretations**

| Cronbach alpha (α) value | Strength of association |
|---|---|
| < 0.6 | Poor |
| 0.6 to < 0.7 | Moderate |
| 0.7 to < 0.8 | Good |
| 0.8 to < 0.9 | Very good |
| >=0.9 | Excellent |

So, only five out of the initial proposed seven criteria was deemed suitable to be used for the study. These are Speed, Navigation, Ease of use, Content and Aesthetic which is otherwise named as SNECA thus given rise to the SNECA website usability model, the model diagram is shown in Figure 4.2. This implies that websites usability in the context of this study based on the experiments and testing conducted, data gathered, analysed and interpreted can be viewed from those criteria point of view.

This model is very simple, unambiguous and easy to implement. It is simply made up of 15 items which is very direct and easy to measure. Moreover, it has relationship with the ISO 9241 model which is based on efficiency, effectiveness and satisfaction.

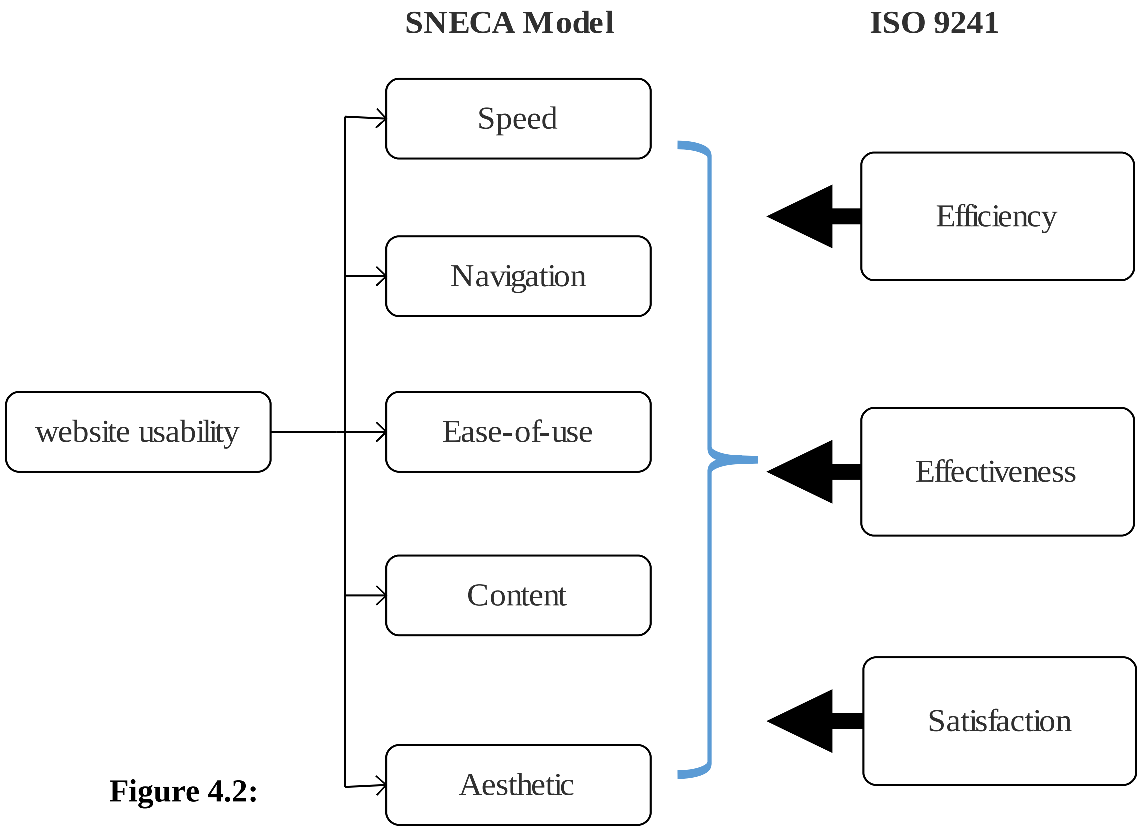



**Figure 4.2: SNECA website usability model**

## 4.3 Fuzzy AHP Model results

In this phase 169 expert users were used and the demographic data are shown in Table 4.

**Table 4.6. Demographic data of participants**

| Item | Option | Value |
|---|---|---|
| Sex | Male | 137 |
| | Female | 32 |
| Status | Student | 159 |
| | IT staff | 6 |
| | Others | 4 |

From the results obtained from these results, only five of the seven criteria were retained for further usage in Fuzzy AHP model. This methodology is developed in order to have a more subjective and better judgement of the websites in question. More so, since it is based on decision making better user judgment is expected. The sample pairwise comparison matrix output used for a participant for criteria and alternative computations are shown in Tables 4.7 and 4.8 respectively

**Table 4.7. Criteria Pairwise Comparison matrix for a user**

| **CR** | $S_{pd}$ | | | $N_{av}$ | | | $E_{ou}$ | | | $C_{on}$ | | | $A_{es}$ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $S_{pd}$ | 1.000 | 1.000 | 1.000 | 2.000 | 3.000 | 4.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 4.000 | 5.000 | 6.000 |
| $N_{av}$ | 0.250 | 0.333 | 0.500 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 0.250 | 0.333 | 0.500 | 4.000 | 5.000 | 6.000 |
| $E_{ou}$ | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 0.250 | 0.333 | 0.500 | 4.000 | 5.000 | 6.000 |
| $C_{on}$ | 1.000 | 1.000 | 1.000 | 2.000 | 3.000 | 4.000 | 2.000 | 3.000 | 4.000 | 1.000 | 1.000 | 1.000 | 6.000 | 7.000 | 8.000 |
| $A_{es}$ | 0.167 | 0.200 | 0.250 | 0.167 | 0.200 | 0.250 | 0.167 | 0.200 | 0.250 | 0.125 | 0.143 | 0.167 | 1.000 | 1.000 | 1.000 |

**Table 4.8. Alternative Pairwise Comparison matrix for a user**

| **ALT** | UI | | | CU | | | OAU | | | UNN | | | UNILAG | | | ABU | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| UI | 1.00 | 1.00 | 1.00 | 0.25 | 0.33 | 0.50 | 0.25 | 0.33 | 0.50 | 1.00 | 1.00 | 1.00 | 0.25 | 0.33 | 0.50 | 1.00 | 1.00 | 1.00 |
| CU | 2.00 | 3.00 | 4.00 | 1.00 | 1.00 | 1.00 | 1.0 | 1.00 | 1.00 | 2.00 | 3.00 | 4.00 | 2.00 | 3.00 | 4.00 | 1.00 | 1.00 | 1.00 |
| OAU | 2.00 | 3.00 | 4.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.0 | 1.00 | 2.00 | 3.00 | 4.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| UNN | 1.00 | 1.00 | 1.00 | 0.25 | 0.33 | 0.50 | 0.25 | 0.33 | 0.50 | 1.00 | 1.00 | 1.00 | 0.16 | 0.20 | 0.25 | 0.25 | 0.33 | 0.50 |
| UNILAG | 2.00 | 3.00 | 4.00 | 0.25 | 0.33 | 0.50 | 1.00 | 1.00 | 1.00 | 4.00 | 5.00 | 6.00 | 1.00 | 1.00 | 1.00 | 0.20 | 0.33 | 0.50 |
| ABU | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 2.00 | 3.00 | 4.00 | 2.00 | 3.00 | 4.00 | 1.00 | 1.00 | 1.00 |

The procedures for the computation have been described in section 3.3.

Tables 4.9 shows the aggregate criteria results obtained for a sample user. Where Speed= $S_{pd}$, Navigation=$N_{av}$, Ease of use=$E_{ou}$, Content=$C_{on}$, Aesthetic=$A_{es}$

The geometric weigh is computed as shown in Table 4.10 by using Buckley method where *l*. *m* and *u* represent the lower, middle and upper fuzzy value.

**Table 4.9 Criteria Comparison Matrix**

| CRITERIA | $S_{pd}$ | $N_{av}$ | $E_{ou}$ | $C_{on}$ | $A_{es}$ |
|---|---|---|---|---|---|
| $S_{pd}$ | (1.000, 1.000,1.000) | (2.000,3.000,4.000) | (1.000,1.000,1.000) | (1.000,1.000,1.000) | (4.000,5.000,6.000) |
| $N_{av}$ | (0.250,0.333,0.500) | (1.000,1.000,1.000) | (1.000,1.000,1.000) | (0.250,0.333,0.500) | (4.000,5.000,6.000) |
| $E_{ou}$ | (1.000,1.000,)1.000 | (1.000,1.000,1.000) | (1.000,1.000,1.000) | (0.250,0.333,0.500) | (4.000,5.000,6.000) |
| $C_{on}$ | (1.000,1.000,1.000) | (2.000,3.000,4.000) | (2.000,3.000,4.000) | (1.000,1.000,1.000) | (6.000,7.000,8.000) |
| $A_{es}$ | (0.167,0.200,0.250) | (0.167,0.200,0.250) | (0.167,0.200,0.250) | (0.125,0.143,0.167) | (1.000,1.000,1.000) |

**Table 4.10 Geometric Mean Computation**

| CRITERIA | *l* | m | u |
|---|---|---|---|
| $S_{pd}$ | 1.5157165665 | 1.7187719276 | 1.8881750226 |
| $N_{av}$ | 0.7578582833 | 0.8890895361 | 1.0844717712 |
| $E_{ou}$ | 1.0000000000 | 1.1075663432 | 1.2457309396 |
| $C_{on}$ | 1.8881750226 | 2.2901720489 | 2.6390158215 |
| $A_{es}$ | 0.2251600064 | 0.2579873368 | 0.3041821709 |

The fuzzy weight is computed as shown in Table 4.11

**Table 4.11 Fuzzy criteria Weight Value**

| **CRITERIA** | | ***Wi*** | |
|---|---|---|---|
| $S_{pd}$ | 0.21164568 | 0.27440696 | 0.26365357 |
| $N_{av}$ | 0.10582284 | 0.14194574 | 0.15142921 |
| $E_{ou}$ | 0.13963407 | 0.17682620 | 0.17394649 |
| $C_{on}$ | 0.26365357 | 0.36563266 | 0.36849653 |
| $A_{es}$ | 0.03144001 | 0.04118843 | 0.04247420 |

Finally, the crisp value average weight criterion (Mi) is calculated using Centre of Average (COA) and Normalised weight criterion ($N_i$) is computed as shown in table 4.12.

**Table 4.12: Crisp and Normalised weight values**

| **CRITERIA** | **Mi** | **Ni** | **Rank** |
|---|---|---|---|
| $S_{pd}$ | 0.24990207 | 0.27240290 | **2** |
| $N_{av}$ | 0.13306593 | 0.14504700 | **4** |
| $E_{ou}$ | 0.16346892 | 0.17818743 | **3** |
| $C_{on}$ | 0.33259425 | 0.36254057 | **1** |

| | | | |
|---|---|---|---|
| $A_{es}$ | 0.03836755 | 0.04182210 | **5** |

The rank for the above is shown in the last column of Table 4.12

This is computed for each of the expert's users and the results obtained. A sample of these results are found in the Appendix D

The above procedure is repeated and computed for all the 169 users. The formula to calculate this is given in equation 4.1

$$Geometric\ Mean\ of\ criteria = = \left(\prod_{j=1}^{k} \mathrm{C_{wj}}\right)^{\frac{1}{k}} \tag{4.1}$$

Where k=169, and $C_{wj}$ is the criteria weight for user j

The same is computed for the alternative with respect to each criterion is given in equation 4.2 as:

$$Geometric\ Mean\ of\ the\ Alternatives = \left(\prod_{j=1}^{k} \mathrm{A_{wcj}}\right)^{\frac{1}{k}} \tag{4.2}$$

$\mathrm{A_{wcj}}$ is the alternative weight for criteria c wrt to user j

The overall result is then obtained using geometric mean for each of the websites based on the criteria is shown in Table 4.13.

**Table 4.13: Overall local weight for the Criteria**

From the results, it implies that the criteria Speed ($S_{pd}$) has the highest local weight and hence it is the most important criteria for websites as computed from the user's data. This is followed by navigation ($N_{av}$) as the second most important criteria, Ease of Use ($E_{ou}$)as the third, Content ($C_{on}$) as the fourth and Aesthetic ($A_{es}$) as the least important criteria respectively. This result shows slight correlation with the study conducted by Nagpal *et al.*(2016b) who observed that ease of navigation plays most important role in websites while using Fuzzy AHP but that response time is the main contributor when entropy approach is used. In the same way ease of use was reported to be most highly rated factor followed by content among other criteria like emotion, promotion and made-for-the-media used in another study (Presley and Fellows, 2013)

| Criteria | Weight | Rank |
|---|---|---|
| Speed- $S_{pd}$ | **0.321** | **1st** |
| Content- $C_{on}$ | **0.166** | **4th** |
| Ease of Use- $E_{ou}$ | **0.197** | **3rd** |
| Aesthetic- $A_{es}$ | **0.108** | **5th** |
| Navigation- $N_{av}$ | **0.208** | **2nd** |

Using the same procedure as described in equations 4.1 and 4.2 the weight for each alternative based on each criteria is also derived and shown in Table 4.14. From the table various alternatives have different ratings across different criteria. For example, while UI takes the lead in Criteria of speed ($S_{pd}$) Navigation ($N_{av}$), Ease of Use ($E_{ou}$) and Content ($C_{on}$), the rank obtained in $A_{es}$ is different. The same is applicable for all other alternative websites where there are variations in ranking across each criteria especially on aesthetic criteria, where OAU has the highest rank.

**Table 4. 14 Weight of each Alternative websites based on each Criteria**

| Alternative | $S_{pd}$ | $N_{av}$ | $E_{ou}$ | $C_{on}$ | $A_{es}$ |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| UI | 0.243527134 | 0.195479559 | 0.214016874 | 0.20198238 | 0.186433527 |
| CU | 0.198354678 | 0.18720352 | 0.176824116 | 0.184169534 | 0.16043228 |
| OAU | 0.160689074 | 0.188767142 | 0.198987011 | 0.186290831 | 0.214555998 |
| UNN | 0.13945927 | 0.148467266 | 0.149365531 | 0.154516181 | 0.129261754 |
| UNILAG | 0.150831843 | 0.156800998 | 0.152224029 | 0.161536822 | 0.179920181 |
| ABU | 0.107138001 | 0.123281516 | 0.108582438 | 0.111504252 | 0.12939626 |

Lastly, to get the overall priority vector for the alternative, matrix multiplication of each criteria ranking and alternatives ranking based on each criteria is done. By using the procedure outlined below.

Alternative weights ($A_w$) criteria weights ($C_w$) Priority Weight ($P_W$)

$$\begin{bmatrix} A_{1c1} & A_{1c2} & A_{1c3} & A_{1c4} & A_{1c5} \\ A_{2c1} & A_{2c2} & A_{2c3} & A_{2c4} & A_{2c5} \\ A_{3c1} & A_{3c2} & A_{3c3} & A_{3c4} & A_{3c5} \\ A_{4c1} & A_{4c2} & A_{4c3} & A_{4c4} & A_{4c5} \\ A_{5c1} & A_{5c2} & A_{5c3} & A_{5c4} & A_{5c5} \\ A_{6c1} & A_{6c2} & A_{6c3} & A_{6c4} & A_{6c5} \end{bmatrix} \text{X} \begin{bmatrix} c_{w1} \\ c_{w2} \\ c_{w3} \\ c_{w4} \\ c_{w5} \end{bmatrix} = \begin{bmatrix} A_{pw1} \\ A_{pw2} \\ A_{pw3} \\ A_{pw4} \\ A_{pw5} \\ A_{pw6} \end{bmatrix} \quad (4..3)$$

Where , $A_{1c1}$ represent the weight of Alternative 1 with respect to Criteria 1,

$A_{1c2}$ is the weight of Alternative 1 with respect to Criteria 2,

$A_{1c3}$ is the weight of Alternative 1 with respect to Criteria 3,

$A_{1c4}$ is the weight of Alternative 1 with respect to Criteria 4

$A_{1c5}$ is the weight of Alternative 1 with respect to Criteria 5 and so on

Also, $c_{w1}$ is the weight of criteria 1, $c_{w2}$ is weight of criteria 2 and so on

And $A_{pw1}$ is priority weight of Alternative 1, $A_{pw2}$ is priority weight of Alternative 2 etc.

The computation is shown table 4.15

The aggregated alternative weight obtained is given as

$$A_w = \begin{bmatrix} 0.243527134 & 0.195479559 & 0.214016874 & 0.20198238 & 0.186433527 \\ 0.198354678 & 0.18720352 & 0.176824116 & 0.184169534 & 0.16043228 \\ 0.160689074 & 0.188767142 & 0.198987011 & 0.186290831 & 0.214555998 \\ 0.13945927 & 0.148467266 & 0.149365531 & 0.154516181 & 0.129261754 \\ 0.150831843 & 0.156800998 & 0.152224029 & 0.161536822 & 0.179920181 \\ 0.107138001 & 0.123281516 & 0.108582438 & 0.111504252 & 0.12939626 \end{bmatrix}$$

Where each row are the alternative websites values and the column are the criteria weight values,

The aggregated criteria weight $C_w$ is given as

| Alternatives | Final Priority Weight | Rank |
|---|---|---|
| UI | 0.215 | **1st** |
| CU | 0.185 | **2nd** |
| OAU | 0.184 | **3rd** |
| UNN | 0.145 | **5th** |
| UNILAG | 0.157 | **4th** |
| ABU | 0.114 | **6th** |

$$\mathbf{C_w} = \begin{bmatrix} 0.3219522038 \\ 0.2082455940 \\ 0.1967537059 \\ 0.1655083117 \\ 0.1075401845 \end{bmatrix}$$

Then the overall priority weights $P_w$ is computed from equation 4.3 as

$$P_w = A_w \times C_w$$

This gives the $P_w$ as = 
$$\begin{matrix} 0.2146993260 \\ 0.1853703397 \\ 0.1841016314 \\ 0.1446796402 \\ 0.1572487392 \\ 0.1139003235 \end{matrix}$$

The result obtained gives the output in Table 4. 15 with the corresponding rank. Figure 4.3 shows the final ranking of the alternative websites based on the whole criteria, while Figures 4.4 to 4.9 show the ranking of each alternative websites with respect to each criteria.

**Table 4.15 Final priority weight of the alternatives**

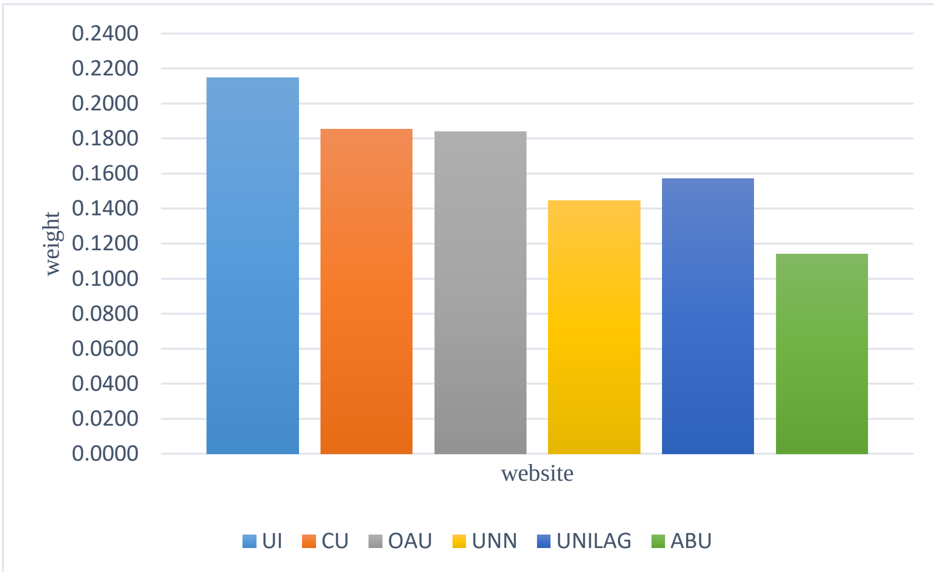



**Figure 4.3: Overall ranking of the Alternative Websites**

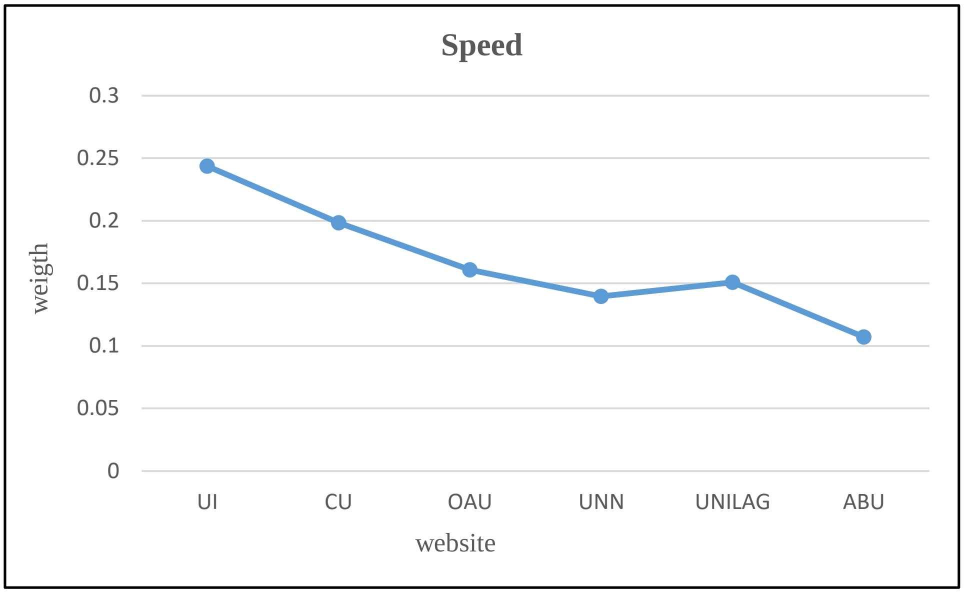



**Figure 4.4: Fuzzy AHP Ranking of Alternative Websites wrt Speed**

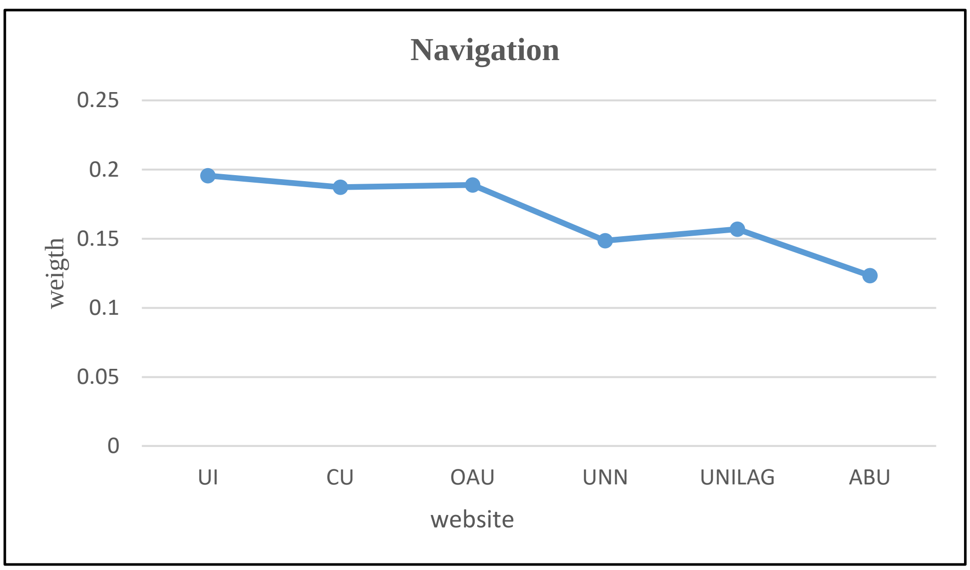



**Figure 4.5: Fuzzy AHP Ranking of Alternative Websites wrt Navigation**

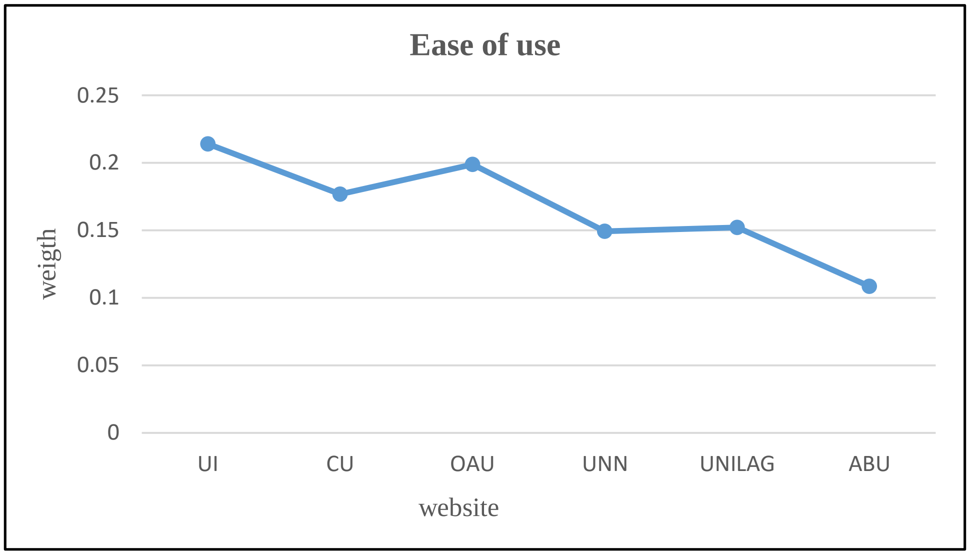



**Figure 4.6: Fuzzy AHP Ranking of Alternative Websites wrt Ease of use**

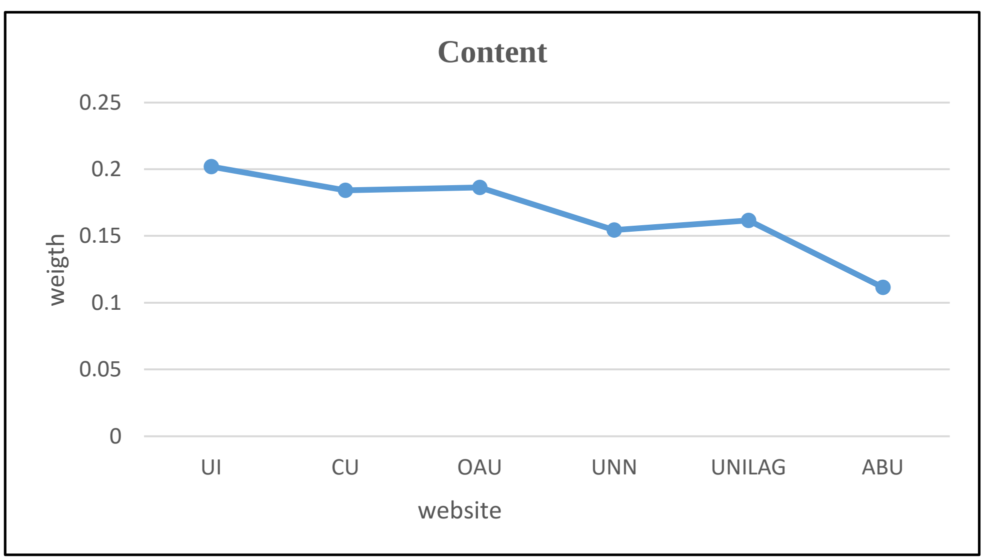



**Figure 4.7: Fuzzy AHP Ranking of Alternative Websites wrt on Content**

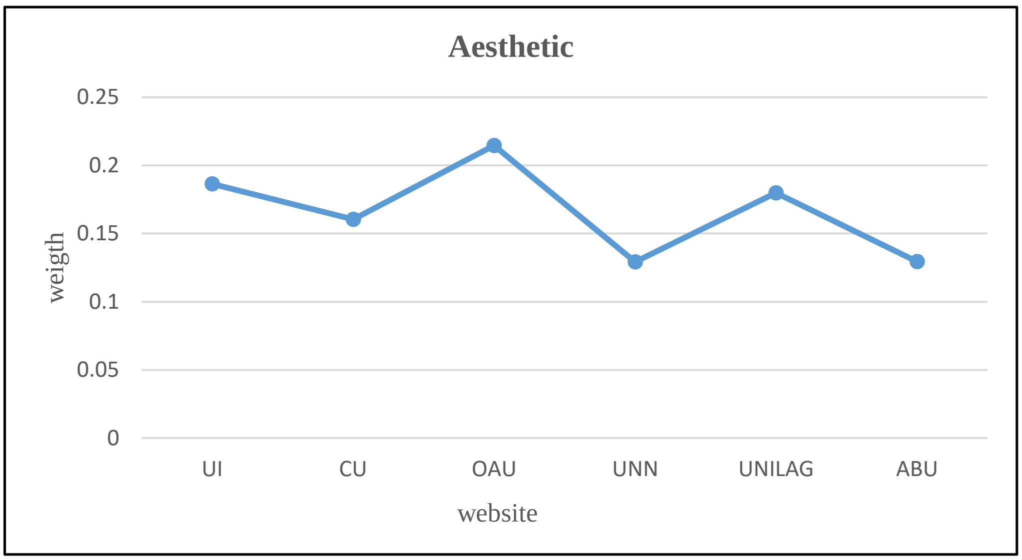



**Figure 4.8 Fuzzy AHP Ranking of Alternative Websites wrt Aesthetic**

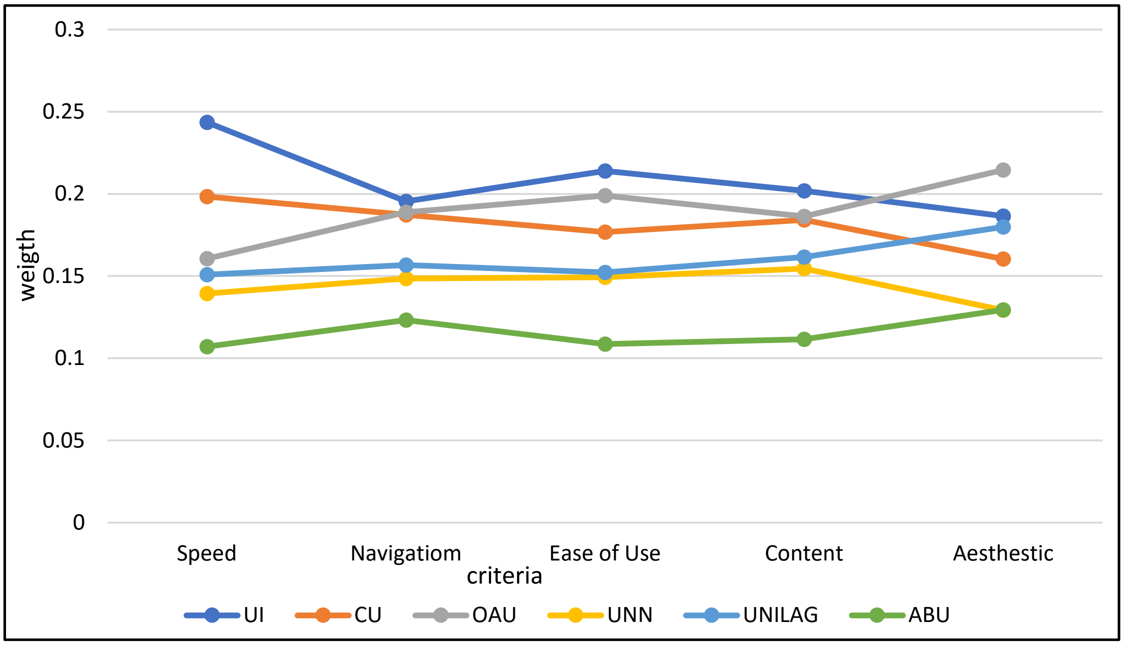



**Figure 4.9: Overall ranking of the Alternative Websites wrt each criteria**

From the results obtained, the rank of the alternative websites is in this order UI, CU, OAU, UNILAG, UNN and ABU (**UI > CU > OAU > UNILAG > UNN >ABU)**. This implies that UI websites is the most preferred among the users based on all the combined criteria and this is followed by others in the same order.

A further break down of UI website ranking shows the same trend for all the other criteria except for aesthetic. On the other hand, CU websites ranked 2nd in speed, 3rd in Navigation, ease of use and Content and 4th in aesthetic. Results of OAU websites shows that it ranked 1st in Aesthetic, 2nd in Navigation, ease of use and content, then 3rd in speed. UNN website ranked 5th in all the criteria, while UNILAG ranked 3rd in aesthetic and 4th in all other criteria. ABU websites ranked 6th in all the criteria according to the results obtained from the study based on usability.This result is different from the preliminary results based by using direct evaluation and Likert scale which placed UNILAG websites as number in the rank and UI in number 5. However, the rank of CU, OAU and ABU websites are the same in both results.

### 4.3.1 Fuzzy AHP model performance evaluation

To determine the validity of fuzzy AHP methodology, the results obtained from conventional AHP methodology is compared with that obtained from Fuzzy AHP in this study. This is done by using Wilcoxon signed Rank Test (Salimi and Rezaei, 2015) as earlier stated in section 3.5.1. This is achieved by examining the median difference between the obtained results at two levels (local weights of the criteria, and the final aggregated weights for the alternatives).

First, the results obtained from AHP model are shown in Table 4.16 by using AHP algorithm which involves the use of crisp value instead of fuzzy value (see section 2.3.1.1). From the two models, fuzzy AHP and conventional AHP result from Tables 4.14, 4.15 and 4.16, the Wilcoxon Signed Rank Test results are shown in Tables 4.17 and 4.18. The results imply that there is no significant difference between the results of the two models ($\alpha = 0.01$). Thus, this shows the validity of the proposed fuzzy AHP model for this study.

**Table 4. 16 AHP results**

| Criteria | Criteria weight | Rank | Alternatives | Priority weight | Rank |
|---|---|---|---|---|---|
| Speed | 0.291546836 | **1st** | UI | 0.2099303278 | **1st** |
| Navigation | 0.196543199 | **2nd** | CU | 0.1754848193 | **3rd** |
| Ease of Use | 0.204332987 | **3rd** | OAU | 0.1832346802 | **2nd** |
| Content | 0.189962978 | **4th** | UNN | 0.1495750078 | **5th** |

| | | | | | |
|---|---|---|---|---|---|
| Aesthetic | 0.117614001 | **5th** | UNILAG | 0.1666818279 | **4th** |
| | | | ABU | 0.1150933370 | **6th** |

**Table 4. 17: Wilcoxon Signed Rank Test on Fuzzy AHP and AHP on criteria weight**

| Ranks (FAHP-AHP) | | | | Test Statistics (FAHP-AHP) [d] | |
|---|---|---|---|---|---|
| | N | Mean Rank | Sum of Ranks | Z | -0.135 |
| Negative Ranks | 2[a] | 3.50 | 7.00 | Asymptotic sig (2-sided test) | 0.893 |
| Positive Ranks | 3[b] | 2.67 | 8.00 | | |
| Ties | 0[c] | | | | |
| Total | 5 | | | | |

a. ahpResult < fahpResult
b. ahpResult > fahpResult
c. ahpResult = fahpResult
d. The significance level $\alpha = 0.01$
e. Based on negative ranks

**Table 4. 18 Wilcoxon Signed Rank Test on fuzzy AHP and AHP alternative websites weight**

| Ranks (FAHP-AHP) | | | | Test Statistics (FAHP-AHP) [d] | |
|---|---|---|---|---|---|
| | N | Mean Rank | Sum of Ranks | Z | -0.105 |
| Negative Ranks | 3[a] | 3.67 | 11.00 | Asymptotic sig (2-sided test) | 0.917 |
| Positive Ranks | 3[b] | 3.33 | 10.00 | | |

| | |
|---|---|
| Ties | 0[c] |
| Total | 6 |

a. ahpResult < fahpResult
b. ahpResult > fahpResult
c. ahpResult = fahpResult
d. The significance level α = 0.01
e. Based on negative rank

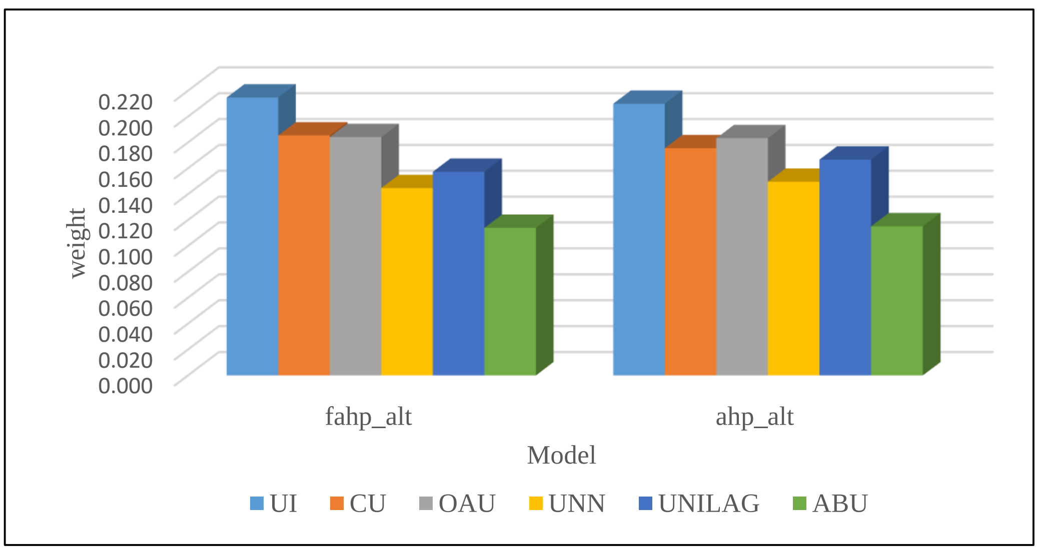
Figure 4.10. shows the pictorial comparison of the two. The closeness of the results is an indication of the higher degree of model validity.

.

**Figure 4. 10 Comparative analyses of AHP and FAHP results**

## 4.4 Website Usability Rating Classification Results

In order to apply machine learning models to classify and predict the usability ratings of the users of the websites, data generated from Fuzzy AHP were used to train the different machine learning model. The initial data obtained was further preprocessed and normalized using MinMax normalization method to ensure proper scaling of the results as earlier discussed in section 3.4.1.2. Furthermore, the



instrument used in collection of the data gives no room for missing value as all the responses are compulsory (required). The input variables to the network are Speed= $S_{pd}$, Navigation=$N_{av}$, Ease of use=$E_{ou}$, Content=$C_{on}$, Aesthetic=$A_{es}$ - which are obtained from the Fuzzy AHP and the output is usability rating $US_{ra}$ which is a binary class denoted as positive rating (Satisfied) or Negative rating (not satisfied).

The sample data obtained are showing in the Appendix E

### 4.4.1 Artificial neural network results

The Confusion matrix for the ANN metric is shown in Figure 4.11 as derived from the model. From the confusion matrix of the ANN model, sixty-three (63) of the usability rating cases were classified correctly as positive (TP). This corresponds to 57.27% of all one hundred and ten (110) usability rating cases. Also, forty-three (43) of the usability rating cases were correctly classified as negative (TN), which gives 39.09% of all usability rating cases. In the same way, three (3) users rating which correspond to 2.73% of all usability rating were classified incorrectly as negative (FN). Similarly, only one (1) case was incorrectly classified as positive (FP) which corresponds to 0.91% of all the usability rating cases.

| Output Class | | | | |
|---|---|---|---|---|
| | 1 | 63 (57.27%) | 3 (0.03%) | (95.45%) (0.05%) |

| | | | |
|---|---|---|---|
| **0** | 1<br>(0.9%) | 43<br>(39.09%) | (97.72%)<br>(2.28%) |
| | 98.44%<br>1.56% | 93.48%<br>6.52% | 96.36%<br>3.64% |
| | **1** | **0** | |

**Target Class**

**Figure 4.11 ANN Confusion matrix**

Furthermore, out of sixty-six (66) Satisfactory rating, sixty-three (63) were correctly classified corresponding to 95.45% of the correctly classified while three (3) cases which correspond to 4.55% were wrongly classified. Similarly, out of forty-four (44) Unsatisfactory rating, forty-three (43) ratings which corresponds to 97.72% were correctly classified as being rated unsatisfactory while one (1) which corresponds to 2.28% were incorrectly classified.

### 4.4.2 Bayesian Network results

From the confusion matrix of the Bayesian Network shown in Figure 4.12, sixty -seven (67) of the usability rating cases were classified correctly as positive (TP). This corresponds to 60.91% of all one hundred and ten (110) usability rating cases. Also, twenty-five (25) of the usability rating cases were correctly classified as negative (TN),

| | | | | |
|---|---|---|---|---|
| **Outp ut Class** | **1** | 67 | 9 | (88.16%) |

| | | | |
|---|---|---|---|
| | (60.91%) | (8,18%) | (11.84%) |
| 0 | 9<br>(8.18%) | 25<br>(22.72%) | (73.53%)<br>(26.47%) |
| | 88.16%<br>11.84% | 73.53%<br>26.47% | 83.63%<br>16.37% |
| | 1 | 0 | |

**Target Class**

**Figure 4.12 BaNet Confusion matrix**

which gives 22.73% of all usability rating cases. In the same way, nine (9) users rating which correspond to 8.18% of all usability rating were classified incorrectly as negative (FN). Similarly, nine (9) cases were incorrectly classified as positive (FP) which corresponds to 8.18% of all the usability rating cases. Also, out of seventy-six (76) satisfied rating, sixty-seven (67) were correctly classified corresponding to 88.16% of the correctly classified while nine (9) cases which correspond to 11.84% were wrongly classified. Similarly, out of thirty-four (34) unsatisfied rating, twenty-five (25) ratings which corresponds to 73.53% were correctly classified as being rated unsatisfied while nine (9) which corresponds to 26.47% were incorrectly classified.

### 4.4.3 Decision tree results

From the confusion matrix of the decision tree shown in Figure 4.13, seventy-six (76) of the usability rating cases were classified correctly as positive (TP). This corresponds to 69.09% of all one hundred and ten (110) usability rating cases. Also, twenty-one (21) of the usability rating cases were correctly classified as negative (TN), which gives 19.09% of all usability rating cases.

In the same way, zero (0) users rating which correspond to 0% of all usability rating were classified incorrectly as negative (FN).

Similarly, thirteen (13) cases were incorrectly classified as positive (FP) which corresponds to 11.82% of all the usability rating cases. Also, out of seventy-six (76) satisfied rating, all were correctly classified corresponding to 100% of the correctly classified while no case was wrongly classified. Similarly, out of thirty-four (34) unsatisfied rating, twenty-one (21) ratings which corresponds to 61.77% were correctly classified as being rated unsatisfied while thirteen (13) which corresponds to 38.23% were incorrectly classified.


**Figure 4.13 Decision Tree Confusion matrix**

### 4.4.4 Logistic model tree results

From the confusion matrix of the Logistic Model Tree shown in Figure 4.14, seventy-six (76) of the usability rating cases were classified correctly as positive (TP).


**Figure 4.14 LMT Confusion matrix**

This corresponds to 69.09% of all one hundred and ten (110) usability rating cases. Also, twenty-two (22) of the usability rating cases were correctly classified as negative (TN), which gives 20% of all usability rating cases. In the same way, zero (0) users rating which correspond to 0% of all usability rating were classified incorrectly as negative (FN).

Similarly, twelve (12) cases were incorrectly classified as positive (FP) which corresponds to 10.91% of all the usability rating cases. Also, out of seventy-six (76) satisfied rating, all were correctly classified corresponding to 100% of the correctly classified while no case was wrongly classified. Similarly, out of thirty-four (34) unsatisfied rating, twenty-two (22) ratings which corresponds to 64.71% were correctly classified as being rated unsatisfied while twelve (12) which corresponds to 35.29% were incorrectly classified.

### 4.4.5 Simple logistic regression results

From the confusion matrix of the Simple logistic regression shown in Figure 4.15, seventy-six (76) of the usability rating cases were classified correctly as positive (TP). This corresponds to 69.09% of all one hundred and ten (110) usability rating cases. Also, twenty-one (21) of the usability rating cases were correctly classified as negative (TN), which gives 19.09% of all usability rating cases. In the same way, zero (0) users rating which correspond to 0% of all usability rating were classified incorrectly as negative (FN). Similarly, thirteen (13) cases were incorrectly classified as positive (FP) which corresponds to 11.82% of all the usability rating cases. Also, out of seventy-six (76) satisfied rating, all were correctly classified corresponding to 100% of the correctly classified while no case was wrongly classified.


**Figure 4.15 SLOG Confusion matrix**

Similarly, out of thirty-four (34) unsatisfied rating, twenty-one (21) ratings which corresponds to 61.77% were correctly classified as being rated unsatisfied while twelve (13) which corresponds to 39.23% were incorrectly classified.

### 4.4.6 Random Forest results

From the confusion matrix of the Random Forest model in Figure 4.16, seventy-three (73) of the usability rating cases were classified correctly as positive (TP). This corresponds to 66.36% of all one hundred and ten (110) usability rating cases. Also, twenty-six (26) of the usability rating cases were correctly classified as negative (TN), which gives 23.63% of all usability rating cases. In the same way, three (3) users rating which correspond to 2.72% of all usability rating were classified incorrectly as negative (FN). Similarly, eight (8) cases were incorrectly classified as positive (FP) which corresponds to 7.27 of all the usability rating cases. Table 4.20 gives the overall summary of the various DM algorithms described above based on performance metrics.

| Output Class | 1 | 0 | |
|---|---|---|---|
| 1 | 73<br>(63.36%) | 3<br>(2.72%) | (96.05%)<br>(3.95%) |
| 0 | 8<br>(7.27%) | 26<br>(23.63%) | (76.47%)<br>(23.53%) |
| | 90.12%<br>9.88% | 89.65%<br>10.35% | 90%<br>10% |

Target Class

**Figure 4.16 RF Confusion matrix**

Also, out of seventy-six (76) satisfied rating, seventy-three (73) were correctly classified corresponding to 96.05% of the correctly classified while three cases were wrongly classified which correspond to 3.95%. Similarly, out of thirty-four (34) unsatisfied rating, twenty-six (21) ratings which corresponds to 76.47% were correctly classified as being rated unsatisfied while eight (8) which corresponds to 23.53% were incorrectly classified.

### 4.5 Comparison among Machine Learning Algorithms

The performance of the data generated from Fuzzy AHP model was tested on different mining algorithms as discussed in sections 3.5. Using the same data set with five features and 732 instances, the dataset used was also divided into training, testing and validation dataset. This experiment has divided the data into 70% training (514 instances), 15% (110 instances) each for testing and validation datasets. For the model 69% are classified as satisfied while 31% are not satisfied during the experimental set up for this stage. The overall comparative results are results are shown in Table 4.19. This is better than previous results obtained by Nayebi (2015) with accuracy of 92%.

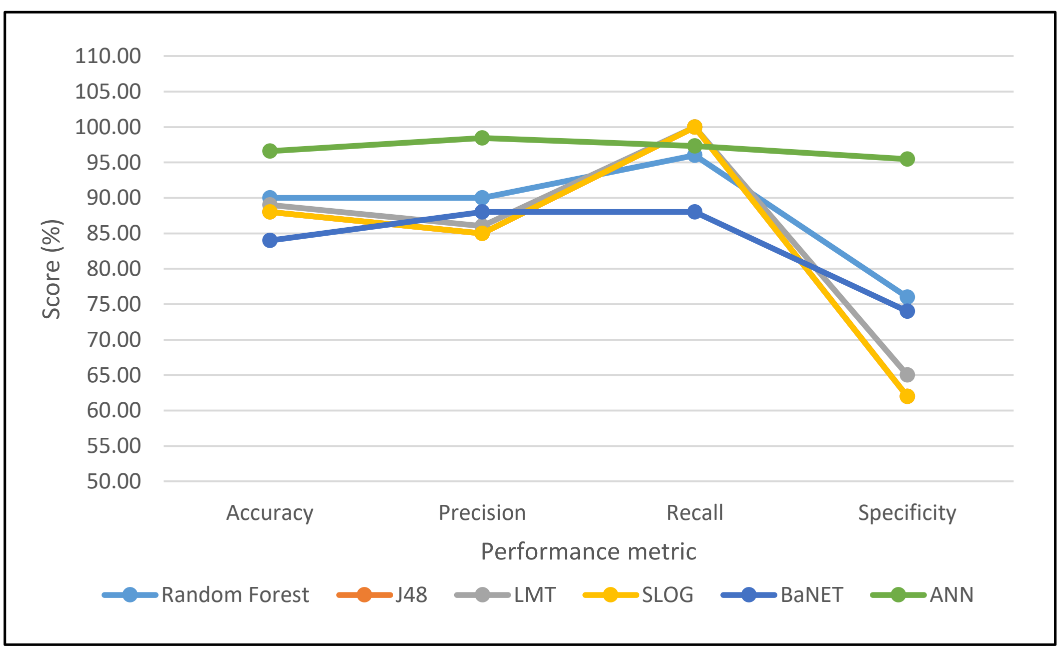
**Table 4. 19 Overall Results of the different Machine learning algorithms**

Where PPV is positive predicted value, NPV is negative predicted value, $TN_r$ is True Negative rate , $TP_r$ is True Positive rate, $FN_r$ is False Negative rate and $FP_r$ False Positive rate respectively. All the classifiers have a good performance and J48 and SLOG performance are very similar except in the RMSE values.

| Classifier | Accuracy ($A_{cc}$) | Precision($P_{re}$) / PPV | Recall ($R_{ec}$) / Sensitivity/ TPr | Specificity / TNr | F Measure | FPr/ fallout | FNr/ Miss out | NPV | MSE |
|---|---|---|---|---|---|---|---|---|---|
| Random Forest | 90.12 | 90 | 96 | 76 | 0.93 | 0.24 | 0.04 | 90 | 0.2982 |
| J48 | 88.18 | 85 | 100 | 62 | 0.92 | 0.38 | 0 | 100 | 0.34 |
| LMT | 89.09 | 86 | 100 | 65 | 0.93 | 0.35 | 0 | 100 | 0.3299 |
| SLOG | 88.18 | 85 | 100 | 62 | 0.92 | 0.38 | 0 | 100 | 0.4238 |
| BaNET | 83.63 | 88 | 88 | 74 | 0.88 | 0.26 | 0.12 | 74 | 0.3579 |
| ANN | 96.36 | 98 | 96 | 98 | 0.96 | 0.02 | 0.05 | 96 | 0.0364 |

Figures 4. 17 and 4.18 show the figurative performance comparison of the various ML models base on some standard performance metric earlier discussed in section 3.7 From the figures the performance of all the classifiers are good.

However, ANN achieved the highest classification in accuracy, precision and specificity above all other models. The performances of SLOG and decision tree (J48) classifiers are the same on all the



performance metrics. Three classifiers; SLOG, J48 and LMT have the highest recall of 100%. Random forest is the second-best performing model in all performance metrics except in recall. BaNet is the least perfuming model in terms of accuracy and recall though better than some models in specificity metric. The specificity is low except for ANN.

**Figure 4. 17 Performance Comparison of Machine Learning Algorithms**

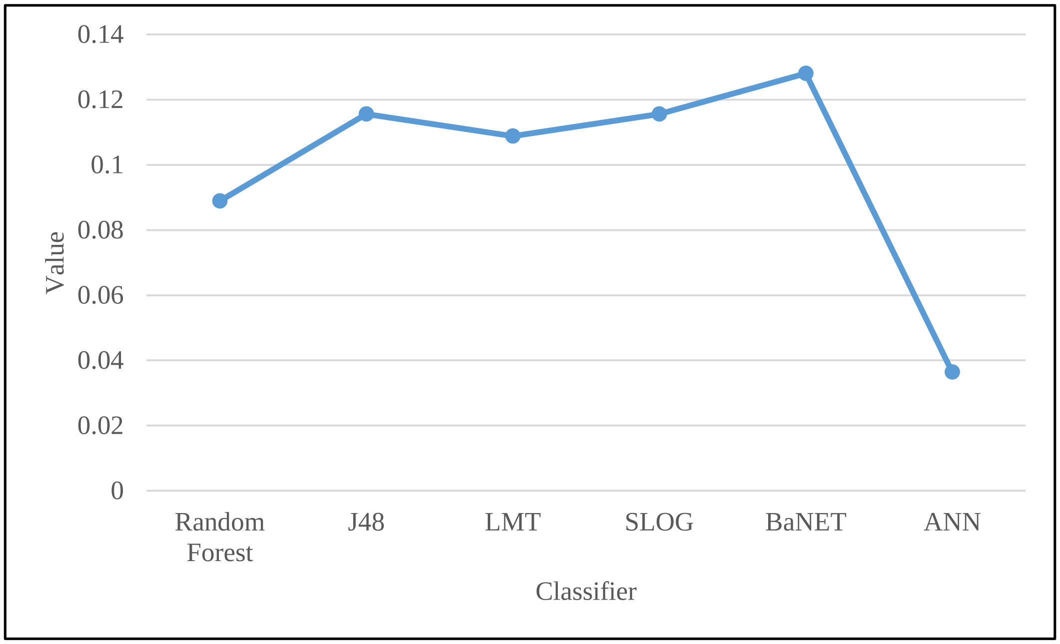



**Figure 4. 18 RMSE Comparison of Machine Learning Algorithms**

ANN has the least RMSE followed by RF, LMT, J48, BaNET and SLOG respectively. This has accounted for the highest accuracy which implies that the higher the accuracy, the less the RMSE. A classification accuracy of over 80% of accuracy were obtained from all the models though the best performing one is ANN with 96.36% $A_{cc}$ . Therefore, the study has demonstrated that if given a reliable data set, it is possible to classify and predict website usability satisfaction rating by using machine learning algorithms. The high degree of accuracy achieved in the course of the research from all the models shows that there is relationship between usability of websites and user given rating.

### 4.6 Integration with ANN results

After transforming and transposing the data as well as resample the data by using the techniques of under sampling the majority class data, a total of 732 instances were used for the ANN modelling. Out of these, the training, testing and validation data were divided into 70:15:15 via the code. In all, 514 instances were used for the Training and 110 each for (testing and validation respectively). In order to obtain the best performance, the learning rate (l), number of hidden layers (h) and momentum (m) were adjusted after several runs and iterations. At the end of the procedure, the values of *l, m and h* used are 0.9, 0.8 and 3 respectively with logarithm sigmoid function (logsig) as activation function while Bayesian regularization (trainbr) is the training function. Other functions like tansig did not give a good performance. All these parameters combined gives the best performance results with threshold values ranging from positive satisfactory results. The model structure is 5x3x1 which is made of 5 inputs, 3 neurons in the hidden layer and 1 output layer is depicted in Figure 4.19. The performance of the model was evaluated using mean square error as shown in Figure 4.20. From the graph there is convergence at $10^{th}$ iteration base on the sample data with value at 0.0171

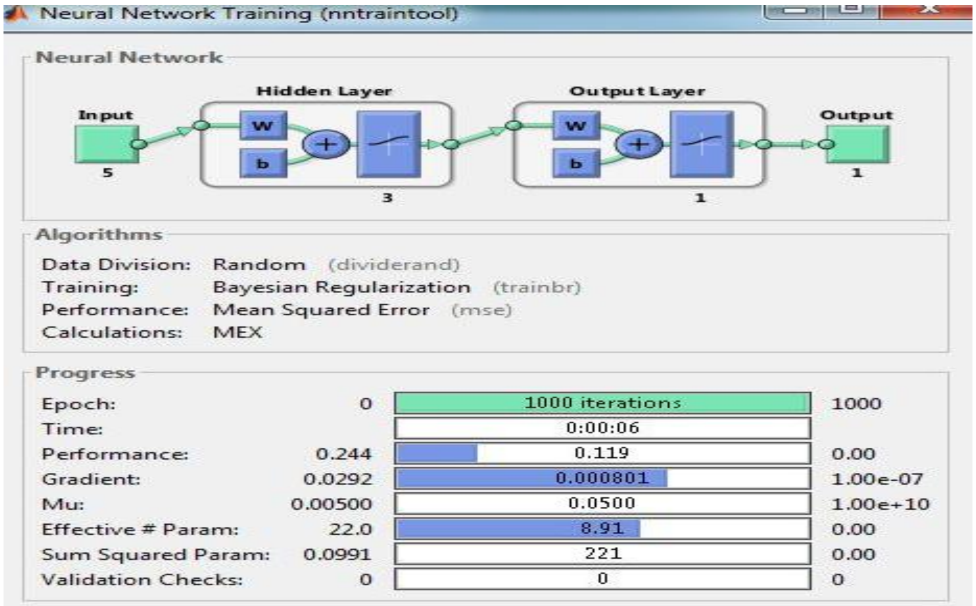



**Figure 4.19 Integrated ANN model network structure**

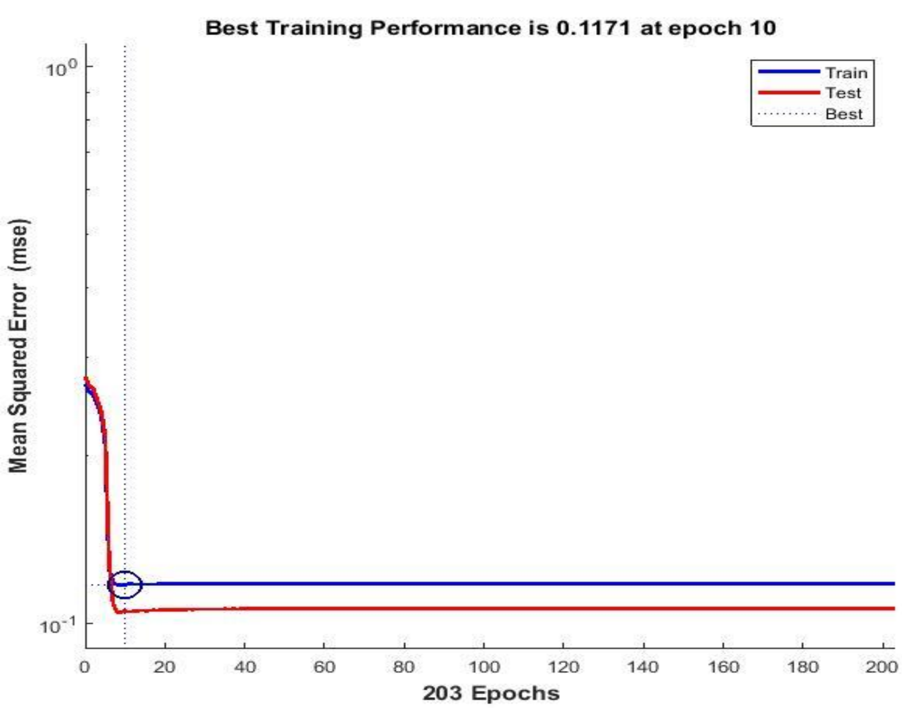



**Figure 4.20 Integrated ANN model performance graph**

Furthermore, the plot of regression analysis of the model showing the training and testing show R values of 0.90394 and 0.99016 for training and testing respectively. While the overall rate for R is 0.91701 This is shown in Figure 4.21

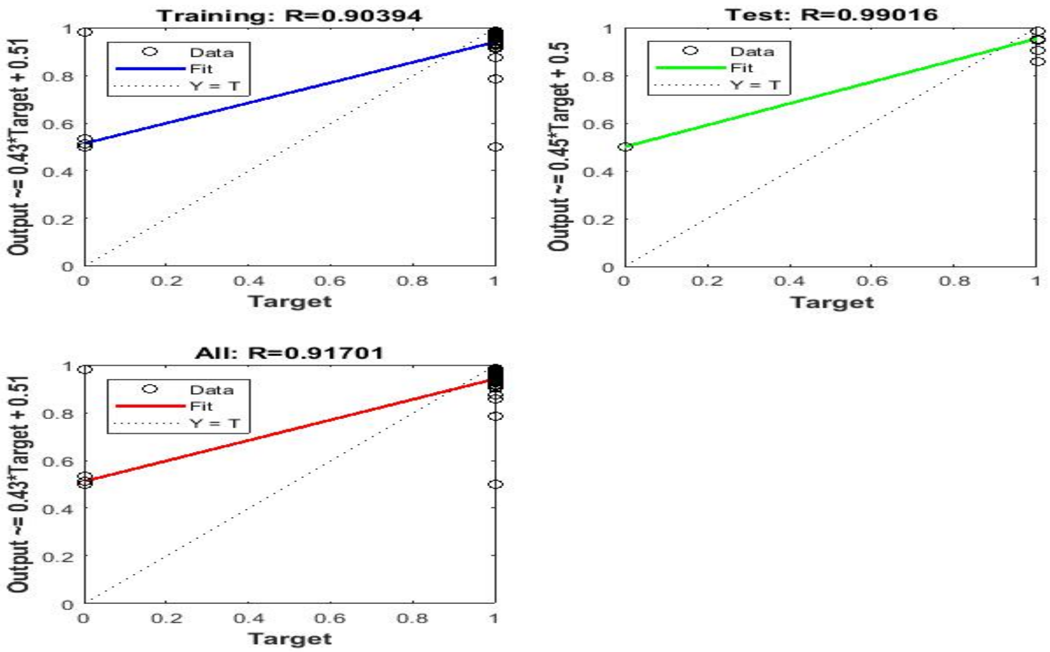



**Figure 4.21  ANN rates of training and testing on testing dataset**

After the training of the model on training data set, further testing was done using the same training dataset in order to know the best threshold value. By using adaptive thresholding algorithm, the testing was done and the results is shown in Table 4.20. The threshold values and the corresponding accuracy values repeated five times with the average and standard deviation computed are depicted in the table.  The best performances were obtained at different threshold values of 0.59-0.60, 0.62-0.64, 0.66-0.68, 0.545.0.72 and 0.72 respectively.

The graph of average accuracy was plotted against threshold values as shown in Figure 4.22. Within the threshold value range between 0.52 and 0.79, about fourteen local maxima values were received. The global maximum is at 0.75 and the highest local minima was at 0.59.

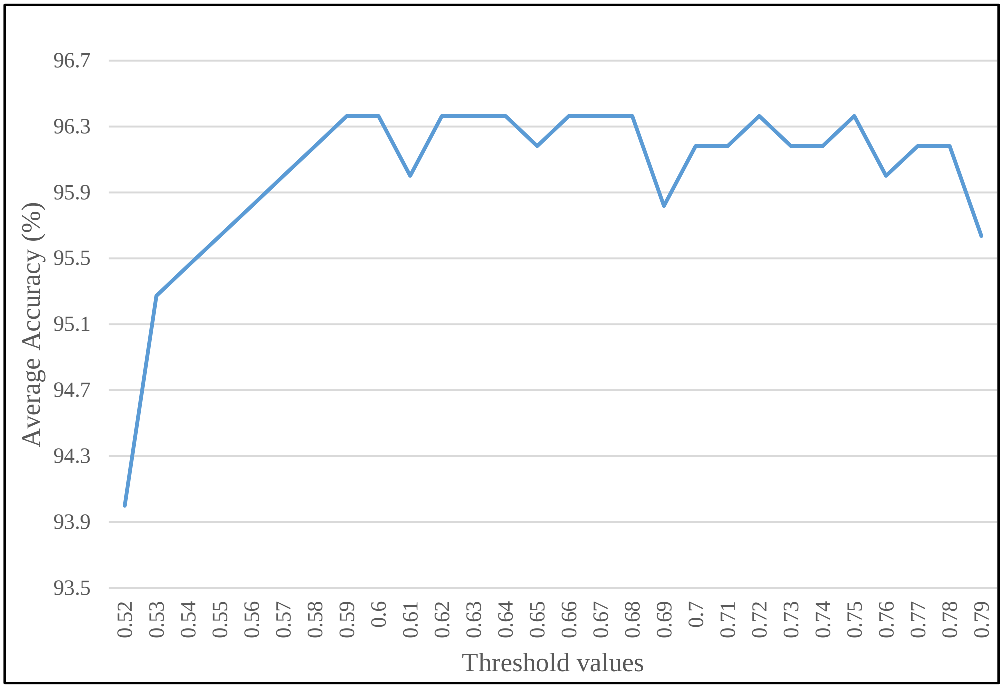



**Figure 4.22 Plot of Average Accuracy against Threshold Values**

**Table 4.20: Threshold Values and Model Performance on the testing Data set**

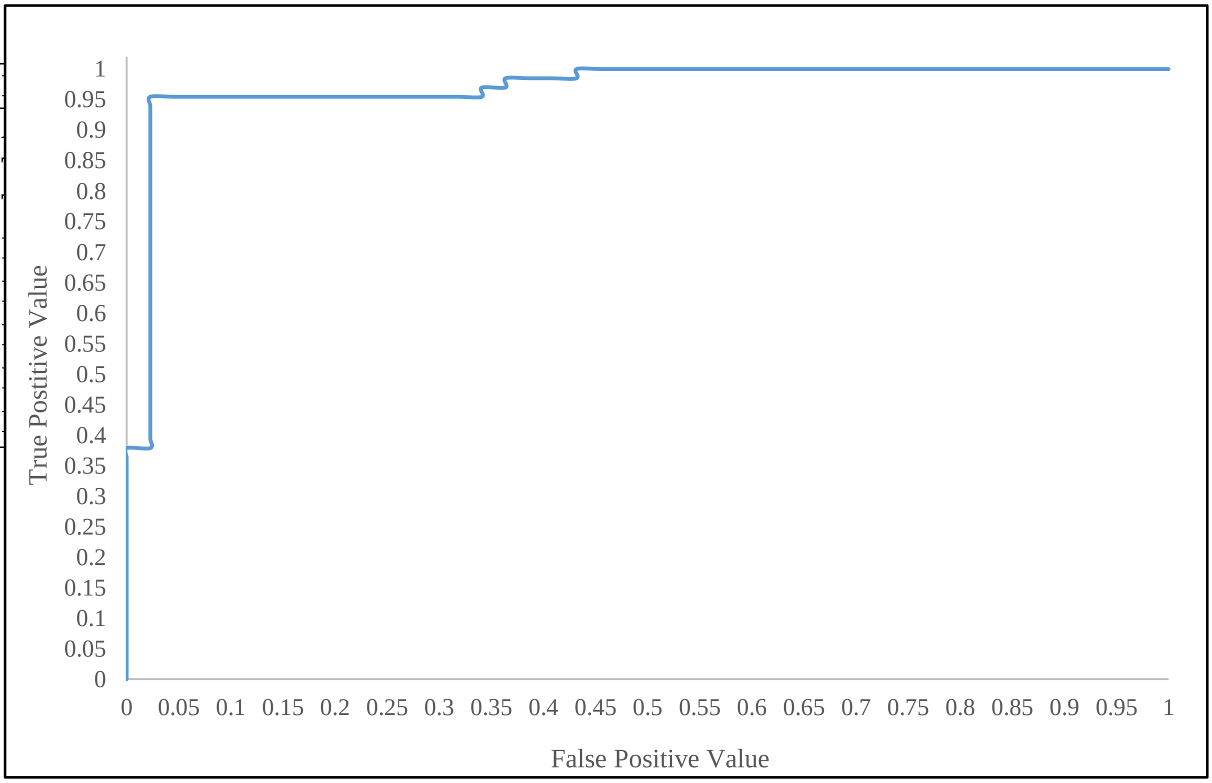
| Threshold | Accuracy | | | | | Average Accuracy | Standard Deviations |
|---|---|---|---|---|---|---|---|
| 0.52 | 93.63636 | 95.45455 | 93.63636 | 93.63636 | 93.63636 | 94 | 0.813116 |
| 0.53 | 95.45455 | 95.45455 | 95.45455 | 95.45455 | 94.54545 | 95.27273 | 0.406558 |
| 0.54 | 95.45455 | 95.45455 | 95.45455 | 95.45455 | 95.45455 | 95.45455 | 0 |
| 0.55 | 94.54545 | 96.36364 | 95.45455 | 95.45455 | 96.36364 | 95.63636 | 0.7606 |
| 0.56 | 96.36364 | 96.36364 | 95.45455 | 95.45455 | 95.45455 | 95.81818 | 0.49793 |
| 0.57 | 95.45455 | 96.36364 | 96.36364 | 95.45455 | 96.36364 | 96 | 0.49793 |
| 0.58 | 95.45455 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.18182 | 0.406558 |
| 0.59 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 0 |
| 0.6 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 0 |
| 0.61 | 96.36364 | 96.36364 | 94.54545 | 96.36364 | 96.36364 | 96 | 0.813116 |
| 0.62 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 0.63 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 0 |
| 0.64 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 0 |
| 0.65 | 96.36364 | 95.45455 | 96.36364 | 96.36364 | 96.36364 | 96.18182 | 0.406558 |
| 0.66 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 0 |
| 0.67 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 0 |
| 0.68 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 0 |
| 0.69 | 96.36364 | 95.45455 | 95.45455 | 96.36364 | 95.45455 | 95.81818 | 0.49793 |
| 0.7 | 95.45455 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.18182 | 0.406558 |
| 0.71 | 96.36364 | 96.36364 | 96.36364 | 95.45455 | 96.36364 | 96.18182 | 0.406558 |
| 0.72 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 0 |
| 0.73 | 96.36364 | 96.36364 | 96.36364 | 95.45455 | 96.36364 | 96.18182 | 0.406558 |
| 0.74 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 95.45455 | 96.18182 | 0.406558 |
| 0.75 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 96.36364 | 0 |
| 0.76 | 95.45455 | 96.36364 | 96.36364 | 95.45455 | 96.36364 | 96 | 0.49793 |
| 0.77 | 96.36364 | 96.36364 | 96.36364 | 95.45455 | 96.36364 | 96.18182 | 0.406558 |
| 0.78 | 96.36364 | 95.45455 | 96.36364 | 96.36364 | 96.36364 | 96.18182 | 0.406558 |
| 0.79 | 96.36364 | 95.45455 | 95.45455 | 94.54545 | 96.36364 | 95.63636 | 0.7606 |

The best performance was achieved at *h*= 3, *m*= 0.9 and *l*=0,8 which the gives the best accuracy at 96.36 %$A_{cc}$ and the error value of 0.0364. However, accuracy has been argued not best performance metric of a classifier (Boughorbel *et al.*, 2017; Saito and Rehmsmeier, 2015).Therefore, others metrics are also be taken into consideration in evaluating the model. Further results show that it has a precision value of 98.44% $P_{re}$, specificity value of 97.73%$S_{pc}$, and recall/sensitivity of 95.45%$R_{ec}$. This is shown in Table 4.21

**Table 4.21: Overall Performance analysis of integrated ANN Model**

In addition, the ROC curve which is a graph of TPR against FPR i.e. sensitivity against (1-specificity) is plotted and the shape of the curve obtained is shown in Figure 4.23. The same of the curve is acceptable as it shows an acceptable value of AUC of the ROC (Cook, 2017; Hand and Anagnostopoulos, 2013). The shape of the ROC curve further shows that the model performance is very good because a good fitness curve was obtained.




. **Figure 4. 23 Receiver Operating Characteristic (ROC) Curve**

### 4.6.1 Website Usability user rating model formulation

Table 4.22 gives the derivation of the model equation. IW is the input weight while LW is the Layer weight. The matrices obtained from both were extracted, transposed and the product obtained which resulted in the computation are as follows

**Table 4.22: Root of Model Equation**

| Input weight | Layered weight |
|---|---|
| Input-Weight = net. IW | Output-Weight = net. LW |
| Input-Weight = **[5×3 double]** | Output-Weight **= [1x3 double]** |
| Root of the Equation = [ $IW^T$] [$LW^T$] | |
| = **5x 1 matrix** | |

From Table 4.21 the root of the model is [ $IW^T$] [$LW^T$] as shown in equation (4.1) is a 5 x 1 matrix that follows:

$$\text{Ro}\boldsymbol{ot} = \begin{bmatrix} 15.51901 \\ 4.603518 \\ 2.3.60932 \\ -1.10852 \\ 2.095603 \end{bmatrix} \qquad (4.1)$$

The usability model is given as by transposing the matrices as S

$$[\text{US}_{ra}] = \begin{bmatrix} \boldsymbol{S_{pd}} \\ \boldsymbol{N_{av}} \\ \boldsymbol{E_{ou}} \\ \boldsymbol{C_{on}} \\ \boldsymbol{A_{es}} \end{bmatrix} [15.5190 \quad 4.6035 \quad 2.3609 \quad -1.1085 \quad 2.0956] \qquad (4.2)$$

To generate the usability rating model, a logsig transfer function mapped the input features into the hidden layer while a trainbr activation function mapped the input from hidden layer to the output layer. By using the transfer functions for each channel, then the output layer $US_{ra}$ of the model is a linear function. Therefore, the ANN-based mathematical model for website usability user rating classification is given as:

$$US_{ra} = 15.52190S_{pd} + 4.6035N_{av} + 2.3609E_{ou} - 1.1085C_{on} + 2.0956A_{es} \qquad (4.3)$$

Thus, to formulate the general model equation

$$Y_{us} = \emptyset(us_{ra} + b) \qquad (4.4)$$

Where $\emptyset$ is the transfer or activation function (logsig) and is given by

$$\emptyset(x) = \frac{1}{1+e^{-x}} \qquad (4.5)$$

b is the bias

Therefore,

The model equation is given as :

$$Y_{us} = \frac{1}{1+e^{-x}}(15.5190S_{pd} + 4.6035N_{av} + 2.3609E_{ou} - 1.1085C_{on} + 2.0956A_{es} + b) \qquad (4.6)$$

# CHAPTER FIVE

## 5.0 SUMMARY, CONCLUSION AND RECOMMENDATIONS

### 5.1 Summary

Websites usability evaluation though has attracted the attention of many researchers of late, yet there has not been any universally acceptable model that can be used to evaluate websites. This is partly due to the dynamic nature of websites as a result of advances in technology as well as variations and differences in users across the globe. Not only this, while attempts have also been made to use multi criteria decision making approach in websites evaluation, most studies focus on website quality and not website usability. Not only that, classifying users rating based on website usability using machine learning techniques is very rare. This is as a result of unavailability of sufficient usability data from users.

Consequently, this study has come up with an integrated model based on the fusion of Fuzzy AHP and ANN. It has transverse three core areas of research spanning Human Computer Interaction (HCI), Multi Criteria Decision Making (MCDM) and Data Mining (DM). The study was conducted in three phases with phase one focusing on identification of usability criteria in academic websites. In this phase, by using exploratory factor analysis, five criteria were extracted from the data gathered from users testing. These are Speed, Navigation, Ease of Use, Content and Aesthetic. This led to formulation of a new website usability model named SNECA model.

Phase two involves the use of modified Buckley fuzzy AHP to select and rank the best university websites base on the criteria identified in the first phase. By using six universities with good web presence which are UI, CU, OAU, UNN, UNILAG and ABU as the alternatives. Results of ranking of priority weighs results show that UI is being ranked first, this is followed by CU, OAU, UNILAG, UNN and ABU respectively. Further results show that speed is the most preferred criteria among website users and aesthetic is the least preferred.

Data obtained from the second phase were later transformed, cleaned and used as input to train various classifiers to classify the users rating base on the usability of the websites. Results from the six machine learning algorithms shows that ANN has the best performance among all. However, the dataset gives a minimum accuracy of 80% on all the algorithms therefore showing that prediction can be dome on the website usability data. The ANN used is a 5 x 3 x 1 architecture having speed, navigation, ease of use, content and aesthetic weight values obtained from fuzzy AHP as inputs, 3 neurons in the hidden layer, and 1 output variable which is a binary class. The ANN model gives a good performance with accuracy of 96.36% with corresponding high Precision, recall, sensitivity and specificity values.

## 5.2 Conclusion

This research work has been able to develop an integrated model using the combination of fuzzy AHP and ANN for websites usability using university websites as a case study. The results have shown that speed is the most important criteria for websites users, aesthetic is the least and there is correlation between usability and webometric ranking. Also, further results show that it is possible to predict user’s website usability rating by using various machine learning algorithms. Despite inconsistency in human behavior, the various algorithms achieve an acceptable high score on all performance metrics with ANN performing best. This is a clear indication that the model will perform very well on other dataset where human behaviour are relatively stable and no bias.

## 5.3 Recommendation

As a result of plethora faced by users of websites in general, it is recommended that web developers make use of the model to test the usability or otherwise of their websites This will reveal the degree of users’ satisfaction with their product. This model in its form is clear, unambiguous and easy to use. It can also be adapted to any type of websites where users’ satisfaction is the ultimate. This will enable them to make improvement on the websites. Moreover, on the practitioner side, due to importance and vital roles website plays, it should be given adequate attention.

It is therefore recommended that, various academic university stake holders should pay adequate attention to the development of their websites. Staff saddled with the responsibility of developing websites should be trained and retrained in the use of latest software and hardware for website development. Another point is that users especially students should be carried along at every developmental stage of website so that they can make inputs as they are the main end user. If this is this is done, they can provide insightful feedback to the developers at that stage and hence make improvement on the websites.

## 5.4 Suggestions for Future Research

Future research should incorporate more criteria due to dynamic nature of websites. Other machine learning algorithms not used in this study or its hybrid /ensemble can be tested on the newly generated dataset so as to know their performance in comparison with the ones used in the study. Also, the criteria proposed in the model can be used and tested on other genre of websites.

## 5.5 Contributions to Knowledge

This thesis has contributed to knowledge in the following ways:

1) Formulation of a new website usability evaluation model otherwise known as SNECA model which further incorporate a new user experience construct of aesthetic criteria.
2) Development of a new data collection method for AHP via google docs and formulation of fuzzy AHP model.
3) Development of a prediction model for website usability rating using ANN with good performance base on data generated from fuzzy AHP

4) Generation of a new dataset for users' website usability prediction. /classification which can be used for further research in data mining.

## REFERENCES


Abdallah, S., & Jaleel, B. (2015). Website Appeal : Development of an Assessment Tool and Evaluation Framework of E-Marketing. *Journal of Theoretical and Applied Electronic Commerce Research*, *10*(3), 45–62. https://doi.org/10.4067/S0718-18762015000300005

Abisoye, O. (2018). *Hybridized support vector machine_Artifical neural network malaria prediction model*. (unpublished doctoral dissertation) University of Ilorin, Nigeria.

Abran, A., Khelifi, A., & Suryn, W. (2003). Usability Meanings and Interpretations in ISO Standards. *Software Quality Journal*, *11*, 325–338.

Adepoju, S. A., & Shehu, I. S. (2014). Usability Evaluation of Academic Websites Using Automated Tools. *3rd International Conference on User Science and Engineering (i-USEr)*, 186–191. https://doi.org/10.1109/IUSER.2014.7002700

Affandy, H. B., Hussain, A., & Nadzir, M. M. (2017). Balancing Usability and Aesthetic Elements in Universities ' Website : A Systematic Review. *Malaysian Journal of Communication*, *33*(4), 190–203. http://103.219.237.47/mjc/article/view/22625

Agirgun, B. (2012). Ranking B2C Web Sites with AHP and TOPSIS Under Fuzzy Environment. *Nevşehir Üniversitesi Fen Bilimleri Enstitü Dergisi*, *1*(2), 65–78. http://dergipark.ulakbim.gov.tr/nevbiltek/article/view/1035000106

Ahishakiye, E., & Niyonzima, I. (2017). Crime Prediction Using Decision Tree ( J48 ) Classification Algorithm. *International Journal of Computer and Information Technology*, *6*(3), 188–195.

Ahmed, F., & Kilic, K. (2018). Fuzzy Analytic Hierarchy Process : A performance analysis of various algorithms. *Fuzzy Sets and Systems, 362*, 110–128. https://doi.org/10.1016/j.fss.2018.08.009

Ahmi, A., & Mohamad, R. (2016). Evaluating Accessibility of Malaysian Public Universities Websites Using Achecker and Wave. *Journal of Information and Communication Technology*, *15*(2), 193–214. http://repo.uum.edu.my/20878/JICT

Akincilar, A., & Dagdeviren, M. (2014). A hybrid multi-criteria decision making model to evaluate hotel websites. *International Journal of Hospitality Management*, *36,* 263–271. https://doi.org/10.1016/j.ijhm.2013.10.002

Alabool, H., Kamil, A., Arshad, N., & Alarabiat, D. (2018). Cloud Service Evaluation Method-based Multi-Criteria Decision-Making: A Systematic Literature Review. *Journal of Systems and Software*, *139,* 161–188. https://doi.org/10.1016/j.jss.2018

Alahmadi, T., & Drew, S. (2016). Accessibility Evaluation of Top-ranking University Websites in World , Oceania , and Arab Categories for Home , Admission , and Course Description Webpages. *Journal of Open, Flexible and Distance Learning*, *21*(1), 7–24. https://files.eric.ed.gov/fulltext/EJ1148198.pdf

Alghamdi, A. S., Al-badi, Al. H., Alroobaea, R., & Mayhew, P. A. M. J. (2013). A Comparative Study of Synchronous and Asynchronous Remote Usability Testing Methods. *International Review of Basic and Applied Sciences*, *1*(3), 61–97. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.800.5708=1&type=pdf

Almahamid, S. M., Tweiqat, A. F., & Almanaseer, M. S. (2016). University website quality characteristics and success : lecturers ' perspective. *International Journal of Business Information System*. *2*(1), 41–61.https://www.inderscienceonline.com

Alptekin, N., Hall, E. E., & Sevim, N. (2015). Evaluation of Websites Quality Using Fuzzy TOPSIS Method. *International Journal of Academic Research in Business and Social Sciences*, *5*(8), 221–242. https://doi.org/10.6007/IJARBSS/v5-i8/1778

Alroobaea, R., & Mayhew, P. J. (2014). How many participants are really enough for usability studies?*Proceedings of Science and Information Conference*. https://doi.org/10.1109

Amancio, D. R., Comin, C. H., Casanova, D., Travieso, G., Bruno, M., Rodrigues, F. A., & Costa, F. (2014). A Systematic Comparison of Supervised Classifiers. *Plus One, 9*(4). https://doi.org/10.1371/journal.pone.0094137

Amin, N., & Habib, A. (2015). Comparison of Different Classification Techniques Using WEKA for Hematological Data. *American Journal of Engineering Research*, *4*(3), 55–61. http://www.academia.edu/download/47617127/H043055061.pdf

Amini, F., & Rezaeenour, J. (2016). Ranking Healthcare Centers using Fuzzy Analytic Hierarchy Process and TOPSIS:Iranian Experience. *International Journal of Applied Operational Research*, *6*(1), 25–39. http://ijorlu.liau.ac.ir/files/admin-A-10-1-154-1f556a2.pdf

Arasid, W., Abdullah, A. G., Wahyudin, D., Abdullah, C. U., Widiaty, I., Zakaria, D., Amelia, N., & Juhana, A. (2018). An Analysis of Website Accessibility in Higher Education in Indonesia Based on WCAG 2.0 Guidelines. *IOP Conference Series: Materials Science and Engineering*, *306*(1), 0–8. https://doi.org/10.1088/1757-899X/306/1/012130

Aydin, S., & Kahraman, C. (2012). Evaluation of E-commerce Website Quality Using Fuzzy Multi-criteria Decision Making Approach. *AENG International Journal of Computer Science*, *39*(1). https://pdfs.semanticscholar.org/d9544c5fc75c7.pdf

Aydin, S., & Kahraman, C. (2011). A Modified Fuzzy Analytic Hierarchy Process Based Multicriteria Decision making Methodology for Assessing E-commerce Website Quality : A Case Study in Turkey. *World Congress on Engineering 2011*, *II*, 5–9. http://iaeng.org/publication/WCE2011/WCE2011_pp1174-1178.pdf

Aytuna, N., Karsak, B., & Albayrak, Y. E. (2012). A Proposed Model for the Turkish Political Parties Websites ' Efficiency : An Integrated Method using Analytic Hierarchy Process. *International Journal of Information Technology and Business Management*, *8*(1), 55–72.

Aziz, N. S., & Adzhar, K. (2015). Using Pre-Test to Validate the Questionnaire for Website Usability (QWU). *4th International Conference on Software Engineering and Computer Systems (ICSECS), Kuantan, Pahang, Malaysia.*, 107–111. https://ieeexplore.ieee.org/abstract/document/7333093/

Bakaev, M., Khvorostov, V., & Laricheva, T. (2017). Assessing Subjective Quality of Web Interaction with Neural Network as Context of Use Model. *International Conference on Digital Transformation and Global Society*, 185–195. https://doi.org/10.1007/978-3-319-69784-0

Bali, O., Burmaoğlu, S., & Kazançoğlu, Y. (2010). Performance Evaluation of Transportation Websites by using Fuzzy AHP. *International Logistics and Supply Chain Congress*, 168–173.

Begum, C., & Unal, D. (2019). Comparison of Data Mining Classification Algorithms Determining the Default Risk. *Scientific Programming*. https://www.hindawi.com

Behzadian, M., Khanmohammadi, S., Morteza, Y., & Ignatius, J. (2012). A state-of the-art survey of TOPSIS applications. *Expert Systems with Applications*, *39*(17), 13051–13069. https://doi.org/10.1016/j.eswa.2012.05.056

Bhardwaj, A., & Siddhu, K. K. (2013). An Approach to Medical Image Classification using Neuro Fuzzy Logic and ANFIS Classifier. *International Journal of Computer Trends and Technology*, *4*(3), 236–240.

Bijan, Y., & Salehi, M. (2013). Comparison of User Satisfaction of Ecommerce Websites by the Analytic Network Process. *International Journal of the Analytical Hierarchy Process*, *5*(2), 223–251. http://ijahp.org/index.php/IJAHP/article/view

Bilsel, R. U., Büyüközkan, G., & Ruan, D. (2006). A Fuzzy Preference-Ranking Model for a Quality Evaluation of Hospital Web Sites. *International Journal of Intelligent Systems*, *21*(21), 1181–1197. https://doi.org/10.1002/int.20177

Botella, P., Burgués, X., Carvallo, J. P., Franch, X., Grau, G., Marco, J., & Quer, C. (2004). ISO / IEC 9126 in practice : what do we need to know ? *Software Measurement European Forum*.

Boughorbel, S., Jarray, F., & El-anbari, M. (2017). Optimal classifier for imbalanced data using Matthews Correlation Coefficient metric. *PLoS ONE*, *12*(6), 1–17. https://doi.org/. https://doi.org/10.1371/journal. pone.0177678

Boza, B. C., Schiaffino, S., Teyseyre, A., & Godoy, D. (2014). An Approach for Knowledge Discovery in a Web Usability Context. *Brazilian Symposium on Human Factors in Computing Systems*, *13*, 393–396.

Brownlee, J. (2019). *A Gentle Introduction to Bayesin Belief Network*. Machine Learning Mastery. https://machinelearningmastery.com/introductionto-bayesian-belief-network

Buckley, J., Feuring, T., & Hayashi, Y. (2001). Fuzzy hierarchical analysis revisited. *European Journal of Operational Research 129*, *129*(1), 48–64. https://www.sciencedirect.com

Burmaoglu, S., & Kazancoglu, Y. (2012). E-government website evaluation with hybrid MCDM method in fuzzy environment. *International Journal Applied Decision Sciences*, *5*(2), 163–181. https://doi.org/10.1504/IJADS.2012.046504

Büyüközkan, G., Arsenyan, J., & Ertek, G. (2010). Evaluation of E-Learning Web Sites Using Fuzzy Axiomatic Design Based Approach. *International Journal of Computational Intelligence Systems*, *3*(1), 28–42. https://doi.org/10.1080/18756891.2010.9727675

Byun, D., & Finnie, G. (2011). An AHP method for evaluating usability of electronic government portals. *Electronic Government, An International Journal*, *8*(4), 343–362. https://doi.org/https://doi.org/10.1504/EG.2011.042811

Cairns, P. (2013). A Commentary on Short Questionnaires for Assessing Usability. *Interacting with Computers*, *25*(4), 312–316. https://doi.org/10.1093/iwc/iwt019

Calisir, F., Bayraktaroglu, A. E., Gumussoy, C. A., Topcu, Y. I., & Mutlu, T. (2009). The relative importance of usability and functionality factors for online auction and shopping web sites. *Online Information Review*, *34*(3), 420–439. https://doi.org/10.1108/14684521011037025

Camargo, F., Sano, E. E., Almeida, C. M., Mura, J. C., & Almeida, T. (2019). A Comparative Assessment of Machine-Learning Techniques for Land Use and Land Cover Classification of the Brazilian Tropical Savanna Using ALOS-2/PALSAR-Polarimetric Images. *Remote Sensing*, *11*(13), 1600. https://www.mdpi.com/2072-4292/11/13/1600/htm

Castro-Lopez, A., Puente, J., & Vazquez-Casielles, R. (2017). Fuzzy inference suitability to determine the utilitarian quality of B2C websites. *Applied Soft Computing Journal*, *57*, 132–143. https://doi.org/10.1016/j.asoc.2017.03.039

Çelik, P., & Cansu, G. K. (2017). Fuzzy AHP-Fuzzy PROMETHEE Approach In Evaluation of E-Service Quality: Case Of Airline Websites. *The Journal of International Social Research*, *10*(52), 1003–1013. https://doi.org/10.17719/jisr

Chen, W., Xie, X., Wang, J., Pradhan, B., Hong, H., & Tien, D. (2017). A comparative study of logistic model tree , random forest , and classification and regression tree models for spatial prediction of landslide susceptibility. *Catena*, *151*, 147–160. https://doi.org/10.1016/j.catena.2016.11.032

Chen, X., & Qiao, L. (2015). The Application of ANP Models in the Web-Based Course Development Quality Evaluation of Landscape Design Course. *International Journal of Multimedia and Ubiquitous Engineering*, *10*(9), 291–298. https://pdfs.semanticscholar.org/c4b0/1a6345c975cfd5a2ef20b723295b613c13fa.pdf

Chou, W., & Cheng, Y. (2012). A hybrid fuzzy MCDM approach for evaluating website quality of professional accounting firms. *Expert Systems With Applications*, *39*(3), 2783–2793. https://doi.org/10.1016/j.eswa.2011.08.138

Colkesen, I., & Kavzoglu, T. (2016). The use of logistic model tree (LMT) for pixel- and object-based classifications using high-resolution WorldView-2 imagery. *Geocarto International*, *32*(1), 71–86. https://doi.org/10.1080/10106049.2015

Cook, J. A. (2017). ROC curves and nonrandom data. *Pattern Recognition Letters*, *85*, 35–41. https://doi.org/10.1016/j.patrec.2016.11.015

Crystal, I. S. T. (2011). *A Fuzzy Analytic Hierarchy Process Evaluation of Hotel Websites* Hong Kong Polytechnic University].http://ira.lib.polyu.edu.hk/handle/10397/4687

Cybermetrics Labs. (2016). *Webometrics Ranking of World Universities*. https://www.webometrics.info/en/Africa/Nigeria

Cybermetrics Labs. (2017). *Webometrics Ranking of World Universities*. https://www.webometrics.info/en/africa/nigeria

Cybermetrics Labs. (2018). *Webometrics Rankings of world universities*. https://www.webometrics.info/en/Africa/Nigeria

Cybermetrics Labs. (2020). *webometrics ranking of world universities*. https://www.webometrics.info/en/Africa/Nigeria

Das, T., & Patil, S. R. (2014). A Review of Current Trends in Usability Evaluation Methods. *International Journal of Engineering Research & Technology (IJERT)*, *3*(9), 837–840. https://www.academia.edu/download/64322926/a-review-of-current-trends-in-usability-evaluation-methods-IJERTV3IS090873.pdf

Delice, E. K., & Gungor, Z. (2009). The usability analysis with heuristic evaluation and analytic hierarchy process. *International Journal of Industrial Ergonomics*, *39*(6), 934–939. https://doi.org/10.1016/j.ergon.2009.08.005

Demirel, T., Demirel, N. Ç., & Kahraman, C. (2008). Fuzzy AHP and its Applications. In C. Kahraman (Ed.), *Fuzzy Multi-Criteria Decision Making* (pp. 65–95). Springer.

Dey, S., Jana, B., Gourisaria, M. K., Mohanty, S. N., & Chatterjee, R. (2015). Evaluation of Indian B2C e-Shopping Websites under Multi Criteria Decision-Making using Fuzzy Hybrid Technique. *International Journal of Applied Engineering Research*, *10*(9), 24551–24580.

Diaby, V., Campbell, K., & Goeree, R. (2013). Multi-criteria decision analysis (MCDA) in health care : A bibliometric analysis. *Operations Research for Health Care*, *2*(1–2), 20–24. https://doi.org/10.1016/j.orhc.2013.03.001

Dingli, A., & Cassar, S. (2014). An intelligent framework for website usability. *Advances in Human-Computer Interaction*, *2014*. https://doi.org/10.1155/2014/479286

Djordj, N. D., Rančić, D. D., & Vulić, I. (2013). The Relative Importance of the Usability Factors for Web Portals. *Telecommunication in Modern Satellite, Cable and Broadcasting Services (TELSIKS)*, 571–574. https://doi.org/10.1109/.2013.670444

Dominic, P. D. ., Jati, H., & Hanim, S. (2013). University Website Quality Comparison by Using Non-parametric Statistical Test: A case study from Malaysia. *International Journal Operational Research*, *16*(3), 349–374. https://doi.org/10.1504/IJOR.201

Dominic, P. D. D., & Jati, H. (2011). A Comparison of Asian Airlines Websites Quality: Using a non-parametric test. *International Journal of Business Innovation and Research*, *5*(5), 599–623.

Dominic, P. D. D., & Jati, H. (2010). Evaluation Method of Malaysian University Website : Quality Website Using Hybrid Method. *Information Technology International Symposium*, 1–6. https://doi.org/10.1109/ITSIM.2010.5561363

Dominic, P. D. D., Jati, H., & Sellappan, P. (2011). A comparison of Asian e-government websites quality : using a non-parametric test. *International Journal of Business Information Systems*, *7*(2), 220–246. https://doi.org/10.1504/IJBIS.2011.038513

Doulah, S. U. (2019). Application of Machine Learning Algorithms in Bioinformatics. *Bioinformatics & Proteomics Open Access Journal*, *3*(1). https://medwinpublishers.com/BPOJ/BPOJ16000127.pdf

Ecer, F. (2014). A hybrid banking websites quality evaluation model using AHP and COPRAS-G : a Turkey case. *Technological and Economic Development of Economy*, *20*(4), 758–782. https://doi.org/10.3846/20294913.2014.915596

Efe, B. (2016). An Integrated Fuzzy Multi Criteria Group Decision Making Approach for ERP System Selection. *Applied Soft Computing Journal*, *38*, 106–117. https://doi.org/10.1016/j.asoc.2015.09.037

Eisavi, V., & Homayouni, S. (2017). Performance evaluation of random forest and support vector regressions in natural hazard change detection. *Journal of Applied Remote Sensing*, *10*(4). https://doi.org/10.1117/1.JRS.10.046030

Elias, I., Hernandez, R., & Shi, W. (2018). A Random Forests classification method for urban land-use mapping integrating spatial metrics and texture analysis. *International Journal of Remote Sensing*, *39*(4),1175–1198. https://doi.org/10.1080/01431161.2017.1395968

Ergu, D., Kou, G., Shi, Y., & Shi, Y. (2014). Analytic network process in risk assessment and decision analysis. *Computers and Operation Research*, *42*, 58–74. https://doi.org/10.1016/j.cor.2011.03.005

Esmeria, G. J., & Seva, R. R. (2017). Web Usability : A Literature Review. *De La Salle University Research Congress*. www.dlsu.edu.ph/conferences/dlsu-research-congress-proceedings/.../SEE-I-013.pdf

Fashoto, S. G., Akinnuwesi, B., Owolabi, O., & Adelekan, D. (2016). Decision support model for supplier selection in healthcare service delivery using analytical hierarchy process and artificial neural network. *African Journal of Business Management*, *10*(9), 209–232. https://doi.org/10.5897/AJBM2016.8030

Fernández-pérez, Y., Febles-estrada, A., Cruz, C., & Verdegay, L. J. (2018). Fuzzy Multi-criteria Decision Making Methods Applied to Usability Software Assessment :An Annotated Bibliography. In Berger-Vachon (Ed.), *Complex Systems: Solutions and Challenges in Economics, Management and Engineering, Studies in Systems, Decision and ControL* (pp. 165–189). sp.

Fernandez, A., Insfran, E., & Abrahão, S. (2011). Usability evaluation methods for the web : A systematic mapping study. *Information and Software Technology*, *53*(8), 789–817. https://doi.org/10.1016/j.infsof.2011.02.007

Freire, L. L., Arezes, P. M., & Campos, J. C. (2012). A literature review about usability evaluation methods for e-learning platforms. *Work*, *41*(SUPPL.1), 1038–1044. https://doi.org/10.3233/WOR-2012-0281-1038

Friedman, J., Hastie, T., & Tibshirani, R. (2000). Additive logistic regression: a statistical view of boosting (with discussion and a rejoinder by the authors). *The Annals of Statistics*, *28*(2), 337–407. https://projecteuclid.org/euclid.aos/1016218223

Galovicova, T., Kremenova, I., & Fabus, J. (2016). *Usability Evaluation of University Websites*.http://www.eunis.org/eunis2017/wpcontent/uploads/sites/10/2017/06/EUNIS_2017_paper_10.pdf

Garg, R., & Jain, D. (2017). Fuzzy Multi-Attribute Decision Making Evaluation of e-learning Websites Using FAHP, COPRAS, VIKOR, WDBA. *Decision Science Letters 6*, *6*, 351–364. https://doi.org/10.5267/j.dsl.2017.2.003

Goh, K. N., Chen, Y. Y., Lai, F. W., Daud, S. C., Sivaji, A., & Soo, S. T. (2013). A Comparison of Multiple Usability Testing Methods to Evaluate and Analyse An e-Commerce Website : A Malaysian Case Study on an Online Gift Shop. *10th International Conference on*

*Information Technology-New Generations.*

Govindan, K., & Jepsen, M. B. (2015). ELECTRE: A comprehensive literature review on methodologies and applications. *European Journal of Operational Research*, *250*(1), 1–29. https://doi.org/10.1016/j.ejor.2015.07.019

Granić, A., & Ćukušić, M. (2011). Usability testing and expert inspections complemented by educational evaluation: A case study of an e-learning platform. *Educational Technology and Society*, *14*(2), 107–123. https://www.jstor.org/stable/pdf

Granić, A., Mitrović, I., & Marangunić, N. (2011). Exploring the usability of web portals: A Croatian case study. *International Journal of Information Management*, *31*(4), 339–349. https://doi.org/10.1016/j.ijinfomgt.2010.11.001

Guimei, Z., & Taowei, Y. (2012). A Quantitative Research into the Usability Evaluation of China's E-Government Websites. *2nd International Congress on Computer Applications and Computational Science*, 437–442. https://link.springer.com

Guinalı, M., Gurrea, R., & Flavia, C. (2006). The role played by perceived usability , satisfaction and consumer trust on website loyalty. *Information Mangement*, *43*(43), 1–14. https://doi.org/10.1016/j.im.2005.01.002

Gulzar, M., Ali, A., & Naqvi, B. (2018). Performance Evaluation and Comparison of Classification Techniques for Outcome Estimation in Strategic Board Games. *International Journal of Computer Science and Network Security*, *18*(7), 103–110.

Gupta, S. (2015). A Comparative study of Usability Evaluation Methods. *International Journal of Computer Trends and Technology*, *22*(3), 103–106. http://www.ijcttjournal.org/2015/Volume22/number-3/IJCTT-V22P121.pdf

Hand, D. J., & Anagnostopoulos, C. (2013). When is the area under the receiver operating characteristic curve an appropriate measure of classifier performance ? *Pattern Recognition Letters*, *34*(5), 492–495. https://doi.org/10.1016/j.patrec.2012.12.004

Hanine, M., Boutkhoum, O., Tikniouine, A., & Agouti, T. (2016). Application of an integrated multi ‑ criteria decision making AHP ‑ TOPSIS methodology for ETL software selection. *SpringerPlus*, *5*(263), 1–17. https://doi.org/10.1186/s40064-016-1888-z

Hasan, L. (2013). Using University Ranking Systems to Predict Usability of University Websites. *Journal of Information Systems and Technology Management*, *10*(2), 235–250. https://doi.org/10.4301/S1807-17752013000200003

Hasan, L., & Abuelrub, E. (2013). Common Usability Problems on Educational Websites. *International Conference on Education and Educational Technologies Common*, 172–177. http://www.academia.edu/download/31809785/EET_201EET2013-Greece.pdf

Hasan, L., & Morris, A. (2017). Usability Problem Areas on Key International and Key Arab e-commerce Websites. *Journal of Internet Commerce*, *16*(1), 80–103. https://doi.org/10.1080/15332861.2017.1281706

Husin, R., Huda, N. A. C., & Othman, A. A. (2012). A Comparative Analysis on Methods for Measuring Web Usability. *3rd International Conference on Technology and Operations Management*, 978–979.

Hussain, M., & Kadhim, M. M. (2014). Design and Implementation of a Website Usability Model. *Al Mansour Journal*, *21*, 31–58. https://www.iasj.net/iasj

Hutcheson, G. D., & Sofroniou, N. (1999). *The Multivariate Social Scienctist.:Introductory statistics using generalised linera model*. Sage.

IEEE. (1990). *IEEE standard glossary of software engineering terminology*. IEEE. www.mit.jyu.fi/ope/kurssit/TIES462/Materiaalit/IEEE_SoftwareEngGlossary.pdf

Insfran, E., & Fernández, A. (2008). A Systematic Review of Usability Evaluation in Web Development. *Web Information Systems Engineering – WISE 2008 Workshops*, *5176*, 81–91. https://doi.org/10.1007/978-3-540-85200-1

Internet World Stats. (2020). *Internet World Stats Usage and Population statistics*. Group, Miniwatts Marketing. http://www.internetworldstats.com/stats1.htm#links

Ismail, A., & Kuppusamy, K. S. (2018). Accessibility of Indian universities ' homepages : An exploratory study. *Journal of King Saud University - Computer and Information Sciences*, *30*(2), 268–278. https://doi.org/10.1016/j.jksuci.2016.06

Ismailova, R., & Kimsanova, G. (2017). Universities of the Kyrgyz Republic on the Web : accessibility and usability. *Universal Access in the Information Society*, *16*(4), 1017–1025. https://doi.org/10.1007/s10209-016-0481-0

ISO/IEC 25010. (2011). Systems and software engineering Software product Quality Requirements and Evaluation (SQuaRE). ISO. http://iso25000.com/index.php

ISO. (1998). ISO 9241-11:Ergonomic requirements for office work with visual display terminals (vdts)-- Part 11: Guidance on usability. *ISO 9241-11: 1998, 1998*. https://www.evs.ee/preview/iso-9241-11-1998-en.pdf

ISO. (2001). *Software engineering -- product quality -- Part 1: Quality model*.

ISO. (2018). *Ergonomics of human-system interaction -- Part 11: Usability: Definitions and concepts*. ISO. https://www.iso.org/standard/63500.html

Jain, A., Sharma, V., & Sharma, V. (2017). Big data mining using supervised machine learning approaches for Hadoop with Weka distribution. *International Journal of Computational Intelligence Research*, *13*(8), 2095–2111.

Jain, D., Garg, R., & Bansal, A. (2015). A Parameterized Selection and Evaluation Of E- Learning Websites Using Topsis Method. *International Journal of Research & Development in Technology and Management Science –Kailash*, *22*(3), 12–26. http://journal.rtmonline.in/vol22iss3/0530111.pdf

Jain, D., Garg, R., Bansal, A., & Saini, K. K. (2016). Selection and ranking of e-Learning Websites using Weighted Distance-based Approximation. *Journal of Computers in Education*, *3*(2), 193–207. https://doi.org/10.1007/s40692-016-0061-6

Jano, Z., Noor, S. M., Ahmad, R., Md Saad, M. S., Saadan, R., Bokhari, M., & Abdullah, A. N. (2015). Website usability and cultural dimensions in Malaysian and Australian universities. *Asian Social Science*, *11*(9), 1–10. https://doi.org/10.5539/ass.v11n9p1

Jati, H., Nurkhamid, & Wardani, R. (2018). Quality Analysis of University Websites from Usability Side with Multicriteria Decision Analysis Method. *Journal of Physics*, *1140*(1). https://doi.org/10.1088/1742-6596/1140/1/012038

Joo, S., Lin, S., & Lu, K. (2011). A Usability Evaluation Model for Academic Library Websites: Efficiency, Effectiveness and Learnability. *Journal of Library and Information Studies*, *9*(2), 11–26. http://jlis.lis.ntu.edu.tw/article/v9-2-2.pdf

Kabak, M., & Burmaoğlu, S. (2013). A Holistic Evaluation of the e-procurement Website by using a Hybrid MCDM Methodology. *Electronic Government, An International Journal*, *10*(2), 125–150. https://doi.org/https://doi.org/10.1504/EG.2013.052598

Kabassi, K., Karydis, C., & Botonis, A. (2020). AHP , Fuzzy SAW , and Fuzzy WPM for the Evaluation of Cultural Websites. *Multimedia Technologies and Interaction*, *4*(1), 5-12

Kabir, G., & Hasin, M. A. A. (2012). Comparative Analysis of TOPSIS and Fuzzy TOPSISs for the Evaluation of Travel Website Service Quality. *International Journal for Quality Research*, *6*(3), 169–185.

Kabir, G., & Sutana, R. (2013). Evaluation of Travel Website Service Quality using Fuzzy TOPSIS. *Suranaree Journal of Science and Technology*, *20*(1), 21–33. https://www.researchgate.net/publication/267240857%0Aevaluation

Kalmegh, S. (2015). Analysis of WEKA Data Mining Algorithm REPTree , Simple Cart and RandomTree for Classification of Indian News. *International Journal of Innovative Science, Engineering & Technology*, *2*(2), 438–446.

Kalutara, P. L. (2013). *Development of an integrated decision - making model for the sustainable management of community buildings in Australia* [RMIT UNIVERSITY]. https://researchbank.rmit.edu.au/view/rmit:160788

Kargar, M. J. (2012). Role of Presentation Quality in University Website Ranking ; A Case Study in IRAN. *International Conference on Soft Computing and Its Applications*, 184–187. https://www.researchgate.net/profile/Mohammad_Shayegan_Fard/publication/264547262_Role_of_Presentation_Quality_in_University_Website_Ranking_A_Case_Study_in_IRAN/links/5c1b5dcd299bf12be38c9011/Role-of-Presentation-Quality-in-University-Website-Ranking-A-C

Kaur, G., & Chhabra, A. (2014). Improved J48 Classification Algorithm for the Prediction of Diabetes. *International Journal of Computer Applications, 98*(22). https://doi.org/10.5120/17314-7433

Kaur, S., Kaur, K., & Kaur, P. (2016a). An Empirical Performance Evaluation of Universities

Website. *International Journal of Computer Applications*, *146*(15), 10–16. https://doi.org/10.5120/ijca2016910922

Kaur, S., Kaur, K., & Kaur, P. (2016b). Analysis of Website Usability Evaluation Methods. *International Conference on Computing for Sustainable Global Development (INDIACom)*, 1043–1046. http://ieeexplore.ieee.org/abstract/document/7724420/

Kaya, T. (2010). Multi-attribute Evaluation of Website Quality in e-business using an Integrated Fuzzy AHP TOPSIS Methodology. *International Journal of Computational Intelligence Systems*, *3*(3), 301–314. https://doi.org/10.1080

Kaya, T., & Kahraman, C. (2011). A Fuzzy Approach to e-banking Website Quality Assessment Based on an Integrated AHP-ELECTRE Method. *Technological and Economic Development of Economy*, *17*(2), 37–41. https://doi.org/10.3846/202949

Khan, H., & Dominic, P. D. D. (2013). Measuring Quality of Asian Airline Websites Using Analytical Hierarchy Process : A Future Customer Satisfaction Approach. *Information Systems International Conference (ISICO)*, 67–72.

Kong, F., & Liu, H. (2005). Applying fuzzy analytic hierarchy process to evaluate success factors of e-commerce. *International Journal of Information and Systems Sciences*, *1*(3–4), 406–412. https://pdfs.semanticscholar.org/6d54/99b105f852edbb5433.pdf

Korvald, C., Kim, E., & Reza, H. (2014). Evaluation and implementation of machine learning techniques in usability testing for websites. *47th Annual Midwest Instruction and Computing Symposium*. http://www.micsymposium.org/mics2014

Kostoglou, V., Papathanasiou, J., & Moschidis, O. (2014). A comparative analysis of Greek universities ' presence on the World Wide Web using an analytical MCDM methodology. *International Journal of Multicriteria Decision Making*, *4*(3), 279–298. https://doi.org/https://doi.org/10.1504/IJMCDM.2014.064794

Kubler, S., Robert, J., Derigent, W., Voisin, A., & Le, Y. (2016). A State-of the-art Survey and Testbed of Fuzzy AHP (FAHP) Applications. *Expert Systems With Applications*, *65*, 398–422. https://doi.org/10.1016/j.eswa.2016.08.064

Kurilovas, E. (2019). Advanced machine learning approaches to personalise learning : learning analytics and decision making. *Behaviour & Information Technology*, *38*(4), 410–421. https://doi.org/10.1080/0144929X.2018.1539517

Lamichhane, R., & Meesad, P. (2011). A Usability Evaluation for Government Websites of Nepal Using Fuzzy AHP. In M. Phayung (Ed.), *I7th International Conference on Computing and Information Technology IC2IT2011* (pp. 99–104).

Law, R. (2007). A Fuzzy Multiple Criteria Decision-making Model for Evaluating Travel Websites. *Asia Pacific Journal of Tourism Research*, *12*(2), 147–159. https://doi.org/10.1080/10941660701243372

Lazar, J., Feng, J. H., & Hochheiser, H. (2017). *Research Methods in Human Computer Interaction* (T. Green (Ed.); second). Elsevier Inc.

Lee, C., Chiang, C., & Chen, C. (2012). An Evaluation Model of E-Service Quality by applying Hierarchical Fuzzy TOPSIS Method. *International Journal of Electronic Business Management*, *10*(1), 38–49. http://dblp.org/db/journals/ijebm10.html

Leung, D., Law, R., & Lee, H. A. (2016). A modified model for hotel website functionality evaluation. *Journal of Travel & Tourism Marketing*, *23*(9). https://doi.org/10.1080/10548408.2015.1117408

Lian, T., Yu, C., Wang, Z., & Hou, Z. (2017). The evaluation study on tourism websites : from the perspective of triangular intuitionistic fuzzy multiple attribute group decision making. *Journal of Applied Statistics*, *44*(16), 2877–2889. https://doi.org/10.1080/02664763.2016.1266466

Liang, R., Wang, J., & Zhang, H. (2017). Evaluation of e-commerce websites: An integrated approach under a single-valued trapezoidal neutrosophic environment. *Knowledge-Based Systems*, *135*, 44–59. https://doi.org/10.1016/j.knosys.2017.08

Lin, H. (2010). An Application of Fuzzy AHP for Evaluating Course Website Quality. *Computers & Education*, *54*(4), 77–88. https://doi.org/10.101j.compedu.2009.09

Madan, A., & Dubey, S. H. (2012). Usability Evaluation Methods : A Literature Review. *International Journal of Engineering Science and Technology*, *4*(2), 590–599.

Majrashi, K., & Hamilton, M. (2015). A Cross-Platform Usability Measurement Model. In *Lecture Notes on Software Engineering* 3(2) 132–144. https://doi.org/10.7763/LNSE.2015.V3.179

Manzoor, M., & Hussain, W. (2012). A Web Usability Evaluation Model for Higher Education Providing Universities of Asia. *Science, Technology and Development*, *31*(2),183–192. https://opus.lib.uts.edu.au/bitstream/10453/118304/1/183-192.pdf

Manzoor, M., Hussain, W., Ahmed, A., & Iqbal, M. J. (2012). The Importance of Higher Education Websites and its Usability. *International Journal of Basic and Applied Sciences*, *1*(2), 150–163. www.sciencepubco.com/index.php/IJBAS

Manzoor, M., Hussain, W., Sohaib, O., Hussain, F. K., & Alkhalaf, S. (2019). Methodological investigation for enhancing the usability of university websites. *Journal of Ambient Intelligence and Humanized Computing*, *10*(2), 531–549. https://doi.org/10.1007/s12652-018-0686-6

Markaki, O. I., Charilas, D. E., & Askounis, D. (2010). Application of Fuzzy Analytic Hierarchy Process to Evaluate the Quality of E-Government Web Sites. *Developments in E-Systems Engineering*, 219–224. https://doi.org/10.1109/DeSE

Masudin, I., & Saputro, T. E. (2016). Evaluation of B2C website based on the usability factors by using fuzzy AHP & hierarchical fuzzy TOPSIS. *IOP Conf. Series: Materials Science and Engineering*, *114*. https://doi.org/10.1088/1757-899X/114/1/012091

Mehrotra, D., Nagpal, R., & Bhatia, P. K. (2017). Identification of Criteria Affecting the Usability of Academic Institutes Websites. *International Journal of Technology Diffusion*, *8*(3), 20–40. https://doi.org/10.4018/IJTD.2017070102

Mentes, A., & Turan, A. (2012). Assessing the Usability of University Websites: An Empirical Study on Namik Kemal University. *The Turkish Online Journal of Educational Technology*, *11*(3), 61–69. https://eric.ed.gov/?id=EJ989199

Mich, L., French, M., & Cilone, G. (2003). The 2QCV3Q Quality model for the analysis of web site requirements. *Journal of Web Engineering*, *2*, 105–127.

Mirbargkar, S. M., & Zadmehr, O. (2015). Investigating the Quality of Electronic Services Using Multiple Attribute Decision- Making Techniques Case Study ( Aria , Ghaem ,and Golsar Hospitals). *Science Journal (CSJ)*, *36*(6), 1233–1240. http://dergi.cumhuriyet.edu.tr/cumuscij/article/view/5000139552

Monzer, M. Q. (2015). A Comparative Analysis of the Usability for Internet Banking in Saudi Arabia. *International Journal of Advanced Research in Computer Science and Software Engineering*,*5*(12),100–109. http://ijarcsse.com/docs/papers/

Moon, J. W., Jung, S. K., Lee, Y. O., & Choi, S. (2015). Prediction Performance of an Artificial Neural Network Model for the Amount of Cooling Energy Consumption in Hotel Rooms. *Energies*, *8*(8), 8226–8243. https://doi.org/10.3390/en8088226

Mosavi, A. (2014). Data mining for decision making in engineering optimal design. *Journal of AI and Data Mining*, *2*(1), 7–14. http://jad.shahroodut.ac.ir/article_125

Mvungi, J., & Tossy, T. (2015). Usability Evaluation Methods and Principles for the Web. *International Journal of Computer Science and Software Engineering*, *4*(7), 2409–4285.http://www.academia.edu/download/38356749/12_Paper_30061517_IJCSIS_Camera_Ready_pp._86-92.pdf

Nagpal, R., Mehrotra, D., & Bhatia, P. (2017). The State of Art in Website Usability Evaluation Methods. In S. Saeed, Y. A. Bamarouf, T. Ramayah, & S. Z. Iqbal (Eds.), *Design Solutions for User-Centric Information Systems* 1,275–296. IGI Global. www.igi-global.com

Nagpal, R., Mehrotra, D., & Bhatia, P. K. (2016a). Analytical Modelling Approach To Measure The Usability of Website. *International Journal of Software Engineering and Its Applications*,*10*(5),125–142. http://dx.doi.org/10.14257/ijseia.2016.10.5.1

Nagpal, R., Mehrotra, D., & Bhatia, P. K. (2016b). Usability evaluation of website using combined weighted method: fuzzy AHP and entropy approach. *International Journal of System Assurance Engineering and Management*, *7*(4), 408–417

Nagpal, R., Mehrotra, D., Bhatia, P. K., & Sharma, A. (2015a). FAHP Approach to Rank Educational Websites on Usability. *International Journal of Computing and Digital Systems*, *4*(4), 251–260. https://doi.org/10.12785/ijcds/040404

Nagpal, R., Mehrotra, D., Bhatia, P., & Sharma, A. (2015b). Rank University Websites Using Fuzzy AHP and Fuzzy TOPSIS Approach on Usability. *International Journal of Information Engineering and Electronic Business*, *10*(1), 29–36. https:///10.5815/ijieeb

Nawaz, A., & Clemmensen, T. (2013). Website Usability in Asia ‘from Within’: An Overview of a Decade of Literature. *International Journal of Human-Computer Interaction*, *29*(4), 256–

273. https://doi.org/10.1080/10447318.2013.765764

Nayebi, F. (2015). *iOS Application User Rating Prediction Using Usability Evaluation and Machine Learning* [(Doctoral dissertation, École De Technologie Superieure Universite Du Quebec, Canada)]. https://espace.etsmtl.ca/id/eprint/1496/

Niazi, M. G., Karbala, M., & Kamran, A. (2020). Presenting a proposed framework for evaluating university websites. *The Electronic Library*, *38*(5), 881–904. https://doi.org/10.1108/EL-06-2020-0141

Nielsen, Jacob. (2012). Usability 101: Introduction to Usability. *Nielsen Norman Group*. https://www.nngroup.com/articles/usability-101-introduction-to-usability/

Nielsen, Jakob. (1994). Usability inspection methods. *Conference Companion on Human Factors in Computing Systems*- 413–414. https://doi.org/10.1145/259963.260

Nirmala, G., & Uthra, G. (2017). Quality of Online Shopping Websites in India : A Study Using Intuitionistic Fuzzy AHP. *Journal of Advance Research in Dynamical & Control Systems*, *9*(4), 117–124.

NUC. (2021, January). List of Approved Universities In Nigeria. *National Unversity Commisison*, 1–23. http://nuc.edu.ng/wp-content/uploads/2020/01/MB-13th-Jan-2020_compressed.pdf

Okello-Obura, C. (2015). Assessment of Quality of East African Governments Websites and Support to SMEs in Business Information Provision. *Library Philosophy and Practice*, *1213*, 1–26. http://citeseerx.ist.psu.edu/10.1.1.1024.3627ep1&type=pdf

Otunaiya, K. A., & Muhammad, G. (2019). Performance of Datamining Techniques in the Prediction of Chronic Kidney Disease. *Computer Science and Information Technology*, *7*(2), 48–53. https://doi.org/10.13189/csit.2019.070203

Özkan, B., Özceylan, E., Kabak, M., & Dağdeviren, M. (2020). Evaluating the websites of academic departments through SEO criteria : a hesitant fuzzy linguistic MCDM. *Artificial Intelligence Review*, *53*(2), 875–905. https://doi.org/10.1007/s10462-019-09681-z

Oztekin, A., Delen, D., Turkyilmaz, A., & Zaim, S. (2013). A Machine Learning-based Usability Evaluation Method for e-Learning Systems. *Decision Support Systems*, *56*(1), 63–73. https://doi.org/10.1016/j.dss.2013.05.003

Parimala, C., & Porkodi, R. (2018). Classification Algorithms in Data Mining : A Survey. *International Journal of Scientific Research in Computer Science*, *3*(1), 349–355.

Parmar, A., Katariya, R., & Vatsal, P. (2018). A review on random Forests An ensemble classifier. *International Conference on Intelligent Data Communication Technologies and Internet of Things*, 758–763. https://link.springer.com/chapter/10.1007/978-3-030-03146-6_86

Pathania, A., & Rasool, G. (2017). Investigating e tailer's perceived Website Quality using Analytical Hierarchy Process Technique. *Procedia Computer Science*, *122*, 1016–1023. https://doi.org/10.1016/j.procs.2017.11.468

Patil, T. R., & Sherekar, S. S. (2013). Performance Analysis of Naive Bayes and J48 Classification Algorithm for Data Classification. *International Journal Of Computer Science And Applications*, *6*(2), 256–261. http://www.researchpublications.org

Paz, F., & Pow-Sang, J. A. (2016). A Systematic Mapping Review of Usability Evaluation Methods for Software Development Process. *International Journal of Software Engineering and Its Applications*, *10*(1), 165–178. http://d/ijseia.2016.10.1.16

Paz, F., & Pow-Sang, J. A. (2014). Current Trends in Usability Evaluation Methods: A Systematic Review. *7th International Conference on Advanced Software Engineering and Its Applications (ASEA)*, 11–15. https://doi.org/10.1109/ASEA.2014.10

Pearson, J. M., & Pearson, A. M. (2008). An Exploratory Study into Determining the Relative Importance of Key Criteria in Web Usability : A Multi-Criteria Approach. *Journal of Computer Information Systems*, *48*(4), 115–127. https://doi.org/10.1080/08874417

Peker, S., Kucukozer-Cavdar, S., & Cagiltay, K. (2016). Exploring the relationship between web pesence and web usability for universities: A case study from Turkey. *Program*, *50*(2), 157–174. https://doi.org/10.1108/PROG-04-2014-0024

Petkovic, D., Altman, R., Wong, M., & Vigil, A. (2018). Improving the explainability of Random Forest classifier – user centered approach. *Pacific Symposium on Biocomputing*, 204–215.

Pohekar, S. D. Ã., & Ramachandran, M. (2004). Application of multi-criteria decision making to sustainable energy planning: A review. *Renewable and Sustainable Energy Review*, *8*, 365–381. https://doi.org/10.1016/j.rser.2003.12.007

Presley, A., & Fellows, P. (2013). An analytic hierarchy process model for evaluating and comparing website usability. *International Journal of Business Information Systems*, *12*(2), 123–139. https://doi.org/10.1504/IJBIS.2013.052047

Qi, S., Law, R., & Buhalis, D. (2017). Comparative evaluation study of the websites of China-based and international luxury hotels. *Journal of China Tourism Research*, *13*(1), 1–25. https://doi.org/10.1080/19388160.2017.1289135

Quiñones, D., & Rusu, C. (2017). How to Develop Usability Heuristics : A Systematic Literature Review. *Computer Standards & Interfaces*, *53*, 89–122. https://doi.org/10.1016/j.csi.2017.03.009

Rahman, M., Ningsheng, C., Islam, M., Dewan, A., & Iqbal, J. (2019). Flood Susceptibility Assessment in Bangladesh using Machine Learning and Multi‑criteria Decision Analysis. *Earth Systems and Environment*, *3*(3), 585–601. https://doi.org/10.1007/s41748-019-00123-y

Rajapaksha, T. I., & Fernando, L. S. (2016). An analysis of the standards of the government websites of Sri Lanka. *Transforming Government: People, Process and Policy*. https://doi.org/10.1108/TG-09-2013-0036

Raju, K. S., Kumar, D. N., & Duckstein, L. (2006). Artificial Neural Networks and Multicriterion analysis for sustainable irrigation planning. *Computers & Operations Research*, *33*(33), 1138–1153. https://doi.org/10.1016/j.cor.2004.09.1

Ramesh, D., Pasha, S. N., & Roopa, G. (2017). A Comparative Analysis of Classification Algorithms on Weather Dataset Using Data Mining Tool. *Oriental Journal of Computer Science and Technology*, *10*(4), 788–792.

Rani, M. D. K., & Sakthivel, S. (2015). Analytical Hierarchy Process – Study on its Applicability on Web Based Environment. *International Journal of Software Engineering and Its Applications*, *9*(4), 37–46. http://dx.doi.org/10.14257

Rekik, R., & Kallel, I. (2013). Fuzz-Web : A Methodology Based on Fuzzy Logic for Assessing Web Sites. *International Journal of Computer Information Systems and Industrial Management Applications.*, *5*(2012), 126–136. http://www.mirlabs.net/ijcisim/index.html

Rekik, R., Kallel, I., & Alimi, A. M. (2016). Ranking Criteria based on Fuzzy ANP for Assessing E-commerce Web Sites. *IEEE International Conference on Systems, Man, and Cybernetics*, 3469–3474. https://doi.org/10.1109/SMC.2016.7844770

Rekik, R., Kallel, I., Casillas, J., & Alimi, A. M. (2016). Using Multiple Criteria Decision Making Approaches to Assess the Quality of Websites. *International Journal of Computer Science and Information Security*, *14*(7), 747–761. http://150.214.190.154/sites/default/files/ficherosPublicaciones/2342_casillas-a35-ijcsis16.pdf

Rendleman, M. C., Buatti, J. M., Braun, T. A., Smith, B. J., Nwakama, C., Beichel, R. R., Brown, B., & Casavant, T. L. (2019). Machine learning with the TCGA-HNSC dataset : improving usability by addressing inconsistency , sparsity , and high- dimensionality. *BMC Bioinformatics*, *20*(1), 1–9. https://doi.org/10.1186/s12859-019-2929-8

Rosson, M. B., & Caroll, J. M. (2002). Usability engineering: scenario-based development of Human-Computer Interaction. In K. Morgan (Ed.), *4th conference on Designing interactive systems: processes, practices, methods, and techniques* (1st ed.).

Roy, S., Kumar, P., & Rajib, P. (2016). Quality assurance of academic websites using usability testing : an experimental study with AHP. *International Journal of System Assurance Engineering and Management*, *8*(1), 1–11. https://doi.org/10.1007/s13198-016-0436-0

Roy, S., Pattnaik, P. K., & Mall, R. (2014). A Quantitative Approach to Evaluate Usability of Academic Websites based on Human Perception. *Egyptian Informatics Journal*, *15*(3), 159–167. https://doi.org/10.1016/j.eij.2014.08.002

Saaty, T.L., & Vargas, L. G. (2012). The Seven Pillars of the Analytic Hierarchy Process. In *Models, Methods, Concepts & Applications of the Analytic Hierarchy Proces* (pp. 23–40). Springer. https://doi.org/10.1007/978-1-4614-3597-6

Saaty, Thomas L., & Ozdemir, M. S. (2003). Why the Magic Number Seven Plus or Minus Two. *Mathematical and Computer Modelling*, *38*(2–4), 233–244. https://www.sciencedirect.com/science/article/pii/S0895717703900835

Saaty, Thomas L. (2008). Decision Making with the Analytic Hierarchy Process. *International*

*Journal of Services Sciences*, *1*(1), 83–98. https://www.inderscienceonline.com/doi/abs/10.1504/IJSSci.2008.01759

Saber Iraji, M., & Mosaddegh, R. (2013). Object Oriented Software Usability Estimate with Adaptive Neuro Fuzzy, Fuzzy Svm. *International Journal of Information Engineering and Electronic Business*, *5*(1), 40–49. https://doi.org/10.5815/ijieeb.2013.01.05

Sagar, K., & Saha, A. (2017). Qualitative usability feature selection with ranking: a novel approach for ranking the identified usability problematic attributes for academic websites using data-mining techniques. *Human-Centric Computing and Information Sciences*, *7*(1), 1–24. https://doi.org/10.1186/s13673-017-0111-8

Saito, T., & Rehmsmeier, M. (2015). The Precision-Recall Plot is more Informative than the ROC Plot when Evaluating Binary Classifiers on Imbalanced Datasets. *PLoS ONE*, *10*(3), 1–21. https://doi.org/10.1371/journal.pone.0118432

Salimi, N., & Rezaei, J. (2015). Multi-criteria university selection: Formulation and implementation using a Fuzzy AHP. *Journal of Systems Science and Systems Engineering*, *24*(3), 293–315. https://doi.org/10.1007/s11518-015-5271-3

Saro, L., Woo, J. S., Kwan-young, O., & Moung-jin, L. (2016). The spatial prediction of landslide susceptibility applying arti cial neural network and logistic regression models : A case study of Inje , Korea. *Open Geosciences*, *8*(1), 117–132. https://doi.org/10.1515/geo-2016-0010

Sarsarabi, S. S., & Sarsarabi, A. H. (2015). Promoting University Website Based on Webometrics. *1st Global Conference On Technology In Language Learning*, 1–10. http://worldconferences.net/

Sauro, J., & Lewis, J. R. (2012). Standardized Usability Questionnaires. In *Quantifying the User Experience*. Elsevier B.V. https://doi.org/10.1016/B978-0-12-384968-7.00008-4

Seffah, A., Donyaee, M., Kline, R. B., & Padda, H. K. (2006). Usability measurement and metrics : A consolidated model. *Software Quality Journal*, *14*, 159–178. https://doi.org/10.1007/s11219-006-7600-8

Sekaran, U., & Bougie, R. (2016). *Research Methods for Business: A Skill Building Approach*. John Wiley and Sons.

Shahin, A., Pool, J. K., & Poormostafa, M. (2014). Evaluating and ranking hotels offering e-service by integrated approach of Webqual and fuzzy AHP. *International Journal of Business Information Systems*, *15*(1), 84–104. https://www.inderscienceonline.com/doi/abs/10.1504/IJBIS.2014.057966

Shakil, K. A., Anis, S., & Alam, M. (2015). Dengue disease prediction using weka data mining tool. *ArXiv Preprint ArXiv*. https://arxiv.org/abs/1502.05167

Shawgi, E., & Noureldien, N. A. (2015). Usability Measurement Model (UMM ): A New Model for Measuring Websites Usability. *International Journal of Information Science*, *5*(1), 5–13. https://doi.org/10.5923/j.ijis.20150501.02

Sheng-li, S., Xiao-yue, Y., Hu-chen, L., & Zhang, P. (2018). DEMATEL Technique : A Systematic Review of the State-of-the-Art Literature on Methodologies and Applications. *Mathematical Problems in Engineering*, *1*. https://doi.org/10.1155/2018/3696457

Shrivastava, R. (2019). Ranking Usability Metrics using Intuitionistic Preference Relations and Group Decision Making. In M. N. Hoda (Ed.), *Software Engineering, Advances in Intelligent Systems and Computing* (pp. 671–679). Springer Singapore. https://doi.org/10.1007/978-981-10-8848-3

Simon, N., Carbonera, B. J., & Custodio, B. (2017). A Comparative Study on the Usability of Educational Platforms Used by Instructors in the University of the Philippines. In I. K. Jussi, T. Barath, N. Salman, & T. Andre (Eds.), *Advances in Human Factors, Business Management, Training and Education* (pp. 187–194). Springer Cham. https://doi.org/https://doi.org/10.1007/978-3-319-42070-7_18

Soleymaninejad, M., Shadifar, M., & Karimi, A. (2016). Evaluation of Two Major Online Travel Agencies of US Using TOPSIS Method. *Digital Technologies*, *2*(1), 1–8. https://doi.org/10.12691/dt-2-1-1

Speicher, M. (2015). What is Usability? A Characterization based on ISO 9241-11 and ISO/IEC 25010. *ArXiv Preprint ArXiv*, 1–10. http://arxiv.org/abs/1502.06792

Stanujkic, D., Paunovic, M., & Stankovic, G. (2014). Multi-criteria model for evaluating quality of websites of the regional tourism organizations. *International Conference on Information and Software Technologies*, 311–316. https://doi.org/10.13140/2.1.1498.7846

Stoimenova, S. T., & Christozov, D. (2013). Informing via Websites : Comparative Assessment of University Websites. *Informing Science and Information Technology Education Conference*, 25–537. https://www.learntechlib.org/p/1146

Subair, S. (2014). Assessing the usability of Institutions Web Pages. *International Journal of Internet and Distributed Systems*, *2*(3), 15–21. https://doi.org/10.4236/ijids.2014.23003

Subair, S., & Aleisa, H. (2016). Statistical Models for Web Pages Usability. *Journal of Data Analysis and Information Processing*, *4*, 40–54. https://doi.org/10.4236/jdaip.2016.41004

Sun, C., & Lin, G. (2009). Using fuzzy TOPSIS method for evaluating the competitive advantages of shopping websites. *Expert Systems With Applications*, *36*(9), 11764–11771. https://doi.org/10.1016/j.eswa.2009.04.017

Sun, S., Fong, D. K. C., Law, R., & He, S. (2017). An updated Comprehensive Review of Website evaluation Studies in Hospitality and Tourism. *International Journal of Contemporary Hospitality Management*, *29*(1), 355–373. https://doi.org/10.1108/IJCHM-12-2015-0736

Taha, Z., & Rostam, S. (2012). A hybrid fuzzy AHP-PROMETHEE decision support system for machine tool selection in flexible manufacturing cell. *Journal of Intelligent Manufacturing*, *23*(6), 2137–2149. https://doi.org/10.1007/s10845-011-0560-2

Taj, S., Mahoto, N. A., & Farah, I. (2019). Product Usability Evaluation : A Machine Learning Approach. !*!St International Conference on Computational Sciences and Technologies*.

https://www.researchgate.net/publication/332343638_Product_Usability_Evaluation_A_Machine_Learning_Approach

Tavanaa, M., Yazdanic, M., & Caprio, D. Di. (2017). An Application of an Integrated ANP-QFD Framework for Sustainable Supplier Selection. *International Journal of Logistics: Research and Applications*, *20*(3), 254–275. https://doi.org/10.1080/13675567.2016.1219702

Tolga, A. C. (2018). Evaluation of ERP softwares with fuzzy AHP integrated TODIM method. *Sakarya University Journal Of Science*, *22*(5), 1–19. https://dergipark.org.tr/en/download/article-file/450388

Trigila, A., Iadanza, C., Esposito, C., & Scarascia-mugnozza, G. (2015). Comparison of Logistic Regression and Random Forests techniques for shallow landslide susceptibility assessment in Giampilieri (NE Sicily, Italy). *Geomorphology*, *249*, 119–136. https://doi.org/10.1016/j.geomorph.2015.06.001

Tsai, W., Chou, W., & Lai, C. (2010). An effective evaluation model and improvement analysis for national park websites : A case study of Taiwan. *Tourism Management*, *31*(6), 936–952. https://doi.org/10.1016/j.tourman.2010.01.016

Ulutaş, A. (2019). University Website Performance Evaluation Using Fuzzy SWARA and WASPAS-F. In *Multi-Criteria Decision-Making Models for Website Evaluation* (pp. 151–165). IGI Global. https://doi.org/10.4018/978-1-5225-8238-0.ch008

Vatansever, K., & Akgu, Y. (2014). Applying Fuzzy Analytic Hierarchy Process For Evaluating Service Quality Of Private Shopping Website Quality: A Case Study In Turkey. *Journal of Business, Economics and Finance*, *3*(3), 283–301. http://dergipark.gov.tr/jbef/issue/32410/360451

Venkatesan, N., & Priya, G. (2015). A Study of Random Forest Algorithm with implemetation using Weka. *International Journal of Innovative Research in Computer Science and Engineering*, *1*(6), 156–162.

Wen-Hsien, T., Jun-Der, L., & Wen-Chin, C. (2009). The Development of an Evaluation Model of E-Commerce Websites for the Taiwanese Airline Industry. *Development*, *1*, 1–2009. https://pdfs.semanticscholar.org/234b/d3b742f7e678a1fd48ee2581.pdf

Yang, X.-S. (2019). *Introduction to Algorithms for data mining and machine learning* (S. Bentley (Ed.)). Candice Janco. https://b-ok.africa/dl/5208178/1e03c9

Yerlikaya, Z., & Durdu, O. (2017). Usability of University Websites : A Systematic Review. In M.Antona & C.Stephanidis (Eds.), *Universal Access in the Information Society* (Vol. 4, pp. 277–287). Springer International Publishing. https://doi.org/10.1007/978-3-319-58706-6

Yi-wen, L., Kwon, Y., & Kang, B. (2007). A Fuzzy AHP approach to evaluating e-commerce websites. *Fifth International Conference on Software Engineering Research and Applications*, 114–122. https://doi.org/10.1109/SERA.2007.29

Younghwa, L., & Kenneth, K. A. (2006). Investigating the effect of website quality on e-business success : An analytic hierarchy process ( AHP ) approach. *Decision Support Systems*, *42*, 1383–1401. https://doi.org/10.1016/j.dss.2005.11.005

Yu, X., Guo, S., Guo, J., & Huang, X. (2011). Rank B2C e-commerce websites in e-alliance based on AHP and fuzzy TOPSIS. *Expert Systems With Applications*, *38*(4), 3550–3557. https://doi.org/10.1016/j.eswa.2010.08.143

Zaim, H., Ramdani, M., & Haddi, A. (2016). Multi-Criteria Analysis Approach based on Consumer Satisfaction to Rank B2C e-commerce Websites. *2016 11th International Conference on Intelligent Systems: Theories and Applications*, 1–6. https://doi.org/10.1109/SITA.2016.7772260

Zare, M., Pahl, C., Rahnama, H., Nilashi, M., Mardani, A., Ibrahim, O., & Ahmadi, H. (2016). Multi-Criteria Decision Making Approach in E-Learning: A Systematic Review and Classification. *Applied Soft Computing Journal*, *45*, 108–128. https://doi.org/10.1016/j.asoc.2016.04.020

Zavadskas, K., Turskis, Z., & Simona, K. (2014). State of Art Surveys of Overviews on MCDM/MADM Methods. *Technological and Economic Development of Economy*, *20*(1), 165–179. https://doi.org/10.3846/20294913.2014.892037

Zer, F. I., Windarto, A. P., & Wanto, A. (2019). Analysis of the ELECTRE Method on the Selection of Student Creativity Program Proposals. *Journal of Physics*, *1255*(1), 01-20. https://doi.org/10.1088/1742-6596/1255/1/012011

Zhang, Y., Zhao, X., Feng, L., & Li, X. (2015). The Usability Evaluation of the Ecological Agriculture Park Website. *International Journal of Multimedia and Ubiquitous Engineering*, *10*(12), 53–60. https://doi.Sorg/10.14257/ijmue.2015.10.12.06

Zyoud, S. H., & Fuchs-hanusch, D. (2017). A bibliometric-based survey on AHP and TOPSIS techniques. *Expert Systems With Applications*, *78*, 158–181. https://doi.org/10.1016/j.eswa.2017.02.016

## APPENDIX A

## PUBLICATIONS

Adepoju, S. A., Oyefolahan, I. O., Abdullahi, M. B., & Mohammed, A. A. (2018). Integrated Usability Evaluation Framework for University Websites. *Proceedings of the 2nd*

*international conference on Information and Communication Technology Applications (ICTA),* Federal University of Technology Minna

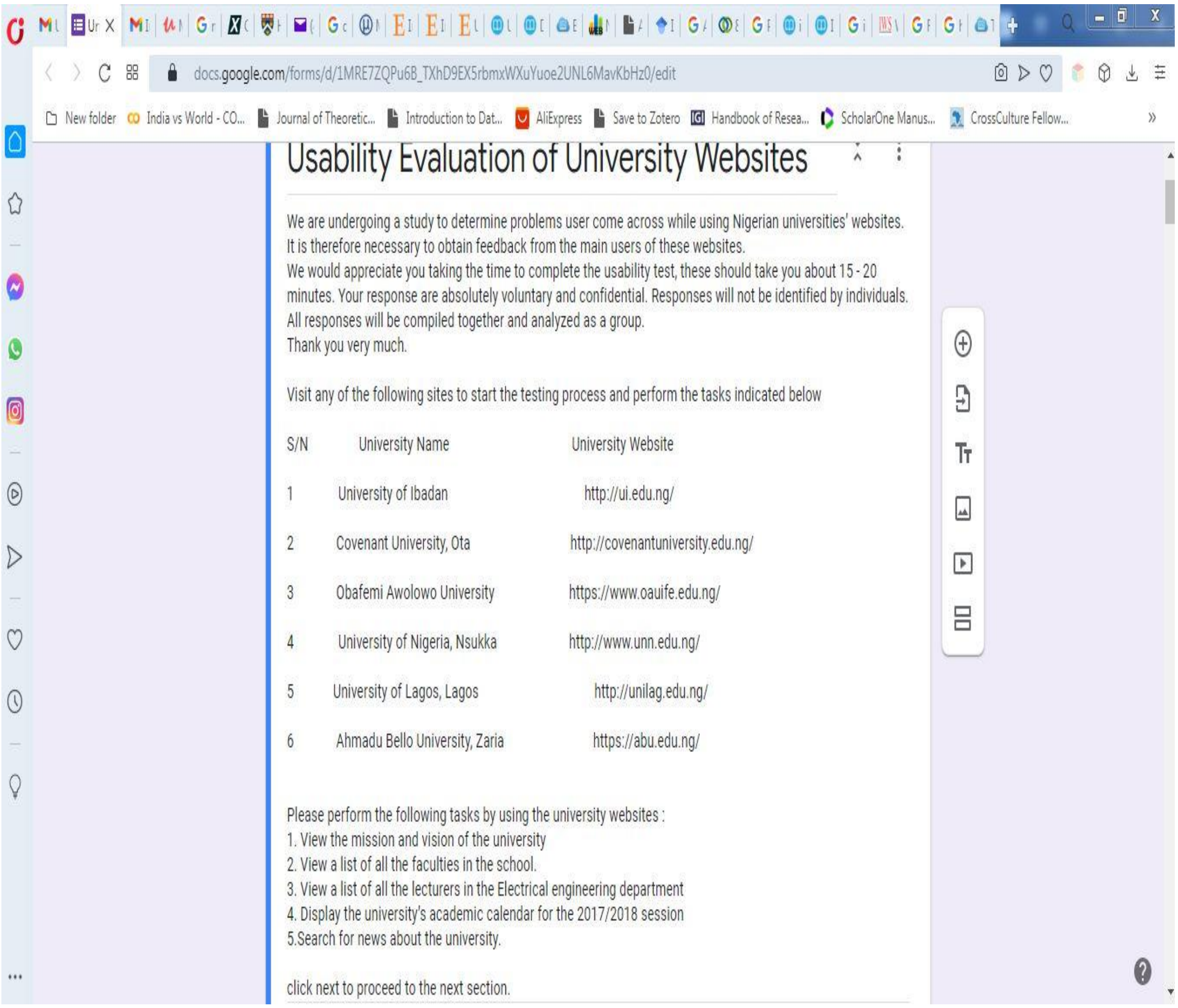
Adepoju, S. A., Oyefolahan, I. O., Abdullahi, M. B., & Mohammed, A. A. (2019). A Survey of Research Trends on University Websites' Usability Evaluation. *i-Manager's Journal on Information Technology*, 8(2). 11-19

Adepoju, S. A., Oyefolahan, I. O., Abdullahi, M. B., Mohammed, A. A., & Ibiyo, M. (2020). A Human-Centered Usability Evaluation of University Websites Using SNECAAS Model. *In Handbook of Research on the Role of Human Factors in IT Project Management* (pp. 173-185). IGI Global.

Adepoju, S. A., Oyefolahan, I. O., Abdullahi, M. B., & Mohammed, A. A. (2020). Multi-Criteria Decision-Making Based Approaches in Website Quality and Usability Evaluation: A Review. *Journal of Information and Communication Technology* 19(3) 399-436

## APPENDIX B

**QUESTIONNAIRE FOR PHASE ONE OF THE STUDY**



docs.google.com/forms/d/1MRE7ZQPu6B_TXhD9EX5rbmxWXuYuoe2UNL6MavKbHz0/edit

# Usability Evaluation of University Websites

We are undergoing a study to determine problems user come across while using Nigerian universities' websites.
It is therefore necessary to obtain feedback from the main users of these websites.
We would appreciate you taking the time to complete the usability test, these should take you about 15 - 20 minutes. Your response are absolutely voluntary and confidential. Responses will not be identified by individuals.
All responses will be compiled together and analyzed as a group.
Thank you very much.

Visit any of the following sites to start the testing process and perform the tasks indicated below

| S/N | University Name | University Website |
|---|---|---|
| 1 | University of Ibadan | http://ui.edu.ng/ |
| 2 | Covenant University, Ota | http://covenantuniversity.edu.ng/ |
| 3 | Obafemi Awolowo University | https://www.oauife.edu.ng/ |
| 4 | University of Nigeria, Nsukka | http://www.unn.edu.ng/ |
| 5 | University of Lagos, Lagos | http://unilag.edu.ng/ |
| 6 | Ahmadu Bello University, Zaria | https://abu.edu.ng/ |

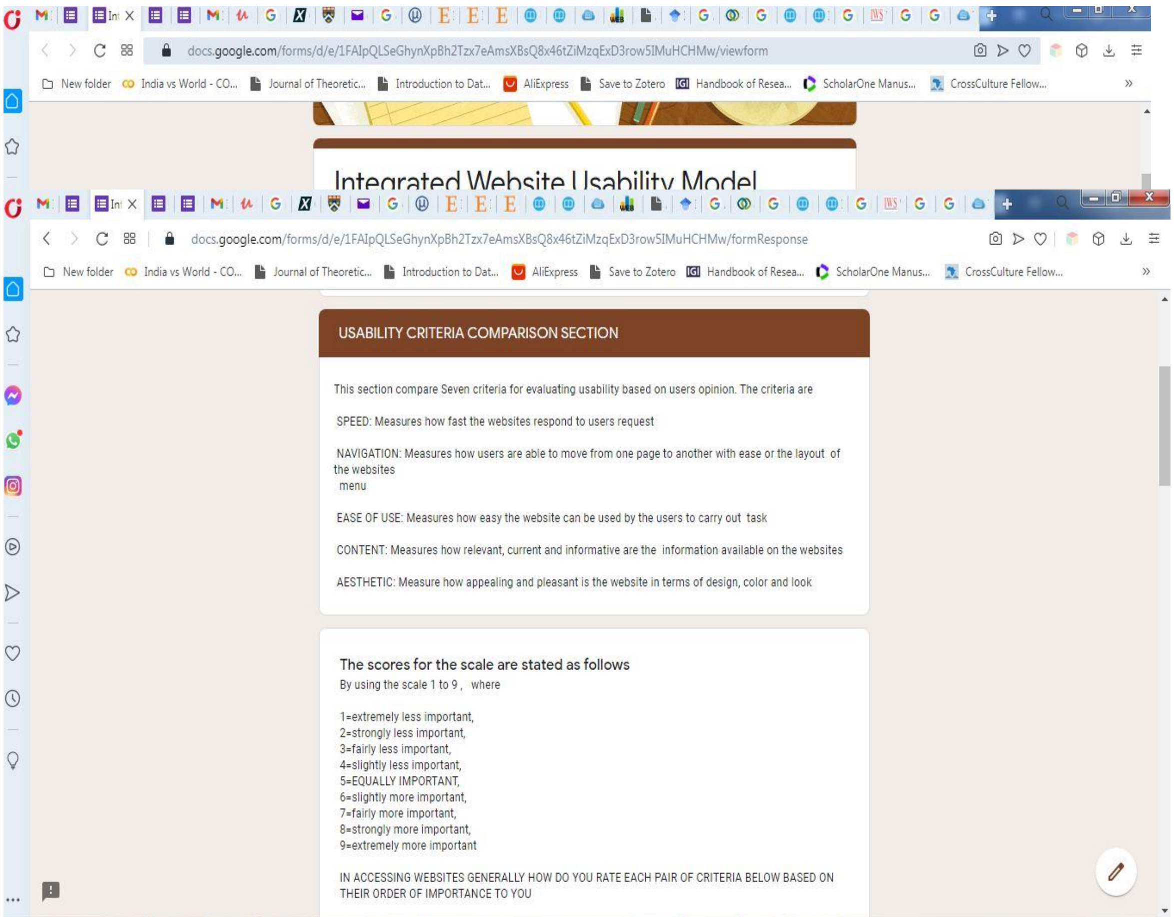
Please perform the following tasks by using the university websites :
1. View the mission and vision of the university
2. View a list of all the faculties in the school.
3. View a list of all the lecturers in the Electrical engineering department
4. Display the university's academic calendar for the 2017/2018 session
5.Search for news about the university.

click next to proceed to the next section.

| Questions | | | | | | |
|---|---|---|---|---|---|---|
| **SPEED** | | SA | A | N | D | SD |
| 1. | I need not wait too long to open a page | | | | | |
| 2. | I am able to quickly complete my work using site. | | | | | |
| 3. | I need not wait too long to download a file, | | | | | |
| **NAVIGATION** | | | | | | |
| 4. | I can easily navigate this site | | | | | |
| 5. | I can easily know where I am at this website | | | | | |
| **6.** | The website does not open too many new windows when I am moving around? | | | | | |
| **7.** | I don't need to scroll left or right on the website. | | | | | |
| **EASE OF USE** | | | | | | |
| **8.** | The website is easy to use | | | | | |
| **9.** | I can use the website without a guide. | | | | | |
| **10.** | The websites require few steps to accomplish tasks | | | | | |
| **CONTENT** | | | | | | |
| **11.** | The information provided on this website is sufficient for me | | | | | |
| **12.** | Content like academic news, publication date is up-to date | | | | | |
| **13.** | The website offers easy access to require details like contact nos., email address, postal address etc. of the university | | | | | |
| **ACCESSIBILITY** | | | | | | |
| **14.** | The website provides alternative text presentation | | | | | |
| **15.** | The website is capable of full functionality via only keyboard | | | | | |
| **16.** | The navigation is designed to assist user in finding content and determine where they are | | | | | |
| **AESTHETICS** | | | | | | |
| **17.** | The website's interface design is attractive? | | | | | |
| **18.** | The website has a clean and simple presentation | | | | | |
| **19.** | I am comfortable with the colours used at this website? | | | | | |
| **SECURITY** | | | | | | |
| **20.** | The website is reachable exclusively over HTTPS. | | | | | |
| **21.** | The university's website shows a warning message related to malicious software etc.? | | | | | |

## APPENDIX C

## QUESTIONNAIRE FOR PHASE TWO OF THE STUDY




Dear Participant,

We are carrying out research on the usability evaluation ranking and assessment of some university websites in Nigeria. Multi Criteria Decision Analysis will be used to model the results of the data collected from the participant. Evaluating usability of websites is complex as it involves many criteria. To get the best websites the criteria need to be evaluated against each website based on user interaction with the websites.

Based on this, the study aims at identifying and evaluate preferable websites based on the criteria As part of this research, multi criteria analysis is being conducted in order to elicit users and stakeholders' opinions for evaluating alternatives websites based on the criteria identified from literature.

In the following pages we would like to obtain your opinion as an expert user through a survey questionnaire, in which you are requested to prioritized six university websites with respect to given criteria.

Your participation in the study is very vital and is much anticipated

Thanks, as your take your time to participate

**Solomon Adelowo ADEPOJU**
PhD candidate
Department of Computer Science
Federal University of Technology
Minna
08035829748
solo.adepoju@futminna.edu.ngs

The Seven criteria used are described as follows:

**Speed**: This metric evaluates the amount of time it takes for the website to render or respond after a request has been made i.e. the load time.

**Navigation**: This metric evaluates the navigation system of the websites. It measures the ease at which a systems user can identify and access correct information, menu, reports, routes, and elements

**Ease of Use**: This metric measures the level of ease at which the user uses and understands the structure, architecture and organization of the website.

**Content**: This metric evaluates the textual, aural and visual information published on the website. It measures the content in respect to information related to universities

**Accessibility**: This metric study the extent to which the websites are compatible for use by people with disabilities.

**Aesthetics**: This metrics evaluates the beauty, attractiveness of the website. This includes the design and colour combination used in the website design.

**Security**: This metric evaluates how secured the websites are, and how they deal with attacks and malicious software

Please carry out the following activities on each of the websites indicated below task

1. Check the news update or bulletin from the university
2. Visit computer science department
3. Check the e resources available in the library
4. find information on school fees and payment
5. observe the color combination, navigation structure and the visual appeal of the websites

The university websites and their URLs are as follows.

1. University of Ibadan -UI- ( https://www.ui.edu.ng)
2. Covenant university Ota -CU- (https://covenantuniversity.edu.ng)
3. Obafemi Awolowo University Ile ife -OAU- (https://oauife.edu.ng)
4. University of Nigeria Nsukka-UNN- (https://www.unn.edu.ng)
5. University of Lagos -UNILAG- (https://unilag.edu.ng)
6. Ahmadu Bello University -ABU- (https://abu.edu.ng)

Use the scale given below to carry out the comparison of the criteria and websites based on each criteria

| Normal number | Linguistic scales |
|---|---|
| 1 | Extremely less preferable |
| 2 | Strongly less preferable |
| 3 | Fairly less preferable |
| 4 | Slightly less preferable |
| 5 | Equally preferable |
| 6 | Slightly more preferable |
| 7 | Fairly more preferable |
| 8 | Strongly more preferable |
| 9 | Extremely more preferable |

.

| Normal number | Linguistic scales |
|---|---|
| 1 | Extremely less important |
| 2 | Strongly less important |
| 3 | Fairly less important |
| 4 | Slightly less important |
| 5 | Equally important |
| 6 | Slightly more important |
| 7 | Fairly more important |
| 8 | Strongly more important |
| 9 | Extremely more important |

| OPTION A | Extremely less important | Strongly less important | Fairly less important | Slightly less important | Equally important | Slightly more important | Fairly more important | Strongly more important | Extremely more important | OPTION B |
|---|---|---|---|---|---|---|---|---|---|---|
| Speed | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Navigation |
| Speed | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Ease of Use |
| Speed | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Content |
| Speed | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Accessibility |
| Speed | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Aesthetic |
| Speed | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Security |
| Navigation | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Ease of use |
| Navigation | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Content |
| Navigation | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Accessibility |
| Navigation | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Aesthetic |
| Navigation | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Security |
| Ease of Use | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Content |
| Ease of Use | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Accessibility |
| Ease of Use | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Aesthetic |
| Ease of Use | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Security |
| Aesthetic | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Content |
| Aesthetic | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Accessibility |
| Aesthetic | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Security |
| Content | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Accessibility |
| Content | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Security |
| Accessibility | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Security |

Give any comments or observation------------------------------------------------------------------------------------------
-------------------------------------------------------------------------------------------------------------------------------
-------------------------------------------------------------------------------------------------------------------------------
------------------------------------------------------------------------------------------

With respect to **SPEED**

Using the scale from 1 to 9 (where 9 is extremely and 1 is equally important), please indicate (X) the relative importance of options **A** (left column) to options **B** (right column).

| OPTION A | Extremely less preferable | Strongly less preferable | Fairly less preferable | Slightly less preferable | Equally preferable | Slightly more preferable | Fairly more preferable | Strongly more preferable | Extremely more preferable | OPTION B |
|---|---|---|---|---|---|---|---|---|---|---|
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | CU |
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | OAU |
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNN |
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNILAG |
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |
| CU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | OAU |
| CU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNN |
| CU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNILAG |
| CU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |
| OAU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNN |
| OAU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNILAG |
| OAU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |
| UNN | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNILAG |
| UNN | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |
| UNILAG | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |

With respect to **AESTHETIC**

Using the scale from 1 to 9 (where 9 is extremely and 1 is equally important), please indicate (X) the relative importance of options **A** (left column) to options **B** (right column).

| OPTION A | Extremely less preferable | Strongly less preferable | Fairly less preferable | Slightly less preferable | Equally preferable | Slightly more preferable | Fairly more preferable | Strongly more preferable | Extremely more preferable | OPTION B |
|---|---|---|---|---|---|---|---|---|---|---|
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | CU |
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | OAU |
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNN |
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNILAG |
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |
| CU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | OAU |
| CU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNN |
| CU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNILAG |
| CU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |
| OAU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNN |
| OAU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNILAG |
| OAU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |
| UNN | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNILAG |
| UNN | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |
| UNILAG | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |

With respect to **NAVIGATION**

Using the scale from 1 to 9 (where 9 is extremely and 1 is equally important), please indicate (X) the relative importance of options **A** (left column) to options **B** (right column

| OPTION A | Extremely less preferable | Strongly less preferable | Fairly less preferable | Slightly less preferable | Equally preferable | Slightly more preferable | Fairly more preferable | Strongly more preferable | Extremely more preferable | OPTION B |
|---|---|---|---|---|---|---|---|---|---|---|
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | CU |
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | OAU |
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNN |
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNILAG |
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |
| CU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | OAU |
| CU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNN |
| CU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNILAG |
| CU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |
| OAU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNN |
| OAU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNILAG |
| OAU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |
| UNN | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNILAG |
| UNN | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |

With respect to **CONTENT**

Using the scale from 1 to 9 (where 9 is extremely and 1 is equally important), please indicate (X) the relative importance of options **A** (left column) to options **B** (right column

| OPTION A | Extremely less preferable | Strongly less preferable | Fairly less preferable | Slightly less preferable | Equally preferable | Slightly more preferable | Fairly more preferable | Strongly more preferable | Extremely more preferable | OPTION B |
|---|---|---|---|---|---|---|---|---|---|---|
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | CU |
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | OAU |
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNN |
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNILAG |
| UI | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |
| CU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | OAU |
| CU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNN |
| CU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNILAG |
| CU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |
| OAU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNN |
| OAU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNILAG |
| OAU | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |
| UNN | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | UNILAG |

**Rate your satisfaction with the websites based on the scale indicated below**

| | EXTREMELY SATISFIED | STRONGLY SATISFIED | MODERATELY SATISFIED | SLIGHTLY SATISFIED | NOT SATISFIED |
|---|---|---|---|---|---|
| UI | 5 | 4 | 3 | 2 | 1 |
| CU | 5 | 4 | 3 | 2 | 1 |
| OAU | 5 | 4 | 3 | 2 | 1 |
| UNN | 5 | 4 | 3 | 2 | 1 |
| UNILAG | 5 | 4 | 3 | 2 | 1 |
| ABU | 5 | 4 | 3 | 2 | 1 |
| OVERALL | 5 | 4 | 3 | 2 | 1 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| UNILAG | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |
| UNILAG | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ABU |

THANKS FOR YOUR PARTICIPATION

**APPENDIX D**

**CORRELATION MATRIX**

**Correlation Matrix[a]**

| | | sp1 | sp2 | sp3 | nav1 | nav2 | nav3 | nav4 | eou1 | eou2 | eou3 | cont1 | cont2 | cont3 | acc1 | acc2 | acc3 | aes1 | aes2 | aes3 | sec1 | sec2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Correlation | sp1 | 1.000 | .388 | .280 | .377 | .288 | .285 | .198 | .294 | .313 | .217 | .240 | .253 | .173 | .088 | .003 | .157 | .130 | .147 | .068 | .081 | .061 |
| | sp2 | .388 | 1.000 | .420 | .416 | .436 | .196 | .213 | .454 | .482 | .316 | .452 | .260 | .297 | .262 | .043 | .333 | .293 | .259 | .196 | .070 | .222 |
| | sp3 | .280 | .420 | 1.000 | .279 | .276 | .242 | .164 | .268 | .215 | .205 | .235 | .201 | .157 | .167 | .037 | .306 | .200 | .065 | .120 | .025 | .060 |
| | nav1 | .377 | .416 | .279 | 1.000 | .381 | .265 | .326 | .507 | .482 | .317 | .402 | .320 | .327 | .241 | .028 | .303 | .263 | .363 | .278 | .165 | .075 |
| | nav2 | .288 | .436 | .276 | .381 | 1.000 | .133 | .166 | .342 | .457 | .334 | .275 | .315 | .289 | .179 | .131 | .418 | .262 | .201 | .185 | .192 | .121 |
| | nav3 | .285 | .196 | .242 | .265 | .133 | 1.000 | .398 | .230 | .328 | .219 | .188 | .243 | .262 | .043 | .012 | .137 | .102 | .189 | .077 | .118 | -.182 |
| | nav4 | .198 | .213 | .164 | .326 | .166 | .398 | 1.000 | .260 | .279 | .190 | .106 | .206 | .217 | .185 | .130 | .186 | .175 | .188 | .133 | .155 | -.014 |
| | eou1 | .294 | .454 | .268 | .507 | .342 | .230 | .260 | 1.000 | .618 | .394 | .368 | .259 | .341 | .252 | .059 | .268 | .282 | .334 | .295 | .094 | .106 |
| | eou2 | .313 | .482 | .215 | .482 | .457 | .328 | .279 | .618 | 1.000 | .448 | .446 | .255 | .377 | .248 | .089 | .309 | .301 | .378 | .310 | .150 | .119 |
| | eou3 | .217 | .316 | .205 | .317 | .334 | .219 | .190 | .394 | .448 | 1.000 | .343 | .254 | .272 | .267 | -.017 | .186 | .341 | .246 | .330 | .091 | .183 |
| | cont1 | .240 | .452 | .235 | .402 | .275 | .188 | .106 | .368 | .446 | .343 | 1.000 | .452 | .376 | .344 | .086 | .333 | .434 | .351 | .288 | .206 | .161 |
| | cont2 | .253 | .260 | .201 | .320 | .315 | .243 | .206 | .259 | .255 | .254 | .452 | 1.000 | .298 | .366 | .075 | .324 | .298 | .281 | .324 | .310 | .183 |
| | cont3 | .173 | .297 | .157 | .327 | .289 | .262 | .217 | .341 | .377 | .272 | .376 | .298 | 1.000 | .313 | .132 | .196 | .294 | .327 | .296 | .219 | .232 |
| | acc1 | .088 | .262 | .167 | .241 | .179 | .043 | .185 | .252 | .248 | .267 | .344 | .366 | .313 | 1.000 | .072 | .226 | .403 | .162 | .300 | .282 | .341 |
| | acc2 | .003 | .043 | .037 | .028 | .131 | .012 | .130 | .059 | .089 | -.017 | .086 | .075 | .132 | .072 | 1.000 | .062 | .167 | .079 | .173 | .245 | .212 |
| | acc3 | .157 | .333 | .306 | .303 | .418 | .137 | .186 | .268 | .309 | .186 | .333 | .324 | .196 | .226 | .062 | 1.000 | .316 | .237 | .239 | .151 | .121 |
| | aes1 | .130 | .293 | .200 | .263 | .262 | .102 | .175 | .282 | .301 | .341 | .434 | .298 | .294 | .403 | .167 | .316 | 1.000 | .497 | .595 | .223 | .145 |
| | aes2 | .147 | .259 | .065 | .363 | .201 | .189 | .188 | .334 | .378 | .246 | .351 | .281 | .327 | .162 | .079 | .237 | .497 | 1.000 | .453 | .205 | .126 |
| | aes3 | .068 | .196 | .120 | .278 | .185 | .077 | .133 | .295 | .310 | .330 | .288 | .324 | .296 | .300 | .173 | .239 | .595 | .453 | 1.000 | .280 | .177 |
| | sec1 | .081 | .070 | .025 | .165 | .192 | .118 | .155 | .094 | .150 | .091 | .206 | .310 | .219 | .282 | .245 | .151 | .223 | .205 | .280 | 1.000 | .359 |
| | sec2 | .061 | .222 | .060 | .075 | .121 | -.182 | -.014 | .106 | .119 | .183 | .161 | .183 | .232 | .341 | .212 | .121 | .145 | .126 | .177 | .359 | 1.000 |
| Sig. (1-tailed) | sp1 | | .000 | .000 | .000 | .000 | .000 | .001 | .000 | .000 | .000 | .000 | .000 | .004 | .090 | .483 | .008 | .024 | .012 | .152 | .109 | .177 |
| | sp2 | .000 | | .000 | .000 | .000 | .001 | .001 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .259 | .000 | .000 | .000 | .001 | .145 | .000 |
| | sp3 | .000 | .000 | | .000 | .000 | .000 | .006 | .000 | .000 | .001 | .000 | .001 | .008 | .006 | .288 | .000 | .001 | .161 | .034 | .353 | .183 |
| | nav1 | .000 | .000 | .000 | | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .335 | .000 | .000 | .000 | .000 | .006 | .127 |
| | nav2 | .000 | .000 | .000 | .000 | | .022 | .006 | .000 | .000 | .000 | .000 | .000 | .000 | .003 | .023 | .000 | .000 | .001 | .002 | .002 | .032 |
| | nav3 | .000 | .001 | .000 | .000 | .022 | | .000 | .000 | .000 | .000 | .002 | .000 | .000 | .258 | .425 | .018 | .061 | .002 | .121 | .036 | .003 |
| | nav4 | .001 | .001 | .006 | .000 | .006 | .000 | | .000 | .000 | .002 | .054 | .001 | .000 | .002 | .024 | .002 | .004 | .002 | .021 | .009 | .416 |
| | eou1 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | | .000 | .000 | .000 | .000 | .000 | .000 | .187 | .000 | .000 | .000 | .000 | .077 | .054 |
| | eou2 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | | .000 | .000 | .000 | .000 | .000 | .088 | .000 | .000 | .000 | .000 | .011 | .036 |
| | eou3 | .000 | .000 | .001 | .000 | .000 | .000 | .002 | .000 | .000 | | .000 | .000 | .000 | .000 | .398 | .002 | .000 | .000 | .000 | .085 | .003 |
| | cont1 | .000 | .000 | .000 | .000 | .000 | .002 | .054 | .000 | .000 | .000 | | .000 | .000 | .000 | .096 | .000 | .000 | .000 | .000 | .001 | .007 |
| | cont2 | .000 | .000 | .001 | .000 | .000 | .000 | .001 | .000 | .000 | .000 | .000 | | .000 | .000 | .126 | .000 | .000 | .000 | .000 | .000 | .003 |
| | cont3 | .004 | .000 | .008 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | | .000 | .022 | .001 | .000 | .000 | .000 | .000 | .000 |
| | acc1 | .090 | .000 | .006 | .000 | .003 | .258 | .002 | .000 | .000 | .000 | .000 | .000 | .000 | | .138 | .000 | .000 | .007 | .000 | .000 | .000 |
| | acc2 | .483 | .259 | .288 | .335 | .023 | .425 | .024 | .187 | .088 | .398 | .096 | .126 | .022 | .138 | | .174 | .005 | .114 | .004 | .000 | .001 |
| | acc3 | .008 | .000 | .000 | .000 | .000 | .018 | .002 | .000 | .000 | .002 | .000 | .000 | .001 | .000 | .174 | | .000 | .000 | .000 | .011 | .033 |
| | aes1 | .024 | .000 | .001 | .000 | .000 | .061 | .004 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .005 | .000 | | .000 | .000 | .000 | .013 |
| | aes2 | .012 | .000 | .161 | .000 | .001 | .002 | .002 | .000 | .000 | .000 | .000 | .000 | .000 | .007 | .114 | .000 | .000 | | .000 | .001 | .027 |
| | aes3 | .152 | .001 | .034 | .000 | .002 | .121 | .021 | .000 | .000 | .000 | .000 | .000 | .000 | .000 | .004 | .000 | .000 | .000 | | .000 | .003 |
| | sec1 | .109 | .145 | .353 | .006 | .002 | .036 | .009 | .077 | .011 | .085 | .001 | .000 | .000 | .000 | .000 | .011 | .000 | .001 | .000 | | .000 |
| | sec2 | .177 | .000 | .183 | .127 | .032 | .003 | .416 | .054 | .036 | .003 | .007 | .003 | .000 | .000 | .001 | .033 | .013 | .027 | .003 | .000 | |

a. Determinant = .001

**COMPONENT MATRIX[A]**

| | Component | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| eou2 | .718 | | | | -.337 |
| nav1 | .668 | | | | |
| eou1 | .666 | | | | -.328 |
| cont1 | .665 | | | | |
| sp2 | .653 | | .353 | | |
| aes1 | .613 | .354 | | | |
| nav2 | .587 | | .303 | | |
| cont2 | .582 | | | | .350 |
| cont3 | .578 | | | | |
| eou3 | .572 | | | | |
| aes2 | .563 | | -.416 | | |
| aes3 | .553 | .415 | -.319 | | |
| acc3 | .528 | | | | .457 |
| acc1 | .508 | .370 | | | |
| sp1 | .452 | -.397 | | | |
| sp3 | .435 | -.308 | .331 | | .362 |
| sec2 | | .536 | .464 | | -.314 |
| sec1 | .365 | .483 | | .479 | |
| nav3 | .392 | -.436 | -.426 | .381 | |
| nav4 | .414 | | -.354 | .468 | |
| acc2 | | .360 | | .459 | |

Extraction Method: Principal Component Analysis.

a. 5 components extracted.

## APPENDIX E
## SAMPLE DATA

### SAMPLE RAW DATA BEFORE TRANSFORMATION

| SPEED vs CONTENT | SPEED vs AESTHETIC | NAVIGATION vs CONTENT | EASE OF USE vs AESTHETIC | CONTENT vs AESTHETIC | UI vs CU (with respect to SPEED) | UI vs UNILAG (with respect to SPEED) | CU vs UNN (with respect to SPEED) |
|---|---|---|---|---|---|---|---|
| 5 | 7 | 6 | 5 | 9 | 3 | 8 | 9 |
| 9 | 6 | 4 | 9 | 4 | 9 | 5 | 4 |
| 5 | 1 | 6 | 5 | 5 | 1 | 9 | 9 |
| 3 | 8 | 5 | 9 | 8 | 5 | 9 | 6 |
| 5 | 6 | 5 | 4 | 5 | 5 | 6 | 5 |
| 9 | 9 | 9 | 5 | 9 | 9 | 9 | 1 |
| 4 | 6 | 5 | 5 | 6 | 7 | 5 | 6 |
| 3 | 5 | 6 | 3 | 3 | 4 | 3 | 2 |
| 8 | 1 | 8 | 7 | 5 | 8 | 7 | 5 |
| 4 | 6 | 6 | 4 | 5 | 8 | 4 | 3 |
| 8 | 8 | 4 | 8 | 6 | 7 | 9 | 5 |
| 3 | 5 | 3 | 4 | 3 | 5 | 7 | 7 |
| 5 | 9 | 3 | 8 | 4 | 3 | 4 | 7 |

## PATTERN MATRIX[A]

| | Component | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| eou2 | .793 | | | | |
| eou1 | .782 | | | | |
| eou3 | .592 | | | | |
| sp2 | .591 | | | | .386 |
| nav1 | .548 | | | | |
| sp1 | .420 | | | | |
| nav2 | .413 | | | | .389 |
| cont3 | .409 | | | | |
| nav3 | | -.781 | | | |
| nav4 | | -.674 | | | |
| aes1 | | | -.754 | | |
| aes3 | | | -.752 | | |
| aes2 | | | -.650 | | |
| sec1 | | | | .721 | |
| sec2 | | .470 | | .688 | |
| acc2 | | | | .647 | |
| acc1 | | | | .346 | |
| acc3 | | | | | .695 |
| sp3 | | | | | .695 |
| cont2 | | | | | .505 |
| cont1 | .304 | | -.332 | | .335 |

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.[a]

a. Rotation converged in 16 iterations.

## SAMPLE FUZZY AHP DATA AFTER TRANSFORMATION

| SPEED vs CONTENT | SPEED vs AESTHETIC | NAVIGATION vs EASE OF USE | NAVIGATION vs AESTHETIC | EASE OF USE vs CONTENT | EASE OF USE vs AESTHETIC | CONTENT vs AESTHETIC | UI vs ABU (with respect to SPEED) |
|---|---|---|---|---|---|---|---|
| 2 | 6 | 3 | 3 | 7 | 8 | 6 | 6 |
| 9 | 9 | 5 | 1 | 8 | 9 | 9 | 8 |
| 8 | 4 | 7 | 5 | 4 | 9 | 6 | 2 |
| 7 | 8 | 7 | 7 | 7 | 9 | 8 | 7 |
| 2 | 5 | 7 | 4 | 7 | 6 | 8 | 6 |
| 7 | 6 | 7 | 6 | 6 | 3 | 3 | 2 |
| 4 | 5 | 4 | 4 | 8 | 2 | 2 | 8 |
| 3 | 7 | 3 | 5 | 8 | 5 | 5 | 6 |
| 5 | 4 | 4 | 7 | 8 | 5 | 6 | 5 |
| 3 | 3 | 4 | 4 | 9 | 7 | 2 | 4 |
| 4 | 3 | 5 | 4 | 4 | 5 | 4 | 5 |
| 8 | 8 | 7 | 8 | 7 | 7 | 8 | 7 |
| 5 | 7 | 4 | 7 | 6 | 6 | 6 | 5 |
| 5 | 8 | 3 | 8 | 8 | 4 | 4 | 5 |
| 7 | 6 | 6 | 6 | 6 | 6 | 5 | 5 |
| 8 | 9 | 9 | 8 | 9 | 9 | 9 | 9 |
| 5 | 8 | 3 | 8 | 8 | 4 | 4 | 5 |
| 5 | 9 | 4 | 8 | 9 | 5 | 3 | 5 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| (1,1,1) | (4,5,6) | (1,1,1) | (1/6,1/5,1/4) | (1,1,1) | (1,1,1) | (8,9,9) | (4,5,6) |
| (8,9,9) | (2,3,4) | (1,1,1) | (2,3,4) | (1/4,1/3,1/2) | (8,9,9) | (1/4,1/3,1/2) | (8,9,9) |
| (1,1,1) | (1/9,1/9,1/8) | (1/8,1/7,1/6) | (1/4,1/3,1/2) | (8,9,9) | (1,1,1) | (1,1,1) | (8,9,9) |
| (1/6,1/5,1/4) | (6,7,8) | (1/4,1/3,1/2) | (6,7,8) | (4,5,6) | (8,9,9) | (6,7,8) | (8,9,9) |
| (1,1,1) | (2,3,4) | (1,1,1) | (1/4,1/3,1/2) | (1,1,1) | (1/4,1/3,1/2) | (1,1,1) | (1,1,1) |
| (8,9,9) | (8,9,9) | (1,1,1) | (1,1,1) | (8,9,9) | (1,1,1) | (8,9,9) | (8,9,9) |
| (1/4,1/3,1/2) | (2,3,4) | (1,1,1) | (2,3,4) | (1,1,1) | (1,1,1) | (2,3,4) | (2,3,4) |
| (1/6,1/5,1/4) | (1,1,1) | (1,1,1) | (1/4,1/3,1/2) | (1/4,1/3,1/2) | (1/6,1/5,1/4) | (1/6,1/5,1/4) | (1/4,1/3,1/2) |
| (6,7,8) | (1/9,1/9,1/8) | (8,9,9) | (1,1,1) | (4,5,6) | (4,5,6) | (1,1,1) | (1,1,1) |
| (1/4,1/3,1/2) | (2,3,4) | (1,1,1) | (1/4,1/3,1/2) | (2,3,4) | (1/4,1/3,1/2) | (1,1,1) | (2,3,4) |
| (6,7,8) | (6,7,8) | (2,3,4) | (4,5,6) | (6,7,8) | (6,7,8) | (2,3,4) | (6,7,8) |
| (1/6,1/5,1/4) | (1,1,1) | (2,3,4) | (1/6,1/5,1/4) | (1/8,1/7,1/6) | (1/4,1/3,1/2) | (1/6,1/5,1/4) | (4,5,6) |
| (1,1,1) | (8,9,9) | (2,3,4) | (6,7,8) | (1/8,1/7,1/6) | (6,7,8) | (1/4,1/3,1/2) | (6,7,8) |
| (1/8,1/7,1/6) | (2,3,4) | (1/6,1/5,1/4) | (1,1,1) | (1/6,1/5,1/4) | (1/6,1/5,1/4) | (4,5,6) | (1,1,1) |
| (8,9,9) | (8,9,9) | (1,1,1) | (6,7,8) | (6,7,8) | (1/9,1/9,1/8) | (6,7,8) | (6,7,8) |
| (6,7,8) | (1/4,1/3,1/2) | (1/9,1/9,1/8) | (1/6,1/5,1/4) | (1,1,1) | (1,1,1) | (1/4,1/3,1/2) | (2,3,4) |
| (4,5,6) | (6,7,8) | (6,7,8) | (4,5,6) | (6,7,8) | (4,5,6) | (4,5,6) | (8,9,9) |
| (1/8,1/7,1/6) | (1,1,1) | (1,1,1) | (1/6,1/5,1/4) | (1,1,1) | (1/4,1/3,1/2) | (4,5,6) | (8,9,9) |
| (4,5,6) | (2,3,4) | (4,5,6) | (2,3,4) | (4,5,6) | (2,3,4) | (2,3,4) | (2,3,4) |
| (1/4,1/3,1/2) | (1,1,1) | (4,5,6) | (1,1,1) | (1/6,1/5,1/4) | (1/4,1/3,1/2) | (6,7,8) | (1,1,1) |
| (1/6,1/5,1/4) | (4,5,6) | (4,5,6) | (4,5,6) | (1/4,1/3,1/2) | (1,1,1) | (6,7,8) | (2,3,4) |
| (1,1,1) | (1/4,1/3,1/2) | (1,1,1) | (1/4,1/3,1/2) | (1,1,1) | (4,5,6) | (6,7,8) | (1,1,1) |
| (1/6,1/5,1/4) | (1/6,1/5,1/4) | (4,5,6) | (2,3,4) | (1/4,1/3,1/2) | (1/4,1/3,1/2) | (8,9,9) | (6,7,8) |
| (1/4,1/3,1/2) | (1/6,1/5,1/4) | (1/4,1/3,1/2) | (1/6,1/5,1/4) | (1,1,1) | (1/4,1/3,1/2) | (1/4,1/3,1/2) | (2,3,4) |
| (6,7,8) | (6,7,8) | (4,5,6) | (2,3,4) | (1,1,1) | (6,7,8) | (4,5,6) | (1,1,1) |
| (1,1,1) | (4,5,6) | (1,1,1) | (4,5,6) | (2,3,4) | (4,5,6) | (2,3,4) | (4,5,6) |
| (1,1,1) | (6,7,8) | (1/6,1/5,1/4) | (1,1,1) | (1/4,1/3,1/2) | (6,7,8) | (6,7,8) | (1,1,1) |
| (4,5,6) | (2,3,4) | (2,3,4) | (2,3,4) | (2,3,4) | (2,3,4) | (2,3,4) | (1,1,1) |
| (6,7,8) | (8,9,9) | (6,7,8) | (8,9,9) | (6,7,8) | (6,7,8) | (8,9,9) | (6,7,8) |
| (1,1,1) | (6,7,8) | (1/6,1/5,1/4) | (1,1,1) | (1/4,1/3,1/2) | (6,7,8) | (6,7,8) | (1,1,1) |

## SAMPLE AHP DATA AFTER TRANSFORMATION

| SPEED vs NAVIGATION | SPEED vs EASE OF USE | NAVIGATION vs EASE OF USE | NAVIGATION vs CONTENT | NAVIGATION vs AESTHETIC | EASE OF USE vs CONTENT | EASE OF USE vs AESTHETIC | CONTENT vs AESTHETIC |
|---|---|---|---|---|---|---|---|
| 9 | 5 | 1 | 3 | 1/5 | 1 | 1 | 9 |
| 7 | 7 | 1 | 1/3 | 3 | 1/3 | 9 | 1/3 |
| 9 | 1 | 1/7 | 3 | 1/3 | 9 | 1 | 1 |
| 3 | 1/5 | 1/3 | 1 | 7 | 5 | 9 | 7 |
| 1 | 1/3 | 1 | 1 | 1/3 | 1 | 1/3 | 1 |
| 9 | 1 | 1 | 9 | 1 | 9 | 1 | 9 |
| 5 | 1 | 1 | 1 | 3 | 1 | 1 | 3 |
| 1/3 | 3 | 1 | 3 | 1/3 | 1/3 | 1/5 | 1/5 |
| 1/7 | 7 | 9 | 7 | 1 | 5 | 5 | 1 |
| 1/3 | 1/3 | 1 | 3 | 1/3 | 3 | 1/3 | 1 |
| 1/7 | 7 | 3 | 1/3 | 5 | 7 | 7 | 3 |
| 1 | 1 | 3 | 1/5 | 1/5 | 1/7 | 1/3 | 1/5 |
| 7 | 5 | 3 | 1/5 | 7 | 1/7 | 7 | 1/3 |
| 5 | 5 | 1/5 | 1/5 | 1 | 1/5 | 1/5 | 5 |
| 7 | 1/9 | 1 | 1 | 7 | 7 | 1/9 | 7 |
| 3 | 1/5 | 1/9 | 5 | 1/5 | 1 | 1 | 1/3 |
| 5 | 5 | 7 | 5 | 5 | 7 | 5 | 5 |
| 1 | 7 | 1 | 5 | 1/5 | 1 | 1/3 | 5 |
| 3 | 3 | 5 | 5 | 3 | 5 | 3 | 3 |
| 7 | 1 | 5 | 1/3 | 1 | 1/5 | 1/3 | 7 |
| 1 | 1 | 5 | 1/5 | 5 | 1/3 | 1 | 7 |
| 3 | 3 | 1 | 1/3 | 1/3 | 1 | 5 | 7 |
| 3 | 5 | 5 | 1/3 | 3 | 1/3 | 1/3 | 9 |
| 1/3 | 1/5 | 1/3 | 1 | 1/5 | 1 | 1/3 | 1/3 |
| 3 | 1 | 5 | 5 | 3 | 1 | 7 | 5 |
| 3 | 1 | 1 | 1/3 | 5 | 3 | 5 | 3 |
| 5 | 3 | 1/5 | 1/5 | 1 | 1/3 | 7 | 7 |
| 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| 7 | 7 | 7 | 9 | 9 | 7 | 7 | 9 |
| 5 | 3 | 1/5 | 1/5 | 1 | 1/3 | 7 | 7 |
| 7 | 3 | 1 | 1/3 | 7 | 1 | 7 | 9 |
| 3 | 1 | 3 | 3 | 1 | 3 | 1/3 | 1/3 |
| 1 | 1/3 | 1/9 | 1 | 3 | 3 | 1/9 | 1/3 |

## SAMPLE AHP COMPARISON MATRICES

## SAMPLE DATASET

```
@relation test110

@attribute speed numeric
@attribute Navigation numeric
@attribute 'ease of use' numeric
@attribute content numeric
@attribute Aesthetic numeric
@attribute usab {Satisifed,'Not satisifed'}

@data
0.380479,0.514796,0.395502,0.523913,0.164198,'Not satisifed'
0.10154,0.275653,0.092364,0.255674,0.288583,'Not satisifed'
0.638204,0.531892,0.174718,0.276635,0.122461,Satisifed
0.643345,0.56945,0.521352,0.838877,0.137823,Satisifed
0.644062,0.650719,0.578039,0.642152,0.453496,Satisifed
0.648058,0.51039,0.568697,0.597878,0.498932,Satisifed
0.304969,0.118642,0.077942,0.512307,0.084968,'Not satisifed'
0.104215,0.048099,0.047592,0.047032,0.020155,'Not satisifed'
0.648639,0.258817,0.678624,0.684126,0.327737,Satisifed
0.652723,0.463738,0.408516,0.446627,0.194972,Satisifed
0.655435,0.688808,0.330801,0.662807,0.085851, Satisifed
0.657148,0.081197,0.6069,0.075572,0.566963, Satisifed
0.012046,0.068522,0.064342,0.028627,0.074381,'Not satisifed'
0.023329,0.031502,0.027985,0.008478,0.05389,'Not satisifed'
0.659283,0.46967,0.322978,0.175745,0.289579, Satisifed
0.672744,0.459025,0.486178,0.633428,0.645681, Satisifed
0.67602,0.467063,0.212783,0.307155,0.361269, Satisifed
0.680488,0.476728,0.301425,0.603294,0.670105, Satisifed
0.106369,0.140941,0.095547,0.144731,0.118037,'Not satisifed'
0.129196,0.145676,0.064015,0.023944,0.025828,'Not satisifed'
0.686912,0.454049,0.378747,0.018769,0.091671, Satisifed
0.689994,0.419918,0.449049,0.720459,0.221413, Satisifed
0.693193,0.729653,0.665352,0.732339,0.659257, Satisifed
0.697992,0.985674,0.778125,0.840179,0.679166, Satisifed
0.358896,0.614353,0.322899,0.76246,0.263156,'Not satisifed'
0.19004,0.075186,0.250868,0.128303,0.350247,'Not satisifed'
0.704081,0.380268,0.464721,0.490984,0.45933, Satisifed
0.708565,0.277932,0.376077,0.430936,0.462055, Satisifed
0.708716,0.163941,0.014902,0.002067,0.105007,Satisifed
0.709016,0.60781,0.629195,0.561199,0.342291,Satisifed
```

0.300035,0.31306,0.207804,0.636452,0.930067,'Not satisifed'
0.156469,0.438768,0.098615,0.38845,0.147559,'Not satisifed'

| | | | SPEED | | | |
|---|---|---|---|---|---|---|
| | **UI** | **CU** | **OAU** | **UNN** | **UNILAG** | **ABU** |
| **UI** | 1 | 1 | 7 | 9 | 7 | 7 |
| **CU** | 1 | 1 | 5 | 7 | 7 | 9 |
| **OAU** | 1/7 | 1/5 | 1 | 1/3 | 1 | 5 |
| **UNN** | 1/9 | 1/7 | 3 | 1 | 5 | 7 |
| **UNILAG** | 1/7 | 1/7 | 1 | 1/5 | 1 | 5 |
| **ABU** | 1/7 | 1/9 | 1/5 | 1/7 | 1/5 | 1 |
| | | | | | | |
| | | | | | | |
| | **UI** | **CU** | **OAU** | **UNN** | **UNILAG** | **ABU** |
| **UI** | 1 | 1 | 3 | 1 | 5 | 7 |
| **CU** | 1 | 1 | 5 | 1 | 3 | 5 |
| **OAU** | 1/3 | 1/5 | 1 | 1 | 3 | 5 |
| **UNN** | 1 | 1 | 1 | 1 | 5 | 7 |
| **UNILAG** | 1/5 | 1/3 | 1/3 | 1/5 | 1 | 5 |
| **ABU** | 1/7 | 1/5 | 1/5 | 1/7 | 1/5 | 1 |
| | | | | | | |
| | | | | | | |
| | **UI** | **CU** | **OAU** | **UNN** | **UNILAG** | **ABU** |
| **UI** | 1 | 1 | 1 | 1 | 1/3 | 1/3 |
| **CU** | 1 | 1 | 1 | 1 | 1/3 | 1/3 |
| **OAU** | 1 | 1 | 1 | 1 | 1/3 | 1/3 |
| **UNN** | 1 | 1 | 1 | 1 | 1/5 | 1/3 |
| **UNILAG** | 3 | 3 | 3 | 5 | 1 | 1 |
| **ABU** | 3 | 3 | 3 | 3 | 1 | 1 |
| | | | | | | |
| | | | | | | |
| | | | | | | |
| | **UI** | **CU** | **OAU** | **UNN** | **UNILAG** | **ABU** |
| **UI** | 1 | 3 | 9 | 5 | 5 | 1/7 |
| **CU** | 1/3 | 1 | 1/3 | 1/3 | 1 | 1/7 |
| **OAU** | 1/9 | 3 | 1 | 1 | 1 | 1/3 |
| **UNN** | 1/5 | 3 | 1 | 1 | 1 | 1 |
| **UNILAG** | 1/5 | 1 | 7 | 1 | 1 | 3 |
| **ABU** | 7 | 7 | 9 | 1 | 1/3 | 1 |
| | | | | | | |
| | | | | | | |
| | **UI** | **CU** | **OAU** | **UNN** | **UNILAG** | **ABU** |
| **UI** | 1 | 9 | 9 | 9 | 1 | 9 |
| **CU** | 1/9 | 1 | 9 | 7 | 9 | 9 |
| **OAU** | 1/9 | 1/9 | 1 | 1/5 | 1/7 | 1/3 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **UNN** | 1/9 | 1/7 | 5 | 1 | 1 | 7 |
| **UNILAG** | 1 | 1/9 | 7 | 1 | 1 | 9 |
| **ABU** | 1/9 | 1/9 | 3 | 1/7 | 1/9 | 1 |
| | | | | | | |
| | | | | | | |

0.709661,0.095065,0.250328,0.377847,0.466803,Satisifed
0.716948,0.806784,0.662224,0.831001,0.661692,Satisifed
0.084193,0.12852,0.154895,0.096005,0.089057,'Not satisifed'
0.723003,0.614194,0.080181,0.1414,0.458108,Satisifed
0.724235,0.833558,0.612462,0.335909,0.583102,Satisifed
0.108515,0.117382,0.11048,0.094949,0.16601,'Not satisifed'
0.247853,0.305018,0.198128,0.258532,0.210774,'Not satisifed'
0.724568,0.3725,0.258917,0.242505,0.273585,Satisifed
0.737847,0.408706,0.240396,0.231649,0.515216,Satisifed
0.739296,0.347141,0.339392,0.290678,0.250668,Satisifed
0.74445,0.756836,0.738752,0.488224,0.491641,Satisifed
0.205539,0.338285,0.269755,0.174352,0.09814,'Not satisifed'
0.093482,0.445943,0.093062,0.208509,0.389211,'Not satisifed'
0.753958,0.63334,0.376053,0.466879,0.207062,Satisifed
0.754992,0.352023,0.149041,0.290364,0.17536,Satisifed
0.042808,0.031127,0.034529,0.069788,0.070882,'Not satisifed'
0.758738,0.352023,0.149041,0.290364,0.199587,Satisifed
0.761343,0.3418,0.527016,0.327094,0.455114,Satisifed
0.133663,0.088105,0.102163,0.08123,0.171449,'Not satisifed'
0.261477,0.220872,0.195525,0.319439,0.207499,'Not satisifed'
0.761343,0.342678,0.527016,0.327094,0.455114,Satisifed
0.764326,0.715055,0.434339,0.535683,0.619415,Satisifed
0.096341,0.029808,0.001827,0.006049,0.001648,'Not satisifed'
0.766963,0.677694,0.708945,0.364844,0.217124,Satisifed
0.781549,0.594245,0.62674,0.455129,0.668695,Satisifed
0.110518,0.146847,0.193813,0.222037,0.249982,'Not satisifed'
0.194318,0.146084,0.177539,0.21305,0.177912,'Not satisifed'
0.790075,0.120088,0.779532,0.783695,0.972909,Satisifed
0.800674,0.702006,0.753214,0.761949,0.289221,Satisifed
0.035379,0.059069,0.039325,0.044988,0.075938,'Not satisifed'
0.815627,0.042227,0.53809,0.090585,0.406497,Satisifed
0.820687,0.868374,0.656429,0.306149,0.667727,Satisifed
0.107307,0.142247,0.327133,0.297921,0.060763,'Not satisifed'
0.826885,0.349888,0.514668,0.445947,0.796736,Satisifed
0.829198,0.667097,0.538635,0.045136,0.082092,Satisifed
0.063049,0.083685,0.161257,0.080776,0.026139,'Not satisifed'
0.834763,0.683748,0.737979,0.595098,0.548642,Satisifed
0.83947,0.945255,0.80872,0.720512,0.628137,Satisifed
0.174712,0.424606,0.109286,0.057099,0.125548,'Not satisifed'
0.079453,0.15815,0.060135,0.12324,0.031602,'Not satisifed'
0.850137,0.821119,0.832145,0.5471,0.313054,Satisifed

0.854107,0.277773,0.707851,0.81763,0.088019,Satisifed
0.575616,0.199196,0.225436,0.330334,0.20189,'Not satisifed'
0.860212,0.587535,0.303966,0.349923,0.329429,Satisifed
0.860975,0.863677,0.77994,0.838772,0.84552,Satisifed
0.600982,0.076677,0.042465,0.135802,0.087827,'Not satisifed'
0.863879,0.386323,0.344238,0.340753,0.368778,Satisifed
0.870089,0.974386,0.217481,0.087278,0.400101,Satisifed
0.085928,0.064892,0.062363,0.060905,0.049347,'Not satisifed'
0.314159,0.307638,0.283576,0.20372,0.253679,'Not satisifed'
0.870823,0.873972,0.772751,0.894273,0.799966,Satisifed
0.88194,0.417502,0.435268,0.666543,0.409047,Satisifed
0.131789,0.214405,0.17842,0.258246,0.23312,'Not satisifed'

| Speed | Navigation | Ease of use | Content | Aesthetic | Usability rating |
|---|---|---|---|---|---|
| 0.03018762 | 0.034584025 | 0.03039215 | 0.042543751 | 0.035735396 | 0 |
| 0.530146291 | 0.103890848 | 0.132852535 | 0.04596744 | 0.30632354 | 1 |
| 0.530196887 | 0.588441935 | 0.723754197 | 0.569862807 | 0.739117517 | 1 |
| 0.531410713 | 0.539110916 | 0.209085351 | 0.415179894 | 0.232443952 | 1 |
| 0.531437789 | 0.623243415 | 0.594234635 | 0.498093729 | 0.695040528 | 1 |
| 0.532489763 | 0.460451291 | 0.294595396 | 0.3205742 | 0.32982523 | 1 |
| 0.249111291 | 0.324847924 | 0.183989343 | 0.243993877 | 0.145990655 | 0 |
| 0.600981639 | 0.076676673 | 0.042464876 | 0.135802216 | 0.08782683 | 0 |
| 0.063049469 | 0.083684645 | 0.161256533 | 0.080775803 | 0.026139066 | 0 |
| 0.096340987 | 0.029808319 | 0.001826627 | 0.006048904 | 0.001647645 | 0 |
| 0.53293877 | 0.040141572 | 0.17167368 | 0.225089389 | 0.168495713 | 1 |
| 0.534000587 | 0.488680385 | 0.362322941 | 0.394279859 | 0.360213716 | 1 |
| 0.08419338 | 0.128519796 | 0.154894665 | 0.096004938 | 0.089057177 | 0 |
| 0.538997177 | 0.54438417 | 0.212297158 | 0.084736124 | 0.211580153 | 1 |
| 0.121488266 | 0.021959269 | 0.194135029 | 0.141651034 | 0.024331726 | 0 |
| 0.544024986 | 0.272395236 | 0.239504461 | 0.515834909 | 0.404023508 | 1 |
| 0.544867581 | 0.526551033 | 0.213465366 | 0.252366594 | 0.502724632 | 1 |
| 0.042807513 | 0.031127116 | 0.034528897 | 0.069787872 | 0.070882293 | 0 |
| 0.547761655 | 0.37793499 | 0.451712853 | 0.351880383 | 0.22743415 | 1 |
| 0.0364562 | 0.182038673 | 0.13079597 | 0.065019311 | 0.098590075 | 0 |
| 0.036057375 | 0.028052151 | 0.04850337 | 0.096069855 | 0.060398742 | 0 |
| 0.548118554 | 0.41321391 | 0.429344031 | 0.314059884 | 0.437350518 | 1 |
| 0.307784158 | 0.11530771 | 0.134383014 | 0.087844684 | 0.053476497 | 0 |
| 0.550261086 | 0.852773383 | 0.566446638 | 0.768051271 | 0.812974109 | 1 |
| 0.088849355 | 0.152560421 | 0.036311832 | 0.143793079 | 0.091106558 | 0 |
| 0.55120055 | 0.458735975 | 0.162462505 | 0.339579099 | 0.3764568 | 1 |
| 0.552019455 | 0.665435052 | 0.821153914 | 0.848822205 | 0.74457293 | 1 |
| 0.553136665 | 0.444038151 | 0.279729333 | 0.283978959 | 0.34937452 | 1 |
| 0.553136665 | 0.444038151 | 0.279729333 | 0.283978959 | 0.34937452 | 1 |
| 0.554141974 | 0.51987365 | 0.426941623 | 0.275545226 | 0.407136202 | 1 |
| 0.557981507 | 0.449156718 | 0.396877542 | 0.294266605 | 0.341969761 | 1 |
| 0.562695942 | 0.298254687 | 0.592929879 | 0.530853709 | 0.357168605 | 1 |
| 0.563359764 | 0.728045791 | 0.621042157 | 0.658643298 | 0.479048097 | 1 |
| 0.566185316 | 0.917572351 | 0.452121985 | 0.737124907 | 0.604834696 | 1 |
| 0.568962646 | 0.685276608 | 0.347775647 | 0.535174494 | 0.41991784 | 1 |
| 0.571958706 | 0.097576598 | 0.525706272 | 0.266640999 | 0.411821422 | 1 |
| 0.572672096 | 0.217318225 | 0.299002684 | 0.14946832 | 0.099830576 | 1 |
| 0.573380483 | 0.278918899 | 0.250327963 | 0.26369701 | 0.253135766 | 1 |
| 0.576311687 | 0.209502203 | 0.342254363 | 0.709263739 | 0.549648474 | 1 |
| 0.578790707 | 0.363248336 | 0.321980665 | 0.299780333 | 0.304635393 | 1 |
| 0.580640296 | 0.713359841 | 0.500899267 | 0.691614856 | 0.511527136 | 1 |
| 0.581713755 | 0.365714027 | 0.284082705 | 0.149349521 | 0.161555238 | 1 |
| 0.58275686 | 0.252341183 | 0.060296615 | 0.19547113 | 0.520706582 | 1 |

| | | | | | |
|---|---|---|---|---|---|
| 0.591803579 | 0.475206822 | 0.310591888 | 0.26369701 | 0.253135766 | 1 |
| 0.594343792 | 0.596488955 | 0.599093176 | 0.554984285 | 0.4390471 | 1 |