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# Measuring the Feasibility of Clustering Techniques on Usability Performance Data

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## Abstract

This paper proposes a methodology that utilizes unsupervised machine learning clustering techniques in performance based usability data. This paper will first discuss the introduction and current works in the aforementioned domain followed by proposing the methodology to compare and find a better clustering algorithm in processing usability performance data in the field of mobile augmented reality interfaces. The paper will then present the results yield from an experiment abiding by the proposed methodology and discusses the analysis. The paper will end with a short discussion followed by proposed future works in the research area.

**Keywords:** Augmented Reality, Clustering, Machine Learning, Mobile, Usability

## 1. Introduction

Machine learning methods and usability performance metrics has to date been underrated in the field of Human-computer interaction studies. The challenges in current field of usability evaluation is the nature of subjectivity and biases risks. Since compliance to human related requirements can be infinite, possibilities of biases and data inconsistencies is high and risks the reliability and consistency of analyzed results. The usage of subjective usability measures has been a regularly practiced methods with self-reported data rather than performance data. The utilization of machine learning methods are still in infancy, where more gaps are to be seen to be explored. With the advancement of technology that affects usability such as Augmented Reality and mobile applications, more research can be explored in applying machine learning and usability performance metrics in the mentioned fields.

## 2. Literature Review

A study done by Santos et al[1]. shows that out of 43 studied Augmented Reality Learning Environment (ARLE) systems, usability evaluation focuses on improving ease of use, satisfaction, immersion, motivation and performance[1]. Most of the surveyed research works conducted as coined by Albert and Tullis[2] as self-reported metrics rather than performance metrics in this field of study. Santos et. al. reported that common tools used among the 43 reviewed ARLE research includes interviews, expert reviews and observation where observation remain solely the only performance metrics that is used in the reported tools[1]. While most reviewed works uses interviews, self-designed questionnaire, there were several works uses established questionnaire sets for their experiment. The data collected shows that performance data are mostly collected through observation and automated activity log. Observation in this case refers to the help of facilitators in registering the time-on-tasks or behavior, while activity log refers to automated application logging time and activ-

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ities of users. From the data shown above, there is only 1 record of automatic usability data logging of engagement by Uras et al[3]. Many reviewed works implemented common manual data collection that requires more effort and human resources. In the work of[4-6] for instance, data were collected by facilitators through observation might be subjected to social desirability bias[2], where respondent tends to self-report comments that will make them sound or look better. Adding to that, controlled environment observation in the likes of[5] requires test respondents to be in a limited space environment, hence sacrificing mobility feature of MAR-learning. Exposing respondents to the mobility feature like the works done[7] on the other hand, will require the facilitators to extend their work scope in monitoring the respondent continuously regardless of location or time. Not only that it is time consuming, the evaluation process might seem not natural for the respondents having a facilitator following them around.

## 2.1 Data Collection Method

Interviews on the other hand in the works of[6,8,9], they were also subjected to social desirability bias and time to collect. A solution to these few issues will be questionnaires with quantifiable Likert scale such as instruments implemented[10-13]. However, these questionnaires need pilot studies to be validated according to local context and might be subjected to Central Tendency Bias[14]. Acknowledging all these issues in current data collection method for MAR-learning, all the 4 usability (effectiveness, efficiency, satisfaction, learnability) data can be collected objectively rather than subjectively. According to a study done by[15], effectiveness data can be measured by the number of correct tasks achieved per unit of time. Efficiency can be measured using the number of errors registration or time spent on errors. Satisfaction can be measured by engagement time after task completion (subsequent play) and learnability can be measured by time-on-tasks performance over time. All the data mentioned above can be acquired automatically through activity log suggested by[3]. While many automated mobile device activity log techniques suggested by authors like[16,17], it is still a question on why usability data has not been collected through the utilization of these automated techniques. As reported by[16] in their study of comparing self-reported versus log data accuracy, they find that self-reported measures suffers from low criterion validity. Boase and Ling also argued that there is a good reason to be in suspicion of works that find significant correlations between the self-reported techniques with other test variables[16]. Several works for instance in the case of[18-20], researchers tested the mentioned parameters for coefficient with statistical techniques like Cronbach's alpha. It is however questionable if the collected data is tangible through a self-reported process. Either ways, data collection processes are gathered subjectively while, data collected are very much dependent on the parameter's subjectivity.

Objective measures or performance metrics in Usability are quantitative evaluation of performance on Usability metrics, which are reliable and repeatable assignments[21,2]. Most objective measures used in the current researches were focusing on students' performance in English proficiency rather than the user interfaces of respective technologies. None of the work in ELT in M-learning, AR-learning or MAR-learning has experimentation conducted using objective measures with objective techniques[2]. This perhaps could be a gap in usability measure pertaining technologies involving ELT. Subjective measures or self-reported metrics on the other hand are technically opinion-based data given by participants expressing their experiences. These rely on the subjective judgment of people and include questionnaires, ratings, rankings, or judgments[21,2]. As mentioned by Olsson in[7], the user experience measurements in general should essentially be self-reported in order to cover the subjective nature of user experience. All the current works discussed in the previous section has adopted subjective measures in evaluating all their metrics. However, despite having standardized subjective measures, self-reported data is still significantly subjected to biases, inconsistencies and validity.

## 2.2 Machine Learning and Usability

Machine learning approaches have been sparsely explored in usability studies. Within the infancy of its domain, researchers such as Oztekin et al.[22] proposes a learning-based usability evaluation method for e-learning systems. Comparing the effectiveness of 3 machine learning methods namely Support Vector Machines (SVM), Neural Networks (NN) and Decision Trees (DT)[22], shows supervised machine learning algorithms assisted the effectiveness of usability improvements in a quantitative manner. Several other notable mentions in supervised machine learning algorithms used in usability. Can be found in the works[22-26]. Unsupervised machine algorithms such as clustering algorithms are technically useful to partition data and finding structures in an assembly of unlabeled data. Applications of clustering algorithms can be widely seen utilized in areas such as medical and biology[27,28], business and marketing[29], disaster managements[30] and many other domains. It is however interesting to realize from the studied literature, little to none of the published works attempted unsupervised machine learning as a solution to the arguably irregular and anomalies of qualitative usability methods in MAR-learning.

### 2.3 Clustering Algorithms

There are generally two variation of clustering algorithms: partitioning-based and hierarchical-based. There were generally two commonly applied partitioning-based clustering namely K-means (Hard C-means) and Fuzzy C-Means algorithms[31-33] K-means also known as Hard C-Means is one of the simplest unsupervised machine learning algorithms used to partition data based on locations and distance between data points[33]. There is however and extension to K-means namely Fuzzy C-Means (FCM) that is applied to wide range of problems connected with feature analysis, clustering and classifier design[33]. Hierarchical-based clustering can be broadly categorized into two different approach depending on either the algorithm recursively find nested clusters in a top-down (Divisive) or bottom up (Agglomerative) fashion[31,34,35]. Divisive hierarchical clustering was however less commonly used[35]. Fahad et al.[32] further introduced three more variation of clustering algorithms namely density-based, grid-based and model-based clustering.

Partitioning-based and hierarchical-based clustering were used very differently in labelling partitioned data. In the works of Kaur and Kaur[34], it has been concluded that partitioning-based algorithms such as K-means is better in performance as compared to hierarchical algorithms. However, hierarchical clustering shows better clustering quality as compared to K-means[34]. They have also found out that K-means algorithm works better for large dataset, while hierarchical algorithm works better in small datasets[34,36,37]. However, authors like Vijaya et al. and Bouguettaya et al. managed to introduce improvements to hierarchical clustering algorithms enabling it to efficiently partitioning large data sets[37,38]. Despite performing well in many domains, clustering algorithms has yet to be explored on usability data sets, which could be similar in features and requirements of commonly clustered data.

### 2.4 Issues with Current Post-Evaluation Analysis

In the work shown by[1], most respondents are evaluated with either between-subject or within-subject environment[2]. The first case being having 2 groups of different respondents testing 2 different scenarios as comparative studies, while the later reuse respondents' initiatives for both test scenarios and this will eventually lead to bias data due to prior experience and carry over effects in testing the first scenario. The work[12] for instance subjectively collect motivation data before and after usability evaluation which somehow might jeopardize the validity of the data collected. This might be one of the leading reason to why usability problems are not identified clearly when demographic features of potential respondents need to be filtered thoroughly to ensure the same test scenarios are tested by similarly experienced people. Most reviewed works requires a benchmark for a comparative results, while comparing usability scores with the benchmarked components only differentiates usability gaps between the proposed solution and the benchmark. Standalone results in the case of usability practice can therefore be hardly justified.

While literature for machine learning techniques application in MAR-learning usability is little to none[22], proposes a learning-based usability evaluation method for e-learning systems[22]. Demonstrates that machine learning classification of usability problems replaces the qualitative issue of conventional usability methods. Despite the effort to solve the qualitative issue of usability methods by producing a quantitative machine learning approach, data collection in their work are still questionnaire based, which triggers the question of the earlier discussion on unreliable self-reported data. It is the classification phase that is quantitative, but not the data collection phase. From the review conducted so far, the work of[22] is however the closest study to the subject of this research. This research therefore aspire to study the feasibility of unsupervised machine learning techniques such as clustering techniques in defining usability issues.

## 3. Methodology

The methodology for this research is divided into 3 phases as in Figure 1. In phase 1, this research project is a continuation of a project previously published[39]. An MAR-learning ELT application named InterviewME has been developed and validated for tangibility through a pilot study reported[39]. In phase 2, research activities embark with sample profiling of volunteered university students. A total of 87 students volunteered for this project. From that total number, 46 students were selected based on 4 predetermined criteria. The selected students have been using smartphone for more than 3 years, often engaged in mobile social media sites, spend more than 3 hours a day on their smartphones and has taken "Business English" (a subject from the university, to avoid content biases since the experiment focuses only on usability factors). Both genders were equally represented to eliminate gender bias[7,40]. Both groups will be given similar device (an Android tab) to experience MAR-learning. Even though[41] shows no significant differences in participants' performance while using devices with different screen size and weight, this study aims to eliminate any possible device handling biases in order to focus only on users' usability interaction. InterviewMe is an application build within the category of Real World Annotation[1]. The experiment in this study uses marker-based object tracking as suggested by[42] where 59% of AR research still uses marker-based as marker-less AR needs more improvement in tracking objects. This experiment focuses on measuring only interface efficiency of InterviewME since efficiency can directly measure usability performance directly through either performance or self-reported metrics[2]. 2 performance metrics will be used as usability instruments, namely time-on-tasks and error registration[2,43]. Both time-on-tasks (Tot) and error registration (Er) is recorded with a screen capture application to monitor users interaction patterns and completion time. For the purpose of this experiment, samples will be given only 1 task on object tracking since object tracking is one of the major interaction parameter in MAR-learning usability[1]. Phase 3 involves data pre-processing, which first involve measuring coefficient of reliability of the data collected from phase 2. Cronbach's alpha will be used to measure the levels of covariance sharing among datasets[17,44,45]. According to[17] the reliabilities of the scales were good when ($\alpha >$ .70). As the nominal value does not usually correspond to the importance of the attribute, there is a need to give all attributes appropriate and comparable weights[38]. In this case of matter, the α value of raw data sets will be compared to normalized datasets in our experiment. Datasets with higher values in comparison will be used in the next process. As for normalization, rescaling formula will be performed on all datasets for Cronbach's alpha's comparison[38]. Correlation, given by can be considered as both an absolute and a relative measure[22]. According to a study done by[22], the recommended correlation value for human related studies should be at least 0.3 in behavioral sciences, specifically in usability studies.

Both HCA and K-means will be used to cluster the dataset with 2 performance features (Tot and Er). Agglomerative clustering is chosen due to the fact that it shows better clustering quality and works better in small datasets, however K-means shows better performance in larger datasets[34,36,37]. HAC will first be performed followed by K-means. For evaluation purposes, the value of K in K-means will match the number of clusters generated by HAC for an unbiased comparison. Once clustering is completed, quality measures will applied to the clustered data including data with newly clustered labels. The first performance criteria, mean squared error (MSE) will be applied. MSE, given does not have a rule-of-thumb threshold cut-off value[22]. The relative way of selecting the best combination of datasets is by choosing the smaller value[22]. The smaller the value will indicate the better the clustering has performed. A post Cronbach's Alpha measure will also applied synchronously with the earlier 2 measures in performance measure data processing. Both equations will be performed on Euclidean distances (practiced by[38]) of each clustered points and their respective centroids within the datasets clustered by either HCA or K-means. For the purpose of triangulation, a measure of paired t-test is introduced into phase 3 in order to verify the result gathered from both MSE and correlation coefficient.

## 4. Results and Discussion

Table 1 shows data analysis of the experiment where this research can conclude that:

- Normalized datasets has better α and correlation value as compared to raw data. The α value (0.8636) is more than 0.70[17] indicating that normalized data has better reliability as compared to raw data (0.4076). The correlation coefficient value (0.8340) is also acceptably good with the rate of more than 0.30[38].
- Using normalized data, HAC produces 3 clusters with centroids of (0.0921, 0.493), (0.5421, 0.4774) and (1.000, 0.7300). The K value in K-means algorithm is set to 3 to match HAC's auto-generated

clusters. K-means produces 3 clusters with centroids of (0.0921, 0.0493), (0.4317, 0.4233) and (0.6650, 0.6607). HAC can be seen produces a skewered graft as compared to a more Gaussian curved in K-means (Table 2 and Figure 2). The clusters boundaries for HAC and K-means are shown (Figure 3 and 4).

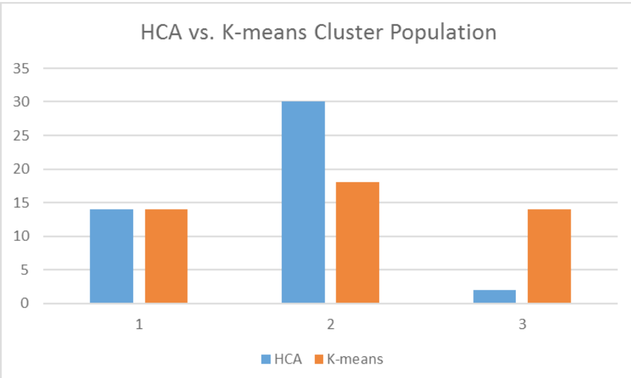


**Figure 2.** HCA and K-means Cluster Population.

**Table 1.** Analysis Data from the Clustered Data Sets

| *Quality Measures* | *HCA* | *K-means* |
|---|---|---|
| *Raw Cronbach's Alpha* | *0.4076* | |
| *Normalized Cronbach's Alpha* | *0.8636* | |
| *Normalized Correlation Coefficient* | *0.8340* | |
| *Number of Clusters* | *3* | *3* |
| *Mean Squared Error* | *0.0107* | *0.0048* |
| *Cronbach's Alpha* | *0.9651* | *0.9760* |

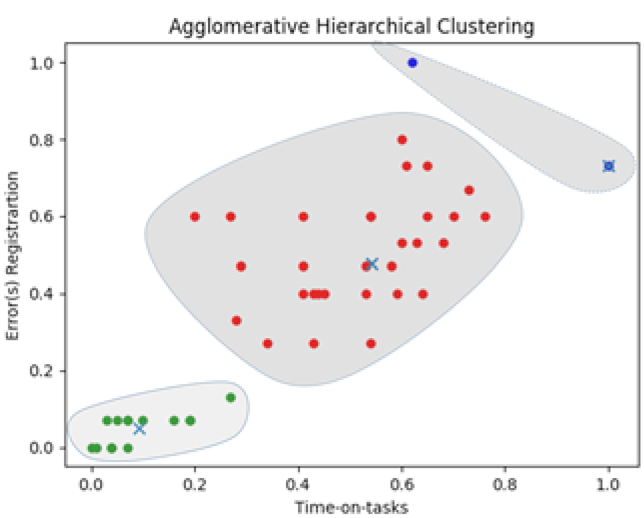


**Figure 3.** HCA and K-means Cluster Population.


**Figure 4.** HCA and K-means Cluster Population.

- The MSE value for K-means (0.0048) is lower than HAC (0.0107), indicating K-means having better quality clusters and performance as compared to HAC[22].
- Results from Cronbach's Alpha suggested the same where K-means ($\alpha$ = 0.9760) performs better as compared to HAC ($\alpha$ = 0.9651) despite both having good values of more than 0.70[38].

In order to triangulate the results collected by MSE and Cronbach's Apha, A paired t-test is used to find the significant differences comparing the distances (distance between each variable to their respective cluster centroids) of HAC and K-means (Refer Table 2).

**Table 2.** T-test Results Comparing HCA and K-means

| **Measures** | **HCA** | **K-means** |
|---|---|---|
| Mean | 0.1530 | 0.0807 |
| Standard Deviation | 0.105 | 0.0698 |
| Degrees of Freedom | 45 | |
| Confidence Level | 95% | |
| P-value | 0.00028 | |
| t-value | 3.94 | |

It can be seen that the standard deviation of HAC (0.105) is relatively higher than K-means (0.0698) indicating further distance threshold from the respective centroids. With the degrees of freedom of 94% confidence level, the probability value comparing HAC and K-means rejects the null hypothesis indicating a significant difference. With a t-value of 3.94, it can be concluded that HAC has a significantly larger Euclidean distance (variables to centroids) as compared to K-means. The paired t-test triangulation verifies the results generated by both MSE and Cronbach's alpha discussed earlier. Despite having significant differences comparing HAC and K-means where in this experiment on human-related usability performance data, it is also concluded that both HAC and K-means still have above-average results in clustering quality and performance abiding by benchmarks given by[38] and[22]. This experiment on performance usability datasets also disagrees with several results shown by[34,36,37] especially on dataset sizes and clustering quality. The contradiction might be due to the nature and conflict of the data requirements.

## 5. Conclusion

This paper shows evidence of how the utilization of unsupervised machine learning techniques such as clustering algorithms on usability performance data can be reliable. The proposed methodology can be an alternative and solution to common practices of subjective and comparative testing in usability, which has been widely argued of data reliability and biases. Usability issues can also be identified independently without the need of competitive evaluation, which are prone to more complex processes in order to solve multiple bias risks. This research will continue to find more feasibility evidence on how machine learning algorithms and performance metrics can be more dependable and utilized as compared to conventional usability data gathering and analysis.

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