Undereducation, Motivating Intervention in Rural Schools with MAPPS

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Abstract
Many primary school students in rural areas of developing countries perform poorly in national final exams, and therefore, fail to transit to secondary schools. This problem causes undereducation and shortage of skilled manpower in the developing countries. Mobile Academic Performance Prediction System (MAPPS) is a technology that categorises students into two groups: those requiring high intervention and those requiring low intervention. This study investigates predicting the students that need high intervention in order to motivate initiation of intervention measures early enough. The focus in this paper is the mobile application design process and the usability evaluation of MAPPS.

Author Keywords
Undereducation: Intervention; Performance; Prediction

Introduction and Background
Although major strides have been made to make education accessible to all children in Kenya, there is inefficiency in the schools, as evidenced by poor academic performance among many rural school students in national examinations. This trend requires intervention because such students eventually drop out [10].

Passing in Kenya the Certificate of Primary Education (KCPE) national examination is pegged on a national pass mark; usually, half the total possible marks a student could score. Students who score below the pass mark do not proceed to secondary schools, but are considered dropouts of the school system.

Educational Data Mining (EDM) techniques have been used successfully in developed countries to predict students' at-risk of failing, long before they sit for standardised exams [2, 10]. Similarly, techniques for determining the most indicative features for use in the prediction models have been applied in various fields to improve classification accuracy [11]. Different classification techniques have been applied in predicting students' marks or grades and at-risk students. Using key student demographic characteristics and scores in a selected number of tests from Hellenic Open University (HOU), student academic performance was predicted using regression techniques [4]. The study determined the best algorithm from a set of six, and also constructed a software prototype for tutors. A related study used a dataset from MOODLE logs to train an RBF neural network to detect students with problems to pass a course[1].

Our study adopted a similar approach of binary classification. A dataset of 2426 student records were manually collected from rural schools and 1105 records from peri-urban schools. An optimal set of features was selected from a total of 22 features [6]. The classification algorithm that achieved the best classification performance was Logistic Regression [7]. MAPPS was then developed, which incorporates the optimal features and the best classifier. It was tested with two sets of test data, 695 records from rural schools, and 441 records from peri-urban schools. A prediction performance of 80% was recorded using the F-Measure metric [8]. The system classified students in into two classes, those requiring high intervention and those requiring low intervention. The reason for choosing high and low intervention is to ensure that the results are aimed at motivating strategic intervention. The main contribution of this work is the academic performance prediction system that incorporates mobile technology. Mobile phones are affordable and can be found everywhere in developing countries. Desktop computers are more expensive and cannot be used because of poor infrastructure [9]. This paper presents the User Centred Design (UCD) process for MAPPS and the usability testing.

Design and Implementation

MAPPS is a system made up of a mobile phone application and the classification algorithm - logistic regression - stored in a server. The components of MAPPS include the mobile application linked to the server via the Internet. The mobile application allows the entry of student records, while the classifier model does the classification according to the two classes, high and low intervention.

Building the Interactive Mobile Application

The design of the mobile application was achieved using the User Centred Design (UCD) approach. UCD was used because it puts a great emphasis on involving the users of the system being developed from the beginning of the design process to the end [5]. Initially, the features for the student record and the classification algorithm used to build the prototype were determined using the EDM process. Then, the options for the selected seven features were obtained from the participants involved in the UCD approach. Two iterations of the design process for the mobile interface are discussed next

First Version Prototype

Figure 1: Mobile phone main interface icons for the first prototype

As shown in Figure 1, the user taps each icon to make a selection from the menu that appears. It is only after all the feature options for student record have been selected that the user can select the send record button. This version was tested with the users and found to have usability issues, for example users had to remember every option they have selected. Suggestions from the users helped in the design of the second version.

Second Version Prototype

The main interface in the second version was modified to use forms as shown in Figure 2. Next to every feature icon is a drop down list arrow that when tapped opens a list of the options. A selected option appears beside the feature icon to eliminate the need for one to remember previous selections.

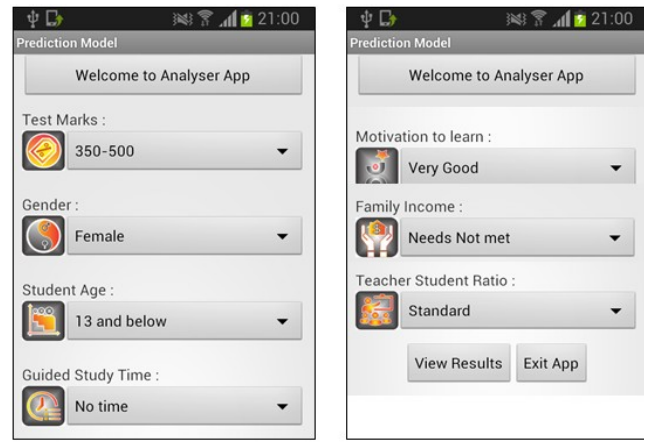

Figure 2: Mobile phone interface showing icons for the second prototype

Further modification is the process of sending a record and viewing results via one button, he view results button. This reduces the number of selections. User evaluation was conducted as discussed next.

User Feedback

To obtain feedback from users, MAPPS was given to teachers in 15 schools for a period of three weeks. A total of 17 teachers participated. In each school MAPPS was used to predict the intervention levels for Class Six and Class Seven students. A total of 1839 students' participated. Standardised County examination results were used as the target for comparison with the MAPPS output.

After the three weeks, teachers were given a set of 36 cards with words which were printed and laminated, describing the possible feedback. The words were a mixture of both positive 60% and negative 40% as was done in [12, 3]. Some of the positive were: useful, motivating, relevant, and reliable. Some of the negative words were: inconsistent, frustrating, confusing, and complex. Teachers were asked to select five top words that describe their opinion about the system. Using these words, they were engaged in an interview to obtain a detailed feedback. This approach was found useful in getting feedback from software users [12, 3].

The experimental analysis is displayed in Figure 3

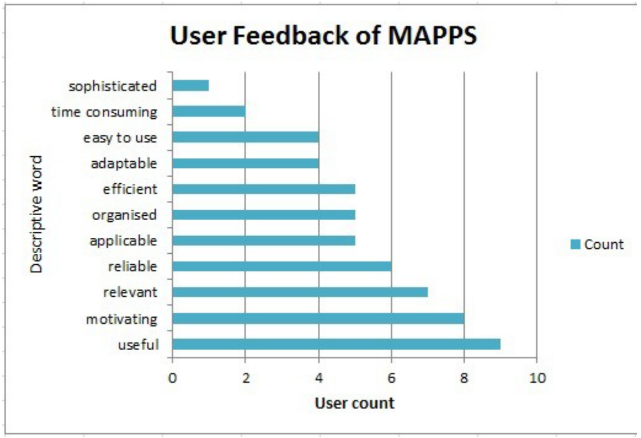

Figure 3: User feedback rating in terms of the selected descriptive words

Discussion

The analysis in Figure 3 shows that majority of users agree the system is useful, that it could improve the students' academic performance. Users noted that, when stakeholders are made aware of the students' status early enough, they are likely to think of ways and means to assist them. Besides, as teachers get data from the students, it helps to understand them. This give teachers information that they could use together with other stakeholders in coming up with strategic intervention.

The system was also found to be motivating, meaning that the system was accepted by both the students and teachers. Students and teachers were both motivated by the fact that the system produced the result of intervention almost immediately. The speed of processing was made possible by Safaricom mobile provider network which covers most of the rural areas where the study was conducted.

The word relevant was also popular because users looked at MAPPS as a device that is student centred because it was about how to improve the students' academic performance. Further, users seemed to agree with the results of prediction for most of their students, which made them conclude that the system is reliable.

Conclusions and Future Work

The study is an investigation of academic performance prediction that used mobile technology to facilitate EDM in building an academic performance prediction system. A mobile phone application was used to make the system usable in rural regions of developing nations. Desktop computers cannot be used in these areas because they lack infrastructure. The paper presented the mobile application design and the usability evaluation of the mobile application. Usability evaluation results show that most users agreed that the system is usable and useful and that, the system is relevant and demonstrates reasonable potential to motivate initiation of intervention measures by education stakeholders.

Future work will be towards improving the system usability by using more participants and different usability evaluation approaches.

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