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Computer Assisted Assessment and The Role it Plays in Educational Decision-Making and Educational Justice: A Case Study of One Teacher Training College in Zimbabwe

Michael Kainose Mhlolo, FRF Mathematics Education Chair,
Rhodes University

Abstract

Although the use of computers in data-driven decision making in education was initially focused on education's core business i.e. computer aided learning (CAL), educational leaders are now using this approach to transform other aspects of their operations e.g. computer-assisted assessment (CAA). The full potential of CAA has yet to be realized and its implementation within higher education can be fraught with difficulties. This paper draws on a research that was carried out in one teachers' college in Zimbabwe. The main aim was to engage with the final grading system used on the teaching practice phase of a group of 600 newly qualified teachers with a view of identifying how the computer was being used to allow humans to benefit from machine decision-making without losing the opportunity for rational thought. This was driven by a sincere conviction that better data-driven decisions in education benefit everyone, including the learners, teachers, administrators, patrons, taxpayers and the state. The researcher employed an approach commonly used in IT, which is called Data Mining. The findings seem to point to a grading system which is using a computer more as a data capture and calculation instrument without questioning the moral argument for letting the computer decide. Such a grading system has potential for loss of human autonomy and for being unfair to the subjects.

Introduction

The demands for accountability have forced administrators to take a more aggressive position on integrating ICT and data-driven processes into all aspects of their operations. But the rush to computing has almost obscured the important question: How are computers to be used effectively in those operations? Modern computerized information systems are facilitating and instilling a greater degree of rationality in decision making in different organizations. While these systems are not replacing the decision maker, they surely are helping to refine the decision making process.

Computer-assisted assessment is an educational concept which borrowed the use of technology from industry into education. Those involved often face serious challenges in their attempts to introduce innovative teaching and assessment methods. There is a more pressing need to rigorously evaluate the use of CAA in educational institutions as the implications and impact are wide reaching and of concern to a range of interested parties.

Because machines make more decisions as they become more advanced, it is necessary to establish a clear set of principles regarding what choices computers should make. In any case where a computer is more likely to make a good decision than a human being, a computer should make the decision. However, computers should never make decisions which humans can make more competently. In other words, humans should always have the authority to override a decision reached by a computer.

Background of the study

As one of the University's External Examiners and a Mathematics Teacher Educator at one teachers' college, I was privileged to travel to different teacher training institutions which are associate colleges of the University of Zimbabwe. There I had the opportunity to listen with keen interest to academic debates that ensued during the ratification of results by the external assessment team. The different interpretations and decisions based on quantitative data as recorded on the mark-profiles usually reflect the different levels at which the computer is being used in making decisions and the quantitative literacy that decision- makers have. Unfortunately, the already pressured academic staff members rarely have time to formally investigate the impact of computer-assisted assessment on their students yet this is critical to the delivery of quality education in a number of ways.

There is consensus the world over that while education and training of teachers is pivotal to quality education, the practicum/teaching-practice component of the training is the most important in that it is where the theory learnt in college is put into practice and it is also where the new teacher demonstrates the ability to teach. This also implies that assessment and data driven decision making on this phase of the course is equally critical to quality education, more so when computer-assisted assessment is being used for summative evaluation purposes at the end of the course. So firstly, for the benefit of the learners who are going to be under the tutelage of this new teacher, the final result must be an accurate indicator of the new teacher's ability to teach. Secondly, for the new teacher, the result must also be accurate because as a final score it becomes symbolic, for life, of the quality of his/her work and may open or close doors to future opportunities for the new teacher. So, data-driven decision making at this point should ensure that the new teacher does not live a lifetime of programmed frustrations and denied opportunities due to human error.

Put simply there is need for validity, reliability and consistency in getting abstract numbers from the concrete teaching performances of the pre-service teachers and in interpreting those numbers as descriptions of the trainees' abilities to teach especially for certification purposes. This would help to enhance quality in education and to underwrite the logic of educational justice.

The logic of educational justice

Most societies subscribe to the premise that individuals are substantially unequal in their merits and subsequently in their claims for desirable benefits such as wealth and power. So some institutional means are required to make inequality appear as normal, a natural factor of the social order and indeed as a deeper expression of social justice. The leading institutional means turns out to be universal education where all individuals are required to be sorted out by assessments of their merits from childhood until adulthood.

Individuals are allowed to compete on an equal basis to demonstrate their competence. The provision of an apparently fair competition allows those who are not successful to accept their own failure thereby controlling resentment among the least privileged and acquiesce in the legitimacy of the prevailing social order. Seen in this view, Broadfoot , cites assessment as a means of social control 'unsurpassed in teaching the doomed majority that their failure was a result of their own inbuilt inadequacy'

However, the logic of educational justice is reminiscent of social Darwinism with its notions of the laws of nature and the survival of the fittest. In theory therefore, inequality is merely accidental and upward mobility is offered to all individuals, hence the logic of educational justice. In practice however upward mobility is achieved only by individuals who have survived fierce competition. Learners who fail would be naturally unfit to survive and would have no claim upon education or society. Admittedly such learners usually don't just cease to survive they live out a lifetime of programmed frustrations and denied opportunities. So while assessment through quantitative data such as marks or scores can symbolize educational justice so readily because society entertains a profound respect for abstract numbers, the human ability to perform precise operations upon such abstract numbers afford many opportunities for error. So the underlying logic of education through its assessment tools need not underwrite educational justice and may indeed foster injustices for which the learners are held responsible if issues to do with the use of technology in critical data analysis and decision making are not taken cautiously.

An increasing number of higher education institutions are now looking to computers to solve some of the problems associated with the burden of assessment. This rush to computer-assisted assessment has almost obscured the important question: "How are computers to be used effectively in educational assessment?"

Computer-assisted assessment (CAA)

Robbins developed three maxims regarding the use of computers as decision makers, which are as follows:

1) In any case where a computer is more likely to make a good decision than a human, the computer should make the decision.

2) Computers should make any decisions that humans have no desire to make.
3) Humans should always have the authority to override a decision reached by a computer.

By these maxims, computers would then be used to make decisions in cases where they perform better than humans or where boredom or danger dictates the use of a machine. However, humans will always have the authority to override the decision of a computer, thus retaining the right to reason. This is so because computers make decisions on the basis of programmed and hopefully rational rules without regarding other factors. Such factors may turn out to be critical in decision-making and must therefore be taken into consideration. The authority to override computers however, demands that the human being in charge of doing so must of necessity possess or develop deeper ·human cognition for effective use of a computer.

Mathematical literacy and effective computer use

Historically the development of digital computers is rooted in the abacus and mechanical calculating devices. A digital computer is designed to process data in numerical form and its circuits perform directly the mathematical operations of addition, subtraction, multiplication and division. The latest digital computers have artificial intelligence AI which is defined as a field that attempts to provide machines with humanlike reasoning and language-processing capabilities Havenstein This development has made the computers to be able to mathematically outwit humans in multiple aspects. But regardless of the success of many expert system applications, critics continue to warn that expert systems still lack three basic necessities; human intelligence, human emotion and freedom from intentional or accidental bias Khalil . So while computers are here to stay and that artificial intelligence is definitely up and coming, researchers still don't believe that computers will take over the everyday tasks of humans. Computers have been designed to assist humans in their daily activities and they will remain that way ... *assistants in our lives!*

Because calculators and computers were developed as "power tools" that assist humans by removing human impediments to mathematical performance and by extending the power of the human mind, there is this symbiotic relationship between humans and computers for the benefit of mankind. But for computers to better assist humans, certain skills are called for. Understandably one of the human skills needed is mathematical reasoning. This human factor is critical for effective use of computers especially in computer-assisted assessment where the fate of humans is at stake. More often than not, indicators of effective teaching/learning and quality education rest in mammoth data-bases. But according to Carr numbers alone won't tell us what we need to know. If we are going to draw conclusions that are meaningful and useful from numerical/quantitative data, we have to get down under the numbers, break them apart, look at trends and see how the information conveys meaning.

Possessing a great deal of quantitative information in a computer by an educational policy maker therefore does not of its own guarantee relevant and optimal data driven decision-making. Making decisions aimed at improving quality of education requires complex data analysis skills, which include proper use of the computer, working and reasoning with numbers and data in a contextual framework. Cozzens refers to this as "quantitative literacy" and argues that it plays an important role in educational decision-making.

In this research therefore, questions were being raised from two complementary perspectives: (1) the complementary use of the computer and the human mind to make accurate interpretation of quantitative data as being critical to *quality* education and (2) the issue of accuracy in data analysis leading to *fairness* in the grading system which in turn would result in underwriting the logic of educational justice to both the pre-service teachers and the learners they will teach.

The grading system under review

The structure of the course at most Primary Teachers' Training Colleges in Zimbabwe is such that pre-service teachers spend 8 months [2 terms of 4 months each] of pre-service theory work at the college then go out into schools for 20 months [5 terms of 4 months each] of teaching practice and then finally come back to college for 8 months [2 terms of 4 months each] of what might be referred to as post-practice theory work leading to final examinations and certification. Hence the model of teacher training is referred to as the [2-5-2] model. During the 20 months the student is on teaching practice he/she is observed while teaching and his/her performance is scored on a scale of 100 by different supervisors, some from the school of his/her teaching practice, some from the college and sometimes some from a team of external examiners as shown in the table 1. The final score for certification purposes is then computed from these three main sets of marks. The pre-service teachers' final mark profile at this particular institution then appeared something like Table 1.

Table 1 shows an extract of the mark profile with 9 pre-service teachers' scores seen a maximum of 5 times teaching by the school administration, and a maximum of 4 times by college lecturers during the 20 months' period that they were on Teaching Practice. The Final result can be read from the column headed Internal Mark and in this sample profile shows three students A, B, and C who were deemed failures by this grading system and the 6 students D, E, F, G, H, and I as passing respectively. The Internal Mark of 37% for student A for example, is a result of computation (12.6 + 6.8 + 18.4) using a weighting of both the school-based scores and the college-based scores as shown in the table. This formula (*20% of last school based score and 40% of the last two college based scores)* is based on the assumption of the *learning curve effect/theory,* i.e. a positive relationship exists between experience and task performance . The argument being raised by the institution is that the last scores to be recorded in each case indicate the best performance of the pre-service teacher due to the experience the student has gained over time. Experience is therefore seen in this learning curve context as a fundamental mechanism through which both organizations and individuals accumulate knowledge and develop competencies.

Table 1

An Extract of the Mark Profile

SCHOOL BASED ASSESSMENT							COLLEGE BASED ASSESSMENT							EXTERNAL BASED
STUDENT	1st	2nd	3rd	4th	5th	20% of last mark	1st	2nd	3rd	4th	40% of 2nd last mark	40% of last mark	Internal Mark	External Mark
A	57	60	55	68		12.6	59	17	46		6.8	18.4	37	
B	75	74	71	75	77	15.4	66	72	68	17	28.8	6.8	49	
C	53	63	67	51		10.2	62	51	14		20.4	5.6	36	
D	67	70	74			14.8	73	74	20		29.6	8	52	
E	59	69	78	80	66	13.2	48	34	68		13.6	27.2	54	
F	70	71	74	70	74	14.8	60	23	71		9.2	28.4	52	
G	68	71	74	73	71	14.2	60	73	23		29.2	9.2	53	
H	54	64	50	52	52	10.4	52	62	42		24.8	16.8	52	
I	57	54	78	59	61	12.2	55	56	52		22.4	20.8	55	

It is against this background that the following research questions were being raised:

- What is the nature and justification for the theoretical framework which forms the basis of the grading system in this particula Teacher Training College?
- How are the computer and the human mind used to complement each other in making rational decisions in this institution?
- To what extent does the grading system promote the educational justice that society expects of any assessment procedure i.e. to what extend is it objective, neutral, rational and fair?

Methodology

In designing the approach and the analytical tools to use in this research, the process was guided by Bull who argues that the implementation of CAA should be pedagogically led, not technologically driven. In his view, allowing technology to drive the assessment process is highly undesirable and merely transferring traditional assessments to electronic format with little thought to the potential for enhancing the assessment in terms of the skills and abilities tested is not a solution to the problems associated with assessment. With this in mind, this research therefore tried to employ a holistic approach by striking a balance as it borrowed from industry, from the technological field and from the educational field to come up with the analytical lenses.

The research therefore started by borrowing an approach commonly used in IT, which is called Data Mining. Data Mining is the most general form of database querying and usually the goal is to discover interesting relationships where all we have is a notion of an interesting database. It involves the extracting of previously unknown or unclear and potentially useful information like rules, constraints, correlations, patterns and irregularities. According to Gorard Data Mining derives its name from the similarities between searching for valuable business information in a large data base and mining a mountain for a vein of valuable ore. Both processes require either sifting through an immense amount of material, or intellectually probing it to find exactly where the value resides.

The technique which this research borrowed from Data Mining is called modeling, which is the act of building an abstraction or model based on certain identified characteristics and then using the induction rule [if-then] to test it against reality. The logic behind modeling is that once the model has been built it can then be used in similar situations where the answer is not known.

In this case the formula for calculating the final score/grade for the new teacher at this particular college was based on the assumption of the learning curve effect/theory which argues that a positive relationship exists between experience and task performance Based on that assumption therefore, the researcher built an abstraction or model by identifying the characteristic features of the learning curve effect/theory and the environment under which there could be a positive relationship between experience and performance. This abstraction was then used to analyze the scores for the 600 new graduands on the mark-profile and subsequently to engage with the different data driven decisions that the college academic board was making vis-a-vis the final grades of their new teachers.

Analytical tool – 1: The learning curve theory

The learning curves, also known as experience curves, cost curves; efficiency curves and productivity curves have wide application in both industry and education. They were adapted from the historical observation that individuals who perform repetitive tasks exhibit an improvement in performance as the task is repeated a number of times. The central notion in the learning curve theory is that accumulating experience leads to improved performance, or learning by doing. Viewed in this context, individuals and systems move down the experience or learning curve by learning to complete repetitive tasks more efficiently, eliminating hesitation and mistakes, automating certain tasks and making adjustments to procedures or systems Beaugrande,1997. The concept occupies a central role in many strands of strategy and organization theory and forms the basis for such ideas as the specialization of labor, organizational learning, knowledge transfer and core competence of the firm, Argote, 1999). Understandably, research indicates that the majority of the studies which have proven the so called learning curve effects drew data from manufacturing or operational settings where: a) tasks were homogenous or of a duplicative nature: b) where tasks were not so complex and therefore could easily be classified as routine: c) where motivation could easily be linked to task performance: d) where performance was easy to measure or where there was a high reliability and validity of performance scores.

If these are the characteristics features of the learning curve theory, whose origins are in industry, then to what extent can the theory be transferred to and applied in a teaching/learning situation? Steen (2001) defines transfer as the ability to appropriately and accurately apply reasoning to new problems and in new contexts. Other issues involved in understanding transfer include the degree of similarity between the concept in which a principle is learned and understood and the new context in which it should be applied. Bull (1999) quickly warns that merely transferring traditional or possibly flawed assessments to electronic format without little thought to the potential for enhancing the assessment in terms of the skills and abilities tested is not a solution to problems of assessment. Because the learning curve effects are closely linked to manufacturing and operational settings, Argote (1999) was quick to point out that the generalisability of the effects elsewhere was constrained.

Levinthal and March (1993), for example have summarized a number of explanations, which have been forwarded by researchers and which explain why experience does not always produce positive performance effects particularly in educational settings and especially in teaching/learning situations.

Firstly, there is need to acknowledge that for a teacher each lesson is a standalone activity in that it differs from the next lesson with respect to a number of characteristics and therefore it becomes very difficult to predict better performance by the teacher in the next lesson. Lesson delivery tasks are complex tasks such that it might not be very easy to quantify performance of that task neither is it easy to classify lesson delivery tasks as routine tasks hence again the prediction of better performance in the next task is constrained. There are cognitive limitations in grasping the applicability of past experiences into the next lesson because of the complexity nature of the tasks of lesson delivery. This limitation is even more pronounced in the Primary School where a teacher is expected to teach more than ten subjects on the curriculum. Motivation also differs in each lesson because naturally teachers are more comfortable and intrinsically motivated teaching certain and not necessarily all the subjects on the Primary School curriculum. The level of confidence which is a result of subject mastery differs also from one subject to the other and so to expect that a teacher who was seen teaching Mathematics would perform better when he/she is next seen teaching English or any other subject would be constrained. The issue of rater reliability is also critical for the learning curve effects to be felt. A rater's philosophy on certain issues influences the grading system. Where one rater is used for example, and the rater is either incompetent or too lenient or too strict, objectivity is compromised and the grading system gets distorted hence the learning curve effects are also constrained.

Analytical tool – 2: Credibility of the assessment system

With regards the credibility that can be attached to a grading system researchers are of the view that if grading by numbers is to underwrite educational justice, then: a) each learner's individual performance should be quantifiable b) a stable relation should obtain between the performance and a quantity c) the quantities can all be expressed across the same scale d) every teacher, marker, scorer is a fully competent quantifying agent e) the quantities can be dependably summed or averaged into a single number representing a fair and accurate assessment of one's total education outcome (Beaugrande, 1997; Gipps & Murphy, 1994)

So the success of any system of assessment can be judged therefore by: a) the extent to which the methods it employs constitute an effective model of valued performance and an effective model of educational practice b) the adequacy of its methods in monitoring these valued performances through the provision of adequate opportunities for all students to display their capabilities in forms that can be documented and c) the effectiveness with which assessment informs the actions of all interested parties d) its development based on a coherent and consistent application of theory Clarke & Stephens, 1996). These indicators then formed the basis of the analysis of the pre-service teachers' scores as captured on the mark profile.

Data analysis

Having said all this, what story did the numbers on the mark profile tell? A look at the sample mark-profile provided on Table 1would reveal that the scores/marks from the two columns headed School based Assessment and College Based Assessment do not in fact show the incremental trend that is expected in the learning curve or experiential learning theory. In fact the marks/scores reflect a stochastic pattern and this was observed in 66% of the cases that were reviewed by the research. This in fact confirms Argotte's (1999) warning of the limitations in the generalisability and applicability of the learning curve concept elsewhere. Barnett and Ceci (2002) also indicate that transfer of concepts, especially with regards quantitative literacy, requires flexible, sophisticated reasoning and application of principles. They further argue that educators were usually guilty of being on the two extremes of the transfer continuum i.e. on one extreme they have the tendency to categorize concepts learnt as either domain-specific and on the other extreme as broadly applicable.

Actually in this particular case, this limitation should have been expected especially when one considers that in this institution the Internal Teaching Practice Policy is that no pre-service teacher shall be seen twice teaching the same subject. This spread of lesson observations over the different subjects taught in the Primary School is to encourage a wide coverage in terms of practice of the curriculum that the pre-service teacher will interact with when they qualify. So those marks on Table 1 were generated from observing pre-service teachers teaching different subjects at their schools of teaching practice and to expect that a teacher seen teaching Social Studies today will perform better when next seen teaching Art, for example, would not be justifiable.

Another important factor to be considered is that the mark profile for teaching practice scores consists of impressionist scores which by nature are subjective as they are based on an individual lecture's philosophy. A rater's philosophy on certain issues influences the score he/she awards to a pre-service teacher during the lesson delivery and this again is not consistent with the learning curve effects. Quantifying or converting a performance of a pre-service teacher when teaching may not be as easy as counting the number of oranges picked by a worker from a fruit plantation. Yet the learning curve theory operates fairly easily in an environment where it is easy to quantify or measure performance. At this particular institution also, it is common practice that pre-service teachers are supervised by any lecturers irrespective of their subject specialization. In other words a Mathematics lecturer could supervise a pre-service teacher teaching a Physical Education lesson and one wonders how much expertise lecturers in the Primary Teachers Colleges hold across all the subjects taught in the Primary Schools. Yet one of the conditions of the learning curve effect to happen is that the rater must be a fully competent quantifying agent.

In the cases where the marks showed an incremental pattern (34%), the rate of improvement was not of a sufficient consistency to allow its use as a prediction tool. It is one of the conditions or characteristic feature of the learning curve theory. This paper takes cognizance of the fact that indeed repetition of certain teaching processes leads to better performances of those processes e.g. lesson planning and schemes of work. However, unless that process can feature as an explanatory element or predominant element (prediction tool) in a relationship, its justification as the basis upon which a formula for a grading system is built might be constrained.

With this in mind therefore, the justification for using the marks 68 and 17 in computing the final mark for candidate B on the mark profile above, for example, is constrained. In fact the same candidate would have scored a final mark of 56 (not 49) if the institution had averaged (arithmetic mean) all the marks as suggested by Beaugrande (1997) . The argument in favour of the mean score is based on the realization that impressionist marks contain elements of chance errors due to various reasons and the sum of such errors of measurement is zero or close to zero when all of an individual's trials are added and averaged. Following the same argument, candidate A on the mark profile Table 1 would also have scored a 40% (supp) as opposed to the 37% (total failure)

Again in support of grade averages, Beaugrande (1997) is of the view that the logic would be that fluctuations among the individual grades of a learner should be balanced out as they are either unseemingly or doubtful. He refers to such extreme scores as "flukes" which are a result of accidental or extraneous circumstances. He further argues that a single failure through a fluke will be far more devastating than its true importance would justify. Going back to the sample mark-profile it is evidently clear that student C for example was negatively affected by such a "fluke" because all his/her marks were around 60"s except the last score of "14" which brought all the efforts down to a failing score of 36. Such a grading system naturally would pose a threat to the educational justice, would deny society the services of such a pre-service teacher and would make such a teacher to live a programmed life of frustration and denied opportunities. In fact there were quite a number of such cases which were observed in this particular grading system.

One of the characteristic features of a fair grading system is the adequacy of its methods in the provision of equal opportunities for all students to display their capabilities. Going back to the same sample mark profile one notices a conspicuous disparity in the number of times pre-service teachers were observed teaching. Some were seen 4 times, some 3 times and some 5 times and this pattern was common in the whole group under review. This kind of disparity has potential not only for abuse but for benefiting some and disadvantaging others. Student B on the sample mark profile would be a typical example of such disadvantaged pre-service teachers in that he/she has more lessons seen than all the others and the last mark then turned out to be that 17 which was then used in the computation and causing the final result to be a failure.

Conclusion

Data in this grading system were analyzed with a view of understanding the logic behind the choice of the theoretical framework and the potential it had of being a fair grading system. It would appear that while the application of the theory of the learning curve would be very noble, its transferability into educational settings needs to be further investigated. In this case it would appear the computer was not being fully utilized since some of the characteristic features of the learning curve theory, which formed the basis of the grading system, could have been tested using a computer. Teachers' colleges might want to take heed of the maxim that in any case where they make better decisions than humans, computers should do so, but humans should always have the authority to override a decision reached by a computer. That way the computer and the human mind are used to complement each other in making rational decisions. Finally, the findings so far would seem to point to some areas which have potential of being unfair to the pre-service teachers and therefore might need institutions with similar systems to review and reconsider their assessment systems.

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