ISSN 2250-3153

The Promise of Data Driven Decision Making In Transforming School Management and Decision Making

Dr. Mary Mugwe Chui

Department of Educational Management and Curriculum Studies
Mount Kenya University

Abstract- The potential for computers and information systems to deliver smart organizations has grown exponentially in the last decade. This potential and promise of smart organizations in the has been considered by policy makers for transforming schools into smart digital environments where data is used to make the best decision to improve student performance. Schools globally, just like other organizations are gathering massive amounts of data; although not all this data has been put into meaningful use, efforts have been directed towards dependency on the analysis of data in schools to drive the decision making. The benefits to the schools, brought about by these transformations in relation to their performance in various aspects have continuously magnified the critical importance of depending on data driven decision making for schools. However, challenges have constantly been highlighted by these institutions as they try to make this technological shift. Senior management in educational institutions has been considered an obstacle in accelerating the shift to knowledge driven decision making. This paper highlights the potential of transforming school management and decision making to smart-digital institutions. This is based on a review of existing literature especially in the areas of data capture, knowledge management and data mining in schools.

Index Terms- Data mining; Knowledge discovery; Management; Organization; Data Driven Decisions.

I. Introduction

The traditional method of turning data into knowledge relies on manual analysis and interpretation (Radermacher, 2014). This points to the fact that dependency on data to drive organizational performance has for long been the norm; the only difference however has been on the sources of this data and the analysis and interpretation method employed. Schools like any other organizations gather massive amounts of data daily.

The **knowledge discovery process** (KDP), also called knowledge discovery in databases, seeks new knowledge in some application domain. It is defined as the nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data. The process generalizes to non-database sources of data, although it emphasizes databases as a primary source of data (Cios, Pedrycz, Swiniarski, & Kurgan, 2007).

Data mining is a process that uses a variety of data analysis tools to discover patterns and relationships in data that may be used to make valid predictions (Two crows Corporation, 1999). The data-mining component of KDD currently relies heavily on known techniques from machine learning, pattern recognition, and statistics to find patterns from data in the data-mining step of the KDD process. A natural question is; how is KDD different from pattern recognition or machine learning (and related fields)? The potential to make schools "smarter" by the application of these IT tools to extract knowledge from every sector of the school and improve the overall performance of learning institutions is great(RAND Education, 2006). Yet these data mining and knowledge discovery techniques have not been exploited by learning institutions to inform their decision making process. This paper therefore seeks to highlight the major benefits that learning institutions can gain by shifting to data driven decision making and entrenching IT tools and facilities to inform their actions and strategies.

II. INTRODUCTION TO KNOWLEDGE MANAGEMENT

Knowledge management is the processing conversion of information into Knowledge and the dissemination of the right knowledge to the right people and at the right time. Knowledge management implies a strong tie to corporate strategy, understanding where and in what form knowledge exists, creating processes that span organizational functions and ensuring that initiatives are accepted and supported by the organizational systems. it includes the creation of new knowledge, sharing, storage and refinement.

Knowledge management is the systematic management of an organization's knowledge assets for the purpose of creating value and meeting tactical and strategic needs of a firm. it consists of all initiatives, processes, strategies and systems that sustain and enhance the storage, assessment, sharing, refinement and creation of knowledge. Knowledge management must therefore provide the right tools, knowledge, people, culture and structures so as to enhance learning ([1]www.knowledge-management–tools.net)

Implication of Knowledge Management and DDDM to Education policy makers

Data driven decision making is an essential process that should be used as the basis for all district and school decisions to improve student achievement. The process generally begins with a collaborative analysis of student Outcome Indicators" (Reeves, 2004). Effect data are systemwide indicators that are required by state statutes. These data points apply to every school in a district and may, for example, include state test scores, attendance figures and dropout rates.

ISSN 2250-3153

While it is important to know where the students in your district are, it is equally important to know how they got there. Accordingly, the DDDM process not only analyzes effect data, but also analyzes “High Leverage Adult Actions” or “cause” data (State of Connecticut, 2006). High Leverage Adult Actions are measurable practices that reflect the decisions of the adults in the school. Some examples of High Leverage Adult Actions that Reeves provides are: the number of times a month teachers convene in data team meetings; the percentage of assessments that are collaboratively scored; or the time devoted to nonfiction writing. By analyzing the relationship between Student Outcome Indicators and High Leverage Adult Actions, districts and schools can determine which practices yield the greatest improvements in student performance (Reeves 2004).

According to the (State of Connecticut, 2006), data driven decision making in schools can be used to investigate the following essential questions: How your school or district is performing as a learning institution; if all the students are learning; what is expected from the students by the end of the year; why you are getting the results you have currently and what practices within your school that you would want to continue, replicate or eliminate.

Based on this knowledge, schools are at a position to make more informed decisions regarding their students, expected learning outcomes as well as streamline their practices to the institutions strategy in order to achieve better results in every aspect.

Knowledge extraction

Historically, the notion of finding useful patterns in data has been given a variety of names, including data mining, knowledge extraction, information discovery, information harvesting, data archaeology, and data pattern processing. The term *data mining* has mostly been used by statisticians, data analysts, and the management information systems (MIS) communities. It has also gained popularity in the database field. The phrase *knowledge discoveryin databases* was coined at the first KDD workshop in 1989(Fayyad, Piatetsky-Shapiro, & Smyth, 1996), to emphasize that knowledge is the end product of a data-driven discovery. It has been popularized in the AI and machine-learning fields.

Businesses are moving to decision making based on information. There has been an exponential growth in data to support the decision making hence too much pressure to extract as much meaningful data as possible from this data. Needless to say that data comes into the organization in various forms hence the organization must find ways in which this data can be made useful despite the state in which it is captured in by the firm.

Knowledge Discovery (KD) is a branch of the Artificial Intelligence (AI) field that aims to extract useful and understandable high-level knowledge from complex and/or large volumes of data. According to Springer (Springer, 2007), knowledge discovery is synonymous to data mining. The book adds that data mining has been referred using other terms such as “*knowledge extraction*, *information discovery*, *information harvesting*, *data archeology*, and *data pattern processing (pp, 10).”* This conflicts with the argument of (Fayyad, Piatetsky-Shapiro, & Smyth, 1996) who argued that thou these two terms are similar, knowledge discover is the overall process of discovering useful knowledge from data whereas data mining is a step in that process.Indeed this is true considering tha[1]t knowledge is defined as the awareness and understanding of the relationships among the pieces of data. Data mining on the other hand is the extraction of meaningful relationships among pieces of data. This means that data mining is a tool for knowledge extraction. Data mining is defined as an iterative and interactive method of discovering novel, valid, useful, comprehensive and understandable patterns and models from massive data sources.

Data → Data mining → Patterns

Knowledge is now recognized as the key driver of productivity and economic growth, leading to a new focus on the role of information, technology and learning in economic performance.Since the mid 80’s, purchases of computer software, growing at a rate of 12 per cent per year outpacing the sales of computer hardware. In global economies economic investment has gradually shifted to high-technology goods and services, particularly information and communications technologies. Computers and related equipment are the fastest-growing component of tangible investment. All this is according to a study by OECD (OECD, 2009). Spending on product enhancement is driving growth in knowledge-based services such as engineering studies and advertising. This information points to the growing importance of computing and information systems within every economy. Computing has gradually taken over every sector in every economy. Gartner estimates that by year 2015, approximately two billion computers would be in use in the world (www.wordometers.info/computers). According to Gartner, over 52,031,040 computers were sold in the first two months of year 2016. In year 2015, out of 3.1 million devices sold in Kenya, 1.8 million were mobile devices.

Motivation for knowledge discovery and data mining

The following factors have played a critical role in advancing knowledge discovery and data mining as a key driver of a school performance.

- Growth of many application areas
- Advanced methods in data extraction and data storing techniques
- More data generated for example by banks, telecommunication companies, scientific data, astronomy, biology, business transactions, web, social media and e-learning.
- Massive data sources such as records and a large number of attributes

Importance of data driven decision making in Schools

Data-driven decision making has become an important topic linked to accountability, school improvement, and educational reforms. Data have been pronounced to be “cool” by educational policy makers. Data use is no longer a passing fad, one to which educators can close their doors and assume it will go away until the next innovative idea appears. The use of data to inform decision making in schools is not new. Highly effective schools

[1]www.knowledge-management–tools.net

and classroom teachers have been using data for years and recognize the value to inform their work across all levels of the educational system by using data as a critical tool for these informed decisions.

Data-Driven Decision Making (DDDM): ongoing review of student data by district leaders, • building leaders and teachers to determine strengths and areas in need of improvement at the district and school level.

Data Teams (DT): ongoing analysis of data from common formative assessments to identify • strengths and weaknesses in student learning, and to identify instructional strategies that will best address student and learning objectives in the classroom.

Data riven decision making process for school and district level application

The department of education of Connecticut proposes a six step process for informing and driving decisions. These steps include:

i. Find the data: Find three years of trend data and matched cohort data that includes such things as student achievement, discipline, expulsion, etc.
ii. Analyze the data to prioritize needs: identify your strengths or needs.
iii. Establish SMART goals: identify your most important objectives for student achievement based on the challenges your school team identified through analyzing the data and the determination of your prioritized needs analysis.
iv. Select specific strategies: for each goal, brainstorm the strategies that could be implemented to increase the likelihood of achieving that prioritized goal.
v. Determine results indicators: results indicators identify whether the strategy is actually being implemented. If the strategy is having the intended effect on student learning and improved performance, determine a results indicator for each of your targeted strategies. If needed for clarification, review the results indicators on the action plan example.
vi. Monitor and evaluate results: to assist with engagement of the continuous improvement cycle that identifies midcourse connections where needed and adjusts strategies to assure fidelity of implementation.

Challenges of integrating data Driven decision making in schools

Integrating data driven decision making in schools is not as easy as it may sound. It calls for the convergence of IT and education. While most school managers continue to view Information communication Technologies (ICTs) as an "interfering technology", the promise of data driven decision making presents so many promises that it cannot be ignored. The associated cost of acquisition and managing knowledge and data in schools is also high; hence, cost has been a prohibitive factor in transitioning to smart decision making in learning institutions. Other challenges that have been associated with integrating data driven decision making in schools include:

Lack of clarity in terminology around data-driven decision making whereby multiple definitions create the potential for confusion; this has limited the understanding of the subject; hindered research into the area by school managers and hence limited the adoption and implementation of the same by schools. The definitions for what data driven decision making is are not straightforward and the authors have had difficulty finding an acceptable and broad definition because data-driven decision making means different things to different people.

Multiple knowledge and skill sets (depending on one's role in the education system) shape perspectives regarding data-driven decision making; the question of merging the various fields in schools with IT still remains. The literature on data-driven decision making indicates that there is a fundamental set of skills and knowledge, although different conceptual frameworks espouse slightly different skills. Most of the frameworks, in fact, describe general processes, rather than skills. For example, (State of Connecticut, 2006)describes the need to identify problems, seek solutions, define research, and monitor progress. (Two crows Corporation, 1999)describe a cycle that includes planning, implementing, assessing, analyzing data, and reflecting on outcomes.

Standards for data-driven decision making are complex and integrated throughout multiple areas of educator expertise;

The knowledge and skills that teachers and administrators need to learn form a developmental continuum rather than a set body of knowledge. The developmental nature of the acquisition of knowledge and skills leading to expertise in data-driven decision making. A general consensus is that expertise does not come until the practitioner has the opportunity to engage in data-driven decision making within the context in which he or she works. The question therefore remains on when educators need professional development in data-driven decision making.

The context in which data-related content can be provided to educators can be structured in multiple ways; Schools of education have multiple programmatic structures into which educator preparation in data-driven decision making will need to be integrated.

Organizational capacity to teach data-driven decision making is not widely established. There is need to improve the educator's capacity to use data. Lack of human capacity around the issue on data driven decision making is clear. Up to date, there is no empirical evidence about the prevalence of course offerings in schools of education or professional development opportunities offered by independent providers that can address the need to develop data literacy in education.

Drivers of data driven decision making in Education

Two phenomenon's are considered to be the key drivers of data driven decision making in education:

(i) First is the development of a variety of technology-based tools that can support data-driven decision making.
(ii) The second is the increasing importance given to assessments other than summative measures. We now know that assessments for learning can inform instructional practice more directly than more standardized tests, which have only grown the pool of data from which we can draw information about learning and achievement.

As data has proliferated, the need to collect, analyze, and examine data in an efficient manner has also grown. Human capacity simply cannot handle the amount of data with which educators are being confronted. Thus, educators have no alternative but to turn to a variety of technological solutions to help them deal with this increasing data load. Technologies, for example, the use of handheld devices on which teachers can assess students' literacy or mathematics skills and immediately provide results so that instructional steps can be prescribed(The Context of Data-Driven Decision Making, ND).

III. Conclusion

In conclusion, a shift to data-driven decision making heralds a new dawn in driving decision making by educators. Hard credible evidence to make informed decisions can now be availed. This does not make it only easier for school management but also for teachers in developing new ways and approaches to deliver contents to their students. Few countries in the world seem to have integrated data driven decision making approach in their educational systems especially in Africa and other emerging economies. Yet this shift holds immense benefits in the global educational system transformation.

References

[1] Cios, K. J., Pedrycz, W., Swiniarski, R. W., & Kurgan, L. (2007). Data Mining: A knowledge Discovery Approach. In *Data Mining: A knowledge Discovery Approach* (pp. 1-24). Hardcover: pringer.

[2] Fayyad, U., Piatetsky-Shapiro, ,. G., & Smyth, P. (1996). From Data Mining to Knowledge discovery in databases. *AI magazine*, pp. 37-54.

[3] (ND). The Context of Data-Driven Decision Making. Self publication.

[4] OECD. (2009). Sustainable Manufacturing and Eco-Innovation: Framework, Practices and Measurement. Synthensis Report. OECD.

[5] Radermacher, W. J. (2014). Decision making In the Informatio Driven Society.

[6] RAND Education. (2006). Making Sense of Data-Driven Decision Making in Education. Santa Monica, CA: www.rand.org.

[7] Reeves, D. B. (2004). *Accountability for Learning: How teachers and school leaders can take charge.* Alexandria: Association for Supervision and Curriculum Development.

[8] Springer. (2007). Data mining: a knowleddge discovery approach. Springer.

[9] State of Connecticut. (2006). *Data Driven decision making process.* Middletown: State of Connecticut, Department of Education.

[10] Two crows Corporation. (1999). Introduction to data mining and knowledge discovery. In *Introduction to data mining and knowledge discovery*.

[11] Mandinach, E. B., Gummer, E. S., & Muller, R.D. (2011). The complexities of integrating data-driven decision making into professional preparation in schools of education: It's harder than you think. Alexandria, VA, Portland, OR, and Washington, DC: CNA Education, Education Northwest, and WestEd

Authors

First Author – Dr. Mary Mugwe Chui, Department of Educational Management and Curriculum Studies
Mount Kenya University, P.O Box 342-01000 Thika:
Email: marychui@yahoo.com Cell: +(254)722-360-069