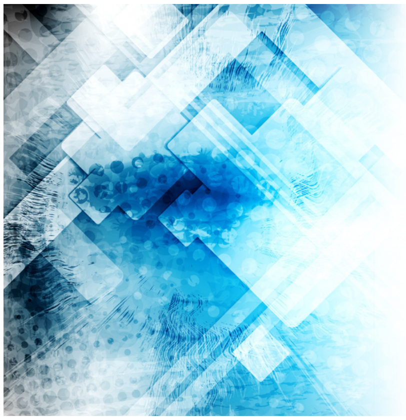

Abstract

In the new era of big educational data, learning analytics (LA) offer the possibility of implementing real–time assessment and feedback systems and processes at scale that are focused on improvement of learning, development of self–regulated learning skills, and student success. However, to realize this promise, the necessary shifts in the culture, technological infrastructure, and teaching practices of higher education, from assessment–for–accountability to assessment–for–learning, cannot be achieved through piecemeal implementation of new tools. We propose here that the challenge of successful institutional change for learning analytics implementation is a wicked problem that calls for new adaptive forms of leadership, collaboration, policy development and strategic planning. Higher education institutions are best viewed as complex systems underpinned by policy, and we introduce two policy and planning frameworks developed for complex systems that may offer institutional teams practical guidance in their project of optimizing their educational systems with learning analytics.

AUTHORS

Leah P. Macfadyen
The University of British Columbia

Shane Dawson
University of South Australia

Abelardo Pardo
The University of Sydney

Dragan Gašević
Athabasca University

Embracing Big Data in Complex Educational Systems: The Learning Analytics Imperative and the Policy Challenge

In education, we are awash in data about our learners and educators, our technologies and activities, achievements and performance. To date these data have rarely been mined intelligently with the goal of improving learning and informing teaching practice, although evidence from other sectors such as marketing, sports, retail, health and technology suggests that the effective use of big data can offer the education sector the potential to enhance its systems and outcomes (Manyika et al., 2011). Norris and Baer (2013) have noted that, "Data expands the capacity and ability of organizations to make sense of complex environments" (p. 13). In this context, learning analytics (LA) offers the capacity to investigate the rising tide of learner data with the goal of understanding the activities and behaviors associated with effective learning, and to leverage this knowledge in optimizing our educational systems (Bienkowski, Feng, & Means, 2012; Campbell, DeBlois, & Oblinger, 2007). Indeed, in a world of larger and larger data sets, increasing populations of increasingly diverse learners, constrained education budgets and greater focus on quality and accountability (Macfadyen & Dawson, 2012), some argue that using analytics to optimize learning environments is no longer an option but an imperative. The value of such analytics is highlighted by the authors of the McKinsey Global Institute (Manyika et al., 2011) noting that, "In a big data world, a competitor that fails to sufficiently develop its capabilities will be left behind…Early movers that secure access to the data necessary to create value are likely to reap the most benefit" (p. 6). Education can no longer afford not to use learning analytics. As Slade and Prinsloo (2013) maintain, "Ignoring information that might actively help to pursue an institution's goals seems shortsighted to the extreme" (p. 1521).

CORRESPONDENCE

Email
leah.macfadyen@ubc.ca

In this article we consider ways in which learning analytics can support and contribute to the development of new approaches to the assessment of learning, and the degree to which new adaptive policy and planning approaches will be needed to bring about the kind of institutional change such proposals demand. We emphasize that successful institutional adoption demands comprehensive development and implementation of policies to address LA challenges of learning design, leadership, institutional culture, data access and security, data privacy and ethical dilemmas, technology infrastructure, and a demonstrable gap in institutional LA skills and capacity (Siemens, Dawson, & Lynch, 2013). Moreover, we take the position that educational institutions are complex adaptive systems (Gupta & Anish, 2009; MacLennan, 2007; Mitleton–Kelly, 2003), and therefore that simplistic approaches to policy development are doomed to fail. Instead, we will introduce strategy and policy frameworks and approaches developed for complex systems, including frameworks that offer the potential to identify points of intervention (Corvalán, Kjellström, & Smith, 1999), with the goal of offering educational institutions practical guidance.

Assessment Practices: A Wicked Problem in a Complex System

Indeed, in a world of larger and larger data sets, increasing populations of increasingly diverse learners, constrained education budgets and greater focus on quality and accountability, some argue that using analytics to optimize learning environments is no longer an option but an imperative.

There is no better exemplar in higher education than assessment to demonstrate how institutional policy can impact practice both positively and negatively. The practice of assessment has for some time been mired in debate over its role as either a measure of accountability or a process for learning improvement. While the majority of education practitioners lean towards assessment as a process for improving student learning, assessment nonetheless remains firmly positioned as an important tool for determining accountability and demonstrating quality. As McDonnell (1994) previously argued, assessment policies function as a mechanism to provide government with a high level of influence over classroom practice. In essence, assessment acts as a powerful tool to manage aspects of learning and teaching. It is not surprising, then, that assessment policy has numerous invested stakeholders – learners, educators, administrators and government – all vying for a larger stake in the game. The diversity of stakeholders, priorities, outcomes and needs make any substantial change to assessment policy and practice a considerable challenge to say the least.

Assessment practice will continue to be intricately intertwined both with learning and with program accreditation and accountability measures. Such interconnectedness in educational systems means that narrow efforts to implement changes in policy and practice in one area (for example, by introducing new approaches to tracking and measuring learning) may have unanticipated consequences elsewhere in the system. For example, the US education policy No Child Left Behind drastically reshaped not only the testing processes employed to identify poor literacy and numeracy standards, but also affected what was taught and how it was taught. Jacob (2005) documented the unintentional outcomes of this new accountability policy classroom practice, noting, for example that such high–stakes testing encouraged teachers to steer low–performing students away from subjects that were included in the accountability program. While the ethos of the policy had some merit in attempting to address declining numeracy and literacy skills in the US, the associated incentives and measures resulted in crossed performance indicators. Dworkin (2005) also expands on this point, noting that teacher promotion standards were linked to class performance in the high stakes tests. This practice essentially encouraged teachers to narrow the curriculum and teach to the test, beautifully illustrating Goodhart's Law, which states that when a measure becomes a target it ceases to be a useful measure (Elton, 2004).

In the complex systems of higher education, current performance assessment and accountability policies may be the forces driving (Corvalán et al., 1999) the continued focus on high–stakes snapshot testing as a means of producing comparative institutional data, in spite of the well–articulated weakness of such an approach for understanding student learning. The continuing primary use of grades in determining entry to university, the Australian Government's National Assessment Plan for Literacy and Numeracy (NAPLAN)[1] measures, the OECD's Programme for International Student Assessment (PISA)[2] and similar programs, demonstrate that there is much invested in the retention of these measures for benchmarking individuals, schools, districts, states and countries. Wall, Hursh and Rodgers (2014) have

[1] http://education.qld.gov.au/naplan/

[2] http:/www.oecd.org/pisa/

argued, on the other hand, that the perception that students, parents and educational leaders can only obtain useful comparative information about learning from systematized assessment is a false one. Instead, alternate complementary assessment practices – practices that make better use of the rich array of educational data now available – may well offer more effective approaches to improving learning, especially processes that reveal development of student understanding over time (Wiliam, 2010).

In his criticism of assessment practices, Angelo (1999) suggested that as educators we must emphasize assessment as a means for improving student learning rather than a mechanistic, technical process used to monitor performance. He argued that assessing for learning necessitates a focus on developing practices that help the educator and learner gather evidence of learning progress, rather than on identifying the students that produce the "right" or "wrong" answers. The importance of developing better formative or embedded assessment models has also been reiterated by the OECD Innovative learning environments project (Dumont, Istance, & Benavides, 2010) and educational researchers have similarly illuminated that regular feedback at the process level is more effective for enhancing deeper learning (for review, see Hattie & Timperley, 2007).

Despite the widespread recognition of the need for a more effective assessment paradigm, implementation is a challenge, and calls for development of new policies and implementation strategies directed at improving accountability for learning though practices driven by learning. Differentiating assessment–for–learning from assessment–for–accountability within the educational system forms part of the wicked problem of institutional change in higher education that we seek to explore here. As with all complex systems, even a subtle change may be perceived as difficult, and be resisted (Head & Alford, 2013). For example, under normal classroom circumstances the use of assessment at the process level for improving learning requires substantial and sustained engagement between the educator and students and can be an extremely time intensive process. Implementing such time intensive assessment models for large (and growing) university classes is not feasible, and typically scalable models of assessment such as multiple choice exams are implemented instead. It is unrealistic to consider that educators will adopt time–consuming longitudinal and personalized assessment models given the massive increase in resources and workload that would be required.

Learning Analytics and Assessment–for–Learning

A wide range of authors in this special issue illustrate ways in which learning analytics – which comes with its own set of implementation challenges and hurdles – has the potential to provide learners with sustained, substantial and timely feedback to aid understanding and improve student learning skills, while circumventing the challenge of educator workload. We also offer a discussion of how learning analytics may support development of self–regulated learning in Box 1, inset. Analytics can add distinct value to teaching and learning practice by providing greater insight into the student learning process to identify the impact of curriculum and learning strategies, while at the same time facilitating individual learner progress. Nor does the adoption of learning analytics preclude traditional or alternate assessment practices that may be required by accreditation and accountability policies. While current assessment policy may be driven by conflicting intentions – accountability and quality assurance requirements versus promotion of student learning – learning analytics can meet both. More simply put, LA addresses the need for quality assurance and learning improvement.

There is no better exemplar in higher education than assessment to demonstrate how institutional policy can impact practice both positively and negatively. The practice of assessment has for some time been mired in debate over its role as either a measure of accountability or a process for learning improvement.

Technological Components of the Educational System and Support of Learning Analytics

The LA–supported approaches to assessment of learning envisioned in this article – indeed, in this entire edition – assumes a technological layer that is capable of capturing, storing, managing, visualizing and processing big educational data – the millions of events occurring in diverse learning scenarios and platforms. Transformation of assessment practices to embrace and integrate learning analytics tools and strategies in support of teaching and learning therefore demands effective institutional technology infrastructures. The production of data in every technology–mediated interaction occurring in a learning environment, the need for more effective provision of feedback, and the need for more

Box 1
Learning Analytics for Assessing Student Learning

Differentiating assessment–for–learning from assessment–for–accountability within the educational system forms part of the wicked problem of institutional change in higher education that we seek to explore here.

Provision (to learners and educators) of automated analytics that provide feedback on learner study behaviors, progress and outcomes will not only enhance academic performance but also develop student self–regulated learning (SRL) skills, and SRL proficiency has been demonstrated to be a significant predictor of academic success (e.g., Butler & Winne, 1995; Pintrich, 1999; Zimmerman, 2002). Student motivation and capacity to undertake accurate self–monitoring had a direct impact on the level and quality of their study and therefore, their overall learning progression and academic achievement (Dunlosky & Thiede, 1998). Conversely, poor performers are poor at evaluating their own ability or judging their own learning skills (Kruger & Dunning, 1999). For these reasons, it is argued that a core goal of any effective pedagogical strategy must include the development of student meta–cognitive skills or judgment of (own) learning (JOL). Feedback on assessment is one key approach that is often adopted to assist students in developing meta–cognitive skills, but because provision of relevant feedback can be labor–intensive, it is often delayed and provided at a time when it is no longer useful to the student to aid their learning.

Recent research posits that SRL is a process of temporal events that evolve during learning (Azevedo & Aleven, 2013). This research, alongside recent developments in learning analytics, data mining and machine learning is providing new methods for developing novel insights into student learning processes. Historically, assessment and development of student SRL has made use of tasks associated with JOL which generally involve asking a student to assess how effectively they have understood a particular concept (Dunlosky & Lipko, 2007). This self–reported rating is then correlated against their overall test performance to gain insight into the student's meta–cognitive proficiency. While JOL has commonly relied on self–report methodologies such as think aloud protocols and surveys, these have inherent limitations such as poor recall, and biased responses (Richardson, 2004).

New options for assessing student learning behaviors are emerging as a result of advances in learning analytics and natural language processing (NLP), and alternate models have sought to capture actual learner behavior (in lieu of self–reports) from interactions with technology–based learning activities. For example, oft–cited SRL researcher Phil Winne has previously reported that student online interaction data can provide significant indicators of SRL proficiency (e.g., Winne, 2010; Zhou & Winne, 2012). Winne has developed the software application nStudy as a web tool that can collect very fine grained, time stamped data about individual learner interactions with online study materials. The trace data is then used to provide insight and feedback into the learner's cognitive choices as they interact with the online information. Essentially, the tool makes data for reflection available to both the individual learner and the educator.

comprehensive formative and summative assessment translates into a rich set of requirements of the current technological infrastructures. Although learning management systems (LMSs) still host a large percentage of technology–mediated educational activities, educational institutions are recognizing the need to re–assess the concept of teaching and learning space to encompass both physical and virtual locations, and adapt learning experiences to this new context (Thomas, 2010). Thus, together with the need for cultural change and a focus on pedagogical relevance, an additional sociotechnical factor critical to the adoption of learning analytics is technology itself (Box 2).

The evolution of technology in recent years offers an unprecedented capacity to store large data sets, and applications using big data are well established in contexts such as business intelligence, marketing and scientific research (Dillon, Wu, & Chang, 2010). Education faces a particular challenge that derives from the rich variety of technological affordances emerging in learning environments. From an LMS–centric approach consolidated in the early 2000s, we are now entering an era in which learning may occur anywhere, at any time, with multiple devices, over a highly heterogeneous collection of resources, and through multiple types of interactions. In this new scenario, learning analytics tools need to comply with requirements in the following areas:

1. Diverse and flexible data collection schemes: Tools need to adapt to increasing data sources, distributed in location, different in scope, and hosted in any platform.
2. Simple connection with institutional objectives at different levels: information needs to be understood by stakeholders with no extra effort. Upper management needs insight connected with different organizational aspects than an educator. User–guided design is of the utmost importance in this area.
3. Simple deployment of effective interventions, and an integrated and sustained overall refinement procedure allowing reflection.

From the technological point of view, learning analytics is an emerging discipline (Siemens, 2013) and its connection with assessment remains largely unexplored (Ellis, 2013). This situation is even more extreme when considering the assessment of competences and learning dispositions (Buckingham Shum, 2012). Educational institutions need technological

Box 2
Sociotechnical Infrastructure Needs for Effective Learning Analytics

Several initiatives are already tackling the problem of flexible data collection schemes. For example the ADL Experience API[3] released in 2013 has been proposed as a solution that can promote interoperability between data collected in different environments and platforms. The interface offers the possibility of capturing a wide variety of events in experiences with heterogeneous scenarios (Glahn, 2013). Similarly, the IMS Global Consortium has proposed that the Learning Measurement Framework IMS Caliper[4] – containing descriptions to represent metrics, sensor API and learning events – will facilitate the representation and processing of big data in the learning field. In parallel, the concept of a *Learning Record Store* (LRS) has been proposed as a framework for storing and manipulating data from distributed events in a learning environment, encoding not only interaction among stakeholders, but among resources. This information is then made available through a service–based interface to other systems within an institution (or across multiple institutions) for further analysis and processing.

Numerous attempts have been made to meet diverse stakeholder reporting and data access needs by production of so–called dashboards that show a canvas of multiple visualizations. Common limitation of these graphical representations, however, are their actual utility and usability (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013). Adapting presentation of information to user context, needs and interests is another important factor that must be taken into account if we wish to facilitate the uptake of learning analytics solutions.

The third requirement for technology supporting learning analytics is that it can facilitate the deployment of so–called interventions, where intervention may mean any change or personalization introduced in the environment to support student success, and its relevance with respect to the context. This context may range from generic institutional policies, to pedagogical strategy in a course. Interventions at the level of institution have been already studied and deployed to address retention, attrition or graduation rate problems (Ferguson, 2012; Fritz, 2011; Tanes, Arnold, King, & Remnet, 2011). More comprehensive frameworks that widen the scope of interventions and adopt a more formal approach have been recently proposed, but much research is still needed in this area (Wise, 2014).

It is unrealistic to consider that educators will adopt time–consuming longitudinal and personalized assessment models given the massive increase in resources and workload that would be required.

[3] http://www.adlnet.gov/tla

[4] http:/www.imsglobal.org/IMSLearningAnalyticsWP.pdf

solutions that are deployed in a context of continuous change, with an increasing variety of data sources, that convey the advantages in a simple way to stakeholders, and allow a connection with the underpinning pedagogical strategies.

In turn, these technological requirements point to a number of other critical contextual factors that must form part of any meaningful policy and planning framework for employing learning analytics in service of improved assessment. Foremost among these is the question of access to data, which needs must be widespread and open. Careful policy development is also necessary to ensure that assessment and analytics plans reflect the institution's vision for teaching and strategic needs (and are not simply being embraced in a panic to be seen to be doing something with data), and that LA tools and approaches are embraced as a means of engaging stakeholders in discussion and facilitating change rather than as tools for measuring performance or the status quo.

The Challenge: Bringing about Institutional Change in Complex Systems

While the vision of improving student learning and assessment through implementation of effective learning analytics tools and approaches holds promise, the real challenges of implementation are significant. In this article we have identified only two of the several critical and interconnected socio–technical domains that need to be addressed by comprehensive institutional policy and strategic planning to introduce such attractive new systems: the challenge of influencing stakeholder understanding of assessment in education, and the challenge of developing the necessary institutional technological infrastructure to support the undertaking. Meanwhile, of course, any such changes must coexist with the institution's business as usual obligations (Head & Alford, 2013).

It may not be surprising, then, that globally, education lags behind all other sectors in harnessing the power of analytics. A preliminary analysis indicates that educational institutions simply lack the practical, technical and financial capacity to effectively gather, manage and mine big data (Manyika et al., 2011). As Bichsel (2012) notes, much concern revolves around "the perceived need for expensive tools or data collection methods" (p. 3). Certainly, evidence suggests that data access and management are proving to be significant hurdles for many institutions. The first survey of analytics implementation in US higher education in 2005 found that of 380 institutions, 70% were at Stage 1 of a five–stage implementation process: "Extraction and reporting of transaction–level data" (Goldstein & Katz, 2005). Four years later, a study of 305 US institutions found that 58% continued to wrangle data in Stage 1, while only 20% reported progress to Stage 2: "Analysis and monitoring of operational performance" (Yanosky, 2009). More recently, investigators have reported that while some 70% of surveyed institutions agreed that analytics is a major priority for their school, the majority of respondents suggested that data issues (quality, ownership, access, and standardization) were considerable barriers to analytics implementation, and as such most were yet to make progress beyond basic reporting (Bichsel, 2012; Norris & Baer, 2013).

Transformation of assessment practices to embrace and integrate learning analytics tools and strategies in support of teaching and learning therefore demands effective institutional technology infrastructures

To further unpack the complexities of analytics adoption a growing number of commentators are exploring the more nuanced sociotechnical factors that are the most likely barriers to institutional LA implementation. For instance, elements of institutional "culture, capacity and behavior" (Norris, Baer, Leonard, Pugliese, & Lefrere, 2008). There is recognition that even where technological competence and data exist, simple presentation of the facts (the potential power of analytics), no matter how accurate and authoritative, may not be enough to overcome institutional resistance (Macfadyen & Dawson, 2012; Young & Mendizabal, 2009).

Why Policy Matters for Learning Analytics

Higher education institutions are a superb example of complex adaptive systems (CASs) (Cilliers, 1998; Gupta & Anish, 2009; MacLennan, 2007; Mitleton–Kelly, 2003) and exist in a state that some have characterized as organized anarchy (Cohen & Marsh, 1986). Together with institutional history and differences in stakeholder perspectives (Kingdon, 1995; Sabatier, 2007), policies are the critical driving forces that underpin complex and systemic institutional problems (Corvalán et al., 1999) and that shape perceptions of the nature of the problem(s) and acceptable solutions. Below, we argue that it is therefore only through implementation of planning processes driven by new policies that institutional change can come about.

The challenge of bringing about institution–wide change in such complex and anarchic adaptive systems may rightly be characterized as a "wicked problem"– a problem that is "complex, unpredictable, open ended, or intractable" (Churchman, 1967; Head & Alford, 2013; Rittel & Webber, 1973). Like all complex systems, educational systems are very stable, and resistant to change. They are resilient in the face of perturbation, and exist far from equilibrium, requiring a constant input of energy to maintain system organization (see Capra, 1996). As a result, and in spite of being organizations whose business is research and education, simple provision of new information to leaders and stakeholders is typically insufficient to bring about systemic institutional change. One factor hindering institutional change for better use of analytics by educational institutions appears to be their "lack of data–driven mind–set and available data" (Manyika et al., 2011, p. 9). Interestingly, this observation is not new, and was reported with dismay in 1979 by McIntosh, in her discussion of the failure of institutional research to inform institutional change. Ferguson et al. (in press) reprise McIntosh's arguments in relation to learning analytics, suggesting that additional barriers to adoption include academics' unwillingness to act on findings from other disciplines; disagreement over the relative merits of qualitative vs. quantitative approaches to educational research; a tendency to base decisions on anecdote; the reality that researchers and decision makers speak different languages; lack of familiarity with statistical methods; a failure to effectively present and explain data to decision makers; and the reality that researchers tend to hedge and qualify conclusions. Norris and Baer (2013) meanwhile note that the analytics IQ of institutional leaders is typically not high, precluding effective planning. In other words, a range of political, social, cultural and technical norms shape educational systems and contribute to their stability and resistance to change.

…we are now entering an era in which learning may occur anywhere, at any time, with multiple devices, over a highly heterogeneous collection of resources, and through multiple types of interactions.

Elsewhere, we reported on a case study failure of learning analytics to inform institutional planning (Macfadyen & Dawson, 2012), and noted that the culture of educational institutions has historically valorized educator/faculty autonomy and resisted any administrative efforts perceived to interfere with teaching and learning practice. We proposed that in order to overcome institutional resistance to innovation and change driven by learning analytics, educational institutions urgently need to implement planning processes that create conditions that allow stakeholders across the institution to both think and feel positively about change – conditions that appeal to both the heart and the head.

Social marketing theorists (Kotler & Zaltman, 1971) and change management experts (Kavanagh & Ashkanasy, 2006; Kotter, 1996) similarly argue that social and cultural change (that is, change in habits, practices and behaviors) is not brought about by simply giving people large volumes of logical data (Kotter & Cohen, 2002). Social theorists have argued that since value perspectives ground the major social issues of modern life, scientific analyses and technical rationality are insufficient mechanisms for understanding and solving complex problems (Head & Alford, 2013; Rein, 1976; Schon & Rein, 1994). Instead, what is needed are comprehensive policy and planning frameworks to address not simply the perceived shortfalls in technological tools and data management, but the cultural and capacity gaps that are the true strategic issues (Norris & Baer, 2013).

Policy and Planning Approaches for Wicked Problems in Complex Systems

Policies are, simply, principles developed to guide subjective and/or objective decision making, with the goal of achieving rational and desirable outcomes. They are statements of intent that capture organizational goals, and are typically implemented via planned procedures or protocols. A large and established literature on policy development already exists in fields such as political science and business, from which have emerged a range of classical policy cycle tools and heuristics that have been highly influential (Nakamura, 1987). Contemporary critics from the planning and design fields argue, however, that these classic, top–down, expert–driven (and mostly corporate) policy and planning models are based on a poor and homogenous representation of social systems mismatched with our contemporary pluralistic societies, and that implementation of such simplistic policy and planning models undermines chances of success (for review, see Head & Alford, 2013). Importantly, they also insist that modern policy problems are not technical puzzles that can be solved through the application of scientific knowledge, but instead exist in continuous states of flux within dynamic systems and have communicative, political and institutional elements. Solutions to such ill–defined and multi–factorial challenges, they argue, will always be provisional, and must be negotiated between multiple stakeholders in situations of ambiguity, uncertainty and values disagreement (Rittel & Webber, 1973). A number of theorists have also emphasized that solutions to wicked problems – actually complex systems of inter–related problems – "can seldom be obtained by independently solving each of the problems of which it is composed . . . Efforts to deal separately with such aspects of urban life as transportation, health, crime, and education seem to aggravate the total situation" (Ackoff, 1974, p. 21).

From the technological point of view, learning analytics is an emerging discipline and its connection with assessment remains largely unexplored.

Systems theory offers two key areas of insight that are significant for policy development for complex educational systems. First, systems theorists recognized that while systems – from a single atom to a universe – may appear to be wildly dissimilar, they are all governed by common patterns, behaviors and properties: their component parts are multiply interconnected by information flows, with identifiable and predictable feedbacks, inputs, outputs, controls and transformation processes; they are dynamic, differentiated and bounded; they are hierarchically organized and differentiated; and new properties can arise within them as a result of interactions between elements. Second, systems theory observes that systems tend to be stable, and that their interconnectedness facilitates resilience (for a review of systems theory, see Capra, 1996).

These observations not only illuminate why piecemeal attempts to effect change in educational systems are typically ineffective, but also explains why no one–size–fits–all prescriptive approach to policy and strategy development for educational change is available or even possible. Usable policy frameworks will not be those which offer a to do list of, for example, steps in learning analytics implementation. Instead, successful frameworks will be those which guide leaders and participants in exploring and understanding the structures and many interrelationships within their own complex system, and identifying points where intervention in their own system will be necessary in order to bring about change.

Drawing on systems and complexity theory, a new generation of authors have begun to develop accounts of so–called adaptive approaches to policy and planning for complex systems which can allow institutions to respond flexibly to ever–changing social and institutional contexts and challenges (Berkhout, Leach, & Scoones, 2003; Haynes, 2003; Milliron, Malcolm, & Kil, 2014; Tiesman, van Buuren, & Gerrits, 2009; Young & Mendizabal, 2009). A full review of adaptive management strategies is beyond the scope of this paper, and has been comprehensively undertaken by Head and Alford (2013), who highlight the critical roles of cross–institutional collaboration, new forms of leadership (moving beyond the orthodox model of transformational leadership) and the development of enabling structures and processes (for example, budgeting and finance systems, organizational structure, human resources management, and approaches to performance measurement and program evaluation). We offer here two sample policy and planning models that may offer valuable practical guidance for collaborative teams and leaders in higher education seeking to bring about systemic institutional change to support learning analytics.

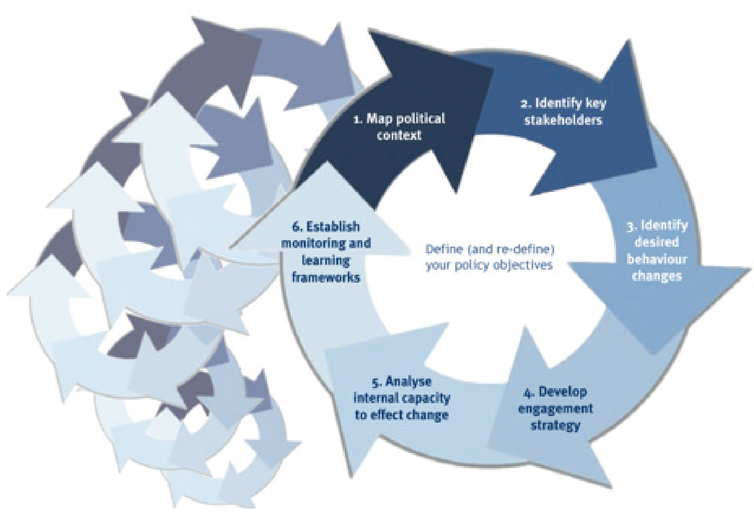

Figure 1. The RAPID Outcome Mapping Approach (ROMA)

First, and as we have proposed elsewhere (Ferguson et al., in press) we offer a modification of Young and Mendizabal's (2009) Rapid Outcome Mapping Approach (ROMA) model (Figure 1) as a policy and planning heuristic for learning analytics implementation. Originally developed to support policy and strategy processes in the complex field of international development, the seven–step ROMA model is focused on evidence–based policy change. It is designed to be used iteratively, and to allow refinement and adaptation of policy goals and the resulting strategic plans over time and as contexts change, emphasizing the provisional nature of any solutions arrived at. Importantly, the ROMA process begins with a systematic effort at mapping institutional context (for which these authors offer a range of tools and frameworks) – the people, political structures, policies, institutions and processes that may help or hinder change. This critical activity allows institutions to identify the key factors specific to their own context that may influence (positively or negatively) the implementation process, and therefore also has the potential to illuminate points of intervention and shape strategic planning.

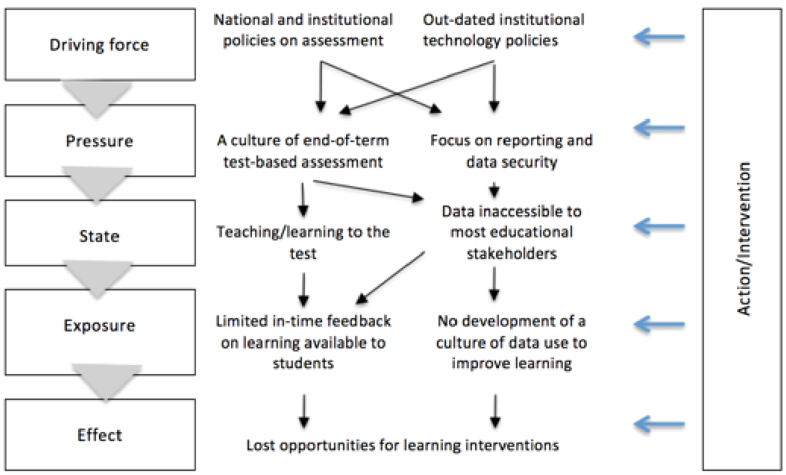

Figure 2. Cause–effect (DPSEEA) framework for institutional assessment and technology policies (modified from Corvalan et al., 1999).

Second, Corvalán et al.'s (1999) "cause–effect framework" (or DPSEEA framework) usefully assists in identifying the multiple linkages that may exist between the driving forces underpinning complex systems, illuminating the multiple points in a complex system of relationships where action may be needed to effect change. Such a framework can, they suggest, "be used to weigh alternatives and to design step–by–step programs for dealing with a particular…problem" (p. 659). Figure 2 offers a preliminary modification of this framework to represent institutional effects of, for example, technology and assessment policies, and may be a useful context mapping tool in the ROMA process.

It may not be surprising, then, that globally, education lags behind all other sectors in harnessing the power of analytics. A preliminary analysis indicates that educational institutions simply lack the practical, technical and financial capacity to effectively gather, manage and mine big data.

Use of these models for institutional LA policy development is only in the very early stages, although we have explored elsewhere (Ferguson et al., in press) the ways in which a small number of apparently successful institutional LA policy and planning processes have pursued change management approaches that map well to such frameworks. In future work, we hope to be able to present more robust and critical review of real–time application of these frameworks in institutional planning, and their possible effectiveness or limitations.

In the meantime, readers may review both frameworks and immediately dispute the stages, levels, linkages, effects or impacts in relation to their own institutional context. But this is, of course, the very point of such adaptive models, which can and should be disputed, negotiated and modified as needed for local institutional contexts, to guide relevant local action. To paraphrase Head and Alford (2013), when it comes to wicked problems in complex systems, there is no one–size–fits–all policy solution, and there is no plan that is not provisional.

Rather, the more important role of such frameworks is to continuously remind us of the need for a holistic understanding of institutional context if the goal is institutional change, including external and internal influences, political and cultural context, the evidence itself, and the links:

"All of the other actors and mechanisms that affect how the evidence gets into the policy process" (Young & Mendizabal, 2009). They can assist in identifying points of intervention (Corvalán et al., 1999) in the complex adaptive system that is education, to offer leaders and practitioners additional insight and tools in their project of optimizing the system with learning analytics.

References

Ackoff, R. L. (1974). *Redesigning the future*. New York, NY: Wiley.

Angelo, T. A. (1999). Doing assessment as if learning matters most. *AAHE Bulletin, 51*(9), 3–6.

Azevedo, R., & Aleven, V. (Eds.). (2013). *International handbook of metacognition and learning technologies.* Amsterdam: Springer.

Berkhout, F., Leach, M., & Scoones, I. (Eds.). (2003). *Negotiating environmental change: New perspectives from social science*. Cheltenham, UK: Edward Elgar.

Bichsel, J. (2012). *Analytics in Higher Education: Benefits, Barriers, Progress, and Recommendations* (Research Report). Louisville, CO: EDUCAUSE Center for Applied Research. http://net.educause.edu/ir/library/pdf/ERS1207/ers1207.pdf

Bienkowski, M., Feng, M., & Means, B. (2012). *Enhancing teaching and learning through educational data mining and learning analytics: An issue brief.* Washington, DC: U.S. Department of Education Office of Educational Technology. http://www.ed.gov/edblogs/technology/files/2012/03/edm–la–brief.pdf

Buckingham Shum, S. (2012). Learning dispositions and transferable competencies: Pedagogy, modelling and learning analytics. In S. Buckingham Shum, D. Gašević, & R. Ferguson (Eds.), *International conference on learning analytics and knowledge* (pp. 92–101). New York, NY: ACM Press.

Butler, D. L., & Winne, P. H. (1995). Feedback and self–regulated learning: A theoretical synthesis. *Review of Educational Research, 65*(3), 245–281.

Campbell, J. P., DeBlois, P. B., & Oblinger, D. G. (2007). Academic analytics: A new tool for a new era. *EDUCAUSE Review, 42*(4), 42–57.

Capra, F. (1996). *The web of life*. New York, NY: Doubleday.

Churchman, C. W. (1967). Free for all. *Management Science, 14*, B141–B142.

Cilliers, P. (1998). *Complexity and postmodernism: Understanding complex systems*. London, UK: Routledge.

Cohen, M. D., & Marsh, J. G. (1986). *Leadership and ambiguity: The American college president*. New York, NY: McGraw Hill.

Corvalán, C. F., Kjellström, T., & Smith, K. R. (1999). Health, environment and sustainable development: Identifying links and indicators to promote action. *Epidemiology, 10*(5), 656–660.

Dillon, T., Wu, C., & Chang, E. (2010). Cloud computing: Issues and challenges. In *IEEE International Conference on Advanced Information Networking and Applications* (pp. 27–33). New York, NY: IEEE Press.

Dumont, H., Istance, D., & Benavides, F. (Eds.). (2010). The nature of learning: Using research to inspire practice. *Educational Research and Innovation series*, OECD Publishing. http://www.oecd.org/edu/ceri/thenatureoflearningusingresearchtoinspirepractice.htm

Dunlosky, J., & Lipko, A. R. (2007). Metacomprehension: A brief history and how to improve its accuracy. *Current Directions in Psychological Science, 16*(4), 228–232.

Dunlosky, J., & Thiede, K. W. (1998). What makes people study more? An evaluation of factors that affect self–paced study. *Acta Psychologica, 98*(1), 37–56.

Dworkin, G. (2005). The No Child Left Behind act: Accountability, high–stakes testing and roles for sociologists. *Sociology of Education, 78*(2), 170–174.

Ellis, C. (2013). Broadening the scope and increasing the usefulness of learning analytics: The case for assessment analytics. *British Journal of Educational Technology, 44*(4), 662–664.

Elton, L. (2004). Goodhart's Law and performance indicators in higher education. *Evaluation & Research in Education, 18*(1–2), 120–128.

Ferguson, R. (2012). Learning analytics: Drivers, developments and challenges. *International Journal of Technology Enhanced Learning, 4*(5/6), 304–317.

Ferguson, R., Macfadyen, L. P., Clow, D., Tynan, B., Alexander, S. & Dawson, S. (in press). Setting learning analytics in context: Overcoming the barriers to large–scale adoption. Invited paper for the *Journal of Learning Analytics* based on a paper presented at the 2014 Learning Analytics and Knowledge, Indianapolis, IN.

Fritz, J. (2011). Classroom walls that talk: Using online course activity data of successful students to raise self–awareness of underperforming peers. *The Internet and Higher Education, 14*(2), 89–97.

Glahn, C. (2013). Using the ADL experience API for mobile learning, sensing, informing, encouraging, orchestrating. In *International conference on next generation mobile apps, services and technologies* (pp. 268–273). New York, NY: IEEE Press.

Goldstein, P. J., & Katz, R. N. (2005). *Academic analytics: The uses of management information and technology in higher education* (Vol. 8). Louisville, CO: EDUCAUSE Center for Applied Research.

Gupta, A., & Anish, S. (2009). Insights from complexity theory: Understanding organisations better. *IIMB Management Review*. http://tejas.iimb.ac.in/articles/12.php

Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research, 77*(1), 81–112.

Haynes, P. (2003). *Managing complexity in the public services*. Maidenhead, UK: Open University Press.

Head, B. W., & Alford, J. (2013). Wicked problems: Implications for public policy and management. *Administration & Society*. doi:10.1177/0095399713481601

Jacob, B. (2005). Accountability, incentives and behavior: Evidence from school reform in Chicago. *Journal of Public Economics, 89*(5–6), 761–796.

Kavanagh, M. H., & Ashkanasy, N. M. (2006). The impact of leadership and change management strategy on organizationsal culture and individual acceptance of change during a merger. *British Journal of Management, 17,* S81–S103.

Kingdon, J. (1995). *Agendas, alternatives and public policies* (2nd ed.). Boston, MA: Longman.

Kotler, P., & Zaltman, G. (1971). Social marketing: An approach to planned social change. *Journal of Marketing, 35*, 3–12.

Kotter, J. P. (1996). *Leading change*. Boston, MA: Harvard Business School Press.

Kotter, J. P., & Cohen, D. S. (2002). *The heart of change*. Boston, MA: Harvard Business School Press.

Kruger, J., & Dunning, D. (1999). Unskilled and unaware of it: How differences in recognizing one's own incompetence lead to inflated self–assessments. *Journal of Personality and Social Psychology, 77*(6), 1121–1134.

Macfadyen, L. P., & Dawson, S. (2012). Numbers are not enough: Why e–learning analytics failed to inform an institutional strategic plan. *Educational Technology & Society, 15*(3), 149–163.

MacLennan, B. (2007). Evolutionary psychology, complex systems, and social theory. *Soundings: An Interdisciplinary Journal, 90*(3/4), 169–189.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Byers, A. H. (2011). Big data: The next frontier for innovation, competition and productivity. McKinsey Global Institute. http://www.mckinsey.com/insights/business_technology/big_data_the_next_frontier_for_innovation

McDonnell, L. M. (1994). Assessment policy as persuasion and regulation. *American Journal of Education, 102*(4), 394–320.

McIntosh, N. E. (1979). Barriers to implementing research in higher education. *Studies in Higher Education, 4*(1), 77–86.

Milliron, M. D., Malcolm, L., & Kil, D. (2014). Insight and action analytics: Three case studies to consider. *Research & Practice in Assessment, 9*(2), 70-89.

Mitleton–Kelly, E. (2003). Ten principles of complexity & enabling infrastructures. In E. Mitleton–Kelly (Ed.), *Complex systems & evolutionary perspectives of organisations: The application of complexity theory to organisations* (pp. 23–50). Philadelphia, PA: Elsevier.

Nakamura, R. T. (1987). The textbook policy process and implementation research. *Review of Policy Research, 7*(1), 142–154.

Norris, D., & Baer, L. L. (2013). *Building organizational capacity for analytics*. Louisville, CO: EDUCAUSE. https://net.educause.edu/ir/library/pdf/PUB9012.pdf

Norris, D., Baer, L., Leonard, J., Pugliese, L., & Lefrere, P. (2008). Action analytics: Measuring and improving performance that matters in higher education. *EDUCAUSE Review, 43*(1), 42–67.

Pintrich, P. R. (1999). The role of motivation in promoting and sustaining self–regulated learning. *International Journal of Educational Research, 31*(6), 459–470.

Rein, M. (1976). *Social science and public policy*. Harmondsworth, UK: Penguin.

Richardson, J. (2004). Methodological issues in questionnaire–based research on student learning in higher education. *Educational Psychology Review, 16*(4), 347–358.

Rittel, H. W. J., & Webber, M. M. (1973). Dilemmas in a general theory of planning. *Policy Sciences, 4*, 155–169.

Sabatier, P. A. (Ed.). (2007). *Theories of the policy process* (2nd ed.). Boulder, CO: Westview Press.

Schon, D. A., & Rein, M. (1994). *Frame reflection: Toward the resolution of intractable policy controversies*. New York, NY: Basic Books.

Siemens, G. (2013). Learning analytics: The emergence of a discipline. *American Behavioral Scientist, 57*(10), 1380–1400. doi:10.1177/0002764213498851

Siemens, G., Dawson, S., & Lynch, G. (2013). *Improving the productivity of the higher education sector: Policy and strategy for systems–level deployment of learning analytics*. Sydney, Australia: Society for Learning Analytics Research for the Australian Government Office for Learning and Teaching. http://solaresearch.org/Policy_Strategy_Analytics.pdf

Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist, 57*(10), 1510–1529.

Tanes, Z., Arnold, K. E., King, A. S., & Remnet, M. A. (2011). Using signals for appropriate feedback: Perceptions and practices. *Computers & Education, 57*(4), 2414–2422. http://www.itap.purdue.edu/learning/docs/research/1–s2.0–S0360131511001229–main.pdf

Thomas, H. (2010). Learning spaces, learning environments and the dis'placement' of learning. *British Journal of Educational Technology, 41*(3), 502–511.

Tiesman, G. R., van Buuren, A., & Gerrits, L. (Eds.). (2009). *Managing complex governance systems*. London, UK: Routledge.

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist*. doi: 10.1177/0002764213479363

Wall, A. F., Hursh, D., & Rodgers, J. W. III. (2014). Assessment for whom: Repositioning higher education assessment as an ethical and value–focused social practice. *Research and Practice in Assessment, 9*(1), 5–17.

Wiliam, D. (2010). The role of formative assessment in effective learning environments. In H. Dumont, D. Istance, & F. Benavides (Eds.), *The nature of learning: Using research to inspire practice* (pp. 135–155): Paris, France: OECD Publishing.

Winne, P. H. (2010). Improving measurements of self–regulated learning. *Educational Psychologist, 45*(4), 267–276.

Wise, A. F. (2014). Designing pedagogical interventions to support student use of learning analytics. In A. Pardo & S. D. Teasley (Eds.), *Proceedings of the International Conference on Learning Analytics and Knowledge*. New York, NY: ACM Press.

Yanosky, R. (2009). *Institutional data management in higher education*. Boulder, CO: EDUCAUSE Center for Applied Research.

Young, J., & Mendizabal, E. (2009). Helping researchers become policy entrepreneurs: How to develop engagement strategies for evidence–based policy–making. (Briefing Paper) ODI briefing Papers. London, UK.

Zhou, M., & Winne, P. H. (2012). Modeling academic achievement by self–reported versus traced goal orientation. *Learning and Instruction, 22*(6), 413–419.

Zimmerman, B. J. (2002). Becoming a self–regulated learner: An overview. *Theory Into Practice, 41*(2), 64–70. doi: 10.1207/s15430421tip4102_2