LEARNING ANALYTICS EVALUATION: AN EXAMINATION OF PRACTICE

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Abstract

The field of learning analytics has developed to address the needs for better evidence-based decision-making in higher education; based on advances in analytical tools and new data sets generated by online learning and student information systems. As a new field, learning analytics research has focused on technical system issues rather than methodological questions such as assessment and evaluation. Consequently, existing evaluation methods for learning analytics are narrowly focused on analytics as a tool: system quality and feature use. In this paper learning analytics is viewed as a process embedded in a work-practice. I develop a model to evaluate learning analytics based on the IS Success model modified by Adaptive Structuration theory. The model extends existing approaches to evaluating learning analytics by focusing on the interrelationships between technology and user activity. Using participant feedback an initial set of user scenarios for the model have been constructed in a real work-practice setting in a third level institution.

Keywords: Learning Analytics, IS Success model, Structuration, IT Use, work-practice.

1 Introduction

In recent years higher education has experienced a paradigm shift to an environment characterised by advanced technologies, complex decision-making processes and increasing demands for quality control (Altbach et al., 2010). The field of learning analytics (LA) has developed to address the needs for better evidence-based decision-making in higher education (Long & Siemens, 2011). Learning analytics is based on advances in analytical tools and the new data sets generated by online learning and student information systems (Ferguson, 2012). Early LA research involved the application of data mining techniques and approaches such as statistics and visualisation, clustering and classification, and association rule mining to learning system web logs and learning content management system data (Romero & Ventura, 2007). Later research involved the application of social network analysis to online discussion forums (Dawson, 2010) and learning monitoring systems integrating pedagogic knowledge and business intelligence methods (Arnold, 2010).As a new field, learning analytics research has focussed on technical issues such as the quality of predictive models (Romero et al., 2008) or the learning theory on which a tool is based (Ferguson, 2012). Questions about effective use and the impact of learning analytics (Dyckhoff et al., 2013), remain largely unexamined. In this study I present a model for learning analytics evaluation, based on existing models of information systems success and use and following a work-practice perspective (Goldkuhl, 2011; Orlikowski, 2000). Section 2 describes the state of existing research in learning analytics evaluation. Section 3 presents an advance on this research using the IS Success model and Structuration theory and section 4 presents initial empirical work with the model. Section 5 presents conclusions.

2 Learning Analytics Evaluation

Learning analytics research (and the related field of educational data mining) has been active for over a decade (Bienkowski et al., 2012; Ferguson, 2012; Romero & Ventura, 2010). In previous work we observed that much of the early work in the field focussed on techniques for conducting the analytics with little attention to evaluation (Murnion & Helfert, 2011). Both practitioners (Norris et al., 2008) and researchers (Dyckhoff, et al., 2013; G. Siemens, 2012) have called for learning analytics to have greater impact on education. In the related field of business analytics, case-based research provides a best practice approach to managing the analytics process (Davenport & Harris, 2007; LaValle et al., 2010) while separate empirical research examines the measurement of analytics effectiveness (Popovič et al., 2012; Trkman et al., 2010). The general perspective adopted is examining analytics as a ‘work-practice’(Goldkuhl, 2011; Orlikowski, 2000). In learning analytics research, in contrast, evaluation research focusses on functionality and usability issues (Ali, Hatala, et al., 2012; Dyckhoff et al., 2012; Mazza & Dimitrova, 2007). Furthermore, evaluation methods are not founded on a conceptual framework and therefore suffer from uncertainty around validity and generalizability. Recent research has identified this issue. Dyckhoff and colleagues (Dyckhoff, et al., 2013) examined evaluation problems in learning analytics and found that few of the projects examined included effective evaluation. Four of the thirty-eight publications included no evaluation; three include evaluations of small size and four included evaluations of functionality and usability. To address the problem they provide an “impact evaluation method” based on the characteristics of action research (Hinchey, 2008). The overall goals of evaluation, based on the existing literature on LA should be to: (a) inform the design of learning analytics tools; (b) support appropriate educator behaviour; and (c) support student behaviour. Underlying these goals is (implicitly) a behavioural model of IS impact (Davis, 1989) in which IT design (a) affects user behaviour (b) and (c), however the model (implied or otherwise) is not examined further or tested empirically.

The use of a conceptual basis for evaluation is explicitly stated in the Learning Analytics Acceptance model (LAAM), proposed by Ali and colleagues (Ali, Asadi, et al., 2012) and based on the Technology Acceptance Model (TAM) (Davis, 1989). The use of an established conceptual model improves the validity of the findings; and the model constructs and inter-construct relationships provide testable hypotheses about effectiveness in Learning Analytics. A noticeable feature of the study is the tool-centric perspective of the evaluation which is designed around a custom-made learning analytics tool (LOCO-Analyst). A second feature is the reliance on the TAM as a basis for evaluation, which relying on behavioural intention to use, tends to focus on quantity of use rather than nature of use. An alternative model, the IS Success model (DeLone & McLean, 1992; Petter et al., 2008) provides a more thorough conceptualisation of IS Use.

3 IS Impact and Success Models

Information systems success models address the problem of measuring information systems effectiveness by providing a measurement framework. The primary contribution of success models is that success or effectiveness cannot be captured in a single dimension (such as improved decision-making or superior system technical qualities). Instead, success is multi-dimensional. The dominant IS success model is the DeLone and McLean model (Delone, 2003; DeLone & McLean, 1992; Petter, et al., 2008). In this model IS success is represented by a taxonomy of success factors: System Quality, Information Quality, Use, User Satisfaction; and Impact. The taxonomy is based on a temporal, process model in which an information system is first created, exhibiting various degrees of system quality, and generates information products which are consumed by users who are either satisfied or dissatisfied with the system or the information products. The use of the systems and its information products then impacts or affects the work of the user and the overall organization. This process view of IS success levels (categories) is based on the communications research of Shannon and Weaver and the information influence theory of Mason (DeLone & McLean, 1992) as shown in table 1.

Shannon and Weaver	Technical	Semantic	Effectiveness or Influence	
Mason	Production	Product	Receipt	Influence
Categories of IS Success	**System Quality**	**Information Quality**	**Use / User Satisfaction**	**Impact**

Table 1. Categories of IS Success

For the purposes of Learning Analytics impact research, the IS Success model provides an established conceptual framework. One of the purposes of a conceptual framework is to direct attention to gaps in the research field. Using the categories of the IS Success model in table, existing learning analytics evaluation research has been focussed on System Quality (Murnion & Helfert, 2011) and somewhat on Information Quality (Dyckhoff, et al., 2013). The LAAM study (Ali, et al., 2012) extends this to User Satisfaction but does not fully address the Use construct, adopting Use measures which are constructed subjectively by the researchers. Furthermore the IS Success model provides a template, for new success models based on the fundamental principal of the underlying causal process model (DeLone & McLean, 1992). A Learning Analytics success model therefore must reflect the fact that the underlying process model is more complex than for a typical mandatory data processing IS.

3.1 Learning Analytics Success model and Adaptive Structuration Theory

Analytical information systems use is largely voluntary and complex (Popovič, et al., 2012; Wu & Wang, 2006). This is especially true for learning analytics where the user base consists of skilled knowledge workers (academics) operating in a loosely controlled decision-making environment (George Siemens, 2012). Users do not interact with a system as such but avail of analytical tools and information sets in a sporadic and piecemeal fashion. The standard directional IS process model (system → information → use) is atypical of analytical technologies; which involve iterative processes of exploration (Marchand & Peppard, 2013) and sense-making (George Siemens, 2012). Learning analytics use is embedded in existing work-practices such as action research (Dyckhoff, 2010) and programme design (Beetham & Sharpe, 2007). In order to address these difficulties, I adopt the framework of Adaptive Structuration Theory (AST) (Markus & Silver, 2008). AST provides a lens to understand and investigate outcomes of IS-induced change in socio-technical work practices (Orlikowski, 2000). In particular AST provides a way of examining the interactions between actions (Use) and technology (System) that incorporates the iterative nature of this interaction. The mediating element between actions and technology is *social structure*: the rules and resources that are instantiated within practice as *relations* between human agents and technical objects (Orlikowski, 2000). The structure consists of two aspects: *functional affordance* and *symbolic expression* (Markus & Silver, 2008). Functional affordance refers to the potential uses one can make of a technical object depending on the features provided. For example the pivot table feature in an Excel spreadsheet provides the affordance of data cross-tabulation. Symbolic expression is the “communicative possibilities of technical objects for a user (group)” (Markus & Silver, 2008), particularly expressions about functionality or purpose. In learning analytics this corresponds to the insight gained as the user interacts with the technology (Long & Siemens, 2011). An example would be the use of a cross-tabulation which is interpreted as a contingency table comparing different groups of categorical data. These two elements of structure provide for a level of abstraction, improving the independence of the model from the particularities of an individual learning analytics tool as shown in the left-hand side of figure 1. Furthermore it allows the evaluation of individual analytic affordances as opposed to complete systems.

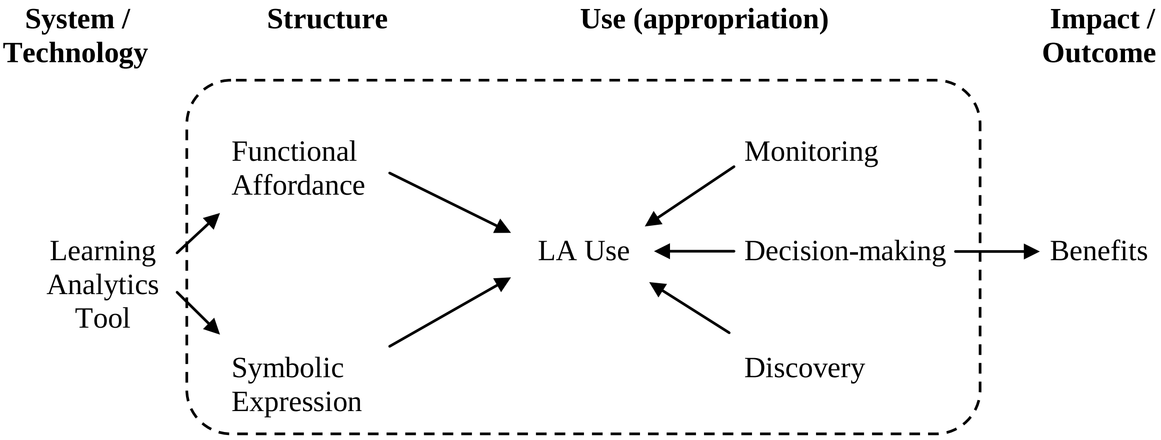

Figure 1. Learning Analytics Success Model

A second contribution of AST is the concept of *appropriations*. Appropriations are the actual use of the structure provided by the IS (unlike affordance which is a potential use) (Markus & Silver, 2008). Appropriations concern the type of use, in contrast to traditional measures of quantity of use. Using the vocabulary of the IS Success model (Delone, 2003) this may be re-phrased as *use for*. Analytical information systems are primarily used for supporting decision-making (Popovič, et al., 2012) and monitoring performance (Laursen & Thorlund., 2010), with advanced use of analytics for knowledge discovery and innovation (Davenport & Harris, 2007). It should be noted that use types are not mutually exclusive. A particular use of analytics might be primarily to monitor a situation and also be used in part to support a particular decision. Adding these three types of use completes the learning analytics success model in figure 1. The focus of this paper is on the relationship between Structure and Use: the dashed box in figure 3. AST has been utilised in previous examinations of IT Use however these have focussed on specific user activities (e.g. using a feature of a software package)

(Sun & Zhang, 2006). In contrast, this study follows a work-practice perspective in which the focus is on a *meaningful unit of work* (Goldkuhl, 2011), such as a group decision, rather than on the activity of a single user with an application.

An illustrative scenario is provided in figure 2. This shows the result of extracting student grades from the student information system (SIS) and generating a pivot table for average and standard deviation for all modules on a single course. The **functional affordances** provided in this instance are: (1) one-dimensional analysis, and (2) descriptive statistics.

StdDev of SHRTCKG_GRDE_COD	GA_BACCG_H08			
SHRTCKN_CRSE_TITLE	St Dev	Avg	- 2 * SD	+ 2 * SD
AUDITING 1	9	63	45	81
AUDITING 2	9	67	49	85
CORPORATE REPORTING 1	9	49	31	68
CORPORATE REPORTING 2	12	52	28	76
ETHICS & CORPORATE GOVERN	13	70	45	95
ETHICS & PROFESSIONAL DEVEI	17	61	27	95
FINANCIAL MANAGEMENT 3 COR	15	65	35	95
MGMT. ACCOUNT. 5 STRAT. MG	15	69	39	99
PROFESSIONAL DEVELOPMENT	17	49	15	83
STRATEGIC MANAGEMENT 1	11	69	47	91
STRATEGIC MANAGEMENT 2	10	68	48	88
TAXATION 3		56	n/a	n/a
Grand Total	12	61		
Range	8	21		

Figure 2. Learning Analytics scenario

The **symbolic expression** is that users can compare course by difficulty and also by discriminating ability. The **use** of this case is primarily to *monitor* the overall stage (the collection of courses) but might also lead to further *decision-making* in relation to programme standards.

4 Empirical work

Evaluation using a success model requires that the model be operationalised (Petter, et al., 2008). The conceptual framework provided by sections 3 and 4 provides a basis but this needs to be supplemented with empirical work. Taxonomy construction in IS involves supporting a conceptual framework with empirical data (Nickerson et al., 2009). Similarly construct development based on a conceptual model is refined using expert opinion and empirical data in pilot studies (Elbashir et al., 2008). A criticism of previous learning analytics (LA) evaluation approaches is that the LA tool lies at the centre of the evaluation process. In contrast to that tool-centric perspective of the IT artefact (Orlikowski & Iacono, 2001) this study centres on a work-practice perspective in which the IT artefact includes the IT tools and the associated practices. From this perspective learning analytics is not represented by a specific IT artefact but rather consists of a toolkit for addressing learning analytics needs; potentially a set of analytics services (Delen & Demirkan, 2012). Therefore operationalising the model requires first a work-practice context. An important work-practice in education involves the process of program evaluation, “the systematic process of assessing a program of study, such as a degree, culminating in a value judgement with regard to the quality of the program being evaluated” (Mizikaci, 2006). In an Irish higher education context, this process is known as programmatic review and is governed by institutional and national regulations (GMIT, 2013; HETAC, 2009, 2011). In this research we conducted documentation research (Palvia et al., 2003) and combining that with researcher professional experience in programmatic review created a number of preliminary learning analytics scebarios for discussion and peer examination (Murnion & Helfert, 2013). Currently the researcher is part of an academic team that is carrying out a formal programmatic review process for an entire School consisting of 35 academic members of staff, approximately 1000 students and 8 academic programmes (degrees). The process commenced in January 2014 and will conclude in September 2014. In addition to membership of the review team, the researcher has access to the data in the institute student information system (SIS) and the institute learning management system (LMS).

The first stage in operationalising the model is to generate a set of learning analytics scenarios in the context of the programmatic review. Based on the preliminary research already mentioned and the current review process now underway, interviews have been conducted with seven members of the School team (three lecturers, two managers, one expert on programmatic review, and one administrator). Each interview took around one hour. Participants were provided with documentation on the programmatic review process plus examples of institutional data and some example analytics outputs in an Excel spreadsheet. Using these as guidance they were asked to generate a brief use scenario for learning analytics to support the ongoing programmatic review process. The interviews have generated 38 scenarios (extract of the data included in appendix). This provides the equivalent in our work-practice approach to the construction of a prototype in a standard tool-based approach.

The next stage is to operationalise each model construct with a set of candidate measures that will act as indicators to the underlying construct. Each measure should accurately reflect the underlying construct and so increase the validity of the model (Petter, et al., 2008). In accordance with the work-practice perspective of this study, the operationalization of each construct will involve the participation of the appropriate practice participants and the outcomes of each operationalised construct will depend on the nature of that construct as illustrated in table 2.

Construct	Participants	Operationalise	Illustrative example
Affordance	Analytics experts	Review scenarios and assign affordances (labels) to each	1. Cross-tabulation 2. Descriptive statistics
Symbolic expression	Users	Create multiple items (statements) that reflect different aspects of the construct	“I can compare my course with other courses at the stage” “I am surprised by that outlying data”
Use	Users and programmatic review experts	Determine the use level for each type of use	“This will be used primarily for monitoring” “This will be used slightly to support a decision”

Table 2. Operationalising constructs

4.1 Discussion

In this research the evaluation of learning analytics is examined, following a work-practice perspective. Existing gaps in learning analytics evaluation methodologies are observed. Thus the impact of learning analytics on the educational system is not clear and best practice in learning analytics is difficult to observe and improve. An evaluation model is constructed, based on the DeLone IS Success model, modified by Adaptive Structuration theory. The next stage is to operationalise the model and apply the completed model within a work practice setting involving a whole school programmatic review. The results should illuminate our understanding of how the technology of learning analytics, users understanding of analytics and actual use in a work-practice interact.

The study is limited by the incomplete operationalization of the model constructs. However this process is currently underway. A more permanent limitation is the generalizability of our constructs across future learning analytics projects. However we expect that the final operational model will be sufficiently specified so that it can be implemented in future projects without losing comparability across projects.

The study contributes to learning analytics research by providing an evidence-base for further research and also to IS Success theory by providing a novel perspective on model constructs. Existing constructs of System quality and Information quality have been tightly bound to the artefact as IT tool perspective. Based on structuration theory these new constructs focus on the interaction between the use and the technology rather than on the technology itself. The study also complements recent research on IT Use which has also adopted a structuration framework (Sun & Zhang, 2006),(Grgecic & Rosenkranz, 2011). However unlike the related work, this study concerns analytical systems rather than operational systems and therefore ‘Use’ is concerned with informational outputs of the system rather than interacting directly with the technology.

Appendix: Learning Analytics Scenarios (illustrative extract)

Case	Interviewee code	Role	Case context	Case question	Affordance	Symbolic expression	Use
1	SD	Manager	Pass/fail vs. CAO (points/choices)	CAO factors in determining student progression?			
2	MM	Lecturer	LtL and progression relationship?	Does LtL work?			
3	SD	Manager	Student progress: need two sittings?	How steady is student progress?			
4	CB	Manager	Transfers across programmes	which modules fail students			
5	MN	Lecturer	Student year one attrition	fail rates			
6	CK	Expert	Drilldown from correlation heat-map	Exception in module relationships?			
:	:		:	:			

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