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Adoption of Learning Analytics in the UK: Identification of Key Factors using the TOE Framework.

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Abstract: Across the UK, Higher Education Institutions (HEIs) are waking up to the fact that data analytics solutions can provide valuable insights across many areas. One key development is the use of analytics to measure and enhance learning and teaching (L&T) strategies. Learning Analytics (LA) is a growing area of research and application, driven by a desire to improve the student experience and enhance engagement in blended learning environments. From a broader institutional view, the desire to improve student retention rates is also a compelling driver to explore LA. This paper reviews the current literature and proposes eight key factors affecting the adoption of LA in higher education within the UK.

Keywords: Learning Analytics (LA); Adoption; Higher Education (HE); Learning and Teaching (L&T); Learning Technology; Technology Organisation Environment (TOE).

Word count: 5,715.

1 Introduction

The 1st International Conference on Learning Analytics and Knowledge (LAK) offered the first public definition of the term, stating that "Learning Analytics is the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs" [LAK '11, 2011]. As with many other attempts at conceptual definition, a single narrative rarely covers all themes. LA seeks to utilise the data trails created by learners in educational contexts, and, from this, provide a beneficial developmental learning framework of student engagement, progression and achievement [Lockyer et al., 2013]. It is not discrete, but an emerging field formed of several established areas. It draws from disciplines such as social network analysis, user modelling, and cognitive modelling [Siemens, 2013] and is closely tied to areas such as business intelligence, web analytics, descriptive and predictive analytics. Learning Analytics (LA) is an emerging and developing field and it is important to distinguish LA from two related, but diverging fields: Academic Analytics and Educational Data Mining.

The Educause Center for Applied Research (ECAR) formulated the term, Academic Analytics (AA), to provide a definition of analytics and business intelligence (IT) in a Higher Education (HE) context. It is an "imperfect equivalent term for business intelligence. We use it to describe the intersection of technology, information, management culture, and the application of information to manage the academic enterprise" [Goldstein, 2005, p. 2]. The same report emphasises that AA should not exclude the broader finance and business areas. It is this broader scope of analytics - beyond that of the learning experience – that distinguishes AA from LA. Thus, AA refers to the use of Management Information Systems (MIS) reporting and analytics technologies across the whole institution, despite the efforts of some authorities [e.g. Campbell et al., 2007] to mistakenly represent it as strictly learner-centred in scope.

Educational Data Mining (EDM) significantly overlaps with LA. For both, the area of study is the data-driven learning environment. EDM, however, refers more specifically to the modelling techniques applied therein, whereas LA encompasses a broader interpretation, with an emphasis on human-centred decision making and application in a learning environment. EDM "has a considerably greater focus on automated discovery, and LA has a considerably greater focus on leveraging human judgment" [Siemens & Baker, 2012, p. 2]. EDM seeks to unearth new patterns in data and from this, develop models and algorithms, while LA seeks to apply known models in learning management systems (LMS) [Bienkowski et al., 2012].

In considering thematic comparisons, two perspectives of LA research emerge:

- Pedagogic/Learner-centric: The emphasis, from a data-driven perspective, of mechanisms of learning, such as feedback, self-regulated learning, and sense-based effects/multimodal learning analytics [e.g. Cutumisu et al., 2015; Pardo et al., 2016; Worsley & Blikstein, 2015]. These elements resonate more closely with aspects of EDM.
- Institutional: The challenges of designing and implementing LA systems in UK HEIs are reasonably well documented in the UK, but more prominently in the USA and Australia, where LA enjoys higher levels of maturity. From this standpoint, a greater focus exists on issues of ownership, data governance, visualisation, transparency, and retention strategies [e.g. Sclater, 2014a; Oster et al., 2016; Tsai & Gasevic, 2017]. This more strategic perspective aligns it more closely with elements of AA.

It is the institutional perspective that drives this study. Fig. 1 seeks to simplify the position of LA in its native HE context.

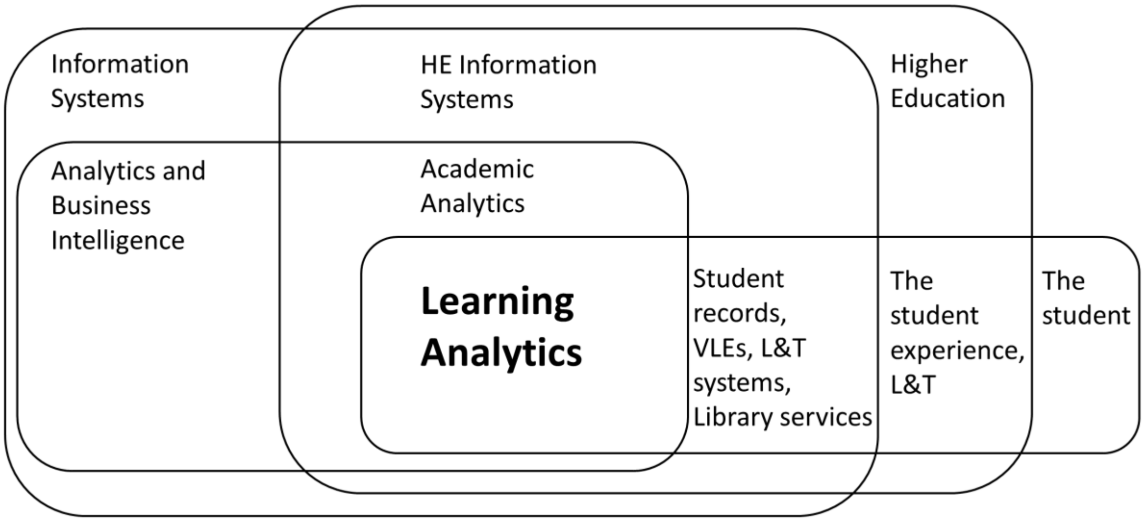

Figure 1: Learning Analytics in context

In 2012, an ECAR study sought to gauge the state of Data Analytics in HE in the United States, in context of perception, benefits, barriers, and progress [Bichsel, 2012]. The report highlighted several successful LA initiatives in the area. The follow-up survey [Arroway et al., 2016] sought to distinguish LA from institutional analytics, but again highlighted the most prominent areas of deployment. Synergising these findings with an empirical review of LA research [Papamitsiou & Economides, 2014], we derive a list of principle LA objectives:

- Prediction of student performance
- Increased student (self-)reflection and (self-)awareness
- Prediction of student dropout and retention
- Improved feedback and assessment services
- Early intervention programmes for potential problem students
- Assessment-based coaching reports to develop study plans
- Institution and Faculty level dashboard interrogation

LA projects are active in the UK, notably by the Open University (OU), Loughborough University, and Nottingham Trent University, amongst others [Sclater, 2014b]. The OU, being a large distance-learning provider, can leverage a wealth of online learner data. As such, it has made significant advances in developing sophisticated models of learning. Such modelling drives informed intervention strategies previously impossible in a distance-learning environment [The Open University, 2017]. Nottingham Trent University developed an academic support platform based on principles of transparency and accessible data visualisation. Their platform offers visibility at student and tutor-level, as well as providing a strategic overview for academic management [JISC, 2017]. In a sense, these projects represent the two flavours of LA: EDM focused (OU) and AA focused (Nottingham Trent). In reality, there is a deal of common ground between the two. Aside from this, Bannert et al. [2014] researched the usage of process mining techniques (as opposed to traditional statistical methods) to model and measure learner behaviours. Jovanović et al. [2017] developed this theme in their study which identifies on-line learner strategies in a flipped learning setting.

It is quite clear that interest in LA is growing. Although enhancement of the student experience is sometimes trumpeted as the main driver for LA, the mitigation of student attrition underpins many implementations. This is a subject of increasing concern for many institutions in strained economic times. Several studies investigate contextual factors and financial implications of the badly managed student experience. These studies [McCulloch, 2014; Soilemetzidis & Dale, 2013; N. Johnson, 2012] underpin real sector concerns over the impact of lost revenue through student attrition.

Sclater [2014b] provides an essential qualitative compilation of UK LA-engaged institutions at HE and FE level, along with deployment descriptions and perceived outcomes. The messages from the study are:

- The majority of LA in UK is concerned with the development of dashboards and other visualisations to monitor and report on student engagement metrics, with a view to managing progress and improving student performance and retention.
- Tribal's1 Strategic Information Technology Systems (SITS) product dominates the UK student records systems market. Virtual Learning Environment (VLE) deployment is split between Blackboard and Moodle. In contrast, LA has no dominant vendor. The significant LA protagonists chose from a wide section of competing systems, which probably reflects its embryonic nature.
- It is too early to truly judge the impact and outcomes from the various initiatives and institutions are necessarily reserved in proclaiming any significant outcomes. Some, however, noted some interesting analytical insights, with several citing a strong correlation between attendance and performance.

2 Opportunities and Challenges

Key drivers for the implementation of LA are i) student success and learning experience, and ii) retention concerns [Sclater, 2014b]. Student success can be considered a driver to benefit the student as an individual, as well as the institution; the success of an institution is defined by the collective success of its students. Debates on student retention and attrition, however, address the pragmatic issue of finance. As well as fees, a student generates revenue through a variety of means e.g. on-campus spending and accommodation. Students also represent an accumulated cost in recruitment and enrolment [Seidman, 2005]. The loss of revenue through attrition takes on a new significance. While many institutions focus on student recruitment and marketing, research suggests that retention initiatives are 3-5 times more cost-effective than recruitment efforts [Cuseo, 2006]. From 2003 to 2008, US State governments collectively spent 6.2 billion dollars through appropriations on students who ultimately dropped out of the educational system after one academic year. In the same period, the government funded 1.4 billion dollars in grant payments to the same failing student population, and 1.5 billion in federal grants [Schneider, 2010]. In the UK, attrition rates vary from 1-2% in the Oxbridge institutions to as much as 35%, with the total estimated cost of attrition amounting to 7.8 billion pounds [Simpson, 2005]. These figures alone should provide motivation for institutions to invest in student retention strategies. Whilst there will always be a financial emphasis, it is important to note that LA should still drive the improvement of the student experience.

To facilitate LA, the existence of on-line or blended-learning platforms is integral for the provision of the actionable data trails. For example, indicators such as academic integration, social factors, and demographic range can explain up to 30% of performance variance through predictive modelling. The usage of a Learning Management System (LMS) can significantly increase this figure [Tempelaar et al., 2014]. We can extrapolate that purer digital offerings, such as massive open online courses (MOOCS) or the Open University programmes, provide the richest data sets for LA projects, in contrast to traditional face-to-face environments [Worsley, 2014]. The evolution of LA cannot, however, depend on the proliferation of the MOOCS model, as this is a minority delivery platform. That said, blended learning, social media, and gamification continue to enjoy growth [L. Johnson et al., 2014], potentially providing very rich data sources for LA.

Despite the inherent challenges that exist, the HE sector is waking up to the necessity of LA, and the body of research and application is growing. A general narrative of the emergence of LA in the UK is conveyed succinctly in the Heads of e-Learning Forum (HELF) 2015 UK LA survey [Newland et al., 2015]; around half of the UK's HEIs have not implemented LA in any form. Amongst those who have, strategic ownership lies predominantly with senior management. The operationalisation is spread over many departments and, as such, there is no cohesive sense of operational ownership. Successful

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projects depend on sustained stakeholder involvement from students, academics and administrators. The macro—level development trajectory is, however, gaining some momentum; the UK-based Joint Information Systems Committee (JISC) is working with 50 Universities in an effort to facilitate cloud-based LA deployments at a national level [Sclater et al., 2016].

This paper focuses on key factors affecting adoption of LA in higher education within the UK. We selected a theoretical framework to capture the organisational perspective for adoption of LA; then we positioned the key factors, identified from literature, into the selected framework.

3 Theoretical Framework Selection

Even in the United States, where LA development enjoys a greater level of maturity than the UK, relatively little is known about the institutional processes that underpin a successful (or otherwise) implementation. Oster et al. [2016] seek to generate a framework for measuring institutional readiness for LA; the Learning Analytics Readiness Instrument (LARI). It identifies factors such as culture, data management expertise, data analysis expertise, communication and policy application, and training as potentially significant factors. Their study provides a partial inspiration for this research. We hope to develop a similarly robust LA deployment framework for the UK HE sector.

In conducting research to evaluate the suitability of the technology-organisation-environment (TOE) model, we evaluated several adoption frameworks. Frameworks such as the Technology Acceptance Model (TAM), as proposed by Davis [1989] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [Venkatesh et al., 2003] enjoy wide utilisation and an empirical solidity. The UTAUT, in particular, excels in explanation of a variance [Williams et al., 2015]. They are, however, suited mainly to the assessment of individual adoption, not institutional, so are unsuitable for this study. Of the remaining institution-level adoption models, two are worthy of consideration: The Diffusion Of Innovation (DOI) model [Rogers, 1995], and the Technology-Organization-Environment (TOE) framework [DePietro et al., 1990]. Sahin claims DOI is most appropriate theory for investigating HE technology adoption [Sahin, 2006], as a way of justifying its usage in his own study [Sahin & Thompson, 2006], but does not underpin this statement empirically. Some authors combine DOI and TOE with effective results. Ultimately, the TOE framework is consistent with DOI theory [Oliveira & Martins, 2011] but The TOE contexts provide a greater sense of alignment with innovative nature of LA. Therefore, we chose the TOE framework for this study.

4 LA Adoption TOE Framework – Justification of Constructs

The main aim of this paper is to identify the factors affecting adoption of LA in HE within the UK using the TOE model that analyse three key contexts: Technological, Organisational, and Environmental. Within these contexts, the following eight constructs are derived:

4.1 Relative Advantage (Technological)

Defined as “the degree to which the innovation is perceived as better than the idea it supersedes” [Rogers, 1995, p.229], relative advantage is a significant factor in the adoption of a wide number of technologies [Gangwar et al., 2014; Oliveira & Martins, 2011]. Other studies show that perceived relative advantage ostensibly drives up the probability of technology adoption [Thong, 1999]. In the context of LA, it is slightly more complex to assess, as the ‘idea it supersedes’ may not be as clearly manifest as it is with other technologies. LA is a defined set of ideas but it potentially replaces a more abstract reality. Nonetheless, a growing number of studies show the potential of LA in the wider sector, as evinced by the number of new deployments in the UK alone [Sclater, 2014b]. Financial drivers also underpin relative advantage; Cuseo [2006] highlights the economic sense of retention over recruitment, and the compelling figures recorded by Schneider [2010] and Simpson [2005] demonstrate how much revenue can be lost through student attrition.

4.2 Complexity (Technological)

This is defined as the degree of perceived difficulty of an innovation deployment and usage [Rogers, 1995]. Various studies [e.g. Accenture 2015; Robb 2012] demonstrate that analytics deployments require a specific level of expertise, be it in-house, third-party, or both. Not only does it necessitate the interrogation of data from various sources (VLEs, online course portals, historical assessment data, for example), but the curation of sophisticated modelling processes. This may drive an unnecessarily skewed perception of the complexity of such deployments. Complexity is found to be significant in technologies that are embryonic in their life-cycle, such as LA.

4.3 Perceived Financial Cost (Technological)

The HE sector is in a much more delicate economic state due to the general global situation, but also due to the challenging immigration policies enacted by the UK Government. These regulations precipitated a downturn in a foreign student market, which is estimated at being worth nearly three billion pounds per year in fees and accommodation alone [Universities UK, 2014]. In this climate, HE management require strong arguments to convince them that LA deployments represent an investment with valuable returns. This is an uncommon variable in majority of studies [Gangwar et al., 2014; Oliveira & Martins, 2011] but it should be remembered that most of these studies exist in the context of more financially robust sectors in more financially robust times.

4.4 Top Management Support (Organisational)

Management support proves to be a vital factor in the adoption of new technologies, as evinced by the number of studies [Gangwar et al., 2014], [Oliveira & Martins, 2011]. The strategic advantages of having on-side senior or executive management are clear. In non-HE Analytics/BI deployments, lack of management buy-in is cited as one of the main reasons for project failures in this area [Gartner, 2011]. In HEIs, this level of support may be represented by the Vice-Chancellor, Chief Executive Officer (CEO), Chief Operating Officer (COO), Chief Information Officer (CIO) or at Faculty level by the Dean or Associate Dean. Although interest in LA from senior management is growing [Sclater et al., 2016], three-quarters have a limited understanding of the true impact of LA [Newland et al., 2015].

4.5 Institution Size (Organisational)

Some authorities state that organisational size positively affects the likelihood of successful innovation adoption. It appears to be one of the most fundamental determinants of adoption [Jeyaraj et al. 2006; Rogers, 1995]. Larger organisations have richer financial and human resources, and perhaps a greater onus to adopt innovation. Studies do exist that contradict this standpoint, and one major inquiry found that although the general positive correlative trend exists, it is not universal, and is moderated by variables such as innovation type, organisation type, and stage-of-adoption, amongst others [Lee & Xia, 2006]. Again, a converse logic suggests that certain smaller organisations, due to a lightness and flexibility of structure, may embrace innovation adoption more readily. Nonetheless, in the context of LA, it seems like the larger institutions are more readily embarking on implementation programmes [Sclater et al., 2016]. Size can be measured by several metrics, such as student population or number of employees, to name a few.

4.6 Technology Competence (Organisational)

In traditional IS environments, the adoption of a new platform relies on a certain amount of institution-wide and skill-specific technological know-how. This case holds true for LA; we argue that analytics solutions require a rich skillset to provide the best return. The lack of these skills undermines the success of analytics/BI deployments [Gartner, 2011] and this factor may map onto LA deployments. It follows then, that a strong combination of Information Systems (IS), Information Technology (IT), and BI competence is a significant factor in adoption success. Siemens [2013] highlights the additional complexities presented in implementing LA, where a specific mix of skills is necessary.

4.7 Competitive Pressure (Environmental)

In the wider industrial sectors, competitive pressure is a very real phenomenon, as demonstrated by its repeated presence in large number of TOE studies [Gangwar et al., 2014; Oliveira & Martins, 2011]. Yoon [2009] derives his most significant results by breaking down this variable into mimetic pressure (an organisation's perception of its competitors' adoption); coercive pressure (the extent of the influence of customers and other associated stakeholders in the decision to adopt); normative pressure (which pertains to the pressure to conform to what is the 'norm'). We considered this categorisation due to its high granularity - and its effectiveness in the study - but ultimately rejected in favour of the broader term. Empirical evidence around LA and competitive pressure is slight but industry sources hint at its potential drive inside the UK [Machin, 2015] and on a global level [Harrow, 2015].

4.8 Vendor Support (Environmental)

Whilst a small number of institutions crafted bespoke LA systems, the majority of UK adopters use one or a combination of third-party vendors, as whole or part of their LA deployments [JISC, 2014]. While SITS claims the market-share of the HEI Student Records market, and Blackboard and Moodle dominate the VLE market, LA has no dominant market leader and is still the subject to healthy vendor competition [Sclater, 2014b]. This could prove vital in the current economic climate, where some institutions still view LA as a niche speciality. HEIs can push vendors to supply intellectual/skills support, as well as financial incentives and competitive licence agreements.

5 Survey Development and Constructs

5.1 Survey Administration

We generated the questionnaire emails from a bespoke MS Access database, built on contact list of 385 potential respondents, covering the majority of the 171 accredited institutions identified by HE [Higher Education Statistics Agency, 2014]. We generated the contact list through manual interrogation of all institutional websites. 50 people responded: 27 from adopter institutions, and 23 from non-adopter institutions, representing a return of 13%. The selection strategy involved targeting individuals whose job description matched the following:

- Academic Registry staff
- eLearning staff/specialists
- Academic Analytics specialists
- Student Registry management
- Strategic/Planning staff members

The email structure included a degree of personalisation, and we included a prize draw to incentivise respondents.

5.2 Survey Design

The survey consists of 34 items in total. Six of these items relate to general demographic and minor qualitative data capture. The remaining 28 Likert items cluster, in groups of four, around seven of the eight TOE constructs. For the two measures relating to the Institution Size construct (student population and academic personnel count), we accessed data from the Higher Education Statistics Agency [2014]. Thus, we included 30 items for consideration for factor analysis. Appendix I contains the survey items.

Table 1: TOE Survey Constructs

Questions	Context	Construct
6-9	Technological	Relative Advantage (RA)
10-13		Complexity (C)
14-17		Perceived Financial Cost (PFC)
18-21	Organisational	Top Management Support (TMS)
22-25		Technology Competence (TC)
Institution Size		Size (S)
26-29	Environmental	Competitive Pressure (CP)
30-33		Vendor Support (VS)

5.3 Assessment of the LA Adoption TOE Framework

We conducted a principle component analysis (PCA) on the 30 items with orthogonal rotation using varimax method, to test the validity of the constructs (using SAS Enterprise Guide 5.1).
Given the sample size and the theoretical dimensions that emerged from the PCA, we retained eight components comprising items with acceptable eigenvalues of > .52 [Hair et al., 2006]. Such values suggest that the items are bound into appropriate conceptual constructs.

The results in table 2 confirm that most items are significantly loaded to their respective constructs. However, after analysing the loading, we eliminated items 6, 11, 13, 19, 24 due to low loading or not loading into any corresponding construct in a meaningful way. Some items loaded themselves to different constructs: 27 from CP to TMS; 8 from RA to CP. These load movements are thematically sound and hence retained. Validity for the dimensions was further tested to achieve the final framework (Figure 2).

Table 2: Principal Component Analysis

#	TMS	VS	PFC	RA	TC	CP	Size	C	N/A
Q.21	**0.864**	-0.121	0.142	-0.004	0.084	-0.096	-0.054	0.008	0.033
Q.20	**0.781**	-0.017	-0.017	0.409	-0.078	0.150	0.218	-0.066	0.183
Q.27	**0.701**	0.033	-0.259	0.318	0.193	0.239	0.112	0.019	0.114
Q.18	**0.693**	-0.069	-0.228	0.127	0.203	0.265	0.123	0.291	-0.250
Q.6	0.440	0.202	-0.347	0.282	-0.038	0.339	-0.104	-0.010	0.309
Q.32	-0.203	**0.912**	0.025	0.093	-0.079	-0.088	-0.142	-0.103	-0.017
Q.31	0.056	**0.891**	-0.029	0.067	-0.088	-0.103	-0.135	0.045	0.117
Q.30	-0.057	**0.835**	-0.010	-0.147	-0.091	0.291	-0.075	-0.107	-0.058
Q.33	0.048	**0.715**	-0.114	0.246	0.020	0.237	0.099	0.180	0.101
Q.15	-0.047	-0.079	**0.779**	-0.364	0.107	0.065	-0.079	0.049	-0.207
Q.16	-0.068	-0.085	**0.756**	-0.389	0.035	-0.242	-0.050	0.132	-0.035
Q.17	-0.160	-0.047	**0.676**	-0.064	0.103	-0.253	-0.062	-0.177	0.097
Q.14	0.280	0.107	**0.626**	-0.145	-0.313	-0.152	0.231	0.316	-0.024
Q.9	0.109	0.116	-0.224	**0.725**	0.008	0.301	0.130	0.116	0.007
Q.7	0.196	0.171	-0.257	**0.723**	0.141	0.040	0.081	0.091	0.119
Q.19	0.475	-0.062	-0.117	0.588	0.060	0.169	0.070	0.220	-0.167
Q.11	-0.205	0.013	0.270	-0.598	-0.262	0.102	-0.314	0.067	-0.137
Q.23	0.055	-0.052	0.120	0.054	**0.853**	0.223	0.083	0.062	0.115
Q.25	0.043	-0.213	0.253	0.182	**0.743**	-0.062	0.145	-0.138	-0.029
Q.22	0.134	0.079	-0.310	0.114	**0.696**	-0.124	0.047	-0.322	-0.039
Q.13	-0.352	0.286	0.464	0.255	-0.537	0.106	-0.114	-0.132	-0.189
Q.28	0.078	0.078	-0.114	0.005	0.000	**0.817**	0.189	0.118	0.013
Q.29	0.361	0.088	-0.276	0.350	0.095	**0.646**	0.054	-0.093	0.128
Q.8	0.245	0.337	-0.222	0.328	0.257	**0.536**	0.121	0.220	-0.098
Q.26	-0.078	-0.015	-0.052	0.153	-0.144	**0.529**	-0.090	-0.343	0.528
S_Total	0.085	-0.134	-0.054	0.163	0.104	0.132	**0.904**	-0.013	0.055
A_Total	0.059	-0.104	0.003	0.129	0.118	0.089	**0.893**	0.001	0.090
Q.12	0.187	0.029	-0.017	-0.020	-0.061	0.138	0.050	**0.877**	0.147
Q.10	-0.092	-0.037	0.084	0.266	-0.150	-0.071	-0.093	**0.782**	-0.152
Q.24	0.096	0.092	-0.076	0.044	0.139	0.021	0.184	0.073	0.836

6 Conclusions and Directions for next cycle of research

LA is a fast-developing field which is moving up the list of priorities for many HEIs in the UK. Implementing an LA solution is defined by the challenges of planning and deploying data analytics combined with cultural and economic peculiarities of the HE sector. The main drivers for implementing LA solutions appear to be organisational, linked to the student retention and progression, as well as a general desire to leverage sophisticated analytics. Although the drivers for LA seem clear, the significant factors that determine a successful deployment are still largely unknown. This work aims to provide a framework for evaluation of these factors.

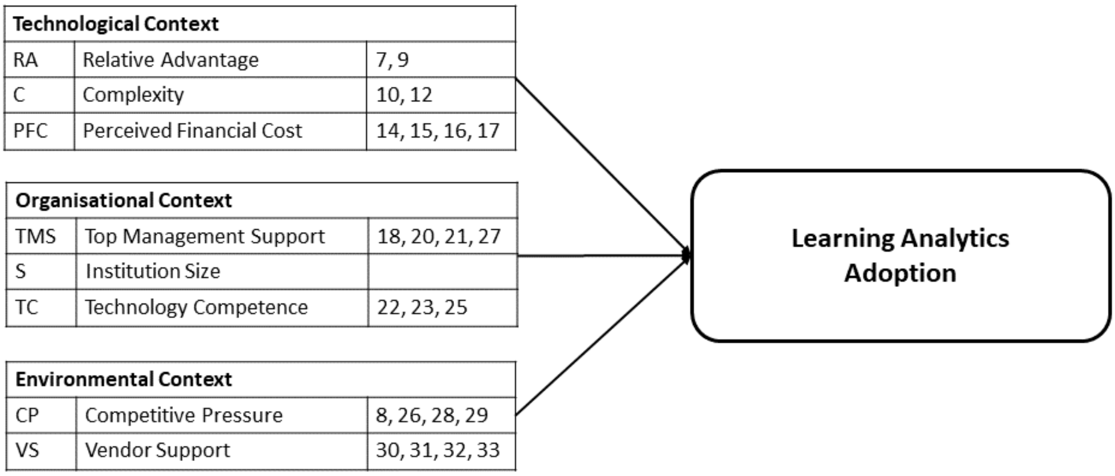

Figure 2: LA TOE Adoption Model

The initial study indicates the validity for the items proposed to evaluate the adoption of LA around the key constructs: Relative Advantage (RA) Complexity (C), Perceived Financial Cost (PFC), Top Management Support (TMS), Institution Size (S), Technology Competence (TC), Competitive Pressure, and Vendor Support (VS).

Informed by the PCA, the survey instrument represents an initial way to assess LA adoption. For future research, we will collect a bigger sample, to improve the instrument, and employ various inferential methods to measure the perceived impact of each construct.

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Appendix I Survey Questions/Evaluative Statements

1.	Has your Institution adopted any form of Learning Analytics?
2.	Please select the option that closest describes the level of adoption.
3.	Please rate the current perceived usefulness of the Learning Analytics project to your institution.
4.	Please submit a sentence or two (or even just a few words) about your Learning Analytics implementation (e.g. Student Retention, Dashboards, At-risk detection, VLE engagement, a specific vendor package etc.)
5.	Does your Institution intend to adopt Learning Analytics in any form?
6.	"Our Institution holds the view that use of Learning Analytics helps achieve a competitive advantage over other institutions".
7.	"Our Institution holds the view that the use of Learning Analytics helps improve the students' learning experience".
8.	"Our Institution holds the view that Learning Analytics provides useful insights that are otherwise unavailable".
9.	"Our Institution holds the view that Learning Analytics helps prevent lost revenue, by improving student retention procedures".
10.	"Our Institution holds the view that Learning Analytics projects are difficult to design and plan due to their complexity".
11.	"Our Institution holds the view that Learning Analytics solutions are too complex to use effectively".
12.	"Our Institution holds the view that Learning Analytics implementations are complex in nature".
13.	"Learning Analytics projects require specialised skills, which are not generally present in our Institution".
14.	"Learning Analytics projects are costly for our Institution to implement".
15.	"Learning Analytics projects would take away resources from more useful projects in our Institution".
16.	"The Return-on-investment (ROI) for Learning Analytics projects does not justify the initial and ongoing costs in our Institution".
17.	"Financially speaking, it is thought that now is not the time for our Institution to invest in Learning Analytics projects".
18.	"Our institution's senior management are generally aware of the potential benefits of Learning Analytics".
19.	"Our institution's senior management would be happy to approve a well-proposed Learning Analytics project".
20.	"Our institution's senior management are driving the adoption of Learning Analytics".
21.	"Our institution's senior management are generally forward-thinking and appreciate innovation"
22.	"Our institution has the required technological infrastructure to support a Learning Analytics implementation".
23.	"Our institution has the required technical skills to support a Learning Analytics project".
24.	"Our institution could invest in the required technical expertise to support a Learning Analytics project".
25.	"We are, as an Institution, technologically competent"
26.	"Our Institution will invest in Learning Analytics if a competitor is seen to be benefiting from it".
27.	"Learning Analytics is a growing trend and our Institution is responding accordingly".
28.	"Other Institutions who have invested in Learning Analytics are going to benefit significantly".
29.	"We need to invest in Learning Analytics now, otherwise we'll be left behind".
30.	"Third-party vendor involvement is crucial in any potential Learning Analytics project at our institution".

31.	"Our institution would not attempt a Learning Analytics solution using purely in-house skills and resources".
32.	"Our institution's investment in Learning Analytics would depend on strong third-party/vendor support".
33.	"With regard to Learning Analytics, my Institution would welcome a long-term relationship with third-party vendor"
34.	Whether you have adopted Learning Analytics or not, feel free to leave your thoughts, ideas, and lessons-learnt from any exposure (however small) you have had to 'Learning Analytics'.