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The Student Expectations of Learning Analytics Questionnaire (SELAQ)

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Expectations of Learning Analytics

Abstract

Student engagement within the development of learning analytics services in Higher Education is an important challenge for the researchers and practitioners to address. Despite calls for greater inclusion of stakeholders, there still remains only a small number of investigations into students' beliefs and expectations towards learning analytics services. To meet the challenge of greater participation from the student population in the implementation of learning analytics services, this paper presents a descriptive instrument to measure student expectations (ideal and predicted) of learning analytics services. The scales used in the instrument have been grounded in theoretical framework of expectations, with a specific focus on ideal (hopes) and predicted (realistic beliefs) expectations. Items were then generated on the basis of four identified themes (*Ethical and Privacy Expectations*, *Agency Expectations*, *Intervention Expectations*, and *Meaningfulness Expectations*), which emerged through the undertaking of a review of the learning analytics literature. The developed instrument was then subject to peer review, pilot testing, and a full roll-out across students at two universities. The results of an exploratory factor analysis and the results from both an exploratory structural equation model and confirmatory factor analysis supported a two-factor structure best accounted for the data pertaining to ideal and predicted expectations. Factor one refers to *Ethical and Privacy Expectations*, whilst factor two covers *Service Feature Expectations*. In addition, both scales (ideal and predicted) were found to have good internal reliability. The 12-item Student Expectations of Learning Analytics Questionnaire (SELAQ) provides researchers and practitioners with a reliable and valid instrument to collect quantitative measures of students' expectations of learning analytics services.

Expectations of Learning Analytics

Keywords: Student Expectations, Ideal Expectations, Predicted Expectations,
Learning Analytics, Higher Education

Expectations of Learning Analytics

1. Introduction

Learning analytics (LA) is commonly defined as “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs” (Siemens & Gašević, 2012). As we have previously stated (Authors, 2017), the implementations of LA into Higher Education Institutions can be viewed as a service offered to optimise learning and learning environments. For example, the Open University has implemented initiatives that aim to improve retention rates (Calvert, 2014). Put differently, this Higher Education Institution implemented LA as a service with the aim of optimising student learning, specifically with a specific view of increasing retention rates. Thus, whilst LA refers to the general field, including the research undertaken, LA services relate to eventual functionalities that are implemented within an educational setting.

In terms of actual LA service implementations, it Higher Education Institutes continue to remain within the exploratory stages of such pursuits (Ferguson et al., 2016; Tsai et al., 2018; Tsai & Gašević, 2016), with most institutes being at the fringes of developing institution-wide LA systems. This parallels what has been referred to as a *definition* stage in information system development, where focus is placed on making decisions as to what data is collected and fed back, and what the system will do (Ginzberg, 1981). At this stage, successful implementation of information systems rests on the inclusion of stakeholders early on their development so that designers can identify and assimilate various expectations to reduce the likelihood of service dissatisfaction in the future (Brown, Venkatesh, & Goyal, 2014; Ginzberg, 1975).

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3 Whilst the need for the early engagement of stakeholders has been
4
5 specifically highlighted for LA (Drachler & Greller, 2016; Ferguson et al., 2014),
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7 there are limited instances where this is actually happening (Tsai & Gašević, 2017a).
8
9 Without stakeholder engagement, it is likely that the multitude of LA policies
10
11 available (Sclater, 2016) are driven primarily by the institutional managers'
12
13 expectations and beliefs. In those cases, even if the key driver for the intention to
14
15 adopt LA is to improve learning performance (Tsai & Gašević, 2017b) and to provide
16
17 additional support to learners (Siemens & Gašević, 2012), that intention is still
18
19 shaped by the managers' preconceived beliefs and ideas – not necessarily reflective
20
21 of what other stakeholders (e.g., students) would expect. This may perpetuate an
22
23 ideological gap (Ng & Forbes, 2009) whereby services reflect a difference between
24
25 what institutions believe students should receive and what students expect to
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27 receive.
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34 LA, by definition, is student-centred (Siemens & Gašević, 2012), but relatively
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36 few attempts have been made to explore students' beliefs towards the use of LA
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38 (Arnold & Sclater, 2017; Ifenthaler & Schumacher, 2016; Roberts, Howell, Seaman,
39
40 & Gibson, 2016; Schumacher & Ifenthaler, 2018; Slade & Prinsloo, 2014). As shown
41
42 in the LA dashboard evaluation work of Park and Jo (2015), students expressed
43
44 negative opinions towards being provided with visualisations of login frequency
45
46 metrics, particularly on the basis of them not being pedagogically meaningful. This is
47
48 concerning, particularly with the attention placed on relaying resource usage
49
50 statistics (75% of 93 student-facing LA dashboard articles, according to Bodily and
51
52 Verbert (2017)), as it exemplifies how LA has largely overlooked student
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54 expectations. Adding to this is the finding that only 6% of 93 articles that have
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56 detailed LA dashboard implementations have explored student expectations of such
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Expectations of Learning Analytics

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3 services (Bodily & Verbert, 2017). Given the importance of actively exploring and
4
5 gauging stakeholder expectations, particularly with regards to future service
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7 satisfaction and usage (Brown, Venkatesh, & Goyal, 2012; Brown et al., 2014),
8
9 student engagement cannot continue to be at a nominal level. Instead, it is
10
11 necessary for research to address this gap through the provision of tools that enable
12
13 Higher Education Institutions to open dialogues with students to understand the LA
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15 service they expect.
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20 From those limited investigations with students, findings have shown that
21
22 whilst students have strong expectations towards the institution's handling of
23
24 educational data (Roberts et al., 2016; Slade & Prinsloo, 2014) and the LA service
25
26 features offered (Roberts, Howell, & Seaman, 2017; Schumacher & Ifenthaler,
27
28 2018), despite largely being unaware of LA practices (Roberts et al., 2016). In light of
29
30 such findings, it can be argued that despite student exposure to LA services being
31
32 limited, they are able to form expectations towards the procedures undertaken and
33
34 the services offered. Moreover, given the relatively small proportion of LA
35
36 implementations readily assessing what students expect of such services, there is a
37
38 need to address this limitation.
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43 As a means to gauge stakeholder expectations of a possible service, Szajna
44
45 and Scamell (1993) have encouraged the use of psychometric instruments during
46
47 different stages of implementations. Within the context of LA, a measure is available
48
49 to assess an institute's readiness for LA (Oster, Lonn, Pistilli, & Brown, 2016), but no
50
51 pre-existing scale is available to gauge student expectations of LA services. Even
52
53 though Arnold and Sclater (2017) used a survey to understand student perceptions
54
55 of data handling, their reported findings can be questioned on the basis of using an
56
57 on the fly scale. Schumacher and Ifenthaler (2018) do, however, present an
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Expectations of Learning Analytics

1
2
3 exploration of expected LA dashboard features from the perspective of students.
4
5 While these authors ground this work in expectations, the distinction between
6
7 expectations and perceptions is not completely conceptualised. As a great majority
8
9 of the student population is unlikely to have experienced institutional LA services,
10
11 measures of experience (perceptions) (Parasuraman, Zeithaml, & Berry, 1988) are
12
13 not always appropriate, particularly given that majority of students are not acquainted
14
15 with LA services (Roberts et al., 2016). Expectations, however, can be measured
16
17 prior to implementations and are an important determinant in the acceptance of
18
19 systems (Davis & Venkatesh, 2004).
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25 As indicated above, whilst the importance of systematically gathering
26
27 university students' expectations about LA is of paramount importance for the
28
29 success of the service, little has been done in this regard and no adequate tool is still
30
31 available. In the present research, we have attempted to close this gap by
32
33 developing and validating a descriptive questionnaire to collect students'
34
35 expectations of LA services. Throughout the development of this instrument, the
36
37 accessibility and understanding of the items from the student perspective were
38
39 always considered. Put differently, while students are largely unaware of LA
40
41 services, the phrasing of each item had to be balanced between providing an
42
43 institution with an informative understanding of what students expect, but also
44
45 general enough for all students to understand. In doing so, the university can identify
46
47 particular areas of focus for their LA implementation, which can then inform direct
48
49 engagement strategies with their students.
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1.1. Expectations as Beliefs

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57 A widely utilised definition of belief presents it as "the subjective probability of
58
59 a relation between the object of the belief and some other object, value, concept, or
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3 attribute” (Fishbein & Ajzen, 1975, p. 131). For example, a student may hold a belief
4
5 that they themselves have the knowledge and skills required to attain a good grade.
6
7 An expectation, on the other hand, can be defined as “the perceived likelihood that a
8
9 product possesses a certain characteristic or attribute, or will lead to a particular
10
11 event or outcome” (Olson & Dover, 1976, p. 169). An example of this would be a
12
13 judgement of whether a future LA service will enable users to receive a full
14
15 breakdown of their learning progress. Taking both aforementioned terms into
16
17 consideration, the only discernible difference is the point in time at which the
18
19 judgement relates to; i.e., expectations are framed as beliefs about the future (Olson
20
21 & Dover, 1976).
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27 Expectations are an important feature of human cognition (Roese & Sherman,
28
29 2007). From the behaviours an individual enacts to the motivation they exert, there is
30
31 an underlying influence of how they expect to manage within a particular setting
32
33 (Bandura, 1977, 1982; Elliot & Church, 1997). In relation to the judgements we form,
34
35 our expectations are an anchor to which we compare our actual experiences
36
37 (Christiaens, Verhaeghe, & Bracke, 2008; Festinger, 1957). As a term, however, an
38
39 expectation is quite ambiguous, particularly in light of the decomposition presented
40
41 by Thompson and Suñol (1995). For these authors, expectations can broke down
42
43 into four subtypes: ideal, predicted, normative, and unformed (Thompson & Suñol,
44
45 1995). An *ideal* expectation refers to a desired outcome, or what an individual hopes
46
47 for in a service (Leung, Silviu, Pimlott, Dalziel, & Drummond, 2009); whereas a
48
49 *predicted* expectation is a realistic belief, an individual’s view of the service they
50
51 believe is the most likely to receive. Evidence does support the view that predicted
52
53 and ideal expectations are two different subtypes (Askari, Liss, Erchull, Staebell, &
54
55 Axelson, 2010; David, Montgomery, Stan, DiLorenzo, & Erbllich, 2004; Dowling &
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Expectations of Learning Analytics

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3 Rickwood, 2016). The two remaining expectation subtypes relate to what service
4 users believe they deserve from a service (*normative* expectation) and the
5
6 circumstances where they are unable to form a set of expectations (*unformed*
7
8 expectations).
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13 The importance of focusing on service user expectations has been
14 demonstrated in both health services (Bowling et al., 2012; Thompson & Suñol,
15
16 1995) and technology adoption research (Brown et al., 2012, 2014; Davis &
17
18 Venkatesh, 2004). In the case of Bowling et al., these researchers explored patients'
19
20 ideal and predicted expectations as it allowed for both an upper and lower reference
21
22 point with regards to knowing what service elements to focus on. Put differently, the
23
24 responses present an idealised perspective of a service, but also a realistic profile of
25
26 what users believe is most likely. This approach would be advantageous for LA
27
28 service implementation decisions as it can differentiate between what features
29
30 students would like, but what should be a priority (i.e., what is realistically expected).
31
32 In addition to providing a deeper understanding of stakeholder perspectives, both
33
34 research streams have shown that failure to gauge user expectations can lead to
35
36 dissatisfaction and low adoption of the implemented service (Bowling et al., 2012;
37
38 Brown et al., 2012, 2014; Davis & Venkatesh, 2004). Thus, by measuring
39
40 stakeholder expectations towards a service early on in the service implementation
41
42 process, the provider can proactively identify main areas of focus and manage
43
44 expectations.
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52 Together, these abovementioned theoretical concepts and considerations
53
54 outlined constitute our reference framework. For the present work, an expectation is
55
56 defined as a belief about the likelihood that future implementation and running of LA
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58 services will possess certain features. Also, our approach is based on the need to
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consider separately the desired outcomes (ideal expectations) and the realistic beliefs (predicted expectations).

1.2. Research Aim

Measuring student expectations of LA services is a fundamental step to the success of future implementations. Although others have offered solutions (Arnold & Sclater, 2017; Schumacher & Ifenthaler, 2018) the use of inconsistent terminology, limited scope, and methodological limitations does leave a lot to be desired. Using the identified expectation themes (*Ethics and Privacy, Agency, Intervention, and Meaningfulness*) and expectation types (ideal and predicted), we aim to develop and validate a descriptive questionnaire that offers a robust and methodologically sound solution to measuring student expectations of LA services. An overview of the steps taken in the current work are presented in Figure 1. This figure provides a breakdown of each of the three studies undertaken, a description of how the items were generated or how the data were analysed, the number of items retained or dropped, and how many responses were collected at each stage. Furthermore, to illustrate the utility of the instrument in measuring students' expectations of LA services, we will present a brief overview of how beliefs toward certain features vary in accordance to the two expectation types (ideal and predicted). It is anticipated that being able to gauge and measure student expectations of potential LA services will promote further engagement with these stakeholders in the implementation process, with a view of understanding the specific requirements of the student population.

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Insert Figure 1 About Here

2. Pilot Study – Study One

2.1. Scale Development

Items for the questionnaire were created on the basis that students are largely unaware of LA services (Roberts et al., 2016) and adoption rates of LA services at an institutional level being low (Tsai & Gašević, 2017b). Thus, the aim was to phrase items so they would be accessible to all students and to provide institutions with a general understanding of what their student population expect of LA services. Underlying this was the view that by having a general measure of student expectations, a Higher Education Institution can begin to open dialogues with students during the implementation process, as is recommended in the technology adoption literature (Brown et al., 2012, 2014).

The current work followed two recommended approaches for the generation of an item pool: undertaking a literature review (Bowling, 2014; Priest, McColl, Thomas, & Bond, 1995; Rattray & Jones, 2007) and seeking input from experts (Streiner, Norman, & Cairney, 2015). Given that there is no model of student expectations towards LA services to draw upon, the review of the literature was guided by an overarching aim of identifying themes raised in by students in qualitative interviews or by research streams in LA. It is important to remain cognisant of the limitations of the adopted approach to item generation, particularly as it may become skewed towards a particular viewpoint (Streiner et al., 2015).

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Nevertheless, the process tried to identify key areas of LA services that could be applicable to the student perspective.

From the literature review and expert feedback, we identified four general themes characterising LA services (Authors, 2017): *Ethical and Privacy Expectations, Agency Expectations, Intervention Expectations, and Meaningfulness Expectations*. It is important to acknowledge that these themes represent categories that embody different research streams and discussions within LA. At no point did we hypothesise that the final model would be composed of these constructs, nor did we assume that these themes were orthogonal from one another. Put differently, the themes pertaining to *Agency, Intervention, and Meaningfulness* are likely to be closely linked, but we discuss them here as separate components for clarity purposes. Each theme is discussed in turn, with an emphasis on how it links to the student perspective.

2.1.1. Ethical and Privacy Expectations

The LA literature is replete with discussions over the provision of a service that is ethical in the collection, handling, and analysis of student data (Arnold & Sclater, 2017; Drachsler & Greller, 2016; Prinsloo & Slade, 2015; Sclater, 2016; Slade & Prinsloo, 2014). Here authors tend to highlight the importance of transparency and consent in LA services (Prinsloo & Slade, 2015; Sclater, 2016). The importance of engaging with students within the data handling decision process (e.g., what data is used and how it will be interpreted) has been stressed by Prinsloo and Slade (2015), who believe it to be key to the progression of LA services.

From those studies exploring student perspective of ethical issues surrounding LA services, they have been shown to hold strong expectations towards

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1
2
3 data handling processes. In their interviews with students, Slade and Prinsloo (2014)
4
5 found a clear expectation that the institution should seek informed consent, or at
6
7 least permit opting out, when it comes to an LA process. Similar remarks were also
8
9 expressed in the work of Roberts et al. (2016), who found students to expect the
10
11 university to respect privacy, seek informed consent, and to be transparent at all
12
13 times. Finally, the work of Ifenthaler and Schumacher (2016) showed that whilst
14
15 students were against the processing of identifiable data, they were open to data
16
17 pertaining to their studies being used.
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22 From each of these aforementioned studies, it is clear that students have
23
24 strong expectations regarding their privacy and being able to make independent
25
26 decisions about how their data is used (Ifenthaler & Schumacher, 2016; Roberts et
27
28 al., 2016; Sharon Slade & Prinsloo, 2014). More importantly, each of these authors
29
30 stress the importance of the university actively engaging students in LA service
31
32 implementation decisions. Thus, based on these two points, the theme of *Ethical and*
33
34 *Privacy Expectations* was decided upon, which was considered to cover elements of
35
36 data security and consent.
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2.1.2. Agency Expectations

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44 When asked about their expectations towards LA services as a form of
45
46 additional support, students do not expect it to undermine their ability to be self-
47
48 determined learners (Roberts et al., 2016). For those students in the samples used
49
50 by Roberts et al., they consider being an independent learner a fundamental
51
52 requirement for university; thus, LA services should not foster a dependency on
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54 metrics.
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Expectations of Learning Analytics

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3 These student views resonate with the concerns towards the obligation to act
4
5 raised by Prinsloo and Slade (2017). Within their discussions on this topic, Prinsloo
6
7 and Slade do state that the analysis of student data should be guided by a view of
8
9 providing improved support, but at no point should it undermine their (the students')
10
11 responsibility to learn. This view has further been captured in the concerns raised by
12
13 Kruse and Pongsajapan (2012), who view intervention-centric LA services as
14
15 creating a culture of passivity. Put in a different way, LA services that are designed
16
17 to intervene when students are struggling ignores their ability to be self-directed
18
19 learners who continually evaluate their progress to set goals (Kruse & Pongsajapan,
20
21 2012). The importance of viewing students as active agent in their own learning
22
23 should be a central tenant to LA services (Gašević, Dawson, & Siemens, 2015;
24
25 Winne & Hadwin, 2012). Therefore, institutions should be considerate of this and not
26
27 implement LA services that remove the ability for students to make their own
28
29 decisions on the data received (Slade & Prinsloo, 2013; Wise, Vytasek, Hausknecht,
30
31 & Zhao, 2016).

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38 Taken together, students hold an expectation of wanting to remain as
39
40 independent learners if any LA service were to be implemented, which is also
41
42 advocated by some researchers. Nevertheless, examples of LA services such as
43
44 Course Signals are focused upon early alerts (Arnold & Pistilli, 2012). This
45
46 establishes the importance of the theme of *Agency Expectations*, which we consider
47
48 as introducing a much needed student perspective on who bears the main
49
50 responsibility for learning under LA services (the student or institution). In doing so, it
51
52 will add to the previous discussions raised by students and researchers (Prinsloo &
53
54 Slade, 2017; Roberts et al., 2016).

2.1.3. Intervention Expectations

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3 The anticipated output following the collection and analysis of student data is
4
5 the introduction of a service designed to optimise both student learning and the
6
7 learning environment (Siemens & Gašević, 2012). Despite this aim to support
8
9 students, there have been few attempts to know what LA services features students
10
11 want (e.g., 6% of LA dashboard research undertook a needs assessment; Bodily &
12
13 Verbert, 2017). As stressed in the work of Schumacher and Ifenthaler (2018),
14
15 student expectations of LA service features should be considered prior to any
16
17 implementation. Thus, as with any technology implementation (Brown et al., 2012,
18
19 2014; Davis & Venkatesh, 2004), steps should be taken to understand what is
20
21 expected from the main stakeholders to ensure future acceptance.
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26
27 Types of LA services offered in the literature vary with respect to the
28
29 educational problem they seek to resolve. A common service implementation has
30
31 been the identification of students who are underperforming or at-risk (Campbell,
32
33 DeBlois, & Oblinger, 2007). In undertaking this pursuit there is a belief that
34
35 interventions can be actioned to mitigate the possibility of the student dropping out
36
37 (Gašević, Dawson, Rogers, & Gašević, 2016), although this may not always be the
38
39 case (Dawson, Jovanovic, Gašević, & Pardo, 2017). Other approaches have moved
40
41 away from building predictive models to identify at risk students; instead, focusing on
42
43 the development of systems aimed at improving the student-teacher relationship
44
45 (Liu, Bartimote-Aufflick, Pardo, & Bridgeman, 2017) or presenting graphical
46
47 overviews of learner behaviour (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013).
48
49 In all cases, the services are designed to with a view to improve education for
50
51 students, but there is a prevailing absence of researchers gauging what students
52
53 expect of these services.
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Expectations of Learning Analytics

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3 Of those studies seeking to understand what students expect of LA services,
4 the findings have presented an important perspective that institutions cannot
5 overlook. For Roberts et al. (2016), some students did not desire a service that
6 allowed for peer comparisons, stating that they were unnecessary. When asked
7 about their views towards receiving information on progress (e.g., underperforming),
8 students did not expect such services on account of the unnecessary anxiety it
9 would create (Roberts et al., 2016). From the work carried out by Schumacher and
10 Ifenthaler (2018), students expected to receive LA service features that facilitated
11 self-regulated learning, which included real-time feedback and updates on how
12 progress compares to a set goal. Similarly, Roberts et al. (2017) found students to
13 expect services such as dashboards to be customisable and contain features to set
14 goals and track progress.

15
16
17 With regards to the LA service features being developed, it appears that
18 researchers are aiming to improve both the learning experience and the learning
19 environment. The issue, however, is that these developments are primarily guided by
20 the views of the researchers, not the students, which may lead to features that are
21 not expected (e.g., the provision of login metrics in Park and Jo (2015)). Student
22 perspectives, on the other hand, show them to expect features that support them
23 being self-directed learners, as opposed to making them passive recipients of a
24 service. Thus, the theme of *Intervention Expectations* was proposed, which entails
25 the various types of service features commonly offered in the LA literature and those
26 raised in the student perspective work.

2.1.4. Meaningfulness Expectations

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Expectations of Learning Analytics

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3 Closely entwined with both *Agency* and *Intervention Expectations* is the
4 theme of *Meaningfulness Expectations*. Whilst *Agency Expectations* captures the
5 importance of students being independent learners and *Intervention Expectations*
6 refer to the LA service features, *Meaningfulness Expectations* relates to the utility of
7 information fed back to students. More specifically, *Meaningfulness Expectations* are
8 associated with the student perspectives towards the information conveyed in LA
9 service features and whether this has any meaning for their learning.
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20 Introducing new forms of feedback as a result of implementing LA services
21 should, theoretically, promote positive changes in student behaviour such as
22 motivating learning (Park & Jo, 2015; Verbert et al., 2013). However, if meaningful
23 inferences about learning progress cannot be drawn from the information received
24 through LA services (i.e., how visual representations of performance relates to
25 personal learning goals), then it is unlikely to be incorporated into any decisions
26 made (Wise et al., 2016). An example of information that was found to not be
27 meaningful for students was the provision of login metrics in Park and Jo's (2015) LA
28 dashboard, which was perceived as being unhelpful for the purposes of reflecting
29 upon their learning. In other words, whilst resource use metrics continue to be used
30 in LA service implementations (e.g., 75% of LA dashboards; Bodily & Verbert, 2017),
31 their utility, from the perspective of students, can be questioned.
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48 It has been shown that usefulness expectations are an important determinant in
49 the future success of a technology (Brown et al., 2014). This is also true of LA
50 services, where beliefs towards the utility of certain features (e.g., visualisations and
51 the level of detail provided) affect adoption rates (Ali, Asadi, Gašević, Jovanović, &
52 Hatala, 2013). Together, this does reinforce the importance of gauging what
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3 stakeholders in a service want, with a focus on the type of information and its
4
5 relevance to learning.
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8 The challenge for LA to provide information that is pedagogically meaningful is
9
10 not a recent concern (Gašević et al., 2015; Macfadyen & Dawson, 2010; Tsai &
11
12 Gašević, 2017a). In particular Gašević et al. (2015) warn against the use of trivial
13
14 measures in LA service implementations on the basis that it will not promote
15
16 effective learning. Taking what is known in relation to self-regulated learning theory,
17
18 students do utilise various information that are fed back to understand how their
19
20 learning is progressing towards set goals (Winne & Hadwin, 2012). Having simple
21
22 performance metrics are unlikely to meet the necessary conditions to facilitate self-
23
24 regulatory behaviour (Ali, Hatala, Gašević, & Jovanović, 2012; Gašević et al., 2015),
25
26 which are to be constructive, promote higher order thinking, and allow students to
27
28 bridge the gap between the current and desired level of performance (Nicol &
29
30 Macfarlane-Dick, 2006). Therefore, for the information presented through LA services
31
32 to become more informative, there is a need to both ground the approach within
33
34 necessary educational frameworks, but also understand what information
35
36 stakeholders need (Gašević et al., 2015). The *Meaningfulness Expectations*
37
38 attempts to meet these recommendations by exploring what forms of information are
39
40 expected from one of the main stakeholders.
41
42
43
44
45
46
47

48 With these four themes in mind, we generated 79 items capturing the various
49
50 aspects of LA services identified in the literature (Appendix 2). Each item was
51
52 phrased as an expectation (e.g., the university will or the learning analytics service
53
54 will). Responses were made on both an ideal (Ideally, I would like that happen) and
55
56 predicted (In reality, I would expect that to happen) expectation Likert scale ranging
57
58 from 1 (strongly disagree) to 7 (strongly agree), which were adapted from the work of
59
60

Expectations of Learning Analytics

1
2
3 Bowling et al. (2012). These preliminary items were subject to peer review by two
4
5 experts in LA, both of whom are well-known in the field of learning analytics and co-
6
7 founders of the Society for Learning Analytics Research. Items were then removed
8
9 or re-worded based on repetition, clarity, and relevance. As noted in Appendix 2, the
10
11 LA experts suggested the addition of one item 'The feedback from analytics will be
12
13 presented as a visualisation (e.g., in the form of a dashboard)' (item 37; Appendix 3).
14
15 This peer review process undertaken by LA experts led to 37 items being retained
16
17
18
19 (Appendix 3).
20
21

22
23 As students were unlikely to be aware of LA and what it entails, an introduction to
24
25 the survey was created (Appendix 1). The contents of this introduction outlines to
26
27 students the various sources of educational data used in LA services such as that
28
29 extracted from the virtual learning environment. In addition, examples of possible LA
30
31 service implementations are provided (e.g., the creation of early alert systems). This
32
33 information provided was peer reviewed by LA experts in order to assess whether
34
35 the scope of LA services was suitable and whether the concept of LA services can
36
37 be easily understood. Moreover, the information contained in this introduction was
38
39 influenced by both the LA definition (Siemens & Gašević, 2012) and the commonly
40
41 used data types in LA studies (Gašević et al., 2016). Ethics approval was obtained
42
43 for data collection at the University of Edinburgh and the University of Liverpool.
44
45
46
47

2.2. Sample

48
49
50
51 Total of 210 student respondents (Females = 131; $M_{age} = 24$ years, $SD =$
52
53 6.12) out of a possible 448 students (47% response rate) from the University of
54
55 Edinburgh completed the 37-item pilot survey (Appendix 3), which was distributed
56
57 through an online survey system. This was a self-selecting sample of students from
58
59
60

Expectations of Learning Analytics

1
2
3 across the University who have agreed to be contacted for research purposes in
4
5 return for monetary reward on a task by task basis. This sample is broadly
6
7 representative of the student population (Undergraduate/Postgraduate Taught
8
9 (UG/PGT), UK (United Kingdom) vs Non-UK, Age/Gender).

2.3. Statistical Analysis

10
11
12
13
14
15 All raw data was analysed using R version 3.4 and the psych package (R
16
17 Core Team, 2017; Revelle, 2017). The predicted and ideal expectation scales were
18
19 analysed separately. If items were removed from one scale (e.g., the predicted
20
21 expectation scale), the corresponding item was removed from the other scale (i.e.,
22
23 the ideal expectation scale). The analysis steps were to first run Bartlett's test (1951)
24
25 to assess whether a factor analysis was appropriate. The Kaiser-Meyer-Olkin (KMO)
26
27 index (Kaiser, 1974) was then calculated to further check whether the data is
28
29 adequate for a factor analysis. The determinant of the correlation matrix was also
30
31 calculated to assess for any multicollinearity problems (Field, Miles, & Field, 2012).
32
33 Following these scale purification steps, an exploratory factor analysis using oblimin
34
35 rotation was ran on the raw data using the results of a parallel analysis to determine
36
37 the sufficient number of factors to extract. Finally, a reliability analysis was run on the
38
39 items of each factor.
40
41
42
43
44
45

46 Each item in the instrument also contained an open textbox to allow
47
48 respondents to provide qualitative comments on each item. Respondents were
49
50 prompted to leave feedback about the clarity and understanding of each item. Thus,
51
52 by obtaining both quantitative and qualitative data from the instrument it allowed the
53
54 researchers to refine items using the scale purification techniques and to re-word
55
56 certain items on the basis of student feedback.
57
58
59
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2.4. Exploratory Factor Analysis Results

Ideal Expectations Scale. 18 items were dropped from the analysis based on the identification of multicollinearity issues, having loadings lower than .40, or whether dropping the item could improve the Cronbach's α value.

An exploratory factor analysis using the minimum residual factor extraction method and oblimin rotation was run on the remaining 19 items. The overall KMO was found to be .88 (great according to Kaiser (1974)), with individual item values being greater than or equal to .75, which was above the acceptable limit of .50. Bartlett's test of sphericity, $\chi^2(190) = 1613, p < .001$, suggested that the correlation matrix did not resemble an identity matrix so factor analysis was appropriate. The parallel analysis suggested to retain two or three factors; in order to align with the predicted expectations scale a two-factor solution was selected. The two-factor solution was deemed sufficient, it accounted for 42% of the variance in the data, and the correlation between the two factors was $r = .30$. Factor one represented *Service Feature Expectations* (items: 1, 9, 13, 18, 20, 22, 26, 30, 31, and 33; Appendix 4), whilst factor two relates to *Ethical and Privacy Expectations* (items: 5, 6, 10, 11, 14, 15, 17, 19, and 21; Appendix 4). Both subscales had high reliabilities, for *Service Feature Expectations* Cronbach's $\alpha = .88$, whilst for *Ethical and Privacy Expectations* Cronbach's $\alpha = .82$.

Predicted Expectations Scale. 18 items were dropped from the analysis based on the identification of multicollinearity issues, having loadings lower than .40, or whether dropping the item could improve the Cronbach's α value.

An exploratory factor analysis using the minimum residual factor extraction method and oblimin rotation was ran on the remaining 19 items. The overall KMO

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1
2
3 was found to be .91 (superb according to Kaiser (1974)), with individual item values
4
5 being greater than or equal to .86, which was above the acceptable limit of .50.
6
7 Bartlett's test of sphericity, $\chi^2 (171) = 1631, p < .001$, suggested that the correlation
8
9 matrix did not resemble an identity matrix so factor analysis was appropriate. The
10
11 parallel analysis suggested to retain two factors. The two factor solution was deemed
12
13 sufficient, it accounted for 44% of the variance in the data, and the correlation
14
15 between the factors was $r = .41$. Factor one represented *Service Feature*
16
17 *Expectations* (items: 1, 9, 13, 18, 20, 22, 26, 30, 31, and 33; Appendix 5), whilst
18
19 factor two related to *Ethical and Privacy Expectations* (items: 5, 6, 10, 11, 14, 15, 17,
20
21 19, and 21; Appendix 5). Both subscales had high reliabilities, for *Service Feature*
22
23 *Expectations* Cronbach's $\alpha = .88$, whilst for *Ethical and Privacy Expectations*
24
25 Cronbach's $\alpha = .86$.

2.5. Discussion

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32
33
34 The results of the pilot study led to the identification of a two-factor solution
35
36 (*Ethical and Privacy Expectations* and *Service Feature Expectations*) that explain
37
38 student expectations of LA services. For both the ideal and predicted expectation
39
40 scales, the same items loaded onto the identified factors. This is important for future
41
42 research directions as it will enable researchers to segment expectations across
43
44 end-users. In other words, desired and realistic beliefs regarding LA services may
45
46 show differences based on demographic information (e.g., level of study).
47
48
49

50
51 Even though four expectation themes were identified from the literature, they are
52
53 captured by this two-factor solution. The *Service Feature Expectation* factor covers
54
55 items relating to whether students believe they should responsibility to make sense
56
57 of their own data (item 18; Appendix 3) and whether teaching staff are obliged to act
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59
60

Expectations of Learning Analytics

when students are at-risk or underperforming (item 31; Appendix 3). Together, these items reflect the *Agency Expectations* theme identified in the literature. Items 26 and 33 (Appendix 3) refer to beliefs about students receiving profiles of their learning following the analysis of their data and LA services being used to offer support directed at academic skill development. It is indicative from these items that there is overlap with the theme of *Intervention Expectations*. The theme of *Meaningfulness Expectations* is well captured by item 20 (Appendix 3), which is concerned with LA services connecting feedback to learning goals. The *Ethical and Privacy Expectations* factor relates to the identified *Ethics and Privacy Expectations* theme. As exemplified by items 6 and 11 (Appendix 3), these cover topics relating to the provision of consent for both universities utilising personal information and prior to giving data to any third-party company, respectively.

3. Study Two

3.1. Sample

Total of 674 student respondents (Females = 429; $M_{Age} = 24.51$ years, $SD = 7.94$) from the University of Edinburgh ($n = 6664$; 10.11% response rate) completed the 19-item survey (Appendix 6), which was distributed through an online system. $N = 6664$ corresponds to one third of the whole university UG and PGT student population based on a random selection; thus, students from the pilot could have also participated in study two. This sample was then checked against College, School, student type (i.e., students being from Scotland, the UK, a European country, or a non-European country), and other demographic information to ensure that the sample was representative of the University as a whole. All respondents consented to taking part in the online survey and were offered the chance to be included in a prize draw. Of these respondents, 396 (59%) were undergraduate

Expectations of Learning Analytics

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2
3 students, 62 (9%) were masters students, and 216 were PhD students (32%). Total
4
5 of 475 (70%) respondents identified themselves as 'Home/EU Students', and 199
6
7 (30%) identified themselves as 'Overseas Students'.
8
9

3.2. Questionnaire

10
11
12
13 Following the pilot study, the 37-item questionnaire was reduced to 19-items
14
15 (Appendix 6). The comments left by respondents in the pilot study were used to
16
17 modify items in order to make them clearer (details of how item wordings were
18
19 changed are presented in Appendix 6). The remaining 19-items (Appendix 6) were
20
21 also reviewed by an LA expert in order to identify any wording issues. As in the pilot
22
23 study, each item contained two scales corresponding to ideal (Ideally, I would like
24
25 that happen) and predicted (In reality, I would expect that to happen) expectations.
26
27 Responses again were made on a 7-point Likert-type scale, ranging from 1 =
28
29 "Strongly Disagree" to 7 = "Strongly Agree".
30
31
32
33
34

3.3. Statistical Analysis

35
36
37 Qualitative comments from the pilot study were used in conjunction with a further
38
39 peer review of the 19-items to clarify and re-write particular items (Appendix 6). An
40
41 example of this was item 1 from the 19-item questionnaire (The university will
42
43 provide me with guidance on how to access the analysis of my educational data).
44
45 Within the 37-item questionnaire, this item (item 1) referred to whether the university
46
47 is expected to instruct students on how frequently they should access educational
48
49 data (The university will provide me with guidance on when and how often I should
50
51 consult the analysis of my educational data). Feedback on this question showed that
52
53 it would not be for an institution to decide how frequently educational data analyses
54
55 should be consulted. A more appropriate alternative, which aligns with LA services
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Expectations of Learning Analytics

1
2
3 being transparent (Sclater, 2016), would be an item on universities clearly telling
4
5 students how to find any analyses of their educational data.
6
7

8
9 Similarly, for item 2 of the 19-item questionnaire (The university will explain all the
10 learning analytics service processes as clearly as possible (e.g., how my educational
11 data is collected, analysed, and used)), this was a slight amendment of item 5 from
12 the 37-item questionnaire (The university will explain all analytic processes as clearly
13 as possible (e.g., how my educational data is collected, analysed, and used)). Within
14 the 37-item version, this item was not connected well with the overall aim of the
15 questionnaire, which was to explore expectations of LA services, which go beyond
16 analytics. Therefore, to make this a more inclusive item that refers to any possible
17 processes involved, the item now refers to LA services in general.
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30 Due to the various amendments to the questionnaire items, it was decided that
31 exploratory factor analysis would again be used in a follow-up sample. This is
32 because subtle changes in the item wordings could lead to different interpretations or
33 model outcomes. What is more, as the pilot study only had 210 respondents, which
34 falls short of what has been recommended as a good sample size (300 according to
35 Comrey and Lee (1992)). Therefore, for the main study the recommended sample
36 sizes proposed by Comrey and Lee (1992), which suggests at least 500 respondents
37 should be used whenever possible. Given the high number of low communalities
38 (below .50) found with the pilot study exploratory factor analysis, it further reinforced
39 the need to re-run the exploratory factor analysis with the data obtained from the
40 larger sample of students in study two (MacCallum, Widaman, Zhang, & Hong,
41 1999).
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Expectations of Learning Analytics

As with the pilot study, the same scale purification steps were undertaken here with an assessment of multicollinearity problems, item KMO inspection, and an assessment of whether factor analysis is appropriate using Bartlett's test of sphericity. Any item removed from one scale (ideal or predicted expectation) was removed from the corresponding scale. After these steps, an exploratory factor analysis using the minimum residual factor extraction method and oblimin rotation was ran on the raw data using the results of a parallel analysis to determine the sufficient number of factors to extract. Finally, a reliability analysis was run on the items of each factor.

3.4. Exploratory Factor Analysis Results

Ideal Expectations Scale. Seven (7) items (1, 2, 4, 9, 12, 14, and 15; Appendix 6) were dropped from the analysis based on the identification of multicollinearity issues, having loadings lower than .40, or whether dropping the item could improve the Cronbach's α value.

An exploratory factor analysis using the minimum residual factor extraction method and oblimin rotation was ran on the remaining 12 items (3, 5, 6, 7, 8, 10, 11, 13, 16, 17, 18, and 19; Appendix 6). The determinant of the correlation matrix exceeded .00001 so there was no issue with multicollinearity (Field et al., 2012). The overall KMO was found to be .90 (superb according to Kaiser (1974)), with individual item values being greater than or equal to .86, which was above the acceptable limit of .50. Bartlett's test of sphericity, $\chi^2(66) = 4093, p < .001$, suggested that the correlation matrix does not resemble an identity matrix so factor analysis was appropriate. The parallel analysis suggested to retain two factors. The two-factor solution was deemed sufficient, it accounted for 56% of the variance in the data, the

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correlation between factors was $r = .37$, all loadings exceeded .40 (Table 1), and communalities were in an acceptable range (Table 1). Factor one represents *Service Feature Expectations* (items: 7, 11, 13, 16, 17, 18, and 19; Appendix 6), whilst factor two relates to *Ethical and Privacy Expectations* (items: 3, 5, 6, 8, and 10; Appendix 6). Both subscales had high reliabilities, for *Service Feature Expectations* the Cronbach's $\alpha = .90$, whilst for *Ethical and Privacy Expectations* Cronbach's $\alpha = .85$.

Insert Table 1 About Here

Predicted Expectations Scale. Seven (7) items (1, 2, 4, 9, 12, 14, and 15; Appendix 6) were dropped from the analysis based on the identification of multicollinearity issues, having loadings lower than .40, or whether dropping the item could improve the Cronbach's α value.

An exploratory factor analysis using the minimum residual factor extraction method and oblimin rotation was ran on the remaining 12 items (3, 5, 6, 7, 8, 10, 11, 13, 16, 17, 18, and 19; Appendix 6). The overall KMO was found to be .93 (superb according to Kaiser (1974)), with individual item values being greater than or equal to .89, which was above the acceptable limit of .50. Bartlett's test of sphericity, $\chi^2 (66) = 4476, p < .001$, suggested that the correlation matrix does not resemble an identity matrix so the factor analysis was appropriate. The parallel analysis suggested to retain two factors. The two-factor solution was deemed sufficient, it accounted for 58% of the variance in the data, the correlation between factors was $r = .57$, all loadings exceeded .40 (Table 2), and all communalities were equal to or exceeded .50 (Table 2). Factor one represents *Service Feature Expectations* (items: 7, 11, 13,

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1
2
3 16, 17, 18, and 19; Appendix 6), whilst factor two relates to *Ethical and Privacy*
4 *Expectations* (items: 3, 5, 6, 8, and 10; Appendix 6). Both subscales had high
5 reliabilities, for *Service Feature Expectations* the Cronbach's $\alpha = .90$, whilst for
6 *Ethical and Privacy Expectations* Cronbach's $\alpha = .88$.
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21 Insert Table 2 About Here
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25

26 3.5. Descriptive Statistics

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29 The descriptive statistics of the final 12-items are presented in Table 3. Across
30 each item, it is clear that average responses for ideal expectations are higher than
31 predicted expectations. Within each expectation type (ideal and predicted), the items
32 relating to the *Ethical and Privacy Expectations* factors (E1-E5) were higher than
33 *Service Feature Expectations* (S1-S7). For the ideal expectations scale, the mean
34 responses for the *Ethical and Privacy Expectations* factor ranged from 6.12 to 6.58,
35 whilst for the *Service Feature Expectations* the range was between 5.56 and 5.74.
36
37 Whereas, for the predicted expectations scale the average responses for the *Ethical*
38 *and Privacy Expectations* factor ranged from 5.37 to 6.05, with the *Service Feature*
39 *Expectations* ranging from 4.54 to 5.09.
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56 Insert Table 3 About Here
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Insert Table 4 About Here

Insert Table 5 About Here

3.6. Discussion

The results of the factor analysis again identified a two-factor solution (*Ethical and Privacy Expectations* and *Service Feature Expectations*), with the same items loading for both the ideal and predicted expectations scales. The communality values for items 3 (.49) and 8 (.44) for the ideal expectations scale are below .50, but given the large sample size used ($n = 674$), we can be confident in the results (MacCallum et al., 1999). More importantly, we are left with a final 12-item questionnaire (Appendix 7) that can be used by researchers to explore student expectations of LA services.

As in the pilot study, these two factors (*Ethical and Privacy Expectations* and *Service Feature Expectations*) relate to the four identified themes: *Ethical and Privacy Expectations*, *Agency Expectations*, *Intervention Expectations*, and *Meaningfulness Expectations*. Item 1 (Appendix 7) asks whether student believe consent should be sought by the university before using any personal data. This

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1
2
3 shows a clear relation to the theme of *Ethical and Privacy Expectations*. Items 4 and
4
5 8 (Appendix 7) are concerned with students expecting to receive regular updates on
6
7 their learning progression (*Intervention Expectations*) and whether LA feedback will
8
9 relate progress to set goals (*Meaningfulness Expectations*), respectively. Whereas,
10
11 *Agency Expectations* are captured by items 7 and 11 (Appendix 7), which
12
13 correspond to students expecting to make their own decisions based on LA feedback
14
15 and whether teaching staff are obliged to act on the evidence of a student
16
17 underperforming.
18
19
20
21

22 The descriptive statistics provide a general insight into student expectations of LA
23
24 services (Table 3; the item numbers refer to Appendix 6). As anticipated, responses
25
26 to the ideal expectations scale demonstrated a ceiling effect. Due to this scale
27
28 corresponding to what students would hope for in a service, responses are likely to
29
30 be unrealistically high. Responses to what students expected to happen in reality
31
32 (predicted expectations), however, were lower than ideal expectation responses.
33
34 This distinction between ideal and predicted expectation responses adds validity to
35
36 the measure, as the results are supportive of two levels of belief. In addition to
37
38 providing descriptive statistics for each item, the mean and standard deviations for
39
40 each item by gender (Table 4) and level of study (Table 5) are also provided.
41
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46 Comparing the *Ethical and Privacy Expectations* and *Service Feature*
47
48 *Expectations* factor responses on both the ideal and predicted scales does suggest
49
50 that beliefs towards the ethical procedures involved in LA service implementations
51
52 are of greater importance. This is based on the range of average responses across
53
54 ideal and predicted expectation scales being greater for *Ethical and Privacy*
55
56 *Expectation* items than *Service Feature Expectation* items (Table 3). A tentative
57
58 conclusion that can be drawn from this is that students do hold stronger beliefs about
59
60

Expectations of Learning Analytics

1
2
3 ethical procedures involved in LA service implementations. Thus, in line with the
4
5 findings of Slade and Prinsloo (2014), it appears that students do place
6
7 considerable importance on how a university handles their educational data,
8
9 particularly with regards to controlling who access to any data and whether consent
10
11 is required. Whilst in the case of *Service Feature Expectations*, students may desire
12
13 such features (e.g., being able to compare current progress to learning goals), but
14
15 the importance of such services are not comparable with the ethical procedures of
16
17 LA services.
18
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21

22 For the *Ethical and Privacy Expectations* factor, the item with both the highest
23
24 mean response across ideal ($M = 6.58$, $SD = .86$; Table 3) and predicted ($M = 6.05$,
25
26 $SD = 1.28$; Table 3) expectations was item 5 (The university will ensure that all my
27
28 educational data will be kept securely; Appendix 6). Slade and Prinsloo (2014)
29
30 summarise student beliefs toward the data collection procedures, with views centring
31
32 on who has access to collected educational data and how data is handled. Thus, the
33
34 current finding that students expect institutions to securely hold all collected
35
36 educational data does substantiate the student beliefs outlined by Slade and
37
38 Prinsloo. More importantly, it demonstrates that students hold strong beliefs toward
39
40 the security and handling of their educational data. This finding can then be used by
41
42 an institution to inform their data handling policies of LA services, as students want
43
44 to be reassured that their data is secure and private so the institution needs to
45
46 determine how such expectations can be effectively met.
47
48
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51

52 *Service Feature Expectation* descriptive statistics, on the other hand, show that
53
54 students' would like teaching staff to have the skills necessary to incorporate LA
55
56 outputs into any feedback provided (item 17; $M = 5.74$, $SD = 1.33$; Table 3).
57
58 Although this is the highest ideal expectation in terms of *Service Feature*
59
60

Expectations of Learning Analytics

1
2
3 *Expectations*, it is the lowest predicted expectation ($M = 4.54$, $SD = 1.76$; Table 3).
4
5 What can be taken away from this is that students would ideally like teaching staff to
6
7 utilise newly emerging data sources to enhance the feedback received. However,
8
9 given the possible complexities of analytics they may not believe this to be easily
10
11 achievable, which is why their realistic beliefs are lower. The highest average
12
13 predicted expectation is for item 13 (The learning analytics service will show how my
14
15 learning progress compares to my learning goals/the course objectives; $M = 5.09$,
16
17 $SD = 1.36$; Table 3). This finding does support the work of Schumacher and
18
19 Ifenthaler (2018), who found students to expect features showing how they are
20
21 progressing toward a set goal. Given the importance of continually monitoring gaps
22
23 between current progress and set goals to self-regulated learning (Winne & Hadwin,
24
25 2012), it is understandable why students would want this particular LA service.
26
27
28
29
30

31
32 The above mentioned information outlines how the SELAQ can effectively be
33
34 used to identify those features of a LA service that students desire, but also what
35
36 they realistically want from such services. Although having teaching staff being
37
38 efficient in using analytics to provide more informed feedback is desirable, students
39
40 may realistically believe that this is not viable in the current circumstances.
41
42 Nevertheless, these initial findings illustrate the importance of students' beliefs
43
44 toward the ethical procedures involved in LA services, which supports previous work
45
46 (Ifenthaler & Schumacher, 2016; Roberts et al., 2016; Slade & Prinsloo, 2014).
47
48
49

4. Study Three

4.1. Sample

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52 The 12-item SELAQ (Appendix 7) was distributed to students at the University
53
54 of Liverpool through an online survey system. The 12 items were identified as per
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the results of the exploratory factor analysis in Study Two. Some 191 responses were collected (Females = 129). Students were aged between 18 and 50 ($M = 20.41$, $SD = 3$). The majority of students were undergraduates ($n = 188$, 98%), whilst the remaining sample was composed of masters students ($n = 3$, 0.02%). Of the sample, 19% were taking a science subject ($n = 36$), 13% were studying engineering ($n = 24$), 21% were studying a social science subject ($n = 41$), 24% were taking an arts and humanities subject ($n = 45$), and 24% were studying a medicine and health care subject ($n = 45$). 80% ($n = 153$) of the sample were Home/EU students, with the remaining being International students (20%, $n = 38$).

4.2. Instrument

The 12-item SELAQ was used for this study (Appendix 7). Responses to the items are made on two 7-point Likert scales (1 = Strongly Disagree; 7 = Strongly Agree) corresponding to ideal (Ideally, I would like that to happen) and predicted (In reality, I would expect that to happen) expectations. As with the survey distributions for the pilot and study two, respondents were given the same introduction to the survey (Appendix 1).

4.3. Data Analysis

Exploratory structural equation modelling using geomin rotation and confirmatory factor analysis was carried out on the raw data using Mplus 8 (Muthén & Muthén, 2017) in order to test the suitability of the two-factor solution (*Ethical and Privacy Expectations* and *Service Feature Expectations*). It is important to note that the exploratory structural equation modelling was used as a confirmatory tool (Marsh, Morin, Parker, & Kaur, 2014). As recommended by Marsh et al. (2014), the model fit indices obtained from both the confirmatory factor analysis and exploratory structural

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equation modelling will be compared. If the fit indices from both models are marginally different, then the confirmatory factor analysis model will be discussed on the basis of parsimony (Marsh et al., 2014).

Table 6 presents the descriptive statistics for the 12 items of the SELAQ, along with the factor key which shows the items to either correspond to the *Ethical and Privacy Expectation* factor (E1-E5) or the *Service Feature Expectation* factor (S1-S7). The ideal expectations scale responses were negatively skewed (Table 6). This ceiling effect was anticipated as the ideal expectation scale corresponds to what an individual hopes for so individuals are likely to respond positively. The predicted expectation scale also showed negatively skewed responses (Table 6). Due to the responses being categorical and skewed, along with the small sample size ($n = 191$), the scale-shifted approach to the unweighted least squares estimation (ULSMV) was used (Muthén, Muthén, & Asparouhov, 2015).

To assess the suitability of the two-factor model for both scales, the X^2 test is presented along with the following alternative fit indexes: the comparative fit index (CFI), Tucker-Lewis index (TLI), and root mean square error of approximation (RMSEA), with 90% confidence intervals. In terms of cut-offs, a RMSEA value within the range of .08 and .10 is indicative of a mediocre fit (MacCallum, Browne, & Sugawara, 1996), whilst values close to or below .06 would support a good fit (Hu & Bentler, 1999). As for both the TLI and CFI, Hu and Bentler (1999) recommend values close to or above .95. These proposed cut-offs, however, were based on continuous data being analysed with the maximum likelihood estimator. In the case of ULSMV, Xia (2016) found the cut-offs proposed by Hu and Bentler (1999) to not be applicable as they are influenced by thresholds. A further consideration that needs to be made is the influence that measurement quality has on fit indices, with

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3 high standardised loadings (around .80) fit index values that are suggestive of poor
4
5 fit (McNeish, An, & Hancock, 2018). Thus, while alternative fit indices are reported,
6
7 this is supplemented by an assessment of measurement quality, which involves the
8
9 presentation of standardised loadings and composite reliability (Raykov, 1997).
10
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13 With regards to the X^2 test of exact fit, Ropovik (2015) does note that it is
14
15 unrealistic for many applications, but it should not be universally dismissed. If the X^2
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17 test is found to be significant, this may then point to possible model
18
19 misspecifications, which can be examined through an assessment of local fit
20
21 (Ropovik, 2015). Of the various approaches to assessing local fit, the current study
22
23 will explore modification indices and standardised expected parameter change
24
25 values, along with an inspection of correlation residuals. Modification index (MI)
26
27 values exceeding 3.84 (Brown, 2015), with standardised expected parameter change
28
29 (SEPC) values $\geq .10$ (Saris, Satorra, & Veld, 2009), point to possible respecifications
30
31 that could improve the model fit. Whereas, for absolute correlation residuals, values
32
33 $\geq .10$ are believed to be indicative of sources of misfit between the model and data
34
35 (Kline, 2015). It is important to remain mindful that engaging in data driven model
36
37 modifications could be entirely based on chance (MacCallum, Roznowski, &
38
39 Necowitz, 1992). To address the issue of capitalising on chance, MacCallum et al.
40
41 (1992) recommend that any modifications to a model be cross-validated in a second
42
43 sample. Given that the current sample is small ($n = 191$), the splitting the sample for
44
45 the purposes of model cross-validation is not advisable. Therefore, if problems in the
46
47 model are identified we recommend that future research is conducted in order to
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49 assess whether these issues are found in independent samples, but also whether
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51 any modifications can be cross-validated.
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Expectations of Learning Analytics

Insert Table 6 About Here

4.4. Confirmatory Factor Analysis Results

Ideal expectation Scale. The purported two-factor model led to an acceptable fitting model using the confirmatory factor analysis approach ($\chi^2(53, n = 191) = 132.24, p < .001, RMSEA = .09$ (90% CI .07, .11), CFI = .95, TLI = .94). Whereas, the exploratory structural equation model led to a marginally worse fit ($\chi^2(43, n = 191) = 129.50, p < .001, RMSEA = .10$ (90% CI .08, .12), CFI = .95, TLI = .92; factor loadings presented in Appendix 8). Taking into account both the better fit obtained from the confirmatory factor analysis model and that it is a more parsimonious model, the results of this model will be reported.

The unstandardised and standardised estimates of the two-factor solution are found in Table 7. The unstandardised estimates were all statistically significant ($ps < .001$), with a mean standardised loading of .76. Estimates of factor loadings showed the factors to explain a moderate to large proportion of the latent continuous response variance (R^2 range = .41 - .73). The two factors of *Ethical and Privacy Expectations* and *Service Feature Expectations* were found to strongly correlate with one another (.57), but remains below those values that could suggest poor discriminant validity (i.e., values exceeding .85; Brown, 2015). Moreover, the average variance extracted values for both factors (.51 for the *Ethical and Privacy*

Expectations of Learning Analytics

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3 *Expectations* factor and .60 for the *Service Feature Expectations* factor) exceeds the
4
5 square of the correlation between the two factors (.32; Fornell & Larcker, 1981). In
6
7 terms of composite reliability, estimates are high for the ideal expectation scale (.94)
8
9 and both subscales (.84 and .91 for the *Ethical and Privacy Expectations* and
10
11 *Service Feature Expectations* factors, respectively).
12
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15 As the X^2 test was found to be significant, it is important to inspect the local fit
16
17 of the model in order to identify any sources of misfit. MI and SEPC values point to
18
19 three possible changes to the model that could improve the overall fit. More
20
21 specifically, these values suggest that freely estimating correlated errors between:
22
23 item 1 and item 2 (MI = 11.28, SEPC = .36), item 2 and item 5 (MI = 20.51, SEPC = -
24
25 .54), and item 11 and item 12 (MI = 14.62, SEPC = .44). From the correlation
26
27 residual matrix (Appendix 9), there are nine instances of absolute values being $\geq .10$.
28
29 In line with the MI and SEPC values, the largest correlation residuals are between
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31 item 1 and item 2 (.14), item 2 and item 5 (-.19), and item 11 and item 12 (.17).
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Insert Table 7 About Here

48 *Predicted Expectation Scale*. Compared to the ideal expectation scale, the two-factor
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50 model was found to have an acceptable fit using the confirmatory factor analysis
51
52 approach ($X^2(53, n = 191) = 143.92, p < .001$, RMSEA = .10 (90% CI .08, .11), CFI =
53
54 .96, TLI = .95). In comparison, the exploratory structural equation model approach
55
56 achieved a marginally better fit to the data ($X^2(43, n = 191) = 119.53, p < .001$,
57
58 RMSEA = .10 (90% CI .08, .12), CFI = .97, TLI = .95; factor loadings are presented
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Expectations of Learning Analytics

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3 in Appendix 10). As with the ideal expectation scale analysis, the confirmatory factor
4
5 analysis results will be reported due to being more parsimonious.
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9 The unstandardised and standardised estimates of the two-factor solution are
10
11 found in Table 8. The unstandardised estimates were all statistically significant ($ps <$
12
13 $.001$), with a mean standardised loading of $.79$. Estimates of factor loadings showed
14
15 the factors to explain a moderate to large proportion of the latent continuous
16
17 response variance (R^2 range = $.47 - .76$). The two factors of *Ethical and Privacy*
18
19 *Expectations* and *Service Feature Expectations* were found to strongly correlate with
20
21 one another ($.63$), but remains below those values that could suggest poor
22
23 discriminant validity (i.e., values exceeding $.85$; Brown, 2015). Moreover, the
24
25 average variance extracted values for both factors ($.58$ for the *Ethical and Privacy*
26
27 *Expectations* factor and $.65$ for the *Service Feature Expectations* factor) exceeds the
28
29 square of the correlation between the two factors ($.40$; Fornell & Larcker, 1981). The
30
31 composite reliability estimate for the predicted expectation scale was high ($.95$) and
32
33 the estimates for both subscales were also high ($.87$ and $.93$ for the *Ethical and*
34
35 *Privacy Expectations* and *Service Feature Expectations* factors, respectively).
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42 As with the ideal expectation scale, the significant X^2 test means that an
43
44 inspection of local misfit within the model is warranted. From the MI and SEPC
45
46 values, there are three suggested modifications that can be made to model, which
47
48 are similar to the ideal expectation scale. These modifications involve freely
49
50 estimating correlated errors between item 2 and item 3 (MI = 10.35, SEPC = $.36$),
51
52 item 2 and item 5 (MI = 10.09, SEPC = $-.34$), and item 11 and item 12 (MI = 13.84,
53
54 SEPC = $.42$). The correlation residual matrix (Appendix 11) shows that there are ten
55
56 absolute values that are $\geq .10$. In line with the MI and SEPC values, the largest
57
58 correlation residuals are between item 2 and item 3 ($.12$), item 2 and item 5 ($-.12$),
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Expectations of Learning Analytics

and item 11 and item 12 (.15); there is also a large correlation residual between item 4 and item 5 (.13).

Insert Table 8 About Here

4.5. Descriptive Statistics

Insert Table 9 About Here

Insert Table 10 About Here

Table 6 presents descriptive statistics for each item across both expectation scales (ideal and predicted); item means and standard deviations are also presented by gender (Table 9) and level of study (Table 10). As with study two, the average responses are higher on the ideal than the predicted expectation scale. In general, the mean values on the *Ethical and Privacy Expectation* items are higher (ranging from 5.77 to 6.53 for ideal expectations, and ranging from 5.19 to 6.27 for predicted expectations; Table 6) than those relating to *Service Feature Expectation* items (ranging from 5.80 to 6.03 for ideal expectations, and ranging from 4.96 to 5.35 for

Expectations of Learning Analytics

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3 predicted expectations; Table 6). This was not the case for item 5 (The university will
4 ask for my consent to collect, use, and analyse any of my educational data (e.g.,
5 grades, attendance, and virtual learning environment accesses)) from the *Ethical*
6 *and Privacy Expectation* factor, which appeared to not elicit a strong response from
7 students for either ideal ($M = 5.77$, $SD = 1.33$; Table 6) or predicted ($M = 5.19$, $SD =$
8 1.62 ; Table 6) expectations. As with study two, the *Ethical and Privacy Expectation*
9 item with the highest average response for both ideal ($M = 6.53$, $SD = .78$; Table 6)
10 and predicted ($M = 6.27$, $SD = 1.08$; Table 6) expectations was item 2 (The
11 university will ensure that all my educational data will be kept securely).

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As for the *Service Feature Expectation* items, the highest average response on the ideal expectation scale is for item 11 (The teaching staff will have an obligation to act (i.e., support me) if the analytics show that I am at-risk of failing, underperforming, or if I could improve my learning; $M = 6.04$, $SD = 1.31$; Table 6). Whilst for the predicted expectation scale, item 12 (The feedback from the learning analytics service will be used to promote academic and professional skill development (e.g., essay writing and referencing) for my future employability) received the highest average response ($M = 5.35$, $SD = 1.43$; Table 6).

4.6. Discussion

Based on the findings of study two, a purported two-factor structure was found to explain student expectations of LA services on both the ideal and predicted expectation scales. In study three, the appropriateness of this two-factor structure was assessed through both confirmatory factor analysis and exploratory structural equation modelling. A decision was made to use the confirmatory factor analysis for the basis of further model discussions as the differences in alternative fit indices

Expectations of Learning Analytics

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3 were marginal and the confirmatory factor analysis model was more parsimonious
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5 (Marsh et al., 2014). Even though the confirmatory factor analysis model results
6
7 were presented, it is important to note that the exploratory structural equation model
8
9 for both scales (ideal and predicted expectations) showed small, yet non-zero, cross-
10
11 loadings (Appendices 8 and 10). This is important as it provides greater knowledge
12
13 about the model that can be considered in future analyses.
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17 For both scales (ideal and predicted expectations), the alternative fit indices
18
19 from the confirmatory factor analyses do suggest that the model provides an
20
21 acceptable fit to the data. Based on the recommendations of McNeish et al. (2018),
22
23 standardised loadings and composite reliability estimates were provided in order to
24
25 provide an assessment of measurement quality. The mean standardised loadings
26
27 are high, with individual item loadings ranging from .64 to .85 for the ideal
28
29 expectation scale and from .69 to .89 for the predicted expectation scale. With
30
31 regards to reliability, both scales were found to have high reliability estimates (.94
32
33 and .95 for the ideal and predicted expectation scales, respectively). Together, this
34
35 provides the necessary context for the interpretation of alternative fit indices such as
36
37 the RMSEA. Put differently, whilst the RMSEA may not be in line with the cut-off
38
39 proposed by Hu and Bentler (1999) (i.e., RMSEA values close to or below .06), its
40
41 function varies in accordance with measurement quality (McNeish et al., 2018). In
42
43 addition, these recommended cut-off values are based on continuous data analysed
44
45 using the maximum likelihood estimator; thus, their applicability to ordinal data
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47 analysed using ULSMV can be questioned (Xia, 2016).
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55 While the measurement quality of both scales (ideal and predicted
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57 expectations) was good and the alternative fit indices show the fit to be acceptable,
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59 the X^2 test was found to be significant ($p < .05$). Following the recommendations set
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Expectations of Learning Analytics

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3 out by Ropovik (2015), the local fit of the model was assessed by examining both MI
4 and SEPC values, along with correlation residuals. This assessment did lead to the
5 identification of possible localised strains within the model, with misfits being found
6 between item 2 and item 5 and item 11 and item 12 on both scales (ideal and
7 predicted expectations). For items 2 and 5, their content relates to the university
8 ensuring all data is kept securely and obtaining consent before engaging in any
9 analysis of data, respectively. Based on the content of these two items, there is
10 some degree of overlap, as the student consenting to allow the university to collect
11 and analyse collected data will be tied to their beliefs regarding data security.
12 However, this does not provide substantial justification for a respecification of the
13 model that allows the errors between items 2 and 5 to correlate. As for items 11 and
14 12, the content is focused upon beliefs towards the implementation of early
15 intervention systems (item 11) and using LA services to develop
16 academic/employability skills (item 12). Thus, from a content perspective there is no
17 overlap, which again means that the respecification of the model by allowing the
18 errors of items 11 and 12 cannot be justified.

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41 For the ideal expectation scale, there was a further source of misfit between
42 items 1 and 2. These items refer to beliefs about the provision of consent towards
43 the collection of identifiable data and ensuring all collected data remain secure,
44 respectively. Whereas, for the predicted expectation scale there was an additional
45 source of misfit between items 2 and 3. These correspond to beliefs about data
46 security and providing consent before data is outsourced to third party companies,
47 respectively. Taking both sources of misfit (between item 1 and 2 for the ideal
48 expectation scale and item 2 and 3 for the predicted expectation scale) into
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Expectations of Learning Analytics

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3 consideration, it is clear that while they all relate to data security procedures, there is
4
5 no substantial justification for allowing these errors between these items to correlate.
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8 Even though an assessment of local strains within the model did identify
9
10 possible modifications, any respecification could be capitalising on chance variation
11
12 (MacCallum et al., 1992). Ideally, the approach of splitting the sample so that
13
14 modifications can be cross-validated would be undertaken (MacCallum et al., 1992);
15
16 however, given the current sample size ($n = 191$) this was not permissible.
17
18 Nevertheless, the identification of localised areas of strain in this study provides
19
20 future researchers with an understanding of where local misfits within the purported
21
22 two-factor structure may lie. In addition, the identification of local misfit, along with
23
24 the small non-zero cross loadings found in the exploratory structural equation model
25
26 (Appendices 8 and 10), provides evidence about the measurement model that can
27
28 be taken into account in future work.
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34 Taking the abovementioned points into consideration, the two-factor structure
35
36 of *Ethical and Privacy Expectations* and *Service Feature Expectations* was found to
37
38 have an acceptable fit on the basis of alternative fit indices. In addition, as
39
40 assessment of measurement quality shows that the standardised loadings for each
41
42 scale (ideal and predicted expectations) are strong and the reliability is good.
43
44 However, the X^2 test was significant and an inspection of localised areas of strain did
45
46 identify some issues with the model that require further investigation. The next steps
47
48 are for researchers to continue to assess the two scales of the SELAQ using larger
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50 sample sizes, with a view of determining whether there are justifiable modifications
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52 that can improve the overall fit.
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Expectations of Learning Analytics

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3 The descriptive statistics are similar to what was found in study two, with average
4 responses being higher for the ideal than the predicted expectation scale, again
5 supporting the validity of the SELAQ in differentiating between two levels of beliefs.
6
7 Similarly, inspection of the mean values for both expectation scales (ideal and
8 predicted) are indicative of *Ethical and Privacy Expectations* being stronger than
9
10 *Service Feature Expectations*. It may be that whilst the prospect of LA services
11 providing features designed to enhance the learning process would address the
12 educational needs of students (e.g., providing a student with regular updates on their
13 learning), they are outweighed by students' need of a service that is ethical. The
14 findings of Roberts et al. (2016) show that whilst students expressed positive
15 attitudes toward LA services keeping them informed, they were concerned about the
16 possible invasion of their privacy. In other words, students place greater weight on
17 universities upholding ethical practices as opposed to wanting the introduction of LA
18 service features designed to support learning.
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36 These aforementioned points, however, do not apply to item 5 (The university will
37 ask for my consent to collect, use, and analyse any of my educational data (e.g.,
38 grades, attendance, and virtual learning environment accesses)), which is the lowest
39
40 *Ethical and Privacy Expectation* item on both scales (ideal and predicted). The
41 highest average response on the *Ethical and Privacy Expectation* subscale for study
42 three, as found with study two, was for item 2 (The university will ensure that all my
43 educational data will be kept securely) for both ideal and predicted expectations.
44
45 Thus, student beliefs toward the provision of consent before the university collect
46 educational data may not be as strong as their expectations toward any data
47 collected remaining secure. This resonates with what Roberts et al. (2016) identified
48 as a pertinent concern raised by students, which was the university ensuring that all
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Expectations of Learning Analytics

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3 data remain private. Similarly, Prinsloo and Slade (2016) state that a Higher
4
5 Education Institute's power to collect and analyse data ultimately increases their
6
7 burden of responsibility to ensure security. Taken together, it can be argued that
8
9 students may recognise that collection of student data is routinely undertaken by
10
11 universities, it nevertheless places a burden of responsibility on these universities to
12
13 ensure that all data remains private.
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17 For the *Service Feature Expectation* items, the highest average response was
18
19 for item 11 (The teaching staff will have an obligation to act (i.e., support me) if the
20
21 analytics show that I am at-risk of failing, underperforming, or if I could improve my
22
23 learning) on the ideal expectation. However, on the predicted expectation scale, the
24
25 highest average response was for item 12 (The feedback from the learning analytics
26
27 service will be used to promote academic and professional skill development (e.g.,
28
29 essay writing and referencing) for my future employability). These two items are
30
31 different to the highest average response items found in study two, which showed
32
33 students to have strong ideal expectations towards teaching staff incorporating LA
34
35 into their feedback (item 10). For predicted expectations, however, study two
36
37 students showed stronger realistic beliefs toward receiving feedback comparing their
38
39 progress to a set goal (item 8). Compared to the study two students, it appears that
40
41 students in study three would like the LA service to incorporate early alert systems,
42
43 but expect the service to be tailored towards the development of academic or
44
45 professional skills.
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52 Based on the results of study three, the purported two-factor structure (*Ethical*
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54 *and Privacy Expectations* and *Service Feature Expectations*) of the SELAQ showed
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56 acceptable fit (based on alternative fit indices). In addition, the two scales (ideal and
57
58 predicted expectations) were found to have good measurement quality in terms of
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Expectations of Learning Analytics

average standardised factor loadings and reliability estimates. However, further work is required due to the significant X^2 test and the identification of local strains within the model. Finally, as with study two, the descriptive statistics for study three show how the SELAQ can be used to provide a general understanding of what students expect from LA services.

5. General Discussion

5.1. Interpretation of the Results

Following a review of the LA literature (Authors, 2017) and input from experts, four themes were identified: *Ethical and Privacy Expectations*, *Agency Expectations*, *Intervention Expectations*, and *Meaningfulness Expectations*. These themes were used to guide the generation of items relating to student expectations of LA services. What is more, we grounded these items within the theoretical framework of expectations, drawing mainly from the work achieved in the technology acceptance literature (Brown et al., 2012, 2014; Davis & Venkatesh, 2004) and health service literature (Bowling et al., 2012; Thompson & Suñol, 1995) that has demonstrated the importance of gauging stakeholder expectations. From this, two levels of expectations (ideal and predicted) were identified (David et al., 2004; Dowling & Rickwood, 2016), which are shown to provide a more nuanced understanding of stakeholder beliefs.

Using the above as a framework, we have been able to develop and validate a descriptive 12-item (Appendix 7) instrument that allows researchers, practitioners, and institutions to obtain a general understanding of students' ideal and predicted expectations towards LA services. The results also show that these 12 expectations can be explained by two first-order factors: *Ethical and Privacy Expectations* and

Expectations of Learning Analytics

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3 *Service Feature Expectations*. The view is that the measurements obtained can then
4
5 direct more specific engagements with students at different intervals throughout the
6
7 implementation process, with a view of managing expectations and identifying main
8
9 areas of focus for the LA service.
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13 The *Ethical and Privacy Expectations* factor (items 1, 2, 3, 5, and 6; Appendix 7)
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15 strongly relates to the identified theme *Ethical and Privacy Expectations*. Items 1, 3,
16
17 5, and 6 refer to expectations towards the provision of consent for universities to use
18
19 identifiable data (e.g., ethnicity, age, and gender), to outsource data to third party
20
21 companies, to collect and use any educational data (e.g., grades, virtual learning
22
23 environment accesses, or attendance), and to use data for purposes beyond what
24
25 was originally stated, respectively. Item 2, however, refers to the belief that
26
27 universities should keep data secure. These items are well supported by the LA
28
29 literature, particularly in the work carried out by Slade and Prinsloo (2014) who found
30
31 students expected universities to require informed consent and to maintain privacy at
32
33 all times. They also add weight to the work of Ifenthaler and Schumacher (2016), as
34
35 these items are centred on beliefs towards the control students have over their data.
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42 Expectation items relating to opting-out (item 9; Appendix 6) and transparency
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44 (item 2; Appendix 6) were not retained in the final 12-item instrument. The omission
45
46 of an opt-out item may be based upon students holding stronger expectations
47
48 towards their right to decide whether an institution uses their educational data from
49
50 the outset. In order to make such a decision, the institution would also have to
51
52 provide details on their proposed uses of such data. The act of obtaining informed
53
54 consent can then also be thought of as intrinsically covering the responsibility of
55
56 being transparent (Sclater, 2016).
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Expectations of Learning Analytics

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3 With informed consent items being retained for identifiable and educational data
4 usage, it does identify a gap with the opinions offered by experts (Sclater, 2016) who
5 believe consent should only be sought for interventions to offset any likelihood of
6 burdening students with documents. This is an example of an ideological gap, as we
7 have shown that the ethical expectations held by students are concerned with having
8 the right to consent to any processes involved in a LA service. Our findings do not
9 advocate institutions undertaking an approach that overloads the student population
10 with requests for consent, rather students should be directly involved in policy
11 developments to offset any risks services that are not reflective of student
12 expectations.
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27 In addition, an inspection of the descriptive statistics obtained from study two and
28 three does provide further details regarding students' *Ethical and Privacy*
29 *Expectations*. For both samples, it was found that the highest average response
30 across each scale (ideal and predicted) was for the expectation toward the university
31 ensuring all collected data is kept secure (item 2; Appendix 7). Thus, these students
32 expect the university to be responsible for upholding the security of any data
33 collected (Prinsloo & Slade, 2016), which may emanate from concerns about who
34 has access to their data (Roberts et al., 2016). From a policy perspective, these
35 findings together suggest that a university must provide easily accessible information
36 regarding data handling processes. More specifically, students should be informed
37 as to how the university will securely hold all collected data and prevent disclosure of
38 such information to unauthorised third parties.
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55 The *Service Feature Expectations* factor (items 4, 7, 8, 9, 10, 11, and 12;
56 Appendix 7) does overlap with the identified themes of *Agency, Intervention, and*
57 *Meaningfulness Expectations*. As stipulated in the introduction, these themes were
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Expectations of Learning Analytics

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3 not assumed to be orthogonal from one another; rather, they were presented as a
4
5 means of collating the various research streams and discussions in LA. Item 8
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7 (Appendix 7) refers to the expectation that the LA service should be aimed at
8
9 updating students on how their progress compares to goals set, which is an example
10
11 of the *Meaningfulness Expectations* theme. Items 7 and 11 (Appendix 7) are
12
13 concerned with students expecting to make their own decisions based on the
14
15 feedback from LA services and whether teaching staff are obligated to act if students
16
17 are underperforming or at-risk, respectively. Together, these two beliefs address the
18
19 *Agency Expectations* theme. Finally, items 4, 9, 10, and 12 (Appendix 7) correspond
20
21 to students expecting regular updates on their learning progress, a complete profile
22
23 of the learning, teaching staff using LA in their feedback, and LA services being
24
25 designed to improve skill development, respectively. These beliefs all refer to what
26
27 students expect to receive from LA services, which relates to the *Intervention*
28
29 *Expectations* theme.
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36 As stated, the *Meaningfulness Expectations* theme is captured by item 8
37
38 (Appendix 7). This refers to the expectation toward receiving feedback that shows
39
40 how a student's learning is progressing in relation to a set goal, which has been
41
42 expressed by students in the work of Schumacher and Ifenthaler (2018). Likewise,
43
44 Roberts, Howell, and Seaman (2017) found students expected LA service features to
45
46 convey information that is meaningful (e.g., learning opportunities). A possible
47
48 reason for students expecting LA services to display information such as progress
49
50 towards a goal does relate to self-regulated learning. As Winne and Hadwin (2012)
51
52 state, being able to identify discrepancies between performance and goals set
53
54 enables learners to regulate their own learning (e.g., adopt an alternative learning
55
56 strategy). Whereas, feeding information back to students that is not pedagogically
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Expectations of Learning Analytics

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3 meaningful (e.g., number of access times to a virtual learning environment) is
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5 unlikely to motivate positive changes in learner behaviour (Gašević et al., 2015; Wise
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7 et al., 2016). Thus, whilst a university may view the provision of more feedback to
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9 students as being advantageous, it may not necessarily reflect what students want,
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11 which is feedback that is pedagogically meaningful.
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15 The results of the studies presented in the paper closely align with the
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17 discussions related to the moral considerations of whether teaching staff are
18
19 obligated to act (Prinsloo & Slade, 2017). According to Prinsloo and Slade, whilst
20
21 institutions should take action when problems are identified, the student still shares a
22
23 responsibility for their own learning. This acknowledges the fact that students are
24
25 active agents who metacognitively monitor their progress towards a set goal
26
27 (Gašević et al., 2015; Winne & Hadwin, 2012), and it is not for LA services to create
28
29 a culture of passivity (Kruse & Pongsajapan, 2012). These concerns have been
30
31 voiced by students in the work of Roberts et al. (2016). More specifically, students
32
33 expressed apprehension toward LA services that would remove the ability to engage
34
35 in self-directed learning (Roberts et al., 2016). This again illustrates the importance
36
37 of gauging student expectations towards elements of the LA service. Whilst
38
39 institutions may view LA favourably on the basis of instructors being able to provide
40
41 timely support to students (Pardo & Siemens, 2014), students may consider such
42
43 systems as a hindrance to independent learning (Roberts et al., 2016). The items of
44
45 the SELAQ capture this balance between students making their own decisions on
46
47 the basis of the LA feedback (item 7; Appendix 7) and institutions being obligated to
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49 act (item 11; Appendix 7), which together reflect the theme of *Agency Expectations*.
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57 The *Intervention Expectations* theme centres on the beliefs students hold
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59 regarding the LA service they receive in exchange for the disclosure of data. While
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Expectations of Learning Analytics

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3 there have been advances in introducing new forms of feedback (Verbert et al.,
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5 2013), developing ways of improving the student-teacher relationship (Liu et al.,
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7 2017), and offering ways to improve retention (Campbell et al., 2007), little has been
8
9 done to ask what students expect institutions to do with their collected data (Arnold &
10
11 Sclater, 2017; Schumacher & Ifenthaler, 2018). Put differently, there have been few
12
13 instances of students being engaged within the development and implementation of
14
15 LA service features. Of those instances where students have been engaged, it has
16
17 been found that students want profiles of their learning, updates on their learning
18
19 progress, and features designed to promote academic skill development (Roberts et
20
21 al., 2017; Schumacher & Ifenthaler, 2018). These expectations are captured by the
22
23 retained items of the SELAQ (items 4, 9, and 12; Appendix 7), in addition to an
24
25 expectation pertaining to teaching staff incorporating LA into their own feedback
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27 (item 10; Appendix 7). Together, these items both represent the *Intervention*
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29 *Expectations* theme and provide an indication of the LA service features students
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31 expect.
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38 From the descriptive statistics obtained in studies two and three that refer to the
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40 *Service Feature Expectations* factor, a general understanding of the LA service
41
42 features students expect does emerge. Moreover, focusing on those items with the
43
44 highest average responses may be indicative of student expectations of LA services
45
46 not being homogenous. In study two, the highest average response for the desired
47
48 expectation scale was for teaching staff to incorporate LA into their feedback (item
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50 10; Appendix 7). Whilst on the predicted expectation scale, the highest average
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52 response was for feedback showing how their progress compares to a set goal (item
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54 8; Appendix 7). For these students, while they desire the possibility of teaching staff
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56 being able to offer more informative feedback, they expect to receive feedback
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Expectations of Learning Analytics

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3 showing how their learning progresses to a set goal. For study three, on the other
4
5 hand, the highest average response on the ideal expectation scale was for the
6
7 university having an obligation to act (item 11; Appendix 7). Whereas, on the
8
9 predicted expectation scale, the highest average response was for the use of LA to
10
11 promote academic or professional skill development (item 12; Appendix 7).
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13 Compared to the students in study two, those in study three desire the inclusion of
14
15 early alert systems, but realistically expect LA services to be tailored towards
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17 promoting academic skill development.
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22 These aforementioned comparisons using items from the *Service Feature*
23
24 *Expectations* factor show that while certain LA service features may be desirable
25
26 (e.g., the introduction of early alert systems), it may not be the LA service features
27
28 students expect (e.g., LA services designed to support academic skills such as self-
29
30 regulated learning). Thus, while there has been extensive attention paid to the
31
32 possibility of LA services identifying underperforming or at-risk students (Campbell et
33
34 al., 2007), students may actually be expecting LA service features aimed at providing
35
36 them with a way of understanding or improving their learning processes. These
37
38 beliefs have also been expressed by teaching staff, who viewed LA service features
39
40 that provide students with insights into their learning more favourably than simple
41
42 performance metrics (Ali et al., 2012; Gašević et al., 2015). Taken together, it shows
43
44 that whilst the provision of certain LA service features (e.g., early alert systems) may
45
46 seem advantageous to a Higher Education Institution, it remains necessary to
47
48 explore what students expect from LA services (Ferguson, 2012).
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5.2. Limitations and Future Research

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Expectations of Learning Analytics

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3 For the purposes of this work, the scale reduction was based solely upon
4 statistical decisions (e.g., weak factor loadings) set out before analysing the data.
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6 Additionally, we wanted the descriptive questionnaire to measure items across two
7
8 scales (ideal and predicted expectations), which may have accounted for a greater
9
10 loss in item numbers. Nevertheless, whilst adherence to statistical decisions were
11
12 followed here, item content can also be considered (Flora & Flake, 2017). Future
13
14 work may then be undertaken to determine whether additional items should be
15
16 included. It is important to recognise, however, that this descriptive questionnaire
17
18 only seeks to provide Higher Education Institutions with a general understanding of
19
20 what students expect of LA services. The anticipated effect of being able to readily
21
22 gauge such expectations is to open dialogues with students at all stages of LA
23
24 service implementations. In doing so, the Higher Education Institution can begin to
25
26 manage expectations and proactively identify main areas to focus upon, which can
27
28 then utilise more specific instruments and/or a qualitative approach.
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36 On the basis of alternative fit indices, the purported two-factor structure resulted
37
38 in an acceptable fit for both scales (ideal and predicted expectations). Moreover, an
39
40 assessment of measurement quality showed the average standardised loadings and
41
42 reliability to be high. Nevertheless, for both scales the X^2 test as found to be
43
44 significant, which should not be ignored (Ropovik, 2015). Based on the
45
46 recommendations of Ropovik (2015), an assessment of local misfit was therefore
47
48 undertaken (i.e., examination of MI and SEPC values, along with an inspection of
49
50 residual correlations). From this assessment of local fit, local sources of strain were
51
52 identified in the model, but possible respecifications of the model were not justified
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54 on conceptual grounds. In addition, the sample size ($n = 191$) did not allow for the
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56 cross-validation of any model modification (MacCallum et al., 1992). It is important
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Expectations of Learning Analytics

1
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3 for future researchers to be aware of the local sources of strain identified in study
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5 three, assess whether these are found using larger samples, and explore whether
6
7 model improvements can be made.
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10 Even though engaging students in the development of LA services is a critical
11
12 factor to success (Ferguson et al., 2014), the expectations of teaching staff cannot
13
14 be ignored. As Ali et al. (2012) show, teaching staff hold beliefs about the type of
15
16 service they want from LA, particularly with regards to utility of the information that is
17
18 fed back. Thus, while the needs of students should continue to guide the
19
20 development of LA services, the expectations teaching staff must also be
21
22 considered. Future research should therefore seek to develop and validate an
23
24 instrument designed to explore the beliefs of teaching staff toward LA services. Then
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26 together with the SELAQ, institutions can provide accommodate a greater number of
27
28 stakeholder perspectives into the implementation of LA services.
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34 An additional consideration that needs to be made is the cultural limitation of the
35
36 SELAQ, as it has only been developed and validated with UK Higher Education
37
38 students. It is therefore necessary for researchers to validate this instrument in other
39
40 contexts. The challenge of unequal stakeholder engagement in LA implementations
41
42 is not limited to UK Higher Education Institutions (Tsai & Gašević, 2017a), and it is
43
44 necessary for each university that is interested in implementing LA services to
45
46 actively engage with their stakeholders. The SELAQ provides a solution to these
47
48 challenges, but further work is required to assess the reliability and validity of the
49
50 instrument in cross-cultural contexts including the validation of the instrumentation
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52 translated into other languages. Work has been undertaken by the current authors to
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54 adapt the SELAQ for use in Dutch, Estonian, and Spanish Higher Education
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56 Institutions.
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Expectations of Learning Analytics

To extend the current work, researchers who use the SELAQ should focus on segmenting students based on their expectations, as it is unlikely that they will hold homogenous beliefs about LA services. It is anticipated that certain groups of students (e.g., undergraduate students) may have higher expectations of the types of feedback they want to receive in comparison to others (e.g., PhD students). Thus, the SELAQ can provide institutions with a means of exploring and understanding the individual differences in student beliefs toward LA services.

5.3. Implications

Research exploring student beliefs toward LA services have provided insightful findings that reinforce the importance of understanding a key stakeholder perspective (Roberts, Howell, & Seaman, 2017; Roberts et al., 2016; Slade & Prinsloo, 2014). While these studies have predominately undertaken a qualitative approach to understand student beliefs towards LA services, the SELAQ provides researchers with a tool that enables them to quantitatively measure LA service expectations. The instrument can be used on its own as a way of gauging what large samples of student expect from LA services. The SELAQ can further be combined with scales measuring attitudes, goal-orientations, or intentions to use. This can provide a way of understanding how expectations towards LA services form (e.g., based on individual differences in goal-orientations) and whether these beliefs are associated with their behaviours or attitude towards the service (e.g., whether students feel positively or negatively about the implemented LA service, or whether they intend to use the service). The SELAQ can also be incorporated into mixed methods approaches as it can be used to understand whether the LA service expectations expressed in interviews are reflective of the beliefs in the general student population.

Expectations of Learning Analytics

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3 The results of the SELAQ can be used to identify key areas of a LA service that
4 need to be met based on the level of predicted expectations. As this the level of
5 service that is expected from a student; therefore, it is essential for the institute to
6 meet these expectations effectively, or dissatisfaction is likely to arise (Authors,
7 2017). Knowing the importance of ethical issues to students, the university can also
8 create LA service policies that address each of the items contained within the
9 SELAQ. What is more, the results of the SELAQ can be accommodated into
10 interviews with students in order to better understand why certain LA service
11 features elicit higher expectations than others.
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5.4. Conclusion

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25 Meeting stakeholder expectations is an important determinant in the eventual
26 acceptance of an implemented service (Brown et al., 2012, 2014). Ways to
27 accommodate these expectation into the design and implementation of services is
28 therefore imperative; approaches include, but are not limited to, focus groups and
29 surveys. In this paper, the authors have discussed how the incorporation of student
30 expectations into the implementation of learning analytics services has been limited,
31 which may increase the risk of future dissatisfaction due to the service not aligning
32 with beliefs. This work builds upon past research that has discussed student
33 expectations as falling into ones referring to ethics and privacy and those associated
34 with service features (Roberts et al., 2016; Schumacher & Ifenthaler, 2018).
35 Specifically, the researchers have attempted to create a questionnaire that measures
36 each of these constructs and, in doing so, allows Higher Education Institutions to
37 accommodate these expectations into any learning analytics service implementation
38 decisions.
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Expectations of Learning Analytics

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3 **Practitioner Notes:**

4 What is currently known about the subject matter:

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 - 7 • Understanding student expectations of learning analytics is an important challenge for
8 higher education institutions to address
 - 9 • Research has measured student beliefs regarding the features and ethical procedures of a
10 learning analytics service

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12 What the paper adds to this subject:

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 - 15 • This study builds on prior work by developing an instrument to measure student
16 expectations of learning analytics services
 - 17 • This study proposes that student expectations of learning analytics can be measured using
18 two subscales – i) *Ethical and Privacy Expectations* and ii) *Service Expectations*

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20 Implications of study findings for practitioners:

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 - 23 • Higher education institutions should understand what students expect from learning
24 analytics services before any implementations are actioned
 - 25 • Higher education institutions have a validated instrument to gauge and understand student
26 expectations of learning analytics services
 - 27 • Results obtained from the instrument can be used to inform the development of specific
28 learning analytics policies for each higher education institution
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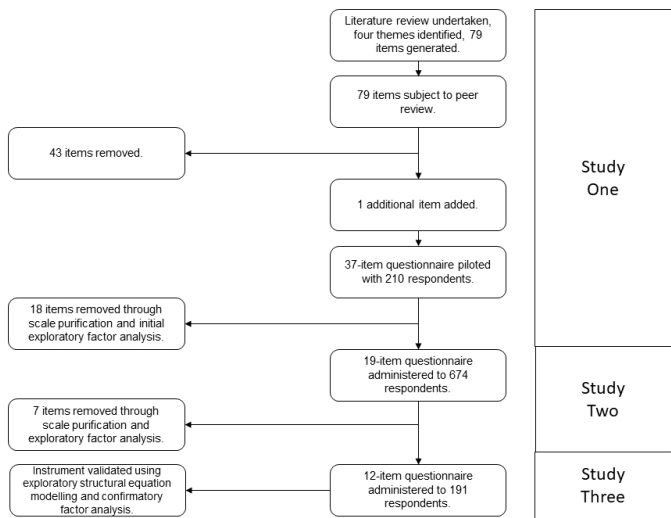


Figure 1. Diagrammatic Overview of the Student Expectations of Learning Analytics Questionnaire Development and Validation Steps

Figure 1. Diagrammatic Overview of the Student Expectations of Learning Analytics Questionnaire Development and Validation Steps

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Table 1. Factor Loadings Obtained from Study Two for the Ideal Expectations Scale

Item	Service Feature Expectations	Ethical and Privacy Expectations	Communalities
16. The learning analytics service will present me with a complete profile of my learning across every module (e.g., number of accesses to online material and attendance)	.82		.67
13. The learning analytics service will show how my learning progress compares to my learning goals/the course objectives	.79		.65
17. The teaching staff will be competent in incorporating analytics into the feedback and support they provide to me	.76		.56
18. The teaching staff will have an obligation to act (i.e., support me) if the analytics show that I am at-risk of failing, underperforming, or if I could improve my learning	.76		.54
19. The feedback from the learning analytics service will be used to promote academic and professional skill development (e.g., essay writing and referencing) for my future employability	.74		.52
7. The university will regularly update me about my learning progress based on the analysis of my educational data	.70		.52
11. The learning analytics service will be used to promote student decision making (e.g., encouraging you to adjust your set learning goals based upon the feedback provided to you and draw your own conclusions from the outputs received)	.68		.51
6. The university will ask for my consent before my educational data is outsourced for analysis by third party companies		.86	.70
5. The university will ensure that all my educational data will be kept securely		.78	.61
10. The university will request further consent if my educational data is being used for a purpose different to what was originally stated		.72	.54
3. The university will ask for my consent before using any identifiable data about myself (e.g., ethnicity, age, and gender)		.70	.49
8. The university will ask for my consent to collect, use, and analyse any of my educational data (e.g., grades, attendance, and virtual learning environment accesses)		.63	.44
Eigenvalues	3.98	2.78	
Variance Explained (%)	33	23	

Table 2. Factor Loadings Obtained from Study Two for the Predicted Expectations Scale

Item	Service Feature Expectations	Ethical and Privacy Expectations	Communalities
17. The teaching staff will be competent in incorporating analytics into the feedback and support they provide to me	.81		.62
19. The feedback from the learning analytics service will be used to promote academic and professional skill development (e.g., essay writing and referencing) for my future employability	.81		.62
18. The teaching staff will have an obligation to act (i.e., support me) if the analytics show that I am at-risk of failing, underperforming, or if I could improve my learning	.80		.63
16. The learning analytics service will present me with a complete profile of my learning across every module (e.g., number of accesses to online material and attendance)	.73		.52
13. The learning analytics service will show how my learning progress compares to my learning goals/the course objectives	.72		.55
11. The learning analytics service will be used to promote student decision making (e.g., encouraging you to adjust your set learning goals based upon the feedback provided to you and draw your own conclusions from the outputs received)	.68		.54
7. The university will regularly update me about my learning progress based on the analysis of my educational data	.64		.50
6. The university will ask for my consent before my educational data is outsourced for analysis by third party companies		.89	.74
5. The university will ensure that all my educational data will be kept securely		.77	.61
3. The university will ask for my consent before using any identifiable data about myself (e.g., ethnicity, age, and gender)		.75	.50
10. The university will request further consent if my educational data is being used for a purpose different to what was originally stated		.70	.60
8. The university will ask for my consent to collect, use, and analyse any of my educational data (e.g., grades, attendance, and virtual learning environment accesses)		.64	.56
Eigenvalues	4.02	2.97	
Variance Explained (%)	33	25	

Table 3. Descriptive Statistics for Ideal and Predicted Expectation Scales

Item	Factor Key	Ideal Expectations		Predicted Expectations	
		<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
3	E1	6.32	1.10	5.86	1.41
5	E2	6.58	.86	6.05	1.28
6	E3	6.52	1.03	5.66	1.68
7	S1	5.59	1.39	4.84	1.53
8	E4	6.12	1.21	5.37	1.61
10	E5	6.46	1.00	5.65	1.59
11	S2	5.69	1.31	5.07	1.41
13	S3	5.68	1.35	5.09	1.36
16	S4	5.59	1.42	5.00	1.42
17	S5	5.74	1.33	4.54	1.76
18	S6	5.56	1.61	4.75	1.69
19	S7	5.62	1.42	4.93	1.52

E1-E5: Ethical and Privacy Expectation Items; S1-S7: Service Feature Expectation Items

Table 4. Descriptive Statistics for Ideal and Predicted Expectation Scales by Gender

Gender	Factor Key	Item	Ideal Expectation		Predicted Expectation		
			<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	
Male	E1	3	6.18	1.27	5.71	1.47	
	E2	5	6.61	.86	6.00	1.33	
	E3	6	6.48	1.15	5.52	1.72	
	S1	7	5.48	1.50	4.84	1.52	
	E4	8	5.95	1.35	5.27	1.62	
	E5	10	6.43	1.08	5.49	1.64	
	S2	11	5.63	1.42	5.03	1.44	
	S3	13	5.61	1.41	5.09	1.37	
	S4	16	5.51	1.52	5.01	1.40	
	S5	17	5.68	1.36	4.44	1.78	
	S6	18	5.30	1.73	4.68	1.67	
	S7	19	5.57	1.43	4.98	1.52	
	Female	E1	3	6.40	.99	5.94	1.37
		E2	5	6.56	.86	6.08	1.26
E3		6	6.55	.95	5.74	1.65	
S1		7	5.66	1.32	4.84	1.54	
E4		8	6.21	1.12	5.43	1.61	
E5		10	6.48	.96	5.74	1.56	
S2		11	5.72	1.24	5.09	1.40	
S3		13	5.72	1.31	5.09	1.37	
S4		16	5.64	1.36	5.00	1.44	
S5		17	5.78	1.32	4.60	1.76	
S6		18	5.71	1.53	4.79	1.71	
S7		19	5.65	1.42	4.90	1.52	

E1-E5: Ethical and Privacy Expectation Items; S1-S7: Service Feature Expectation Items

Table 5. Descriptive Statistics for Ideal and Predicted Expectation Scales by Level of Study

Level of Study	Factor Key	Item	Ideal Expectation		Predicted Expectation		
			<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	
Undergraduate	E1	3	6.28	1.11	5.80	1.43	
	E2	5	6.53	.87	6.03	1.25	
	E3	6	6.52	1.00	5.66	1.64	
	S1	7	5.71	1.36	4.78	1.54	
	E4	8	6.09	1.25	5.30	1.61	
	E5	10	6.41	1.07	5.63	1.56	
	S2	11	5.72	1.28	4.99	1.43	
	S3	13	5.75	1.36	5.01	1.39	
	S4	16	5.72	1.37	4.94	1.46	
	S5	17	5.84	1.25	4.48	1.82	
	S6	18	5.69	1.56	4.69	1.72	
	S7	19	5.71	1.40	4.88	1.52	
	Masters	E1	3	6.32	1.20	6.16	1.30
		E2	5	6.55	1.05	6.27	1.18
E3		6	6.35	1.34	5.82	1.71	
S1		7	5.74	1.40	5.06	1.60	
E4		8	6.16	1.20	5.74	1.46	
E5		10	6.40	1.18	5.97	1.43	
S2		11	5.89	1.16	5.37	1.35	
S3		13	5.82	1.35	5.53	1.33	
S4		16	5.79	1.44	5.32	1.39	
S5		17	5.94	1.32	5.10	1.70	
S6		18	5.89	1.49	5.16	1.72	
S7		19	5.77	1.37	5.39	1.47	
PhD		E1	3	6.39	1.06	5.88	1.39
		E2	5	6.68	.78	6.03	1.38
	E3	6	6.58	.96	5.62	1.74	
	S1	7	5.34	1.40	4.89	1.49	
	E4	8	6.15	1.15	5.39	1.65	
	E5	10	6.58	.80	5.59	1.70	
	S2	11	5.58	1.39	5.12	1.38	
	S3	13	5.50	1.32	5.11	1.30	
	S4	16	5.31	1.47	5.02	1.36	
	S5	17	5.50	1.45	4.50	1.66	
	S6	18	5.22	1.69	4.74	1.63	
	S7	19	5.41	1.46	4.89	1.53	

E1-E5: Ethical and Privacy Expectation Items; S1-S7: Service Feature Expectation Items

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Table 6. Descriptive Statistics for Ideal and Predicted Expectation Scales

Factor Key	Item	Ideal Expectations			Predicted Expectations		
		<i>M</i>	<i>SD</i>	Skew	<i>M</i>	<i>SD</i>	Skew
E1	1	5.97	1.28	-1.77	5.94	1.20	-1.43
E2	2	6.53	.78	-2.90	6.27	1.08	-2.26
E3	3	6.39	.93	-2.24	5.94	1.37	-1.65
S1	4	5.91	1.22	-1.75	5.05	1.64	-.78
E4	5	5.77	1.33	-1.35	5.19	1.62	-.85
E5	6	6.34	1.06	-2.31	5.84	1.39	-1.45
S2	7	5.80	1.15	-1.40	5.16	1.36	-.81
S3	8	5.91	1.17	-1.50	5.28	1.44	-.78
S4	9	5.92	1.25	-1.50	5.31	1.43	-.86
S5	10	5.86	1.25	-1.87	4.96	1.70	-.73
S6	11	6.04	1.31	-1.87	5.20	1.64	-.82
S7	12	5.95	1.13	-1.48	5.35	1.43	-.98

E1-E5: Ethical and Privacy Expectation Items; S1-S7: Service Feature Expectation Items

Table 7. Standardised and Unstandardised Loadings Obtained from Study Three for Ideal Expectations Confirmatory Factor Analysis

Item	Latent Variable	Unstandardised Loading	Standardised Loading	Standard Error
1	Ethical and Privacy Expectations	1.00	.64	.05
2	Ethical and Privacy Expectations	1.10	.70	.05
3	Ethical and Privacy Expectations	1.13	.72	.05
5	Ethical and Privacy Expectations	1.10	.71	.05
6	Ethical and Privacy Expectations	1.23	.79	.05
4	Service Feature Expectations	1.00	.70	.04
7	Service Feature Expectations	1.20	.84	.03
8	Service Feature Expectations	1.23	.85	.03
9	Service Feature Expectations	1.09	.76	.03
10	Service Feature Expectations	1.19	.83	.03
11	Service Feature Expectations	.95	.66	.04
12	Service Feature Expectations	1.08	.75	.04

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Table 8. Standardised and Unstandardised Loadings Obtained from Study Three for Predicted Expectations Confirmatory Factor Analysis

Item	Latent Variable	Unstandardised Loading	Standardised Loading	Standard Error
1	Ethical and Privacy Expectations	1.00	.76	.04
2	Ethical and Privacy Expectations	.91	.69	.05
3	Ethical and Privacy Expectations	1.02	.78	.04
5	Ethical and Privacy Expectations	1.00	.75	.04
6	Ethical and Privacy Expectations	1.11	.84	.04
4	Service Feature Expectations	1.00	.80	.03
7	Service Feature Expectations	1.05	.84	.03
8	Service Feature Expectations	1.09	.87	.02
9	Service Feature Expectations	.98	.79	.03
10	Service Feature Expectations	1.06	.85	.03
11	Service Feature Expectations	.96	.77	.03
12	Service Feature Expectations	.90	.72	.04

Table 9. Descriptive Statistics for Ideal and Predicted Expectation Scales by Gender

Gender	Factor Key	Item	Ideal Expectation		Predicted Expectation	
			<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Male	E1	1	5.98	1.17	5.89	1.20
	E2	2	6.68	.59	6.26	1.16
	E3	3	6.40	.82	5.81	1.46
	S1	4	5.97	1.23	5.26	1.57
	E4	5	5.77	1.35	5.16	1.71
	E5	6	6.15	1.27	5.58	1.65
	S2	7	5.71	1.18	5.27	1.20
	S3	8	5.87	1.19	5.48	1.30
	S4	9	6.00	1.15	5.53	1.30
	S5	10	5.85	1.35	4.95	1.63
	S6	11	6.03	1.23	5.16	1.60
	S7	12	5.97	1.09	5.42	1.45
Female	E1	1	5.96	1.33	5.96	1.20
	E2	2	6.47	.85	6.27	1.04
	E3	3	6.39	.99	6.01	1.33
	S1	4	5.88	1.22	4.95	1.67
	E4	5	5.77	1.33	5.21	1.58
	E5	6	6.43	.93	5.97	1.24
	S2	7	5.84	1.14	5.10	1.43
	S3	8	5.92	1.17	5.19	1.49
	S4	9	5.88	1.30	5.21	1.48
	S5	10	5.87	1.21	4.97	1.74
	S6	11	6.05	1.35	5.22	1.66
	S7	12	5.95	1.16	5.31	1.42

E1-E5: Ethical and Privacy Expectation Items; S1-S7: Service Feature Expectation Items

Table 10. Descriptive Statistics for Ideal and Predicted Expectation Scales by Level of Study

Level of Study	Factor Key	Item	Ideal Expectation		Predicted Expectation	
			<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Undergraduate	E1	1	5.98	1.28	5.95	1.17
	E2	2	6.54	.78	6.27	1.08
	E3	3	6.39	.94	5.93	1.38
	S1	4	5.90	1.22	5.05	1.63
	E4	5	5.77	1.33	5.19	1.63
	E5	6	6.34	1.06	5.85	1.40
	S2	7	5.80	1.15	5.15	1.36
	S3	8	5.91	1.17	5.28	1.44
	S4	9	5.93	1.25	5.31	1.43
	S5	10	5.85	1.26	4.96	1.69
	S6	11	6.03	1.32	5.21	1.62
	S7	12	5.94	1.14	5.35	1.41
Masters	E1	1	5.33	1.15	5.00	2.65
	E2	2	6.33	.58	6.33	1.15
	E3	3	6.67	.58	6.67	.58
	S1	4	6.67	.58	5.00	2.65
	E4	5	5.67	1.53	5.67	1.53
	E5	6	6.00	1.00	5.67	1.53
	S2	7	5.67	1.53	5.67	1.53
S3	8	5.67	1.53	5.67	1.53	
S4	9	5.67	1.53	5.67	1.53	
S5	10	6.67	.58	5.00	2.65	
S6	11	6.67	.58	4.67	3.21	
S7	12	6.67	.58	5.00	2.65	

E1-E5: Ethical and Privacy Expectation Items; S1-S7: Service Feature Expectation Items