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The Student Expectations of Learning Analytics Questionnaire (SELAQ)

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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.

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

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).

Whilst the need for the early engagement of stakeholders has been specifically highlighted for LA (Drachsler & Greller, 2016; Ferguson et al., 2014), there are limited instances where this is actually happening (Tsai & Gašević, 2017a). Without stakeholder engagement, it is likely that the multitude of LA policies available (Sclater, 2016) are driven primarily by the institutional managers' expectations and beliefs. In those cases, even if the key driver for the intention to adopt LA is to improve learning performance (Tsai & Gašević, 2017b) and to provide additional support to learners (Siemens & Gašević, 2012), that intention is still shaped by the managers' preconceived beliefs and ideas – not necessarily reflective of what other stakeholders (e.g., students) would expect. This may perpetuate an ideological gap (Ng & Forbes, 2009) whereby services reflect a difference between what institutions believe students should receive and what students expect to receive.

LA, by definition, is student-centred (Siemens & Gašević, 2012), but relatively few attempts have been made to explore students' beliefs towards the use of LA (Arnold & Sclater, 2017; Ifenthaler & Schumacher, 2016; Roberts, Howell, Seaman, & Gibson, 2016; Schumacher & Ifenthaler, 2018; Slade & Prinsloo, 2014). As shown in the LA dashboard evaluation work of Park and Jo (2015), students expressed negative opinions towards being provided with visualisations of login frequency metrics, particularly on the basis of them not being pedagogically meaningful. This is concerning, particularly with the attention placed on relaying resource usage statistics (75% of 93 student-facing LA dashboard articles, according to Bodily and Verbert (2017)), as it exemplifies how LA has largely overlooked student expectations. Adding to this is the finding that only 6% of 93 articles that have detailed LA dashboard implementations have explored student expectations of such services (Bodily & Verbert, 2017). Given the importance of actively exploring and gauging stakeholder expectations, particularly with regards to future service satisfaction and usage (Brown, Venkatesh, & Goyal, 2012; Brown et al., 2014), student engagement cannot continue to be at a nominal level. Instead, it is necessary for research to address this gap through the provision of tools that enable Higher Education Institutions to open dialogues with students to understand the LA service they expect.

From those limited investigations with students, findings have shown that whilst students have strong expectations towards the institution's handling of educational data (Roberts et al., 2016; Slade & Prinsloo, 2014) and the LA service features offered (Roberts, Howell, & Seaman, 2017; Schumacher & Ifenthaler, 2018), despite largely being unaware of LA practices (Roberts et al., 2016). In light of such findings, it can be argued that despite student exposure to LA services being limited, they are able to form expectations towards the procedures undertaken and the services offered. Moreover, given the relatively small proportion of LA implementations readily assessing what students expect of such services, there is a need to address this limitation.

As a means to gauge stakeholder expectations of a possible service, Szajna and Scamell (1993) have encouraged the use of psychometric instruments during different stages of implementations. Within the context of LA, a measure is available to assess an institute's readiness for LA (Oster, Lonn, Pistilli, & Brown, 2016), but no pre-existing scale is available to gauge student expectations of LA services. Even though Arnold and Sclater (2017) used a survey to understand student perceptions of data handling, their reported findings can be questioned on the basis of using an on the fly scale. Schumacher and Ifenthaler (2018) do, however, present an exploration of expected LA dashboard features from the perspective of students. While these authors ground this work in expectations, the distinction between expectations and perceptions is not completely conceptualised. As a great majority of the student population is unlikely to have experienced institutional LA services, measures of experience (perceptions) (Parasuraman, Zeithaml, & Berry, 1988) are not always appropriate, particularly given that majority of students are not acquainted with LA services (Roberts et al., 2016). Expectations, however, can be measured prior to implementations and are an important determinant in the acceptance of systems (Davis & Venkatesh, 2004).

As indicated above, whilst the importance of systematically gathering university students' expectations about LA is of paramount importance for the success of the service, little has been done in this regard and no adequate tool is still available. In the present research, we have attempted to close this gap by developing and validating a descriptive questionnaire to collect students' expectations of LA services. Throughout the development of this instrument, the accessibility and understanding of the items from the student perspective were always considered. Put differently, while students are largely unaware of LA services, the phrasing of each item had to be balanced between providing an institution with an informative understanding of what students expect, but also general enough for all students to understand. In doing so, the university can identify particular areas of focus for their LA implementation, which can then inform direct engagement strategies with their students.

1.1. Expectations as Beliefs

A widely utilised definition of belief presents it as "the subjective probability of a relation between the object of the belief and some other object, value, concept, or attribute” (Fishbein & Ajzen, 1975, p. 131). For example, a student may hold a belief that they themselves have the knowledge and skills required to attain a good grade. An expectation, on the other hand, can be defined as “the perceived likelihood that a product possesses a certain characteristic or attribute, or will lead to a particular event or outcome” (Olson & Dover, 1976, p. 169). An example of this would be a judgement of whether a future LA service will enable users to receive a full breakdown of their learning progress. Taking both aforementioned terms into consideration, the only discernible difference is the point in time at which the judgement relates to; i.e., expectations are framed as beliefs about the future (Olson & Dover, 1976).

Expectations are an important feature of human cognition (Roese & Sherman, 2007). From the behaviours an individual enacts to the motivation they exert, there is an underlying influence of how they expect to manage within a particular setting (Bandura, 1977, 1982; Elliot & Church, 1997). In relation to the judgements we form, our expectations are an anchor to which we compare our actual experiences (Christiaens, Verhaeghe, & Bracke, 2008; Festinger, 1957). As a term, however, an expectation is quite ambiguous, particularly in light of the decomposition presented by Thompson and Suñol (1995). For these authors, expectations can broke down into four subtypes: ideal, predicted, normative, and unformed (Thompson & Suñol, 1995). An *ideal* expectation refers to a desired outcome, or what an individual hopes for in a service (Leung, Silvius, Pimlott, Dalziel, & Drummond, 2009); whereas a *predicted* expectation is a realistic belief, an individual’s view of the service they believe is the most likely to receive. Evidence does support the view that predicted and ideal expectations are two different subtypes (Askari, Liss, Erchull, Staebell, & Axelson, 2010; David, Montgomery, Stan, DiLorenzo, & Erblich, 2004; Dowling &

Rickwood, 2016). The two remaining expectation subtypes relate to what service users believe they deserve from a service (*normative* expectation) and the circumstances where they are unable to form a set of expectations (*unformed* expectations).

The importance of focusing on service user expectations has been demonstrated in both health services (Bowling et al., 2012; Thompson & Suñol, 1995) and technology adoption research (Brown et al., 2012, 2014; Davis & Venkatesh, 2004). In the case of Bowling et al., these researchers explored patients' ideal and predicted expectations as it allowed for both an upper and lower reference point with regards to knowing what service elements to focus on. Put differently, the responses present an idealised perspective of a service, but also a realistic profile of what users believe is most likely. This approach would be advantageous for LA service implementation decisions as it can differentiate between what features students would like, but what should be a priority (i.e., what is realistically expected). In addition to providing a deeper understanding of stakeholder perspectives, both research streams have shown that failure to gauge user expectations can lead to dissatisfaction and low adoption of the implemented service (Bowling et al., 2012; Brown et al., 2012, 2014; Davis & Venkatesh, 2004). Thus, by measuring stakeholder expectations towards a service early on in the service implementation process, the provider can proactively identify main areas of focus and manage expectations.

Together, these abovementioned theoretical concepts and considerations outlined constitute our reference framework. For the present work, an expectation is defined as a belief about the likelihood that future implementation and running of LA services will possess certain features. Also, our approach is based on the need to 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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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).

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 data handling processes. In their interviews with students, Slade and Prinsloo (2014) found a clear expectation that the institution should seek informed consent, or at least permit opting out, when it comes to an LA process. Similar remarks were also expressed in the work of Roberts et al. (2016), who found students to expect the university to respect privacy, seek informed consent, and to be transparent at all times. Finally, the work of Ifenthaler and Schumacher (2016) showed that whilst students were against the processing of identifiable data, they were open to data pertaining to their studies being used.

From each of these aforementioned studies, it is clear that students have strong expectations regarding their privacy and being able to make independent decisions about how their data is used (Ifenthaler & Schumacher, 2016; Roberts et al., 2016; Sharon Slade & Prinsloo, 2014). More importantly, each of these authors stress the importance of the university actively engaging students in LA service implementation decisions. Thus, based on these two points, the theme of *Ethical and Privacy Expectations* was decided upon, which was considered to cover elements of data security and consent.

2.1.2. Agency Expectations

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

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

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

2.1.3. Intervention Expectations

The anticipated output following the collection and analysis of student data is the introduction of a service designed to optimise both student learning and the learning environment (Siemens & Gašević, 2012). Despite this aim to support students, there have been few attempts to know what LA services features students want (e.g., 6% of LA dashboard research undertook a needs assessment; Bodily & Verbert, 2017). As stressed in the work of Schumacher and Ifenthaler (2018), student expectations of LA service features should be considered prior to any implementation. Thus, as with any technology implementation (Brown et al., 2012, 2014; Davis & Venkatesh, 2004), steps should be taken to understand what is expected from the main stakeholders to ensure future acceptance.

Types of LA services offered in the literature vary with respect to the educational problem they seek to resolve. A common service implementation has been the identification of students who are underperforming or at-risk (Campbell, DeBlois, & Oblinger, 2007). In undertaking this pursuit there is a belief that interventions can be actioned to mitigate the possibility of the student dropping out (Gašević, Dawson, Rogers, & Gašević, 2016), although this may not always be the case (Dawson, Jovanovic, Gašević, & Pardo, 2017). Other approaches have moved away from building predictive models to identify at risk students; instead, focusing on the development of systems aimed at improving the student-teacher relationship (Liu, Bartimote-Aufflick, Pardo, & Bridgeman, 2017) or presenting graphical overviews of learner behaviour (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013). In all cases, the services are designed to with a view to improve education for students, but there is a prevailing absence of researchers gauging what students expect of these services.

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

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

2.1.4. Meaningfulness Expectations

Closely entwined with both *Agency* and *Intervention Expectations* is the theme of *Meaningfulness Expectations*. Whilst *Agency Expectations* captures the importance of students being independent learners and *Intervention Expectations* refer to the LA service features, *Meaningfulness Expectations* relates to the utility of information fed back to students. More specifically, *Meaningfulness Expectations* are associated with the student perspectives towards the information conveyed in LA service features and whether this has any meaning for their learning.

Introducing new forms of feedback as a result of implementing LA services should, theoretically, promote positive changes in student behaviour such as motivating learning (Park & Jo, 2015; Verbert et al., 2013). However, if meaningful inferences about learning progress cannot be drawn from the information received through LA services (i.e., how visual representations of performance relates to personal learning goals), then it is unlikely to be incorporated into any decisions made (Wise et al., 2016). An example of information that was found to not be meaningful for students was the provision of login metrics in Park and Jo's (2015) LA dashboard, which was perceived as being unhelpful for the purposes of reflecting upon their learning. In other words, whilst resource use metrics continue to be used in LA service implementations (e.g., 75% of LA dashboards; Bodily & Verbert, 2017), their utility, from the perspective of students, can be questioned.

It has been shown that usefulness expectations are an important determinant in the future success of a technology (Brown et al., 2014). This is also true of LA services, where beliefs towards the utility of certain features (e.g., visualisations and the level of detail provided) affect adoption rates (Ali, Asadi, Gašević, Jovanović, & Hatala, 2013). Together, this does reinforce the importance of gauging what stakeholders in a service want, with a focus on the type of information and its relevance to learning.

The challenge for LA to provide information that is pedagogically meaningful is not a recent concern (Gašević et al., 2015; Macfadyen & Dawson, 2010; Tsai & Gašević, 2017a). In particular Gašević et al. (2015) warn against the use of trivial measures in LA service implementations on the basis that it will not promote effective learning. Taking what is known in relation to self-regulated learning theory, students do utilise various information that are fed back to understand how their learning is progressing towards set goals (Winne & Hadwin, 2012). Having simple performance metrics are unlikely to meet the necessary conditions to facilitate self-regulatory behaviour (Ali, Hatala, Gašević, & Jovanović, 2012; Gašević et al., 2015), which are to be constructive, promote higher order thinking, and allow students to bridge the gap between the current and desired level of performance (Nicol & Macfarlane-Dick, 2006).Therefore, for the information presented through LA services to become more informative, there is a need to both ground the approach within necessary educational frameworks, but also understand what information stakeholders need (Gašević et al., 2015). The *Meaningfulness Expectations* attempts to meet these recommendations by exploring what forms of information are expected from one of the main stakeholders.

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

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

As students were unlikely to be aware of LA and what it entails, an introduction to the survey was created (Appendix 1). The contents of this introduction outlines to students the various sources of educational data used in LA services such as that extracted from the virtual learning environment. In addition, examples of possible LA service implementations are provided (e.g., the creation of early alert systems). This information provided was peer reviewed by LA experts in order to assess whether the scope of LA services was suitable and whether the concept of LA services can be easily understood. Moreover, the information contained in this introduction was influenced by both the LA definition (Siemens & Gašević, 2012) and the commonly used data types in LA studies (Gašević et al., 2016). Ethics approval was obtained for data collection at the University of Edinburgh and the University of Liverpool.

2.2. Sample

Total of 210 student respondents (Females = 131; M_{age} = 24 years, SD = 6.12) out of a possible 448 students (47% response rate) from the University of Edinburgh completed the 37-item pilot survey (Appendix 3), which was distributed through an online survey system. This was a self-selecting sample of students from across the University who have agreed to be contacted for research purposes in return for monetary reward on a task by task basis. This sample is broadly representative of the student population (Undergraduate/Postgraduate Taught (UG/PGT), UK (United Kingdom) vs Non-UK, Age/Gender).

2.3. Statistical Analysis

All raw data was analysed using R version 3.4 and the psych package (R Core Team, 2017; Revelle, 2017). The predicted and ideal expectation scales were analysed separately. If items were removed from one scale (e.g., the predicted expectation scale), the corresponding item was removed from the other scale (i.e., the ideal expectation scale). The analysis steps were to first run Bartlett's test (1951) to assess whether a factor analysis was appropriate. The Kaiser-Meyer-Olkin (KMO) index (Kaiser, 1974) was then calculated to further check whether the data is adequate for a factor analysis. The determinant of the correlation matrix was also calculated to assess for any multicollinearity problems (Field, Miles, & Field, 2012). Following these scale purification steps, an exploratory factor analysis using 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.

Each item in the instrument also contained an open textbox to allow respondents to provide qualitative comments on each item. Respondents were prompted to leave feedback about the clarity and understanding of each item. Thus, by obtaining both quantitative and qualitative data from the instrument it allowed the researchers to refine items using the scale purification techniques and to re-word certain items on the basis of student feedback.

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 qreater than or equal to .75, which was above the acceptable limit of .50. Bartlett's test of sphericity, χ^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 α = .88, whilst for *Ethical and Privacy Expectations* Cronbach's α = .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 was found to be .91 (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, χ^2 (171) = 1631, 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 factors. The two factor solution was deemed sufficient, it accounted for 44% of the variance in the data, and the correlation between the factors was r = .41. Factor one represented *Service Feature Expectations* (items: 1, 9, 13, 18, 20, 22, 26, 30, 31, and 33; Appendix 5), whilst factor two related to *Ethical and Privacy Expectations* (items: 5, 6, 10, 11, 14, 15, 17, 19, and 21; Appendix 5). Both subscales had high reliabilities, for *Service Feature Expectations* Cronbach's α = .88, whilst for *Ethical and Privacy Expectations* Cronbach's α = .86.

2.5. **Discussion**

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

Even though four expectation themes were identified from the literature, they are captured by this two-factor solution. The *Service Feature Expectation* factor covers items relating to whether students believe they should responsibility to make sense of their own data (item 18; Appendix 3) and whether teaching staff are obliged to act 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 students, 62 (9%) were masters students, and 216 were PhD students (32%). Total of 475 (70%) respondents identified themselves as ‘Home/EU Students’, and 199 (30%) identified themselves as ‘Overseas Students’.

3.2. **Questionnaire**

Following the pilot study, the 37-item questionnaire was reduced to 19-items (Appendix 6). The comments left by respondents in the pilot study were used to modify items in order to make them clearer (details of how item wordings were changed are presented in Appendix 6). The remaining 19-items (Appendix 6) were also reviewed by an LA expert in order to identify any wording issues. As in the pilot study, each item contained two scales corresponding to ideal (Ideally, I would like that happen) and predicted (In reality, I would expect that to happen) expectations. Responses again were made on a 7-point Likert-type scale, ranging from 1 = “Strongly Disagree” to 7 = “Strongly Agree”.

3.3. **Statistical Analysis**

Qualitative comments from the pilot study were used in conjunction with a further peer review of the 19-items to clarify and re-write particular items (Appendix 6). An example of this was item 1 from the 19-item questionnaire (The university will provide me with guidance on how to access the analysis of my educational data). Within the 37-item questionnaire, this item (item 1) referred to whether the university is expected to instruct students on how frequently they should access educational data (The university will provide me with guidance on when and how often I should consult the analysis of my educational data). Feedback on this question showed that it would not be for an institution to decide how frequently educational data analyses should be consulted. A more appropriate alternative, which aligns with LA services being transparent (Sclater, 2016), would be an item on universities clearly telling students how to find any analyses of their educational data.

Similarly, for item 2 of the 19-item questionnaire (The university will explain all the learning analytics service processes as clearly as possible (e.g., how my educational data is collected, analysed, and used)), this was a slight amendment of item 5 from the 37-item questionnaire (The university will explain all analytic processes as clearly as possible (e.g., how my educational data is collected, analysed, and used)). Within the 37-item version, this item was not connected well with the overall aim of the questionnaire, which was to explore expectations of LA services, which go beyond analytics. Therefore, to make this a more inclusive item that refers to any possible processes involved, the item now refers to LA services in general.

Due to the various amendments to the questionnaire items, it was decided that exploratory factor analysis would again be used in a follow-up sample. This is because subtle changes in the item wordings could lead to different interpretations or model outcomes. What is more, as the pilot study only had 210 respondents, which falls short of what has been recommended as a good sample size (300 according to Comrey and Lee (1992)). Therefore, for the main study the recommended sample sizes proposed by Comrey and Lee (1992), which suggests at least 500 respondents should be used whenever possible. Given the high number of low communalities (below .50) found with the pilot study exploratory factor analysis, it further reinforced the need to re-run the exploratory factor analysis with the data obtained from the larger sample of students in study two (MacCallum, Widaman, Zhang, & Hong, 1999).

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, χ^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 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 α = .90, whilst for *Ethical and Privacy Expectations* Cronbach's α = .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, χ^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, 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 α = .90, whilst for *Ethical and Privacy Expectations* Cronbach's α = .88.

Insert Table 2 About Here

3.5. **Descriptive Statistics**

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

Insert Table 3 About Here

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 shows a clear relation to the theme of *Ethical and Privacy Expectations*. Items 4 and 8 (Appendix 7) are concerned with students expecting to receive regular updates on their learning progression (*Intervention Expectations*) and whether LA feedback will relate progress to set goals (*Meaningfulness Expectations*), respectively. Whereas, *Agency Expectations* are captured by items 7 and 11 (Appendix 7), which correspond to students expecting to make their own decisions based on LA feedback and whether teaching staff are obliged to act on the evidence of a student underperforming.

The descriptive statistics provide a general insight into student expectations of LA services (Table 3; the item numbers refer to Appendix 6). As anticipated, responses to the ideal expectations scale demonstrated a ceiling effect. Due to this scale corresponding to what students would hope for in a service, responses are likely to be unrealistically high. Responses to what students expected to happen in reality (predicted expectations), however, were lower than ideal expectation responses. This distinction between ideal and predicted expectation responses adds validity to the measure, as the results are supportive of two levels of belief. In addition to providing descriptive statistics for each item, the mean and standard deviations for each item by gender (Table 4) and level of study (Table 5) are also provided.

Comparing the *Ethical and Privacy Expectations* and *Service Feature Expectations* factor responses on both the ideal and predicted scales does suggest that beliefs towards the ethical procedures involved in LA service implementations are of greater importance. This is based on the range of average responses across ideal and predicted expectation scales being greater for *Ethical and Privacy Expectation* items than *Service Feature Expectation* items (Table 3). A tentative conclusion that can be drawn from this is that students do hold stronger beliefs about ethical procedures involved in LA service implementations. Thus, in line with the findings of Slade and Prinsloo (2014), it appears that students do place considerable importance on how a university handles their educational data, particularly with regards to controlling who access to any data and whether consent is required. Whilst in the case of *Service Feature Expectations*, students may desire such features (e.g., being able to compare current progress to learning goals), but the importance of such services are not comparable with the ethical procedures of LA services.

For the *Ethical and Privacy Expectations* factor, the item with both the highest mean response across ideal (M = 6.58, SD = .86; Table 3) and predicted (M = 6.05, SD = 1.28; Table 3) expectations was item 5 (The university will ensure that all my educational data will be kept securely; Appendix 6). Slade and Prinsloo (2014) summarise student beliefs toward the data collection procedures, with views centring on who has access to collected educational data and how data is handled. Thus, the current finding that students expect institutions to securely hold all collected educational data does substantiate the student beliefs outlined by Slade and Prinsloo. More importantly, it demonstrates that students hold strong beliefs toward the security and handling of their educational data. This finding can then be used by an institution to inform their data handling policies of LA services, as students want to be reassured that their data is secure and private so the institution needs to determine how such expectations can be effectively met.

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

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

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

4. Study Three

4.1. Sample

The 12-item SELAQ (Appendix 7) was distributed to students at the University of Liverpool through an online survey system. The 12 items were identified as per 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 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 high standardised loadings (around .80) fit index values that are suggestive of poor fit (McNeish, An, & Hancock, 2018). Thus, while alternative fit indices are reported, this is supplemented by an assessment of measurement quality, which involves the presentation of standardised loadings and composite reliability (Raykov, 1997).

With regards to the X^2 test of exact fit, Ropovik (2015) does note that it is unrealistic for many applications, but it should not be universally dismissed. If the X^2 test is found to be significant, this may then point to possible model misspecifications, which can be examined through an assessment of local fit (Ropovik, 2015). Of the various approaches to assessing local fit, the current study will explore modification indices and standardised expected parameter change values, along with an inspection of correlation residuals. Modification index (MI) values exceeding 3.84 (Brown, 2015), with standardised expected parameter change (SEPC) values ≥ .10 (Saris, Satorra, & Veld, 2009), point to possible respecifications that could improve the model fit. Whereas, for absolute correlation residuals, values ≥ .10 are believed to be indicative of sources of misfit between the model and data (Kline, 2015). It is important to remain mindful that engaging in data driven model modifications could be entirely based on chance (MacCallum, Roznowski, & Necowitz, 1992). To address the issue of capitalising on chance, MacCallum et al. (1992) recommend that any modifications to a model be cross-validated in a second sample. Given that the current sample is small (n = 191), the splitting the sample for the purposes of model cross-validation is not advisable. Therefore, if problems in the model are identified we recommend that future research is conducted in order to assess whether these issues are found in independent samples, but also whether any modifications can be cross-validated.

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 (X^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 (X^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 factor and .60 for the *Service Feature Expectations* factor) exceeds the square of the correlation between the two factors (.32; Fornell & Larcker, 1981). In terms of composite reliability, estimates are high for the ideal expectation scale (.94) and both subscales (.84 and .91 for the *Ethical and Privacy Expectations* and *Service Feature Expectations* factors, respectively).

As the X^2 test was found to be significant, it is important to inspect the local fit of the model in order to identify any sources of misfit. MI and SEPC values point to three possible changes to the model that could improve the overall fit. More specifically, these values suggest that freely estimating correlated errors between: item 1 and item 2 (MI = 11.28, SEPC = .36), item 2 and item 5 (MI = 20.51, SEPC = -.54), and item 11 and item 12 (MI = 14.62, SEPC = .44). From the correlation residual matrix (Appendix 9), there are nine instances of absolute values being ≥ .10. In line with the MI and SEPC values, the largest correlation residuals are between item 1 and item 2 (.14), item 2 and item 5 (-.19), and item 11 and item 12 (.17).

Insert Table 7 About Here

Predicted Expectation Scale. Compared to the ideal expectation scale, the two-factor model was found to have an acceptable fit using the confirmatory factor analysis approach (X^2(53, n = 191) = 143.92, p < .001, RMSEA = .10 (90% CI .08, .11), CFI = .96, TLI = .95). In comparison, the exploratory structural equation model approach achieved a marginally better fit to the data (X^2(43, n = 191) = 119.53, p < .001, RMSEA = .10 (90% CI .08, .12), CFI = .97, TLI = .95; factor loadings are presented in Appendix 10). As with the ideal expectation scale analysis, the confirmatory factor analysis results will be reported due to being more parsimonious.

The unstandardised and standardised estimates of the two-factor solution are found in Table 8. The unstandardised estimates were all statistically significant (*ps* < .001), with a mean standardised loading of .79. Estimates of factor loadings showed the factors to explain a moderate to large proportion of the latent continuous response variance (R^2 range = .47 - .76). The two factors of *Ethical and Privacy Expectations* and *Service Feature Expectations* were found to strongly correlate with one another (.63), 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 (.58 for the *Ethical and Privacy Expectations* factor and .65 for the *Service Feature Expectations* factor) exceeds the square of the correlation between the two factors (.40; Fornell & Larcker, 1981). The composite reliability estimate for the predicted expectation scale was high (.95) and the estimates for both subscales were also high (.87 and .93 for the *Ethical and Privacy Expectations* and *Service Feature Expectations* factors, respectively).

As with the ideal expectation scale, the significant X^2 test means that an inspection of local misfit within the model is warranted. From the MI and SEPC values, there are three suggested modifications that can be made to model, which are similar to the ideal expectation scale. These modifications involve freely estimating correlated errors between item 2 and item 3 (MI = 10.35, SEPC = .36), item 2 and item 5 (MI = 10.09, SEPC = -.34), and item 11 and item 12 (MI = 13.84, SEPC = .42). The correlation residual matrix (Appendix 11) shows that there are ten absolute values that are ≥ .10. In line with the MI and SEPC values, the largest correlation residuals are between item 2 and item 3 (.12), item 2 and item 5 (-.12), 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 predicted expectations; Table 6). This was not the case for item 5 (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)) from the *Ethical and Privacy Expectation* factor, which appeared to not elicit a strong response from students for either ideal (*M* = 5.77, *SD* = 1.33; Table 6) or predicted (*M* = 5.19, *SD* = 1.62; Table 6) expectations. As with study two, the *Ethical and Privacy Expectation* item with the highest average response for both ideal (*M* = 6.53, *SD* = .78; Table 6) and predicted (*M* = 6.27, *SD* = 1.08; Table 6) expectations was item 2 (The university will ensure that all my educational data will be kept securely).

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 were marginal and the confirmatory factor analysis model was more parsimonious (Marsh et al., 2014). Even though the confirmatory factor analysis model results were presented, it is important to note that the exploratory structural equation model for both scales (ideal and predicted expectations) showed small, yet non-zero, cross-loadings (Appendices 8 and 10). This is important as it provides greater knowledge about the model that can be considered in future analyses.

For both scales (ideal and predicted expectations), the alternative fit indices from the confirmatory factor analyses do suggest that the model provides an acceptable fit to the data. Based on the recommendations of McNeish et al. (2018), standardised loadings and composite reliability estimates were provided in order to provide an assessment of measurement quality. The mean standardised loadings are high, with individual item loadings ranging from .64 to .85 for the ideal expectation scale and from .69 to .89 for the predicted expectation scale. With regards to reliability, both scales were found to have high reliability estimates (.94 and .95 for the ideal and predicted expectation scales, respectively). Together, this provides the necessary context for the interpretation of alternative fit indices such as the RMSEA. Put differently, whilst the RMSEA may not be in line with the cut-off proposed by Hu and Bentler (1999) (i.e., RMSEA values close to or below .06), its function varies in accordance with measurement quality (McNeish et al., 2018). In addition, these recommended cut-off values are based on continuous data analysed using the maximum likelihood estimator; thus, their applicability to ordinal data analysed using ULSMV can be questioned (Xia, 2016).

While the measurement quality of both scales (ideal and predicted expectations) was good and the alternative fit indices show the fit to be acceptable, the X^2 test was found to be significant (p < .05). Following the recommendations set out by Ropovik (2015), the local fit of the model was assessed by examining both MI and SEPC values, along with correlation residuals. This assessment did lead to the identification of possible localised strains within the model, with misfits being found between item 2 and item 5 and item 11 and item 12 on both scales (ideal and predicted expectations). For items 2 and 5, their content relates to the university ensuring all data is kept securely and obtaining consent before engaging in any analysis of data, respectively. Based on the content of these two items, there is some degree of overlap, as the student consenting to allow the university to collect and analyse collected data will be tied to their beliefs regarding data security. However, this does not provide substantial justification for a respecification of the model that allows the errors between items 2 and 5 to correlate. As for items 11 and 12, the content is focused upon beliefs towards the implementation of early intervention systems (item 11) and using LA services to develop academic/employability skills (item 12). Thus, from a content perspective there is no overlap, which again means that the respecification of the model by allowing the errors of items 11 and 12 cannot be justified.

For the ideal expectation scale, there was a further source of misfit between items 1 and 2. These items refer to beliefs about the provision of consent towards the collection of identifiable data and ensuring all collected data remain secure, respectively. Whereas, for the predicted expectation scale there was an additional source of misfit between items 2 and 3. These correspond to beliefs about data security and providing consent before data is outsourced to third party companies, respectively. Taking both sources of misfit (between item 1 and 2 for the ideal expectation scale and item 2 and 3 for the predicted expectation scale) into consideration, it is clear that while they all relate to data security procedures, there is no substantial justification for allowing these errors between these items to correlate.

Even though an assessment of local strains within the model did identify possible modifications, any respecification could be capitalising on chance variation (MacCallum et al., 1992). Ideally, the approach of splitting the sample so that modifications can be cross-validated would be undertaken (MacCallum et al., 1992); however, given the current sample size (n = 191) this was not permissible. Nevertheless, the identification of localised areas of strain in this study provides future researchers with an understanding of where local misfits within the purported two-factor structure may lie. In addition, the identification of local misfit, along with the small non-zero cross loadings found in the exploratory structural equation model (Appendices 8 and 10), provides evidence about the measurement model that can be taken into account in future work.

Taking the abovementioned points into consideration, the two-factor structure of *Ethical and Privacy Expectations* and *Service Feature Expectations* was found to have an acceptable fit on the basis of alternative fit indices. In addition, as assessment of measurement quality shows that the standardised loadings for each scale (ideal and predicted expectations) are strong and the reliability is good. However, the X^2 test was significant and an inspection of localised areas of strain did identify some issues with the model that require further investigation. The next steps are for researchers to continue to assess the two scales of the SELAQ using larger sample sizes, with a view of determining whether there are justifiable modifications that can improve the overall fit.

The descriptive statistics are similar to what was found in study two, with average responses being higher for the ideal than the predicted expectation scale, again supporting the validity of the SELAQ in differentiating between two levels of beliefs. Similarly, inspection of the mean values for both expectation scales (ideal and predicted) are indicative of *Ethical and Privacy Expectations* being stronger than *Service Feature Expectations*. It may be that whilst the prospect of LA services providing features designed to enhance the learning process would address the educational needs of students (e.g., providing a student with regular updates on their learning), they are outweighed by students' need of a service that is ethical. The findings of Roberts et al. (2016) show that whilst students expressed positive attitudes toward LA services keeping them informed, they were concerned about the possible invasion of their privacy. In other words, students place greater weight on universities upholding ethical practices as opposed to wanting the introduction of LA service features designed to support learning.

These aforementioned points, however, do not apply to item 5 (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)), which is the lowest *Ethical and Privacy Expectation* item on both scales (ideal and predicted). The highest average response on the *Ethical and Privacy Expectation* subscale for study three, as found with study two, was for item 2 (The university will ensure that all my educational data will be kept securely) for both ideal and predicted expectations. Thus, student beliefs toward the provision of consent before the university collect educational data may not be as strong as their expectations toward any data collected remaining secure. This resonates with what Roberts et al. (2016) identified as a pertinent concern raised by students, which was the university ensuring that all data remain private. Similarly, Prinsloo and Slade (2016) state that a Higher Education Institute's power to collect and analyse data ultimately increases their burden of responsibility to ensure security. Taken together, it can be argued that students may recognise that collection of student data is routinely undertaken by universities, it nevertheless places a burden of responsibility on these universities to ensure that all data remains private.

For the *Service Feature Expectation* items, the highest average response was 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) on the ideal expectation. However, on the predicted expectation scale, the highest average response was for 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). These two items are different to the highest average response items found in study two, which showed students to have strong ideal expectations towards teaching staff incorporating LA into their feedback (item 10). For predicted expectations, however, study two students showed stronger realistic beliefs toward receiving feedback comparing their progress to a set goal (item 8). Compared to the study two students, it appears that students in study three would like the LA service to incorporate early alert systems, but expect the service to be tailored towards the development of academic or professional skills.

Based on the results of study three, the purported two-factor structure (*Ethical and Privacy Expectations* and *Service Feature Expectations*) of the SELAQ showed acceptable fit (based on alternative fit indices). In addition, the two scales (ideal and predicted expectations) were found to have good measurement quality in terms of 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 descriptive12-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

Service Feature Expectations. The view is that the measurements obtained can then direct more specific engagements with students at different intervals throughout the implementation process, with a view of managing expectations and identifying main areas of focus for the LA service.

The *Ethical and Privacy Expectations* factor (items 1, 2, 3, 5, and 6; Appendix 7) strongly relates to the identified theme *Ethical and Privacy Expectations*. Items 1, 3, 5, and 6 refer to expectations towards the provision of consent for universities to use identifiable data (e.g., ethnicity, age, and gender), to outsource data to third party companies, to collect and use any educational data (e.g., grades, virtual learning environment accesses, or attendance), and to use data for purposes beyond what was originally stated, respectively. Item 2, however, refers to the belief that universities should keep data secure. These items are well supported by the LA literature, particularly in the work carried out by Slade and Prinsloo (2014) who found students expected universities to require informed consent and to maintain privacy at all times. They also add weight to the work of Ifenthaler and Schumacher (2016), as these items are centred on beliefs towards the control students have over their data.

Expectation items relating to opting-out (item 9; Appendix 6) and transparency (item 2; Appendix 6) were not retained in the final 12-item instrument. The omission of an opt-out item may be based upon students holding stronger expectations towards their right to decide whether an institution uses their educational data from the outset. In order to make such a decision, the institution would also have to provide details on their proposed uses of such data. The act of obtaining informed consent can then also be thought of as intrinsically covering the responsibility of being transparent (Sclater, 2016).

With informed consent items being retained for identifiable and educational data usage, it does identify a gap with the opinions offered by experts (Sclater, 2016) who believe consent should only be sought for interventions to offset any likelihood of burdening students with documents. This is an example of an ideological gap, as we have shown that the ethical expectations held by students are concerned with having the right to consent to any processes involved in a LA service. Our findings do not advocate institutions undertaking an approach that overloads the student population with requests for consent, rather students should be directly involved in policy developments to offset any risks services that are not reflective of student expectations.

In addition, an inspection of the descriptive statistics obtained from study two and three does provide further details regarding students' *Ethical and Privacy Expectations*. For both samples, it was found that the highest average response across each scale (ideal and predicted) was for the expectation toward the university ensuring all collected data is kept secure (item 2; Appendix 7). Thus, these students expect the university to be responsible for upholding the security of any data collected (Prinsloo & Slade, 2016), which may emanate from concerns about who has access to their data (Roberts et al., 2016). From a policy perspective, these findings together suggest that a university must provide easily accessible information regarding data handling processes. More specifically, students should be informed as to how the university will securely hold all collected data and prevent disclosure of such information to unauthorised third parties.

The *Service Feature Expectations* factor (items 4, 7, 8, 9, 10, 11, and 12; Appendix 7) does overlap with the identified themes of *Agency, Intervention, and Meaningfulness Expectations*. As stipulated in the introduction, these themes were not assumed to be orthogonal from one another; rather, they were presented as a means of collating the various research streams and discussions in LA. Item 8 (Appendix 7) refers to the expectation that the LA service should be aimed at updating students on how their progress compares to goals set, which is an example of the *Meaningfulness Expectations* theme. Items 7 and 11 (Appendix 7) are concerned with students expecting to make their own decisions based on the feedback from LA services and whether teaching staff are obligated to act if students are underperforming or at-risk, respectively. Together, these two beliefs address the *Agency Expectations* theme. Finally, items 4, 9, 10, and 12 (Appendix 7) correspond to students expecting regular updates on their learning progress, a complete profile of the learning, teaching staff using LA in their feedback, and LA services being designed to improve skill development, respectively. These beliefs all refer to what students expect to receive from LA services, which relates to the *Intervention Expectations* theme.

As stated, the *Meaningfulness Expectations* theme is captured by item 8 (Appendix 7). This refers to the expectation toward receiving feedback that shows how a student's learning is progressing in relation to a set goal, which has been expressed by students in the work of Schumacher and Ifenthaler (2018). Likewise, Roberts, Howell, and Seaman (2017) found students expected LA service features to convey information that is meaningful (e.g., learning opportunities). A possible reason for students expecting LA services to display information such as progress towards a goal does relate to self-regulated learning. As Winne and Hadwin (2012) state, being able to identify discrepancies between performance and goals set enables learners to regulate their own learning (e.g., adopt an alternative learning strategy). Whereas, feeding information back to students that is not pedagogically meaningful (e.g., number of access times to a virtual learning environment) is unlikely to motivate positive changes in learner behaviour (Gašević et al., 2015; Wise et al., 2016). Thus, whilst a university may view the provision of more feedback to students as being advantageous, it may not necessarily reflect what students want, which is feedback that is pedagogically meaningful.

The results of the studies presented in the paper closely align with the discussions related to the moral considerations of whether teaching staff are obligated to act (Prinsloo & Slade, 2017). According to Prinsloo and Slade, whilst institutions should take action when problems are identified, the student still shares a responsibility for their own learning. This acknowledges the fact that students are active agents who metacognitively monitor their progress towards a set goal (Gašević et al., 2015; Winne & Hadwin, 2012), and it is not for LA services to create a culture of passivity (Kruse & Pongsajapan, 2012). These concerns have been voiced by students in the work of Roberts et al. (2016). More specifically, students expressed apprehension toward LA services that would remove the ability to engage in self-directed learning (Roberts et al., 2016). This again illustrates the importance of gauging student expectations towards elements of the LA service. Whilst institutions may view LA favourably on the basis of instructors being able to provide timely support to students (Pardo & Siemens, 2014), students may consider such systems as a hindrance to independent learning (Roberts et al., 2016). The items of the SELAQ capture this balance between students making their own decisions on the basis of the LA feedback (item 7; Appendix 7) and institutions being obligated to act (item 11; Appendix 7), which together reflect the theme of *Agency Expectations*.

The *Intervention Expectations* theme centres on the beliefs students hold regarding the LA service they receive in exchange for the disclosure of data. While there have been advances in introducing new forms of feedback (Verbert et al., 2013), developing ways of improving the student-teacher relationship (Liu et al., 2017), and offering ways to improve retention (Campbell et al., 2007), little has been done to ask what students expect institutions to do with their collected data (Arnold & Sclater, 2017; Schumacher & Ifenthaler, 2018). Put differently, there have been few instances of students being engaged within the development and implementation of LA service features. Of those instances where students have been engaged, it has been found that students want profiles of their learning, updates on their learning progress, and features designed to promote academic skill development (Roberts et al., 2017; Schumacher & Ifenthaler, 2018). These expectations are captured by the retained items of the SELAQ (items 4, 9, and 12; Appendix 7), in addition to an expectation pertaining to teaching staff incorporating LA into their own feedback (item 10; Appendix 7). Together, these items both represent the *Intervention Expectations* theme and provide an indication of the LA service features students expect.

From the descriptive statistics obtained in studies two and three that refer to the *Service Feature Expectations* factor, a general understanding of the LA service features students expect does emerge. Moreover, focusing on those items with the highest average responses may be indicative of student expectations of LA services not being homogenous. In study two, the highest average response for the desired expectation scale was for teaching staff to incorporate LA into their feedback (item 10; Appendix 7). Whilst on the predicted expectation scale, the highest average response was for feedback showing how their progress compares to a set goal (item 8; Appendix 7). For these students, while they desire the possibility of teaching staff being able to offer more informative feedback, they expect to receive feedback showing how their learning progresses to a set goal. For study three, on the other hand, the highest average response on the ideal expectation scale was for the university having an obligation to act (item 11; Appendix 7). Whereas, on the predicted expectation scale, the highest average response was for the use of LA to promote academic or professional skill development (item 12; Appendix 7). Compared to the students in study two, those in study three desire the inclusion of early alert systems, but realistically expect LA services to be tailored towards promoting academic skill development.

These aforementioned comparisons using items from the *Service Feature Expectations* factor show that while certain LA service features may be desirable (e.g., the introduction of early alert systems), it may not be the LA service features students expect (e.g., LA services designed to support academic skills such as self-regulated learning). Thus, while there has been extensive attention paid to the possibility of LA services identifying underperforming or at-risk students (Campbell et al., 2007), students may actually be expecting LA service features aimed at providing them with a way of understanding or improving their learning processes. These beliefs have also been expressed by teaching staff, who viewed LA service features that provide students with insights into their learning more favourably than simple performance metrics (Ali et al., 2012; Gašević et al., 2015). Taken together, it shows that whilst the provision of certain LA service features (e.g., early alert systems) may seem advantageous to a Higher Education Institution, it remains necessary to explore what students expect from LA services (Ferguson, 2012).

5.2. **Limitations and Future Research**

For the purposes of this work, the scale reduction was based solely upon statistical decisions (e.g., weak factor loadings) set out before analysing the data. Additionally, we wanted the descriptive questionnaire to measure items across two scales (ideal and predicted expectations), which may have accounted for a greater loss in item numbers. Nevertheless, whilst adherence to statistical decisions were followed here, item content can also be considered (Flora & Flake, 2017). Future work may then be undertaken to determine whether additional items should be included. It is important to recognise, however, that this descriptive questionnaire only seeks to provide Higher Education Institutions with a general understanding of what students expect of LA services. The anticipated effect of being able to readily gauge such expectations is to open dialogues with students at all stages of LA service implementations. In doing so, the Higher Education Institution can begin to manage expectations and proactively identify main areas to focus upon, which can then utilise more specific instruments and/or a qualitative approach.

On the basis of alternative fit indices, the purported two-factor structure resulted in an acceptable fit for both scales (ideal and predicted expectations). Moreover, an assessment of measurement quality showed the average standardised loadings and reliability to be high. Nevertheless, for both scales the X^2 test as found to be significant, which should not be ignored (Ropovik, 2015). Based on the recommendations of Ropovik (2015), an assessment of local misfit was therefore undertaken (i.e., examination of MI and SEPC values, along with an inspection of residual correlations). From this assessment of local fit, local sources of strain were identified in the model, but possible respecifications of the model were not justified on conceptual grounds. In addition, the sample size (n = 191) did not allow for the cross-validation of any model modification (MacCallum et al., 1992). It is important for future researchers to be aware of the local sources of strain identified in study three, assess whether these are found using larger samples, and explore whether model improvements can be made.

Even though engaging students in the development of LA services is a critical factor to success (Ferguson et al., 2014), the expectations of teaching staff cannot be ignored. As Ali et al. (2012) show, teaching staff hold beliefs about the type of service they want from LA, particularly with regards to utility of the information that is fed back. Thus, while the needs of students should continue to guide the development of LA services, the expectations teaching staff must also be considered. Future research should therefore seek to develop and validate an instrument designed to explore the beliefs of teaching staff toward LA services. Then together with the SELAQ, institutions can provide accommodate a greater number of stakeholder perspectives into the implementation of LA services.

An additional consideration that needs to be made is the cultural limitation of the SELAQ, as it has only been developed and validated with UK Higher Education students. It is therefore necessary for researchers to validate this instrument in other contexts. The challenge of unequal stakeholder engagement in LA implementations is not limited to UK Higher Education Institutions (Tsai & Gašević, 2017a), and it is necessary for each university that is interested in implementing LA services to actively engage with their stakeholders. The SELAQ provides a solution to these challenges, but further work is required to assess the reliability and validity of the instrument in cross-cultural contexts including the validation of the instrumentation translated into other languages. Work has been undertaken by the current authors to adapt the SELAQ for use in Dutch, Estonian, and Spanish Higher Education Institutions.

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.

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

5.4. **Conclusion**

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

References

Ali, L., Asadi, M., Gašević, D., Jovanović, J., & Hatala, M. (2013). Factors influencing beliefs for adoption of a learning analytics tool: An empirical study. *Computers & Education*, *62*, 130–148. https://doi.org/10.1016/j.compedu.2012.10.023

Ali, L., Hatala, M., Gašević, D., & Jovanović, J. (2012). A qualitative evaluation of evolution of a learning analytics tool. *Computers & Education*, *58*(1), 470–489. https://doi.org/10.1016/j.compedu.2011.08.030

Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue: using learning analytics to increase student success. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*, 267–270. Retrieved from http://dl.acm.org/citation.cfm?id=2330666

Arnold, K. E., & Sclater, N. (2017). Student Perceptions of Their Privacy in Leaning Analytics Applications. *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, 66–69. https://doi.org/10.1145/3027385.3027392

Askari, S. F., Liss, M., Erchull, M. J., Staebell, S. E., & Axelson, S. J. (2010). Men Want Equality, But Women Don't Expect It: Young Adults' Expectations for Participation in Household and Child Care Chores. *Psychology of Women Quarterly*, *34*(2), 243–252.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191–215. https://doi.org/10.1037/0033-295X.84.2.191

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist*, *37*(2), 122–147. https://doi.org/10.1037/0003-066X.37.2.122

Bartlett, M. S. (1951). The Effect of Standardization on a chi square Approximation in Factor Analysis. *Biometrika*, *38*, 337–344.

Bodily, R., & Verbert, K. (2017). *Trends and issues in student-facing learning analytics reporting systems research*. 309–318. https://doi.org/10.1145/3027385.3027403

Bowling, A, Rowe, G., Lambert, N., Waddington, M., Mahtani, K., Kenten, C., … Francis, S. (2012). The measurement of patients' expectations for health care: a review and psychometric testing of a measure of patients' expectations. *Health Technology Assessment*, *16*(30), 1–532. https://doi.org/10.3310/hta16300

Bowling, Ann. (2014). *Research methods in health : investigating health and health services*. Maidenhead : Open University Press, 2014. (London Campus Library Copy location:).

Brown, S. A., Venkatesh, V., & Goyal, S. (2012). Expectation Confirmation in Technology Use. *Information Systems Research*, *23*(2), 474–487. https://doi.org/10.1287/isre.1110.0357

Brown, S. A., Venkatesh, V., & Goyal, S. (2014). Expectation Confirmation in Information Systems Research: A Test of Six Competing Models. *Mis Quarterly*, *38*(3), 729–756.

Brown, T. A. (2015). *Confirmatory Factor Analysis for Applied Research* (Second Edition). New York: The Guilford Press.

Calvert, C. E. (2014). Developing a model and applications for probabilities of student success: a case study of predictive analytics. *Open Learning: The Journal of Open, Distance and e-Learning*, *29*(2), 160–173. https://doi.org/10.1080/02680513.2014.931805

Campbell, J. P., DeBlois, P. B., & Oblinger, D. G. (2007). Academic analytics: A new tool for a new era. *EDUCAUSE Review*, *42*(4), 40–57.

Christiaens, W., Verhaeghe, M., & Bracke, P. (2008). Childbirth expectations and experiences in Belgian and Dutch models of maternity care. *Journal of Reproductive & Infant Psychology*, *26*(4), 309–322. https://doi.org/10.1080/02646830802350872

Comrey, A. L., & Lee, H. B. (1992). *A first course in factor analysis.* Hillsdale, NJ.

David, D., Montgomery, G. H., Stan, R., DiLorenzo, T., & Erblich, J. (2004). Discrimination between hopes and expectancies for nonvolitional outcomes: psychological phenomenon or artifact? *Personality and Individual Differences*, *36*(8), 1945–1952. https://doi.org/10.1016/j.paid.2003.08.013

Davis, F. D., & Venkatesh, V. (2004). Toward Preprototype User Acceptance Testing of New Information Systems: Implications for Software Project Management. *IEEE Transactions on Engineering Management*, *51*(1), 31–46. https://doi.org/10.1109/TEM.2003.822468

Dawson, S., Jovanovic, J., Gašević, D., & Pardo, A. (2017). From prediction to impact: evaluation of a learning analytics retention program. *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, 474–478. https://doi.org/10.1145/3027385.3027405

Dowling, M., & Rickwood, D. (2016). Exploring hope and expectations in the youth mental health online counselling environment. *Computers in Human Behavior*, *55*, *Part A*, 62–68. https://doi.org/10.1016/j.chb.2015.08.009

Drachsler, H., & Greller, W. (2016). Privacy and Analytics – it's a DELICATE issue. A Checklist to establish trusted Learning Analytics. *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge*, 89–98. Retrieved from http://dspace.ou.nl/handle/1820/6381

Elliot, A. J., & Church, M. A. (1997). A hierarchical model of approach and avoidance achievement motivation. *Journal of Personality and Social Psychology*, *72*(1), 218–232. https://doi.org/10.1037/0022-3514.72.1.218

Ferguson, R. (2012). Learning analytics: drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, *4*(5/6), 304. https://doi.org/10.1504/IJTEL.2012.051816

Ferguson, R., Brasher, A., Clow, D., Cooper, A., Hillaire, G., Mittelmeier, J., … Vuorikari, R. (2016). *Research evidence on the use of learning analytics: Implications for education policy*. Retrieved from Joint Research Centre, European Commission website: http://dx.doi.org/10.2791/955210

Ferguson, R., Macfadyen, L. P., Clow, D., Tynan, B., Alexander, S., & Dawson, S. (2014). Setting Learning Analytics in Context: Overcoming the Barriers to Large-Scale Adoption. *Journal of Learning Analytics*, *1*(3), 120–144. https://doi.org/10.18608/jla.2014.13.7

Festinger, L. (1957). *A Theory of Cognitive Dissonance*. Stanford, California: Stanford University Press.

Field, A., Miles, J., & Field, Z. (2012). *Discovering Statistics Using R*. SAGE.

Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research.* Reading, MA: Addison-Wesley.

Flora, D. B., & Flake, J. K. (2017). The purpose and practice of exploratory and confirmatory factor analysis in psychological research: Decisions for scale development and validation. *Canadian Journal of Behavioural Science / Revue Canadienne Des Sciences Du Comportement*, *49*(2), 78–88. https://doi.org/10.1037/cbs0000069

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312

Gašević, D., Dawson, S., Rogers, T., & Gašević, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicating academic success. *Internet and Higher Education*, *28*, 68–84. https://doi.org/10.1016/j.iheduc.2015.10.002

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends*, *59*(1), 64–71.

Ginzberg, Michael J. (1981). Early Diagnosis of MIS Implementation Failure: Promising Results and Unanswered Questions. *Management Science*, *27*(4), 459–478.

Ginzberg, Michael Jay. (1975). *A process approach to management science implementation.* (Massachusetts Institute of Technology). Retrieved from https://dspace.mit.edu/bitstream/handle/1721.1/27382/02046587-MIT.pdf?sequence=2

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Ifenthaler, D., & Schumacher, C. (2016). Student perceptions of privacy principles for learning analytics. *Educational Technology Research and Development*, *64*(5), 923–938. https://doi.org/10.1007/s11423-016-9477-y

Kaiser, H. F. (1974). An index of factor simplicity. *Psychometrika*, *39*(1), 31–36.

Kline, R. B. (2015). *Principles and Practice of Structural Equation Modeling, Fourth Edition*. Guilford Publications.

Kruse, A., & Pongsajapan, R. (2012). Student-centered learning analytics. *CNDLS Thought Papers*, 1–9.

Leung, K. K., Silvius, J. L., Pimlott, N., Dalziel, W., & Drummond, N. (2009). Why health expectations and hopes are different: the development of a conceptual model. *Health Expectations*, *12*(4), 347–360. https://doi.org/10.1111/j.1369-7625.2009.00570.x

Liu, D. Y.-T., Bartimote-Aufflick, K., Pardo, A., & Bridgeman, A. J. (2017). Data-Driven Personalization of Student Learning Support in Higher Education. In A. Peña-Ayala (Ed.), *Learning Analytics: Fundaments, Applications, and Trends* (Vol. 94, pp. 143–169). Retrieved from https://link-springer-com.liverpool.idm.oclc.org/chapter/10.1007/978-3-319-52977-6_5

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*, *1*(2), 130.

MacCallum, R. C., Roznowski, M., & Necowitz, L. B. (1992). Model modifications in covariance structure analysis: The problem of capitalization on chance. *Psychological Bulletin*, *111*(3), 490–504. https://doi.org/10.1037/0033-2909.111.3.490

MacCallum, R. C., Widaman, K. F., Zhang, S., & Hong, S. (1999). Sample Size in Factor Analysis. *Psychological Methods*, *4*(1), 84–99.

Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an “early warning system” for educators: A proof of concept. *Computers & Education*, *54*(2), 588–599. https://doi.org/10.1016/j.compedu.2009.09.008

Marsh, H. W., Morin, A. J. S., Parker, P. D., & Kaur, G. (2014). Exploratory structural equation modeling: an integration of the best features of exploratory and confirmatory factor analysis. *Annual Review of Clinical Psychology*, *10*, 85–110. https://doi.org/10.1146/annurev-clinpsy-032813-153700

McNeish, D., An, J., & Hancock, G. R. (2018). The thorny relation between measurement quality and fit index cutoffs in latent variable models. *Journal of Personality Assessment*, *100*(1), 43–52.

Muthén, B. O., Muthén, L. K., & Asparouhov, T. (2015). *Estimator choices with categorical outcomes*.

Muthén, L. K., & Muthén, B. O. (2017). *Mplus User's Guide* (Eighth Edition). Los Angeles, CA: Muthén & Muthén.

Ng, I. C. L., & Forbes, J. (2009). Education as Service: The Understanding of University Experience Through the Service Logic. *Journal of Marketing for Higher Education*, *19*(1), 38–64. https://doi.org/10.1080/08841240902904703

Nicol, D. J., & Macfarlane-Dick, D. (2006). Formative assessment and self-regulated learning: A model and seven principles of good feedback practice. *Studies in Higher Education*, *31*(2), 199–218.

Olson, J. C., & Dover, P. (1976). Effects of Expectation Creation and Disconfirmation on Belief Elements of Cognitive Structure. *Advances in Consumer Research*, *3*(1), 168–175.

Oster, M., Lonn, S., Pistilli, M. D., & Brown, M. G. (2016). The learning analytics readiness instrument. *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge*, 173–182. https://doi.org/10.1145/2883851.2883925

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). SERVQUAL: A Multiple-Item Scale for Measuring Consumer Perceptions of Service Quality. *Journal of Retailing*, *64*(1), 12–40.

Pardo, A., & Siemens, G. (2014). Ethical and privacy principles for learning analytics. *British Journal of Educational Technology*, *45*(3), 438–450. https://doi.org/10.1111/bjet.12152

Park, Y., & Jo, I.-H. (2015). Development of the Learning Analytics Dashboard to Support Students' Learning Performance. *J. UCS*, *21*(1), 110–133.

Priest, J., McColl, E., Thomas, L., & Bond, S. (1995). Developing and refining a new measurement tool. *Nurse Researcher*, *2*(4), 13.

Prinsloo, P., & Slade, S. (2015). Student privacy self-management: implications for learning analytics. *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge*, 83–92. https://doi.org/10.1145/2723576.2723585

Prinsloo, P., & Slade, S. (2016). Student vulnerability, agency, and learning analytics: An exploration. *Journal of Learning Analytics*, 159–182. https://doi.org/10.18608/jla.2016.31.10

Prinsloo, P., & Slade, S. (2017). An elephant in the learning analytics room: the obligation to act. *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, 46–55. https://doi.org/10.1145/3027385.3027406

R Core Team. (2017). R: A language and environment for statistical computing. *Statistical Computing, Vienna, Austria*. Retrieved from https://www.R-project.org/

Rattray, J., & Jones, M. C. (2007). Essential elements of questionnaire design and development. *Journal of Clinical Nursing*, *16*(2), 234–243. https://doi.org/10.1111/j.1365-2702.2006.01573.x

Raykov, T. (1997). Estimation of Composite Reliability for Congeneric Measures. *Applied Psychological Measurement*, *21*(2), 173–184. https://doi.org/10.1177/01466216970212006

Revelle, W. (2017). psych: Procedures for Personality and Psychological Research. *Northwestern University, Evanston, Illinois, USA*. Retrieved from https://CRAN.R-project.org/package=psych

Roberts, L. D., Howell, J. A., & Seaman, K. (2017). Give Me a Customizable Dashboard: Personalized Learning Analytics Dashboards in Higher Education. *Technology, Knowledge and Learning*, *22*(3), 317–333. https://doi.org/10.1007/s10758-017-9316-1

Roberts, L. D., Howell, J. A., Seaman, K., & Gibson, D. C. (2016). Student Attitudes toward Learning Analytics in Higher Education: “The Fitbit Version of the Learning World.” *Frontiers in Psychology*, *7*. https://doi.org/10.3389/fpsyg.2016.01959

Roese, N. J., & Sherman, J. W. (2007). Expectancy. In A. W. Kruglanski & E. T. Higgins (Eds.), *Social Psychology: A Handbook of Basic Principles* (Vol. 2, pp. 91–115). New York: Guilford Press.

Ropovik, I. (2015). A cautionary note on testing latent variable models. *Frontiers in Psychology*, *6*. https://doi.org/10.3389/fpsyg.2015.01715

Saris, W. E., Satorra, A., & Veld, W. M. van der. (2009). Testing Structural Equation Models or Detection of Misspecifications? *Structural Equation Modeling: A Multidisciplinary Journal*, *16*(4), 561–582. https://doi.org/10.1080/10705510903203433

Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior*, *78*, 397–407. https://doi.org/10.1016/j.chb.2017.06.030

Sclater, N. (2016). Developing a code of practice for learning analytics. *Journal of Learning Analytics*, *3*(1), 16–42. https://doi.org/10.18608/jla.2016.31.3

Siemens, G., & Gašević, D. (2012). Guest editorial-Learning and knowledge analytics. *Educational Technology & Society*, *15*(3), 1–2.

Slade, S., & Prinsloo, P. (2013). Learning Analytics: Ethical Issues and Dilemmas. *American Behavioral Scientist*, *57*(10), 1510–1529. https://doi.org/10.1177/0002764213479366

Slade, Sharon, & Prinsloo, P. (2014). Student perspectives on the use of their data: between intrusion, surveillance and care. *European Distance and E-Learning Network*, *18*(1), 291–300.

Streiner, D. L., Norman, G. R., & Cairney, J. (2015). *Health Measurement Scales: A Practical Guide to Their Development and Use*. Oxford University Press.

Szajna, B., & Scamell, R. W. (1993). The Effects of Information System User Expectations on Their Performance and Perceptions. *MIS Quarterly*, *17*(4), 493–516. https://doi.org/10.2307/249589

Thompson, A. G., & Suñol, R. (1995). Expectations as determinants of patient satisfaction: concepts, theory and evidence. *International Journal for Quality in Health Care: Journal of the International Society for Quality in Health Care*, *7*(2), 127–141.

Tsai, Y.-S., & Gašević, D. (2016). *Executive summary of the literature on learning analytics adoption in higher education*. Retrieved from http://sheilaproject.eu/wp-content/uploads/2016/06/Adoption-of-Learning-Analytics-in-Higher-Education_Executive-Summary.pdf

Tsai, Y.-S., & Gašević, D. (2017a). Learning Analytics in Higher Education — Challenges and Policies: A Review of Eight Learning Analytics Policies. *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, 233–242. https://doi.org/10.1145/3027385.3027400

Tsai, Y.-S., & Gašević, D. (2017b). The State of Learning Analytics in Europe – Executive Summary – SHEILA. Retrieved July 1, 2017, from http://sheilaproject.eu/2017/04/18/the-state-of-learning-analytics-in-europe-executive-summary/

Tsai, Y.-S., Gaševic, D., Whitelock-Wainwright, A., Munoz-Merino, P. J., Moreno-Marcos, P. M., Fernández, A. R., … Kollom, K. (2018). *SHEILA: Supporting higher education to integrate learning analytics* (p. 44). Retrieved from University of Edinburgh website: http://sheilaproject.eu/wp-content/uploads/2018/11/SHEILA-research-report.pdf

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist*, *57*(10), 1500–1509.

Whitelock-Wainwright, A., Gašević, D., & Tejeiro, R. (2017). What Do Students Want?: Towards an Instrument for Students' Evaluation of Quality of Learning Analytics Services. *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, 368–372. https://doi.org/10.1145/3027385.3027419

Winne, P., H., & Hadwin, A., F. (2012). The Weave of Motivation and Self-Regulated Learning. In D. Schunk H. & B. Zimmerman J., *Motivation and Self-Regulated Learning: Theory, Research, and Applications* (pp. 297–314). New York: Routledge.

Wise, A. F., Vytasek, J. M., Hausknecht, S., & Yuting Zhao. (2016). Developing Learning Analytics Design Knowledge in the "Middle Space": The Student Tuning Model and Align Design Framework for Learning Analytics Use. *Online Learning*, *20*(2), 48–75.

Xia, Y. (2016). *Investigating the chi-square-based model-fit indexes for WLSMV and ULSMV estimators* (PhD Thesis). The Florida State University.

Practitioner Notes:

What is currently known about the subject matter:

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

What the paper adds to this subject:

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

Implications of study findings for practitioners:

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

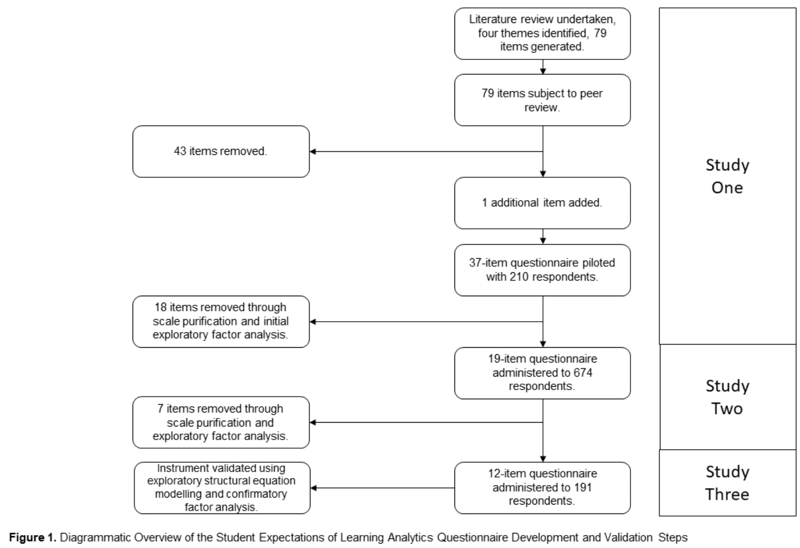

Figure 1. Diagrammatic Overview of the Student Expectations of Learning Analytics Questionnaire Development and Validation Steps

338x190mm (96 x 96 DPI)

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	
		M	*SD*	*M*	*SD*
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	
			M	*SD*	*M*	*SD*
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	
			M	*SD*	*M*	*SD*
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

Table 6. Descriptive Statistics for Ideal and Predicted Expectation Scales

		Ideal Expectations			Predicted Expectations		
Factor Key	Item	*M*	*SD*	Skew	*M*	*SD*	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

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	
			M	*SD*	*M*	*SD*
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	
			M	*SD*	*M*	*SD*
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