What do students want? Developing and Validating a Scale to Measure Student Expectations of Learning Analytics

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Abstract

Higher education institutions are becoming increasingly interested in implementing learning analytics services. Reasons that are driving these intention to implement learning analytics services cover the desire to improve retention rates, learning performance, and satisfaction, to name a few. Despite these motivations, the implementation of learning analytics services remains at a nominal level, which can be attributed to the challenges that such adoptions introduce. One of these challenges refers to students having not been equally engaged in the implementation process. An example of this has been the development of learning analytics policies, which have been solely created on the basis of input from institutional managers and researchers, not students. Failing to gauge and understand what students expect from learning analytics is likely to result in a service that students are not satisfied as it does not align with their expectations.

This thesis forms part of an overall multinational project known as SHEILA (Supporting Higher Education to Integrate Learning Analytics) aimed at creating a framework to address such challenges as improving student engagement in policy decision making. The main contribution of this work is the creation of a psychometrically sound instrument that provides higher education institutions with the means of measuring students' expectations (predicted and ideal) of learning analytics services (the Student Expectations of Learning Analytics Questionnaire; SELAQ).

Chapter 2 presents the development of the SELAQ, which was based on the theoretical framework of expectations. The items included in the SELAQ were generated on the basis of a set of themes identified following an extensive review of

the learning analytics literature. This process led to the generation of 79 items, these were then subject to peer review, which reduced the total number to 37 items. Three studies were then conducted in UK (United Kingdom) Higher Education Insitutions (pilot study, n = 191; study two, n = 674; study three, n = 191), which reduced the items from 37 to 19 (pilot study) and then from 19 to 12 (study two). In the pilot study and study two, exploratory factor analysis was used to reduce the number of items and also led to the identification of a two factor structure (*Ethical and Privacy Expectations* and *Service Expectations*). The validity of this two factor structure was supported using confirmatory factor analysis in study three.

Chapter 3 presents the steps taken to increase the use of SELAQ by translating it for use in Estonia, the Netherlands, and Spain. Following the translation of the instrument for each locale, data was collected from Higher Education Institutions in each country (Estonia, n = 161; the Netherlands, n = 1247; Spain, n = 543). The collected data in each country was subject to factor analysis (confirmatory factor analysis and exploratory structural equation modelling) to evaluate the validity of the originally proposed two factor structure (*Ethical and Privacy Expectations* and *Service Expectations*) in Chapter 2. Findings showed the Dutch and Spanish versions of the SELAQ to be valid, whilst problems were encountered with the Estonian version.

Chapter 4 utilises the data collected in Chapter 2 and Chapter 3 (Dutch student sample, n = 1247; English student sample, n = 191; Spanish student sample, n = 543) to determine whether the ideal and predicted scales are invariant. Utilising factor analysis techniques, specifically multi-group confirmatory factor analysis and alignment, it was found that the SELAQ scales were invariant. Moreover, the Dutch student sample was found to have high *Ethical and Privacy Expectations*, but low

Service Expectations. The English student sample had high *Service Expectations*, whilst their *Ethical and Privacy Expectations* were low for the ideal expectation scale and comparable to the Dutch sample on the predicted expectation scale. As for the Spanish student sample, they had low *Ethical and Privacy Expectations*; however, their *Service Expectations* were high on the ideal expectation scale and low on the predicted expectation scale.

Chapter 5 re-uses the data collected in Chapter 3, specifically the Dutch student sample (n = 1240; 7 respondents were dropped due to missing data), to explore whether student expectations of learning analytics are homogenous. Data from both SELAQ scales (ideal and predicted expectations) was subject to latent class analysis. For the ideal expectation scale, three groups were identified: *Inflated Ideal Expectation* group, *High Ideal Expectation* group, and *Low Ideal Service Expectation* group. Whereas, for the predicted expectation scale, four groups were identified: *Inflated Predicted Expectation* group, *High Predicted Expectation* group, *Indifferent Predicted Expectation* group, and *Low Predicted Service Expectation* group.

Chapter 6 uses data collected from an additional sample of Irish students (n = 237) to determine whether the Big Five dimensions are personality are associated with student expectations of learning analytics. Using exploratory structural equation modelling, it was found that extraversion and neuroticism were positively related to students' *Service Expectations*. No personality dimension was found to be associated with *Ethical and Privacy Expectations*.

The findings of this thesis are important for the future implementation of learning analytics services and for addressing the challenge of insufficient stakeholder engagement (Tsai, Moreno-Marcos, Tammets, Kollom, & Gašević, 2018). For one, the thesis provides a much needed framework to understand what students expect from learning analytics services, but also an instrument that can be used in multiple contexts. Furthermore, the work shows that student expectations are not homogenous and that they can be associated with specific background variables (e.g., age and personality). As for the wider implications of this work, it is clear that students should be engaged in any form of learning analytics service implementation as they are shown to have strong expectations. As for policy makers, the work shows that an accessible policy is required that addresses data security and consent, which is based upon students have stronger expectations towards these elements than service features. Finally, for Higher Education Institutions, the work shows that any learning analytics service implementation needs to be user-centred. Based on the responses to the SELAQ from students, it is clear that student agency should be upheld. This means that services should provide information that facilitates self-regulated learning and also enable students to make self-informed decisions using their data.

Lay Summary

This thesis presents a novel instrument designed to measure student expectations of learning analytics services. In doing so, it provides higher education institutions with a tool to address the challenge of not equally engaging with student stakeholders in the implementation process. A theoretical framework on expectations is presented, in conjunction with a detailed review of literature related to student expectations towards learning analytics services. This provides the underlying model and themes that were used to inform both the scale and items of the Student Expectations of

Learning Analytics Questionnaire (SELAQ). A series of analyses are then undertaken with the purpose of understanding whether the instrument provides higher education institutions with a valid means of measuring student expectations of learning analytics services. After this, we present an assessment of cultural differences in student expectations, along with an investigation into the effects of individual differences on these expectations. Throughout the thesis, all findings are used to inform the development of learning analytics service policies for higher education institutions.

Declaration of Authorship

I declare that this thesis has been composed solely by myself and that it has not been submitted, either in whole or in part, in any previous application for a degree. The work presented is entirely my own and contains four articles under peer review and one article awaiting submission.

Acknowledgements

I would first like to thank my supervisor team: Professor Dragan Gašević, Professor Kate Bennett, and Dr Ricardo Tejeiro. Dragan, you have gone above and beyond in providing support in the form of weekly meetings and encouraging me to seek opportunities I would never have considered, for which I will be forever grateful. Kate, you are the reason for me pursuing a career as a researcher and despite any setbacks you have always been there for me. Ricardo, your input has been greatly appreciated, particularly when times were tough, and I will always be thankful for our discussions over the odd flat white. I would also like to thank the friends I have made along the way: Sunghwan Kim, Dr Yi-Shan Tsai, Dr Warren Donnellan, Caroline Hands, and Ben Bayman.

Finally, I would like to dedicate this work to my mum, dad, and wife; the PhD can be a daunting and isolating experience, but with your unfaltering support, enthusiasm, and kindness I have been able to complete this work. A further thank you also goes to my grandma, aunty Pauline, and Diane. And to Charlie and Lola, thank you for distracting me in times of stress.

Contributor Statement

Alexander Whitelock-Wainwright was primarily responsible for the conception and design of the studies in this thesis. Professor Dragan Gašević, Dr Kate Bennett, and Dr Ricardo Tejeiro provided additional direction in conception and design. Access to the student samples used throughout this thesis was made possible due to both the SHEILA (Supporting Higher Education to Integrate Learning Analytics) project members (the University of Edinburgh, Open University of the Netherlands, Tallinn University, and Universidad Carlos III de Madrid) and associate partners (the University of Liverpool and the Institute of Technology Blanchardstown). The SHEILA project team further contributed to the work by translating the questionnaire for use in Estonia, the Netherlands, and Spain.

Alexander Whitelock-Wainwright was responsible for data collection, data analysis, data interpretation, and drafting of initial manuscripts.

Both Chapters 2 and 3 have been submitted for review at the Journal of Computer Assisted Learning. Currently awaiting on reviewer feedback.

Chapter 4 has been submitted to Internet and Higher Education. Currently awaiting on reviewer feedback.

Chapter 5 has been submitted to Educational Technology Research and Development. Currently awaiting on reviewer feedback.

Chapter 6 is being prepared for submission.

Contents

List of Tables

List of Figures

Chapter 1: Overview of the Thesis

1.1 Introduction

The Higher Education Commission (HEC) report published in 2016 recommends for all higher education institutions to implement learning analytics services for the purposes of improving student support and performance (The Higher Education Commission, 2016). Despite these calls for the need to introduce learning analytics services in higher education institutions (The Higher Education Commission, 2016), in addition to the global interest in learning analytics (Pardo et al., 2018), the implementation rates are low (Tsai & Gašević, 2017b). For example, in the interviews with institutional managers, Tsai and Gašević (2017) found 17.65% (n = 9) of 51 institutions to have institution wide learning analytics services.

Even though implementation of learning analytics services are at a nominal level, higher education institutions recognise the benefits that learning analytics can bring (Tsai & Gašević, 2017b). The HEC report outlines four motivations driving a higher education institution towards the implementation of learning analytics services, these are: improving retention, providing better feedback, capturing attendance data, and enhancing teaching (The Higher Education Commission, 2016). Similar drivers were also identified by Tsai and Gašević (2017), in addition to a motivation for students to make their owned data-informed decisions, teachers to be provided with evidence-based support, and institutions to improve student satisfaction.

An example of learning analytics services being successfully implemented is the dashboard offered to students at Nottingham Trent University (Nottingham Trent University, 2016; Sclater, Peasgood, & Mullan, 2016). This implementation was motivated by an exploration of student retention rates, which found one third of students to have considered dropping out at some point within their first year (Sclater et al., 2016). These considerations to withdraw from university were attributed to students not feeling like they belong in a learning group (e.g., course peers) and having weak relationships with teaching staff (Sclater et al., 2016). As shown in the work of Tinto (1997), having a network of supportive peers is positively associated with attendance at university, in addition to opening dialogues between students and teaching staff. The implemented dashboard addressed these issues by allowing students to see their course progress in relation to their peers and providing teaching staff with metrics that allowed for early interventions (Sclater et al., 2016; The Higher Education Commission, 2016). The outcome of this implementation has ranged from positive behavioural changes (e.g., increased course engagement) to targeted interventions (Sclater et al., 2016).

Even though the aforementioned learning analytics service implementation was successful, this is not something which is commonplace. Whilst there are clear drivers that have motivated higher education institutions to look into the possibilities of implementing learning analytics services, there are challenges that impede the road to adoption (Tsai & Gašević, 2016, 2017a; Tsai, Moreno-Marcos, et al., 2018). More specifically, the work of the SHEILA (Supporting Higher Education to Integrate Learning Analytics) project[1] team identified six challenges to the implementation of learning analytics services (Tsai & Gašević, 2016, 2017a; Tsai, Moreno-Marcos, et al., 2018), which are presented in Figure 1.1.

[1] http://sheilaproject.eu/

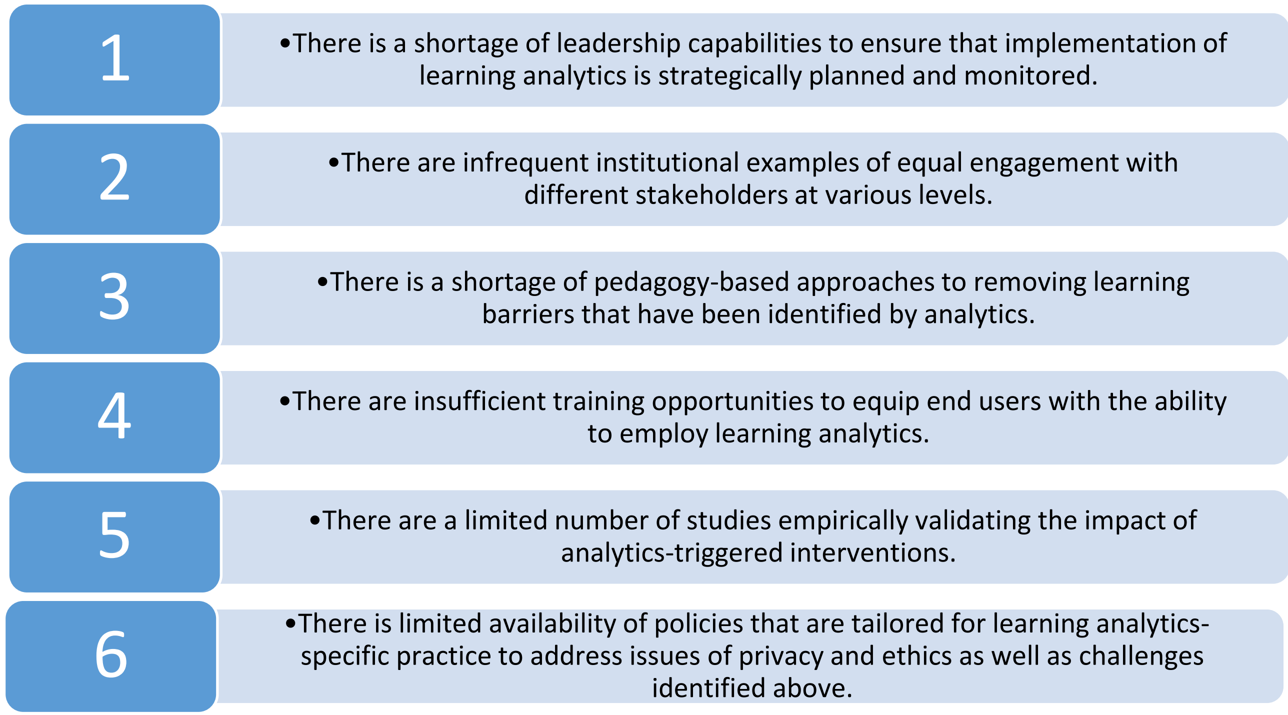

Figure 1.1. Six Challenges to Learning Analytics Service Adoption Taken from Tsai and Gašević (2017)

Each of these six challenges needs to be considered by any higher education institution that is interested in the implementation of learning analytics services and is central to the SHEILA framework. The SHEILA framework itself is composed of six dimensions (map political context, identify key stakeholders, identify desired behaviour changes, develop engagement strategy, analyse internal capacity to effect change, and establish monitoring and learning framework) that higher education institutions work through. These dimensions are further broken down into three categories: actions, which corresponds to the strategies to achieve a particular goals or objectives; challenges, which covers any issues that may hinder the institutional implementation of learning analytics services; and policy, which are the strategies that will address the action points and challenges. Through the use of this framework, it enables higher education institutions to create learning analytics policies that are tailored to the specific culture of the university (Tsai & Gašević, 2017a; Tsai, Moreno-Marcos, et al., 2018).

For the purposes of this thesis, the aim is to address challenge two, which refers to the institutional engagement with stakeholders being insufficient (Tsai & Gašević, 2016, 2017a; Tsai, Moreno-Marcos, et al., 2018). Although stakeholders could refer to teaching staff, researchers, or institutional managers, this thesis focus solely on the perspectives of students. This decision was largely based on a current gap in learning analytics policy development, which has tended to focus on the inputs of institutional managers (Sclater, 2016), whilst engagement with students has been quite minimal (Tsai & Gašević, 2017a). The importance of including students in implementation decisions has not been overlooked (Ferguson et al., 2014), but if steps are not taken to include their expectations into the policies created then ideological gaps become a likely result (Ng & Forbes, 2009; Whitelock-Wainwright, Gašević, & Tejeiro, 2017). This is where the service provided reflects what managers want, but not what students expect, which contributes to service dissatisfaction (Ng & Forbes, 2009).

To enable higher education institutions to overcome this challenge of limited student engagement, this thesis presents a psychometrically robust instrument that can measure student expectations of learning analytics services. Through the analysis of student data (n = 3263) collected from six European universities, a model of student expectations of learning analytics services is presented. This model allows for an understanding of what students expect in relation to the ethical and privacy issues surrounding learning analytics, but also what types of features students expect to receive. The dimensions of this model can then be used to inform the development of learning analytics service policies that align with what students expect.

1.2. Research Goals and Questions

The work of this thesis was undertaken with five research goals in mind. The first goal was to develop a theoretical model to understand student expectations of learning analytics service, which could then inform the development of a psychometric instrument. The specific research question was

RQ1. What should a theoretically sound model of student expectations towards learning analytics consist of to allow for and to inform the development and validation of a psychometric instrument?

The second goal of the thesis was to understand whether the psychometric tool developed and validated in one cultural context was both reliable and valid in additional cultural contexts. Specifically, the validity of the latent variable model identified in the first study was assessed in three European countries (Estonian, the

Netherlands, and Spain) to determine whether the psychometric instrument can assist learning analytics service implementations beyond the United Kingdom (UK). The second research was a follows

RQ2. Is the purported factor structure of student expectations towards learning analytics services applicable to European universities outside of the UK?

The third goal of this research was to assess whether the validated instrument to measure student expectations of learning analytics was invariant across different European contexts. Although steps can be taken to validate the purported factor structure in each context, to be able to make meaningful comparisons there is a need to establish invariance. In other words, it is essential to determine that the same constructs are being measured in each location. The outcome of this would then be a psychometric instrument that can identify cross-cultural differences in student expectations of learning analytics, which has important implications for the suitability of one size fits all policy decisions. Put in a different way, if cultural differences are identified then a global policy to regulate learning analytics services would be considered as inappropriate; instead, context specific policies would be more appropriate. With this in mind, the third research question was

RQ3. Is the psychometric instrument used to measure student expectations invariant across multiple European higher education contexts? And, if so, are there possible cultural reasons for any differences in factor means that are identified?

The fourth research goal was to provide a case study of how the psychometric instrument can be used by higher education institutions to gauge student expectations of learning analytics services. The aim was to highlight how researchers and institutional managers should not consider the expectations held by students as being homogenous. Rather, expectations are likely to be heterogeneous, which requires additional considerations by the higher education institution as to how to scaffold services in order to sufficiently address these expectations and avoid blanket policies. The specific research question was

RQ4. Are student expectations towards learning analytics services homogenous? If not, how do the identified groups of students differ with respect to their expectations and are the subpopulations determined by specific demographic covariates?

The final research goal of the thesis was to determine whether student expectations of learning analytics are associated with individual differences. Specifically, the goal was to assess whether the Big Five dimensions of personality (agreeableness, conscientiousness, extraversion, neuroticism, and openness; Rammstedt & John, 2007) were associated with the expectations students held. The decision to explore this association was based upon the work of Ajzen (2011) who proposed that beliefs are influenced by a myriad of background variables such as personality. Thus, given the overlap between beliefs and expectations (Olson & Dover, 1976), it was theorised that personality may be an important determinant in the expectations students hold towards learning analytics services. As such, the fifth research question was

RQ5. Are the dimensions of personality associated with the expectations that students hold towards learning analytics services?

1.3. Methodology

1.3.1. Theoretical Framework

The psychometric instrument used in this work was grounded in the theoretical framework of expectations (Olson & Dover, 1976), which defines an expectation as a belief about the future. However, expectations, as a concept, is broad and does not necessarily differentiate between various levels. On this basis, the deconstruction of expectations outlined by Thompson and Suñol (1995) was followed. More specifically, Thompson and Suñol theorised four types of expectations: ideal (what is desired), predicted (what is realistically expected), normative (what is deserved), and unformed (no expectations formed). For the purposes of this work, a decision was made to focus on the ideal and predicted levels of expectations as they provide both an upper and lower reference point. In other words, it provides an understanding of what students may desire from learning analytics services, but also what they realistically expect. Together, this theoretical framework was used to inform the development of the scales used to measure student expectations of learning analytics services (RQ1).

As for the items of the questionnaire, these were generated on the basis of four themes (*Ethical and Privacy Expectations, Agency Expectations, Intervention Expectations,* and *Meaningfulness Expectations*) identified from a review of the learning analytics literature. *Ethical and Privacy Expectations* captures the discussions related to students providing consent to data handling processes, including whether consent should be sought before data is passed to third party companies (Slade & Prinsloo, 2014). *Agency Expectations* are concerned with the concept of student-centred learning analytics and whether students expect to make informed decisions on the basis of feedback they receive (Kruse & Pongsajapan, 2012). *Intervention Expectations* are generally associated with the concept of whether teaching staff have an obligation to act when students are identified as being at-risk of failing or underperforming (Prinsloo & Slade, 2017). *Meaningfulness Expectations* refer to how learning analytics service feedback can be pedagogically meaningful for students, particularly with an emphasis on how it can support self-regulated learning (Pardo, 2018). Together, these four themes were used to generate the initial 79 items that were subject to peer review, pilot testing, and follow-up distributions that resulted in a final 12-item questionnaire.

1.3.2. Data Analysis

Throughout the work of this thesis, the obtained data was analysed using various psychometric methods. Each method was used to address one of the five aforementioned research questions. Exploratory factor analysis (EFA), exploratory structural equation modelling (ESEM), and confirmatory factor analysis (CFA) were used to psychometrically evaluate the questionnaire, specifically by assessing the validity of an identified factor structure (RQ1; Asparouhov & Muthén, 2009; Flora & Flake, 2017; Marsh, Morin, Parker, & Kaur, 2014). The identified factor structure was then used in three additional European contexts to assess the validity following translation; CFA and ESEM were used for this purpose (RQ2; Asparouhov & Muthén, 2009; Marsh et al., 2014). Two ways of assessing the measurement invariance were carried out, these were the traditional multi-group CFA approach and the alignment approach (RQ3; Asparouhov & Muthén, 2014; Flake & McCoach, 2018; Marsh et al., 2017). This analysis allowed for the factor means of three European higher education institutions to be compared and discussed in relation to cultural differences. To illustrate how the psychometric instrument can assist higher education institutions to understand the heterogeneity in student expectations of learning analytics services, the three step method to latent class analysis was used (RQ4; Asparouhov & Muthén, 2014a). This allowed for the detection of different latent classes based on the responses collected and whether class assignment was determined by specific demographic covariates. Finally, ESEM was used to assess whether the expectations students have towards learning analytics services are determined by dimensions of personality (RQ5; Asparouhov & Muthén, 2009). The abovementioned correspondence between statistical analyses and research questions are also summarised in Figure 1.2.

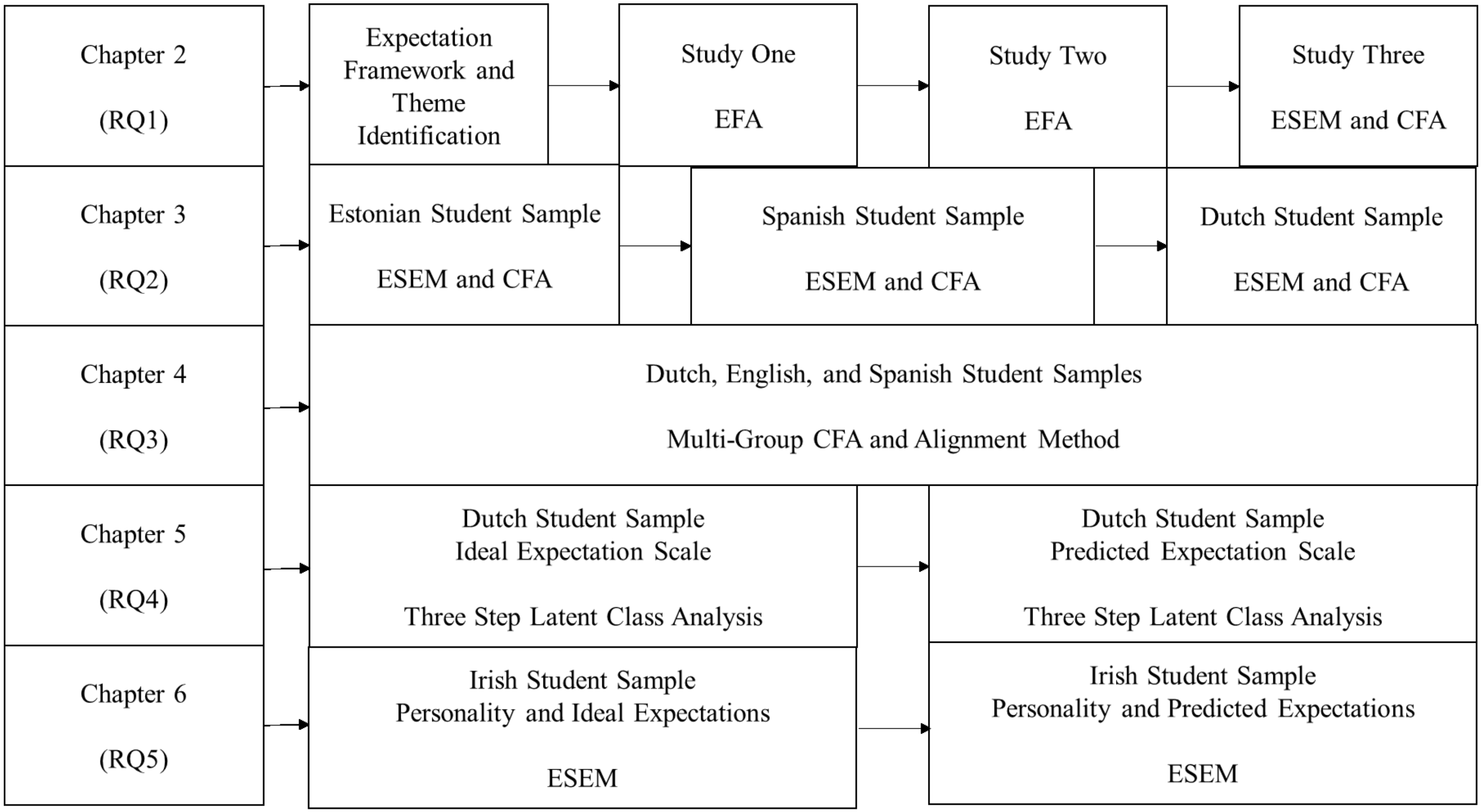

Figure 1.2. Alignment between Research Questions and Methodology

1.4. Thesis Structure and Overview

To address the five research questions, a step-by-step process was followed from initial model conceptualisation to assessing structural relations being psychological constructs. The chapter structure of this thesis is aligned so that each chapter answers a specific research question (Figure 1.3). Each chapter has been written as a manuscript for publication; thus, repetition of detail is likely. In addition, all chapters include a summary of the research findings and details on how this relates to the specific research question being addressed. Ethical approval was obtained for all the work undertaken in this thesis (Appendix 1).

The next steps of this section provide an overview of each chapter and details on the findings that contribute to answering each research question.

RQ1	•Chapter 2
RQ2	•Chapter 3
RQ3	•Chapter 4
RQ4	•Chapter 5
RQ5	•Chapter 6

Figure 1.3. Alignment between Research Questions and Thesis Chapters

1.4.1. Overview of Chapter 2: "The Student Expectations of Learning Analytics Questionnaire" (RQ1)

To develop a psychometrically sound instrument to measure student expectations of learning analytics services, it first needed to be grounded in a theoretical framework. The decision was made to focus on the work outlined by Olson and Dover (1976) and the decomposition of expectations put forward by Thompson and Suñol (1995). These frameworks were used to inform the scales of the instrument, whilst an extensive review of the learning analytics literature was used to generate items. The developed instrument was piloted and tested using three samples, with the collected data being assessed using EFA, CFA, and ESEM (Asparouhov & Muthén, 2009; Flora & Flake, 2017; Marsh et al., 2014).

Research Contributions:

- A 12-item Student Expectations of Learning Analytics Questionnaire (SELAQ) was developed and validated.
- Student expectations of learning analytics can be explained by a two-factor structure (*Ethical and Privacy Expectations* and *Service Expectations*).
- The SELAQ can be used to gauge and understand what students expect from learning analytics services, which can facilitate policy development.

1.4.2. Overview of Chapter 3: "Assessing the validity of a learning analytics expectation instrument: A multinational study" (RQ2)

Even though the SELAQ was validated, this was only in the context of UK higher education institutions. Interest in learning analytics implementations, however, is global (Pardo et al., 2018). It was therefore necessary for the SELAQ to be translated and validated in contexts beyond those in which it was originally developed. To address this limitation, the SELAQ was translated for use in three countries: Estonia, the Netherlands, and Spain. Collected data was then used to assess the validity of the purported two factor structure (*Ethical and Privacy Expectations* and *Service Expectations*) using ESEM and CFA (Asparouhov & Muthén, 2009; Marsh et al., 2014).

Research Contributions:

- The two factor structure of the SELAQ (*Ethical and Privacy Expectations* and *Service Expectations*) was supported in the Netherlands and Spain.
- Descriptive data obtained from the translated SELAQ was used to understand whether there are possible cultural differences in student expectations towards learning analytics services.

1.4.3. Overview of Chapter 4: "Student Expectations of Learning Analytics Services: Do they align? A multinational assessment of measurement invariance" (RQ3)

While a comparison of average responses were undertaken in Chapter 3, there was no attempt to establish measurement invariance. Without establishing that a scale is invariant across groups (e.g., gender or countries), it cannot stated that the same constructs are being measured (Horn & Mcardle, 1992; Liu et al., 2017; Meade & Lautenschlager, 2004). Thus, to address this issue, the invariance of the SELAQ's two-factor structure (*Ethical and Privacy Expectations* and *Service Expectations*) was assessed across three countries (England, the Netherlands, and Spain) using traditional multi-group CFA and alignment (Asparouhov & Muthén, 2014b; Flake & McCoach, 2018; Marsh et al., 2017). The data collected from Estonia was not used here as the results of chapter 3 showed problems with the identified factor structure; therefore, the sample was not used in this chapter. Results of chapter 4 showed the SELAQ scales to be invariant, but also that there are differences across the student samples with regards to the expectations that students hold towards learning analytics services.

Research Contributions:

- The work provides a psychometrically robust method of comparing student expectations of learning analytics services across cultures.
- The limitations of using a one size fits all solution to learning analytics policy are discussed and emphasises the need to understand the cultural background of the students and align the policy with their views.

1.4.4. Overview of Chapter 5: "Subgroups in Learning Analytics Expectations: An Exploratory Latent Class Analysis of Student Expectations Towards Learning Analytics Services" (RQ4)

Following the validation steps of the SELAQ, there was a need to utilise the instrument to gauge and understand differences in what students expect from learning analytics services. To do this, data collected from the Netherlands was analysed using the three-step approach to latent class analysis (Asparouhov & Muthén, 2014a). This allowed for the identification of specific groups of students who responded similarly to the SELAQ instrument. In addition, the findings showed how class assignment was associated with specific demographic covariates.

Research Contributions:

- Findings showed expectations towards learning analytics service features were not homogenous within the student population.
- Based on the ideal expectation responses, three classes of students were identified: a low service expectation group, a high expectation group, and an inflated expectation group.

- Based on the predicted expectation responses, four classes of students were identified: a low service expectation group, an indifferent expectation group, a high expectation group, and an inflated expectation group.
- Age was found to be a significant predictor of being assigned to a class characterised by inflated expectations.
- Results were used to discuss how implementation of learning analytics need to account for the differences in what students expect. In other words, the service needs to prevent students from becoming dependent (Roberts, Howell, Seaman, & Gibson, 2016), but also prevent students from missing out on valuable support (Sclater, 2017)

1.4.5. Overview of Chapter 6: "The Big Five Personality Dimensions and Student Expectations of Learning Analytics: An Exploratory Structural Equation Modelling Approach" (RQ5)

The penultimate chapter of this thesis is concerned with exploring whether background variables (specifically the Big Five) are associated with differences in student expectations of learning analytics services. The SELAQ was used in conjunction with the 10-item short version of the Big Five inventory (Rammstedt & John, 2007) to collect data pertaining to student expectations of learning analytics services and personality from an additional sample of English speaking students. This collected data allowed for an additional assessment of the validity of the SELAQ and to establish whether personality dimensions were associated with student expectations.

Research Contributions:

- The SELAQ was again found to be a valid measure of student expectations towards learning analytics services.
- Neuroticism and extraversion were found to be associated with the *Service Expectations* factor of the SELAQ.
- The findings of this study are important as they show that personality characteristics of students may result in an over-reliance on learning analytics services, which has important implications for policy development.

1.4.6. Overview of Chapter Seven: “Conclusions and Future Directions”

Finally, in chapter seven the results of this work are discussed in relation to the five aforementioned research questions. Directions for future work are included in these discussions, along with a consideration of how these findings can directly affect policy decision making. A final conclusion is presented, which summarises its key contributions.

Chapter 2: The Student Expectations of Learning Analytics Questionnaire

2.1. Summary

This chapter provides the theoretical background to expectations and the identification of themes from the learning analytics literature. Together, the expectation framework and identified themes were used to generate a series of items for a questionnaire aimed at measuring student expectations of learning analytics services. The remainder of the chapter covers the analysis and refinement of this questionnaire following peer review and three distributions to students attending higher education institutions. The findings are used to provide a much needed student perspective towards the implementation of learning analytics services.

2.2. 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 (Whitelock-Wainwright et al., 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, Brasher, et al., 2016; Tsai & Gašević, 2016; Tsai, Gaševic, et al., 2018), 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 three item survey to understand student perceptions of data handling, their reported findings can be questioned on the basis of using an on-the-fly scale (e.g., no steps were taken to validate the measure).

Moreover, the use of both leading questions and a dichotomous scale does limit the level of understanding of what students expect from LA services (Arnold & Sclater, 2017), these were also the reasons as to why this scale was not adapted for use in the current work. 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.

2.2.1. 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).

2.2.2. 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 are presented in Figure 2.1). 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.

To achieve these aims of developing a scale to measure student expectations of learning analytics, the current work employs the use of factor analytic techniques. As discussed by Flora and Flake (2017), factor analysis is regularly employed by researchers to explore whether the items of a newly developed scale are consistent with the construct it intends to measure. Data collected during the initial stages of scale development are typically subject to exploratory factor analysis if there is no hypothesised factor structure (Flora & Flake, 2017). Confirmatory factor analysis, on the other hand, is typically used when there is extensive knowledge that can be used to evaluate a hypothesised factor structure (Flora & Flake, 2017) . Given that our aim is to establish a new scale to measure student expectations of LA services, the initial use of exploratory factor analysis is apt as there is no hypothesised factor structure. When a suitable factor structure has been identified in this work, a confirmatory approach will then be used to evaluate our predictions.

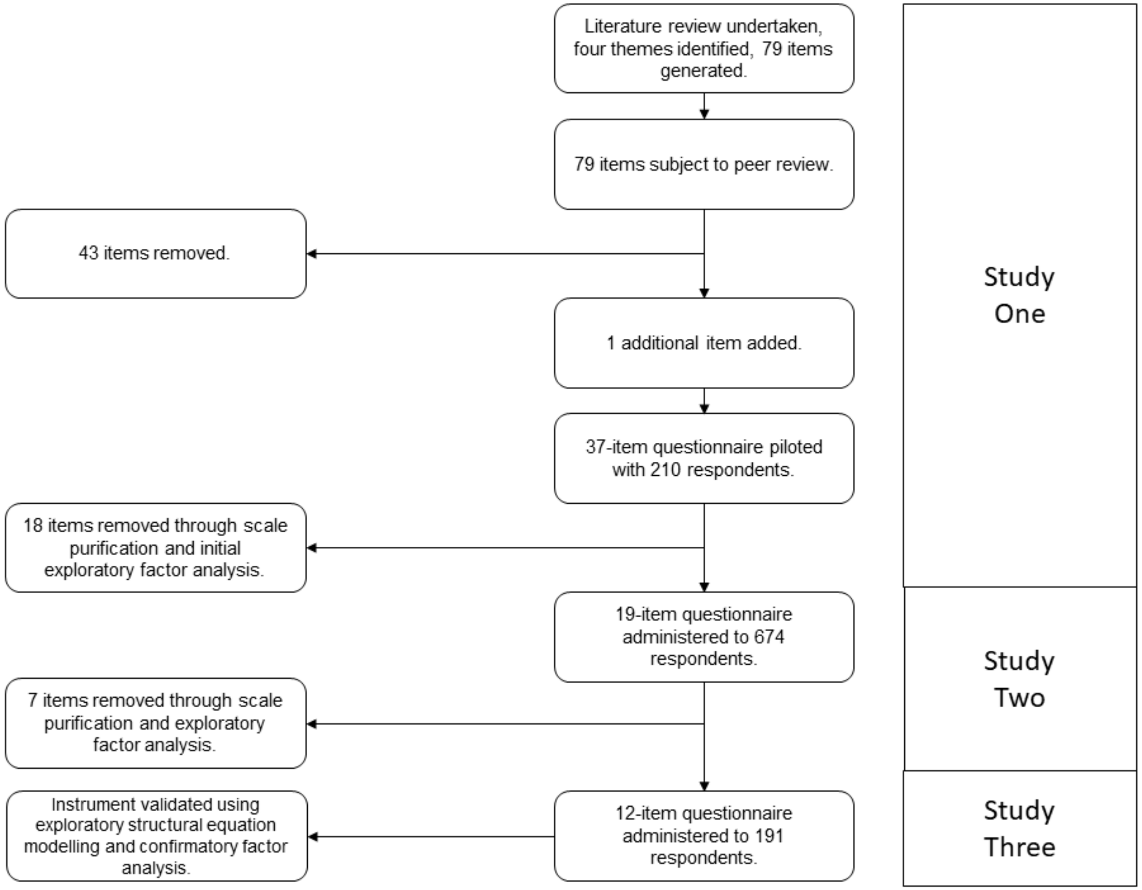

Figure 2.1. Diagrammatic Overview of the Student Expectations of Learning Analytics Questionnaire Development and Validation Steps

2.3. Pilot Study – Study One

2.3.1. 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). Running a series of focus groups with students was not possible as the SHEILA (Supporting Higher Education to Integrate Learning Analytics) project schedule required the pilot questionnaire to be rolled out at the same time as the focus groups. Nevertheless, the generation of items based on themes in the literature has been shown to be a useful approach (Dapko, 2012). However, the importance of undertaking a mixed methods approach will be stated within the suggestions for future research.

Given that there was 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 at this point 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.

Following the literature review and expert feedback, we identified four general themes that characterise LA services (Whitelock-Wainwright et al., 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.

2.3.1.1 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.

2.3.1.2. 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; P. Winne H. & 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).

2.3.1.3. 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.

2.3.1.4. 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 H. & 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 2.2). 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 2.2, 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 2.3). This peer review process undertaken by LA experts led to 37 items being retained (Appendix 2.3).

As students are unlikely to be aware of LA and what it entails, an introduction to the survey was created (Appendix 2.1). 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).

2.3.2. Sample

Total of 210 volunteer 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 2.3), 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). Of the sample, 26.20% were from Arts and Humanities (n = 55), 3.81% were from Engineering (n = 8), 14.80% were from Medicine and Health Sciences (n = 31), 31% were from Science (n = 65), and 24.30% were from Social Sciences (n = 51). This demographic information is also presented in Table 2.1.

Table 2.1. Demographic Information for the Pilot Study

Characteristic	*M*	*SD*	*N*	%
Gender				
Male			79	62.40
Female			131	37.60
Age	24	6.12		
Subject				
Arts and Humanities			55	26.20
Engineering			8	3.81
Medicine and Health Sciences			31	14.80
Science			65	31
Social Sciences			51	24.30

2.3.3. 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 run 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.

2.3.4. Results

2.3.4.1. Exploratory Factor Analysis

Ideal Expectations Scale. 18 items were dropped from the analysis based on the identification of multicollinearity issues (determinant of the correlation less than

.00001), 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 is above the acceptable limit of .50. Bartlett's test of sphericity, χ^2 (190) = 1613, $p < .001$, suggested that the correlation matrix does not resemble an identity matrix so factor analysis was appropriate. The parallel analysis suggested to retain two 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 Expectations* (items: 1, 9, 13, 18, 20, 22, 26, 30, 31, and 33; Appendix 2.4), whilst factor two related to *Ethical and Privacy Expectations* (items: 5, 6, 10, 11, 14, 15, 17, 19, and 21; Appendix 2.4). Both subscales had high reliabilities, for *Service 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 (determinant of the correlation less than .00001), 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 .91 (superb according to Kaiser (1974)), with individual item values being greater than or equal to .86, which is above the acceptable limit of .50. Bartlett's test of sphericity, χ^2 (171) = 1631, $p < .001$, 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 44% of the variance in the data, and the correlation between the factors was $r = .41$. Factor one represented *Service Expectations* (items: 1, 9, 13, 18, 20, 22, 26, 30, 31, and 33; Appendix 2.5), whilst factor two related to *Ethical and Privacy Expectations* (items: 5, 6, 10, 11, 14, 15, 17, 19, and 21; Appendix 2.5). Both subscales had high reliabilities, for *Service Expectations* Cronbach's α = .88, whilst for *Ethical and Privacy Expectations* Cronbach's α = .86.

2.3.5. Discussion

The results of the pilot study led to the identification of a two-factor solution (*Ethical and Privacy Expectations* and Service Expectations) that explain student expectations of LA services. For both the ideal and predicted expectation scales, the same items load 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 expectation factor covers items relating to whether students believe they should responsibility to make sense of their own data (item 18; Appendix 2.3) and whether teaching staff are obliged to act when students are at-risk or underperforming (item 31; Appendix 2.3). Together, these items reflect the *Agency Expectations* theme identified in the literature. Items 26 and 33 (Appendix 2.3), 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 captured well by item 20 (Appendix 2.3), 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 2.3), 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.

2.4. Study Two

2.4.1. 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 2.6), which was distributed through an online system (all responses were voluntary). *N* = 6664 corresponds to one third of the whole university UG and PGT student population based on a random selection. This 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%). In terms of faculty, 211 of the students were from Arts and Humanities (31.10%), 71 were from Engineering (10.50%), 103 were from

Medicine and Health Sciences (15.20%), 162 were from Science (23.90%), 131 were from Social Sciences (19.30%), and one student failed to provide a response (.15%). Total of 475 (70%) respondents identified themselves as ‘Home/EU Students’, and 199 (30%) identified themselves as ‘Overseas Students’. This demographic information is also presented in Table 2.2.

Table 2.2. Demographic Information for the Second Study

Characteristic	*M*	*SD*	*N*	%
Gender				
Male			245	36.35
Female			429	63.65
Age	24.51	7.94		
Subject				
Arts and Humanities			211	31.10
Engineering			71	10.50
Medicine and Health Sciences			103	15.20
Science			162	23.90
Social Sciences			131	19.30
No Response			1	.15
Level of Study				
Undergraduate			396	59
Masters			62	9
PhD			216	32
Student Type				
Home/EU			475	70
Overseas			199	30

2.4.2. Questionnaire

Following the pilot study, the 37-item questionnaire was reduced to 19-items (Appendix 2.6). 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 2.6). The remaining 19-items (Appendix 2.6) 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".

2.4.3. 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 2.6). 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, 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 a larger sample (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 run 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.

2.4.4. Results

2.4.4.1. Exploratory Factor Analysis

Ideal Expectations Scale. Seven (7) items (1, 2, 4, 9, 12, 14, and 15; Appendix 2.6) were dropped from the analysis based on the identification of multicollinearity issues (determinant of the correlation matrix less than .00001), having loadings lower than .40, or whether dropping the item could improve the Cronbach's α value.

An exploratory factor analysis using minimum residual factor extraction method and oblimin rotation was run on the remaining 12 items (3, 5, 6, 7, 8, 10, 11, 13, 16, 17, 18, and 19; Appendix 2.6). 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 is 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 2.3), and communalities were in an acceptable range (Table 2.3). Factor one represented *Service Expectations* (items: 7, 11, 13, 16, 17, 18, and 19; Appendix 2.6), whilst factor two related to *Ethical and Privacy Expectations* (items: 3, 5, 6, 8, and 10; Appendix 2.6). Both subscales had high reliabilities, for *Service*

Expectations the Cronbach's $\alpha = .90$, whilst for *Ethical and Privacy Expectations* Cronbach's $\alpha = .85$.

Table 2.3. Factor Loadings Obtained from Study Two for the Ideal Expectations Scale

Item	Service 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

Table 2.3. Factor Loadings Obtained from Study Two for the Ideal Expectations Scale Continued

Item	Service Expectations	Ethical and Privacy Expectations	Communalities
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	

Predicted Expectations Scale. Seven (7) items (1, 2, 4, 9, 12, 14, and 15; Appendix 2.6) were dropped from the analysis based on the identification of multicollinearity issues (determinant of the correlation less than .00001), having loadings lower than .40, or whether dropping the item could improve the Cronbach's α value.

An exploratory factor analysis using minimum residual factor extraction method and oblimin rotation was run on the remaining 12 items (3, 5, 6, 7, 8, 10, 11, 13, 16, 17, 18, and 19; Appendix 2.6). 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 is 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 accounts for 58% of the variance in the data, the correlation between factors was r = .57, all loadings exceeded .40 (Table 2.4), and all communalities were equal to or exceeded .50 (Table 2.4). Factor one represented *Service Expectations* (items: 7, 11, 13, 16, 17, 18, and 19; Appendix 2.6), whilst factor two related to *Ethical and Privacy Expectations* (items: 3, 5, 6, 8, and 10; Appendix 2.6). Both subscales had high reliabilities, for *Service Expectations* the Cronbach's α = .90, whilst for *Ethical and Privacy Expectations* Cronbach's α = .88.

Table 2.4. Factor Loadings Obtained from Study Two for the Predicted Expectations Scale

Item	Service 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

Table 2.4. Factor Loadings Obtained from Study Two for the Predicted Expectations Scale Continued

Item	Service Expectations	Ethical and Privacy Expectations	Communalities
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	

2.4.4.2. Descriptive Statistics

The descriptive statistics of the final 12-items are presented in Table 2.5. 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 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 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 Expectations* ranging from 4.54 to 5.09.

Table 2.5. 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

Table 2.6. Descriptive Statistics for Ideal and Predicted Expectation Scales by

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

Table 2.7. 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

Table 2.7. Descriptive Statistics for Ideal and Predicted Expectation Scales by Level of Study Continued

Level of Study			Factor Key		Item	
					M	*SD*
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

2.4.5. Discussion

The results of the factor analysis again identified a two-factor solution (*Ethical and Privacy Expectations* and *Service 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 2.7) 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 Expectations*) relate to the four identified themes: *Ethical and Privacy Expectations, Agency Expectations, Intervention Expectations,* and *Meaningfulness Expectations*. Item 1 (Appendix 2.7) 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 2.7) 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 2.7), 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 an interesting insight into student expectations of LA services (Table 2.5). 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 2.6) and level of study (Table 2.7) are also provided.

Comparing the *Ethical and Privacy Expectations* and *Service 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 inference is based on the range of average responses to the *Ethical and Privacy Expectation* items being greater than the *Service Expectation* items on both the ideal and predicted scales (Table 2.5). 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 has access to any data and whether consent is required. Whilst in the case of *Service 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 2.5) and predicted (M = 6.05, SD = 1.28; Table 2.5) expectations was item 5 (The university will ensure that all my educational data will be kept securely; Appendix 2.6). 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 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 2.5). Although this is the highest ideal expectation in terms of *Service Expectations*, it is the lowest predicted expectation ($M = 4.54$, $SD = 1.76$; Table 2.5). 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 2.5). 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).

2.5. Study Three

2.5.1. Sample

The 12-item SELAQ (Appendix 2.7) 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 volunteer 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). This demographic information is also presented in Table 2.8.

Table 2.8. Demographic Information for the Third Study

Characteristic	*M*	*SD*	*N*	%
Gender				
Male			62	32.46
Female			129	67.54
Age	20.41	3		
Subject				
Arts and Humanities			45	24
Engineering			24	13
Medicine and Health Sciences			45	24
Science			36	19
Social Sciences			41	24
Level of Study				
Undergraduate			188	98
Masters			3	.02
Student Type				
Home/EU			153	80
Overseas			38	20

2.5.2. Instrument

The 12-item SELAQ was used for this study (Appendix 2.7). 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 2.1).

2.5.3. 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 Expectations*). It is important to note that the exploratory structural equation modelling was used as a confirmatory tool (Marsh et al., 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 2.9 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 Expectation* factor (S1-S7). The ideal expectations scale responses were negatively skewed (Table 2.9). 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 2.9). 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) resulting in 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.

Table 2.9. 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

2.5.4. Results

2.5.4.1. Confirmatory Factor Analysis

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 2.8). 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 2.10. 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 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 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 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 suggested to freely estimate 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 2.9), 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).

Table 2.10. 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 Expectations	1.00	.70	.04
7	Service Expectations	1.20	.84	.03
8	Service Expectations	1.23	.85	.03
9	Service Expectations	1.09	.76	.03
10	Service Expectations	1.19	.83	.03
11	Service Expectations	.95	.66	.04
12	Service Expectations	1.08	.75	.04

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 2.10). 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 2.11. 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 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 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 Expectations* factors, respectively).

As with the ideal expectation scale, the significant X^2 test means that an inspection of local misfit within the model was warranted. From the MI and SEPC values, there were three suggested modifications that could 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 2.11) shows that there are ten absolute values that are ≥ .10. In line with the MI and SEPC values, the largest correlation residuals were between item 2 and item 3 (.12), item 2 and item 5 (-.12), and item 11 and item 12 (.15); there was also a large correlation residual between item 4 and item 5 (.13).

Table 2.11. 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 Expectations	1.00	.80	.03
7	Service Expectations	1.05	.84	.03
8	Service Expectations	1.09	.87	.02
9	Service Expectations	.98	.79	.03
10	Service Expectations	1.06	.85	.03
11	Service Expectations	.96	.77	.03
12	Service Expectations	.90	.72	.04

2.5.4.2. Descriptive Statistics

Table 2.9 presents descriptive statistics for each item across both expectation scales (ideal and predicted); item means and standard deviations are also presented by gender (Table 2.12) and level of study (Table 2.13). 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 2.9) than those relating to *Service Expectation* items (ranging from 5.80 to 6.03 for ideal expectations, and ranging from 4.96 to 5.35 for predicted expectations; Table 2.9). 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 2.9) or predicted (M = 5.19, SD = 1.62 Table 2.9) expectations.

Table 2.12. 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

Table 2.13. 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

2.5.5. 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 2.8 and 2.10). 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 2.8 and 2.10), provides evidence about the measurement model that can be assimilated into a Bayesian structural equation model (Muthén & Asparouhov, 2012).

Taking the abovementioned points into consideration, the two-factor structure of *Ethical and Privacy Expectations* and *Service 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 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 (*M* = 6.53, *SD* = .78; Table 2.9) and predicted (*M* = 6.27, *SD* = 1.08; Table 2.9) 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 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 2.9). 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 2.9). Interestingly, these 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 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.

2.6. General Discussion

2.6.1. Interpretation of the Results

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

Using the above as a framework, we have been able to develop and validate a descriptive 12-item (Appendix 2.7) 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 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 2.7) 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 if data is to be used for an alternative purpose than 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.

Surprisingly, expectancy items relating to opting-out (item 9; Appendix 2.6) and transparency (item 2; Appendix 2.6) were not retained in the final 12-item instrument. The omission of an opt-out item may be based upon students holding stronger beliefs 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 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 beliefs 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 to services that are not reflective of student beliefs.

In addition, an inspection of the descriptive statistics obtained from study two and three does provide an interesting insight into the perspectives of students with regards to *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 2.7). 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 Expectations* factor (items 4, 7, 8, 9, 10, 11, and 12; Appendix 2.7) does overlap with the identified themes of *Agency, Intervention, and Meaningfulness Expectations*. Item 8 (Appendix 2.7) refers to the belief 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 2.7) 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 2.7) 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 2.7). This refers to the belief 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 (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 indicate the importance of a moral consideration over whether teaching staff are obligated to act (Prinsloo & Slade, 2017). According to Prinsloo and Slade, whilst institutions should take action, 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 (Abelardo 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 2.7) and institutions being obligated to act (item 11; Appendix 2.7), 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). 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 beliefs are captured by the retained items of the SELAQ (items 4, 9, and 12; Appendix 2.7), in addition to an expectation pertaining to teaching staff incorporating LA into their own feedback (item 10; Appendix 2.7). 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 Expectation* factor, a general understanding of the LA service 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

2.7). 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 2.7). 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 2.7). 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 2.7). Compared to the students in study two, those in study three desire the inclusion of early alert systems, but expect LA services to be tailored towards promoting academic skill development.

These aforementioned comparisons using items from the *Service Expectation* 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).

2.6.2. Limitations and Future Research

The items of the SELAQ were generated on the basis of a literature review (Bowling, 2014; Priest et al., 1995; Rattray & Jones, 2007) and expert opinion (Streiner et al., 2015), which means there is a risk of items not addressing all student expectations (Streiner et al., 2015). As previously mentioned, it was not possible to use the findings obtained from student focus groups to inform this item generation. Nevertheless, it is important for future work to utilise a mixed methods approach to triangulate the findings presented here. Particular emphasis should be on exploring whether the same expectations captured by the SELAQ are being elicited by students in qualitative interviews.

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 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 insufficient 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.

Furthermore, the current work has also only sought to develop and validate an instrument, as opposed to fully exploring the collected data. Researchers who use this instrument 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.

2.6.3. 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 realistically expected from a student; therefore, it is essential for the institute to meet these expectations effectively, or dissatisfaction is likely to arise

(Whitelock-Wainwright et al., 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.

Chapter 3: Assessing the validity of a learning analytics expectation instrument: A multinational study

3.1. Summary

Validity of the 12-item student expectations of learning analytics questionnaire (SELAQ) was only established using data obtained from UK (United Kingdom) higher education institutions. Given the interest in implementing learning analytics services extending into other European contexts (Ferguson et al., 2015), there was a need to both translate and validate the questionnaire for use elsewhere. To address this, the current chapter covers the collection and analysis of data obtained from three European universities based in Estonia, the Netherlands, and Spain. The collected data from each context was factor analysed to assess whether the originally identified factor structure was supported. Descriptive statistics are also presented to provide a general overview of how student expectations of learning analytics may not be homogenous.

3.2. Introduction

The Student Expectations of Learning Analytics Questionnaire (SELAQ; Chapter 2) was developed as a solution to the continuing challenge for higher education institutions to engage more with stakeholders when implementing learning analytics (LA) services (Tsai & Gašević, 2017a). Under this framework, a LA service expectation is defined as a 'belief about the likelihood that future implementation and running of LA services will possess certain features' (Chapter 2). As the term expectation is quite general, it was decomposed on the basis of the work of Thompson and Suñol (1995) into ideal and predicted expectations. These specific forms of expectations refer to what an individual desires (ideal expectation) and what are the conditions students expect in reality (predicted expectation). In other words, while desires reflect an unrealistic expectation, a more realistic expectation of the LA service can also be obtained. Thus, researchers and practitioners who utilise the SELAQ can differentiate between those LA service features students would ideally want and those that students believe they are most likely to receive.

The development and validation of the SELAQ led to 12-items being retained (Appendix 3.1), which are explained by a purported two-factor structure (Figure 3.1). These two factors correspond to *Ethical and Privacy Expectations* and *Service Expectations*, which can refer to student beliefs toward the ethical procedures involved in LA services (e.g., the university will obtain consent for the collection and analysis of any educational data) and how they would like to benefit from such services (e.g., students receiving regular updates about their learning progress), respectively. These two constructs are largely supported by the literature from the LA field and from prior work with the student population (Arnold & Sclater, 2017; Ifenthaler & Schumacher, 2016; Roberts et al., 2017, 2016; Schumacher &

Ifenthaler, 2018; Slade & Prinsloo, 2014; Tsai, Gašević, & Whitelock-Wainwright, Under Review).

Up to now, the SELAQ has only been validated within UK (United Kingdom) higher education institutions. Consequently, this means that the SELAQ is restricted in its use as the cross-cultural validation of the instrument has yet to be explored. The current study seeks to address the limitation of the SELAQ by investigating whether the original factor structure (Figure 3.1) can be recovered and validated in three European contexts (Spain, Netherlands, and Estonia). In doing so, this will enable a greater number of institutions to use the SELAQ in their pursuit of implementing LA services. More importantly for the field of LA, it will increase the engagement from the student population, meeting the challenge (Tsai & Gašević, 2017a) identified.

3.2.1. Expectations of Learning Analytics

The initial items of the SELAQ were generated on the basis of four themes that were identified from a review of the LA literature; these were: *Ethical and Privacy Expectations, Agency Expectations, Intervention Expectations,* and *Meaningfulness Expectations* (Chapter 2; Whitelock-Wainwright et al., 2017). Each of these four themes are well captured by the items of the SELAQ (Chapter 2) and thereby offers higher education institutions a wide-ranging insight into student expectations of LA services. In order to provide a comprehensive understanding of the theoretical basis for the SELAQ, each theme, along with their representative factor, will be discussed in turn.

Discussions relating to the ethical procedures involved in LA service implementations have been extensive. In particular, the work undertaken by Sclater

(2016) has played an important role in making higher education institutions aware of privacy and ethical issues associated with the collection and analysis of students' educational data. However, this particular work has been dominated by the inputs of institutional managers, practitioners, and researchers; whereas, student input has been relatively low. Even though the development of a code of practice is fundamental to the establishment of LA services that uphold ethical and privacy concerns (Sclater, 2016), the input from students cannot be overlooked (Aguilar, 2017), particularly with reference to ethical and privacy decisions (Slade & Prinsloo, 2014).

When engaged in discussions regarding potential LA services, students have been found to express discomfort once they are made aware that their educational data is amenable to analysis (Roberts et al., 2016). Additional work by Ifenthaler and Schumacher (2016) shows that students may in fact be open to the collection of educational data, but draw the line at the use of identifiable data. The importance of engaging students in discussions centred on ethical and privacy beliefs is further reinforced in our explorations of student attitudes toward LA practices (Tsai et al., Under Review). In this work, we found that students are open to a higher education institution collecting and analysing data, but only for purposes that are considered to be legitimate (Tsai et al., Under Review). Taken together, these abovementioned points show students to hold beliefs towards the ethical and privacy elements of LA services. In particular, while students may consider it acceptable for a university to collect and analyse specific forms of data, but not when data is identifiable or when data is used for illegitimate purposes.

Existing frameworks attempt to encourage institutions to engage data subjects in the implementation of LA services (Drachsler & Greller, 2016), yet input from students in LA services continues to be limited (Tsai & Gašević, 2017a). With accumulating evidence showing students holding strong beliefs toward the privacy and ethical elements of LA services (Arnold & Sclater, 2017; Ifenthaler & Schumacher, 2016; Roberts et al., 2016; Slade & Prinsloo, 2014; Tsai et al., Under Review), and the potential ideological gap that may arise following insufficient engagement of stakeholders (Tsai & Gašević, 2017a; Whitelock-Wainwright et al., 2017), the inclusion of the *Ethical and Privacy Expectations* theme items was considered to be important. Of the 12 retained SELAQ items, five items relate to the theme of *Ethical and Privacy Expectations* (Appendix 3.1), which cover beliefs toward providing consent to third party usage of educational data, whether universities seek additional consent for any further usage of the data, and consenting to use any identifiable data (Chapter 2). These items were found to load onto a distinct factor titled *Ethical and Privacy Expectations* (Chapter 2) and thereby increases the level of student engagement in issues of transparency and consent (Sclater, 2016; Slade & Prinsloo, 2015).

The remaining seven items of the SELAQ load onto a *Service Expectations* factor, which is composed of items related to the *Agency Expectations, Intervention Expectations,* and *Meaningfulness Expectations* themes (Chapter 2; Whitelock-Wainwright et al., 2017). This distinction between *Ethical and Privacy Expectations* and *Service Expectations* is important, as it shows that student beliefs toward LA are not restricted to only ethical and privacy issues, but extends into the types of services they want to receive. Researchers have explored student beliefs toward LA services, but this has been restricted to expectations of dashboard features (Roberts et al., 2017; Schumacher & Ifenthaler, 2018). Although important in the development of a specific LA service, dashboards are not the only service that can be offered through an institution's implementation of LA (Pardo, Jovanovic, Dawson, Gašević, & Mirriahi, 2017). The SELAQ addresses this particular issue by providing institutions, researchers, and practitioners with an insight into students' general beliefs towards the possible services introduced with LA.

The theme of *Agency Expectations* relates to the central tenant of self-regulated learning, which is the ability of students to make their own choices based on the feedback received from LA services (Winne & Hadwin, 2012). This further relates to the need for student-centred learning analytics, as put forward by Kruse and Pongsajapan (2012). LA viewed through the perspective argued by Kruse and Pongsajapan (2012) suggests that students should be able to make sense of their own data, make reflections on their progress, and use this information to decide whether to change their current learning strategy. It is important for students to remain active agents within their own learning, rather than LA services creating a culture of passivity. The SELAQ contains two *Service Expectation* items pertaining to the *Agency Expectations* theme. These items seek to explore student beliefs toward making their own decisions on the basis of LA service feedback (item 7, Appendix 3.1) and whether teaching staff are obligated to act (item 11, Appendix 3.1). As stated by Prinsloo and Slade (2017), while a higher education institution holds a moral responsibility to act in situations where a student may underperform, this does not remove the responsibility of a student to learn. LA services are typically associated with the implementation of early interventions to offset the possibility of students failing a course (Campbell et al., 2007). Nevertheless, it is important for institutions to be mindful of not removing student independence, but balancing this with a level of awareness of whether any student is at-risk of failing or is underperforming. Results from items 7 and 11 can then provide an important insight into whether the student population expect institutions to make decisions on their behalf, or whether learner agency should be upheld.

The *Intervention Expectations* theme items of the SELAQ encompass the regularity of feedback (item 4, Appendix 3.1), the incorporation of LA input in teacher feedback (item 10, Appendix 3.1), and the use of feedback to promote academic skill development (item 12, Appendix 3.1). While the development of early alert systems has come to characterise LA services (Campbell et al., 2007), implemented intervention programmes have fallen short of expectations (Dawson et al., 2017). However, focusing only on early alert systems is an overly narrow perspective of LA services, particularly in light of developing tools aimed at facilitating self-regulated learning (Winne & Hadwin, 2013), improving the student-teacher relationship (Liu et al., 2017), or improved student reporting systems (Bodily & Verbert, 2017). Although these LA services are advantageous for students, it remains necessary for the perspectives of students to be accommodated into these developments (Ferguson, 2012).

The importance of engaging students in discussions around LA service developments such as dashboards have been recommended (Verbert et al., 2014), and progress is being made (Roberts et al., 2017; Schumacher & Ifenthaler, 2018). More specifically, the work of Schumacher and Ifenthaler (2018) and Roberts et al. (2017) show students to want features that allow students to compare their performance to their peers or the provision of real-time feedback, to name a few. In other words, LA services should not be centred on the inclusion of early alert systems; instead, higher education institutions should be seeking to offer a wider variety of support (Ifenthaler & Schumacher, 2016). Moreover, to ensure that students are satisfied with the LA service implemented, it is necessary for researchers to continue to understand what students expect following the disclosure of personal information, and this extends beyond ethical and privacy discussions. Thus, the items of the SELAQ related to the purported *Intervention Expectations* theme can be used to add weight to the abovementioned findings by providing an insight into the features students want from the implemented LA service.

The remaining theme of *Meaningfulness Expectations* refers to the LA services being in a format that is applicable and relevant to students (Chapter 2). Put differently, positive changes in behaviour following the exposure to LA service feedback is predicated on their perceived utility (Wise et al., 2016). The importance of feedback that is pedagogical meaningful has also been raised by teaching staff, who expressed preference for information that can provide an informative understanding of a student's learning activity (Ali et al., 2012). For students, feedback from LA services needs to promote effective learning (Gašević et al., 2015), as feeding back trivial measures is unlikely to make positive changes to their learning. As outlined by Nicol and Macfarlane-Dick (2006), feedback should provide students with the information they require to understand how to proceed in their learning. In other words, feedback should identify gaps and provide insight into how the student can move from their current learning state to a desired state (Nicol & Macfarlane-Dick, 2006). This form of feedback is therefore facilitating a student's ability to metacognitively monitor and subsequently regulate their learning (Winne & Hadwin, 2012). Provision of simple performance measures are unlikely to facilitate such changes in learner behaviour and may not reflect what students want. As identified by Schumacher and Ifenthaler (2018), students expect to receive feedback that facilitates their ability to monitor their learning progress, which reinforces the need to engage students in LA service implementation decisions

(Gašević et al., 2015). Without understanding or aligning a LA service with the expectations students hold toward the meaningfulness of feedback, it is unlikely that LA services will be used to their full extent due to the dissatisfaction that arises as their expectations have not been met (Brown, Venkatesh, & Goyal, 2014). As shown by the work of Schumacher and Ifenthaler (2018), it is necessary to understand what LA service features students expect in order for it to be meaningful to support their learning. Those SELAQ items capturing the *Meaningfulness Expectations* theme can add weight to the growing body of work showing that students hold beliefs toward the types of LA service features that could support their learning.

3.2.2. Current Research

As outlined by Chapter 2, the four themes identified in the LA literature (*Ethical and Privacy Expectations, Agency Expectations, Intervention Expectations,* and *Meaningfulness Expectations*) were used to generate 79 items. These were then subject to peer review and reduced down to 37 items. The remaining items were then piloted using students (n = 210) from a higher education institution. Respondents completed the survey and provided comments on the clarity and understanding of each item. The quantitative results obtained were used in a scale purification process (remove highly correlated items, remove cross-loading items), whilst the qualitative comments were used to make adjustments to the wordings of each item. In addition to using student feedback to alter the wordings of each item, further peer review was undertaken. Following these steps, the 37 items were reduced down to 19 items. As the items had been re-worded and communalities remained low, a further distribution to students (n = 674) at the same higher education institution was undertaken, with the results being subject to exploratory factor analysis (EFA). The authors were left with a 12-item instrument, with five items loading onto an *Ethical and Privacy*

Expectations factor (items 1, 2, 3, 5, and 6; Appendix 3.1) and seven items loading onto a *Service Expectations* factors (items 4, 7, 8, 9, 10, 11, and 12; Appendix 3.1).

The model presented in Figure 3.1 is the purported factor structure identified through the exploratory analysis stages of the instrument development (Chapter 2). In order to validate this factor structure using confirmatory factor analysis (CFA) and exploratory structural equation modelling (ESEM), which was used as a confirmatory tool (Marsh et al., 2014), a further sample of students (n = 191) from a different higher education institution completed the 12-item instrument (Chapter 2). For both the ideal and predicted expectation scales, the findings supported the original two-factor structure of the SELAQ (Chapter 2). In addition, study 3 showed that the subscales (*Ethical and Privacy Expectations* and *Service Expectations*) had good measurement quality across both scales (ideal and predicted expectations). Thus, in the context of UK higher education institutions, the SELAQ was found to be both internally consistent and valid.

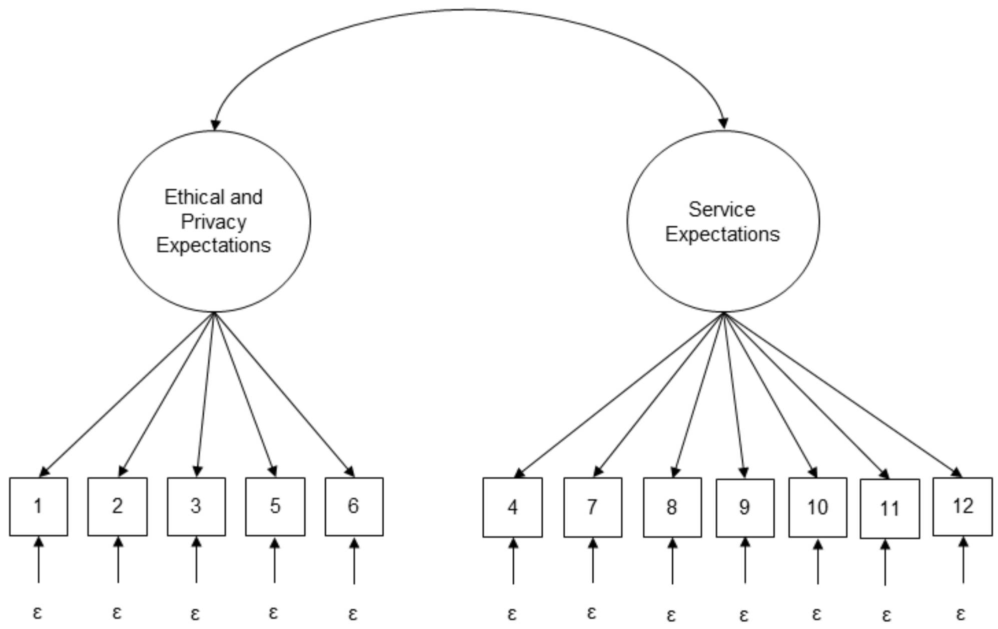

Figure 3.1. 12-Item SELAQ Factor Structure

Irrespective of the SELAQ strengths, it has only been validated in a single language. Given the interest of LA services outside of the UK (Ferguson et al., 2015), it is important that stakeholders are readily engaged in implementation decisions across each context. To address this particular limitation, the SELAQ needs to be translated and validated in each context to allow a greater number of higher education institutions the ability to incorporate the needs of students into their LA services implementation decisions. Thus, the aim of the current paper is to extend the use of the SELAQ into three different contexts (i.e., Spain, Estonia, and the Netherlands).

3.3. Analysis Overview

Students from Estonia, the Netherlands, and Spain were chosen as the SHEILA (Supporting Higher Education to Integrate of Learning Analytics) project, which this work is a part of, has partners in each country (Tallinn University, Open University of the Netherlands, and Universidad Carlos III de Madrid, respectively). It is also important to be aware that the collected samples are unlikely to be representative of the countries or cultures.

For each sample (Estonian, Spanish, and Dutch students), the raw data was analysed using both CFA and ESEM in Mplus 8 (Muthén & Muthén, 2017), and geomin rotation was used for the ESEM (Asparouhov & Muthén, 2009). Therefore, to avoid reiterating the same analysis details for each sample, this section presents all the details regarding the methodological steps undertaken. This will involve an assessment of response distributions, details regarding how the model fit will be assessed, and how localised sources of strain will be identified.

The decision to analyse the data using both CFA and ESEM was based on the work of Marsh et al. (2014), which questioned the suitability of CFA. This is due to the requirement of zero cross-loadings, which results in instruments that appear ill-fitting (Marsh et al., 2014), and factor correlations that are inflated (Asparouhov & Muthén, 2009). In contrast, ESEM allows for items to cross-load, and can be used as either an exploratory or confirmatory tool (Marsh et al., 2014). Thus, by allowing cross-loadings, ESEM leads to more accurate factor correlation estimates, but also the identification of problematic items (i.e., items with high loadings on the non-target factors). This may then allow for the identification of problems that would go unnoticed when only using CFA.

An inspection of the skewness statistics for each sample (Estonian, Spanish, and Dutch students) and scale (ideal and predicted) showed the data to generally be negatively skewed (Table 3.1). An additional examination of the response distributions (Appendices 3.2 to 3.4) also showed there to be a ceiling effect, particularly in relation to the ideal expectation scale. This was anticipated, as this level of expectation refers to what students desire from a LA service; thus, representing an upper reference point of the service students want. Due to the presence of this ceiling effect, the scale-shifted approach to the unweighted least squares estimation (ULSMV) was used for both the CFA and ESEM (Muthén, Muthén, & Asparouhov, 2015). This estimator choice was also based upon it being advantageous in small sample sizes, but also yields more accurate parameter estimates when it converges (Forero, Maydeu-Olivares, & Gallardo-Pujol, 2009; Muthén et al., 2015).

To assess the fit of each model, the X^2 test is reported along with the following alternative fit indices: Comparative Fit Index (CFI), Tuker-Lewis Index

(TLI), and Root-Mean Square Error of Approximation (RMSEA). In relation to the alternative fit indices, Hu and Bentler's (1999) suggested cut-offs of .95 for CFI and TLI, and .06 for RMSEA have been regularly used as indicators of good fitting models. Whilst others have suggested that RMSEA values between .08 and .10 to be indicative of a mediocre fit (MacCallum et al., 1996). The problem, however, is that these cut-offs were based on the maximum likelihood estimator, not categorical estimators such as ULSMV. As shown in the work of Xia (2016), it is inappropriate to generalise the Hu and Bentler criteria to occasions when the ULSMV estimator is used due to its dependency upon thresholds. In addition, the simulation study of McNeish, An, and Hancock (2018) has shown these alternative fit indices (i.e., CFI and RMSEA) to be affected by the measurement quality of the model. Specifically, increased standardised factor loadings result in model fit indices that would be indicative of poor fit (Hancock & Mueller, 2011). For McNeish and colleagues, they recommend that evidence of measurement quality should be given in order to provide a context for fit indices (McNeish et al., 2018). Thus, for the CFA the standardised factor loadings will be presented along with the average loading for each scale. In terms of the ESEM, the range and mean absolute factor loadings will be provided.

In the case of a significant X^2 test, an assessment of localised strain within the model is necessary (Kline, 2015; Ropovik, 2015). To do this, an examination of residual correlations is presented (Kline, 2015), in conjunction with modification index (MI) and standardised expected parameter change (SEPC) values (Saris et al., 2009). For residual correlations, absolute values $\geq .10$ are indicative of localised strains (Kline, 2015). Whereas, MI values ≥ 3.84 (Brown, 2015), in addition to SEPC values $\geq .10$ (Saris et al., 2009), point to local misfit within the model. In the event that misfit is identified, it is then important to consider whether a respecification of the model, which allows for correlated errors between the problematic variable pair, is theoretically justified. As shown in our previous work, both scales of the SELAQ (ideal and predicted expectations) showed local misfits between items 2 and 5 and items 11 and 12 (Chapter 2). However, based on the content of these items there was no justification for the respecification of the model that allowed the errors of these aforementioned items to correlate. This evidence was taken into account if the same sources of misfit were found in the current work.

Finally, it is important to note that the ESEM is being used in a confirmatory approach, as recommended by Marsh et al. (2014). Based on prior work, we have proposed a two-factor structure (*Ethical and Privacy Expectations* and *Service Expectations*; Figure 3.1) that explains students' expectations towards LA services. Thus, there is a defined factor structure that is guiding the current work, which is to validate the SELAQ in three contexts (Estonian, Spanish, and Dutch students). In addition, the approach put forward by Marsh et al. (2014) is followed, which is to compare the fits from both the CFA and ESEM. According to Marsh and colleagues if, on comparison, the models show differences in fits that are marginal then the results of the more parsimonious CFA model are presented.

Table 3.1. Skewness Statistics for each Sample and Scale

Items	Estonian Student Sample (n = 161)		Spanish Student Sample (n = 543)		Dutch Student Sample (n = 1247)	
	Ideal Expectations	Predicted Expectations	Ideal Expectations	Predicted Expectations	Ideal Expectations	Predicted Expectations
1	-1.59	-.80	-2.26	-.78	-2.79	-1.44
2	-2.52	-1.35	-3.91	-1.22	-3.99	-1.58
3	-1.88	-.77	-2.55	-.71	-3.23	-1.35
4	-1.17	-.40	-2.01	-.33	-1.24	-.74
5	-1.30	-.62	-1.51	-.46	-2.00	-.92
6	-2.02	-.70	-3.09	-.66	-3.72	-1.16
7	-.84	-.32	-1.96	-.65	-1.26	-.82
8	-.91	-.38	-1.57	-.69	-1.32	-.89
9	-1.21	-.71	-1.44	-.67	-.69	-.66
10	-1.22	-.24	-1.84	-.41	-1.09	-.55
11	-.83	.13	-1.87	-.05	-.28	-.35
12	-.86	-.23	-1.77	-.47	-.88	-.52

3.4. Estonian Version of the SELAQ

3.4.1. Sample

The translated version of the SELAQ was distributed through an online survey system at an Estonian university. A total of 161 volunteer responses were received (Females = 137). Students were aged between 19 and 60 (*Mean* = 29.63, *Median* = 27, *SD* = 9.38). Majority of the sample were undergraduates (63%, *n* = 101), 35% of the sample were masters students (*n* = 56), and 2% were PhD students (*n* = 4). Of the sample, 11% were taking a science subject (*n* = 18), 4% were taking an engineering subject (*n* = 7), 38% were studying a social science subject (*n* = 61), 39% were taking an arts and humanities subject (*n* = 62), 2% were studying a medicine and health science subject (*n* = 4), and 6% categorised their subject as other (*n* = 9). This demographic information is also presented in Table 3.2.

Table 3.2. Demographic Information for the Estonian Student Sample

Characteristic	*M*	*SD*	*N*	%
Gender				
Male			24	14.91
Female			137	85.09
Age	29.63	9.38		
Subject				
Arts and Humanities			62	39
Engineering			7	4
Medicine and Health Sciences			4	2
Science			18	11
Social Sciences			61	38
Level of Study				
Undergraduate			101	63
Masters			56	35
PhD			4	2

3.4.2. Instrument

The 12-item SELAQ was translated into Estonian (Appendix 3.5) for the purposes of the data collection. The process by which the SELAQ was translated involved one researcher initially translating the survey into Estonian. A further researcher then translated the Estonian version back to English and this was then check by other colleagues to understand the meaning conveyed in the items. This enabled the researchers to determine whether the original meaning of the SELAQ items were preserved in the translated version. Following these steps, slight amendments were made to the Estonian version of the SELAQ in order to align the concepts and terms within the educational system. As with previous distributions (Chapter 2), responses to the items were 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.

3.4.3. Results of the ESEM and CFA

Ideal Expectation Scale

The two-factor model, when fitted using ESEM, resulted in an acceptable fit ($X^2(43, n = 161) = 107.42$, $p < .001$, RMSEA = .10 (90% CI .07, .12), CFI = .95, TLI = .93) and was marginally better than the CFA model ($X^2(53, 161) = 145.58$, $p < .001$, RMSEA = .10 (90% CI .08, .13), CFI = .93, TLI = .92; output presented in Appendix 3.6). Given the marginal improvement obtained by the ESEM, the results of this model are presented.

The ESEM results showed the two factors (*Ethical and Privacy Expectations* and *Service Expectations*) to be strongly correlated (.60). The factor loadings are presented in Table 3.3, which shows all items to load highly (> .40) on their target factors (i.e., items 1, 2, 3, 5, and 6 load on the *Ethical and Privacy Expectations* factor and items 4, 7, 8, 9, 10, 11, and 12 load on the *Service Expectations* factor). The absolute factor loadings, $|\lambda|$, for the *Ethical and Privacy Expectations* factor ranged from .01 to .86, with a mean of .42. Whereas, the $|\lambda|_{\text{Service Expectations}}$ ranged from 0 to 1.01 (M = .45). Even though the item loadings were stronger for their target factor, there are two cross-loadings that needed to be highlighted. These were for item 11 and item 12, which had cross-loadings of -.30 and -.39 on the *Ethical and Privacy Expectation* factor. However, these loadings remained lower than their target factor loadings (.72 and 1.01 for items 11 and 12, respectively). While the target factor loading of item 12 exceeded 1, this can be found when factors are correlated (Jöreskog, 1999).

Although the alternative fit indices were suggestive of an acceptable fit, the X^2 test was found to be significant; thus, an inspection of local fit was warranted (Kline, 2015; Ropovik, 2015). Starting with the modification indices and standardised expected parameter change values, there were two possible modifications to be made by freely estimating the correlated errors between items 7 and 8 (MI = 10.19, SEPC = .37) and items 11 and 12 (MI = 18.47, SEPC = .61). An assessment of the absolute correlation residual values (Appendix 3.7) provided further evidence of localised strain between these items, with values of .12 (between items 7 and 8) and .13 (between items 11 and 12). Previous work on this scale (Chapter 2) identified localised strain within the purported two-factor structure, specifically between items 11 and 12. As discussed within this prior work, there is no justification for modifying the model to permit correlated errors between items 11 and 12. With regards to the misfit between items 7 and 8, this has not been previously identified, but from a content perspective there is no justification for a respecification that allows the errors of these items to correlate.

Table 3.3. Ideal Expectation Factor Loadings Obtained from the ESEM

Items	Ethical and Privacy Expectations		Service Expectations	
	Estimate	Standard Error	Estimate	Standard Error
1	.74	.05	.01	.04
2	.77	.05	0	.03
3	.86	.07	-.03	.09
4	.18	.10	.59	.09
5	.83	.07	.02	.08
6	.64	.09	.20	.10
7	.21	.08	.56	.07
8	.08	.09	.74	.07
9	.02	.07	.83	.06
10	.01	.03	.73	.05
11	-.30	.11	.72	.10
12	-.39	.10	1.01	.07

Predicted Expectation Scale

An improved model fit was obtained using ESEM ($X^2(43, n = 161) = 118.05, p <$ .001, RMSEA = .10 (90% CI .08, .13), CFI = .97, TLI = .95) compared to the CFA ($X^2(53, n =161) = 197.79, p < .001$, RMSEA = .13 (90% CI .11, .15), CFI = .94, TLI = .93; output presented in Appendix 3.8). As the ESEM resulted in a better fitting model, the results of this are reported.

The results of the ESEM showed the two factors to strongly correlate (.62), with all items strongly loading (> .40) onto their target factors (items 1, 2, 3, 5, and 6 on the *Ethical and Privacy Expectations* factor, and items 4, 7, 8, 9, 10, 11, and 12 on the *Service Expectations* factor; Table 3.4). More specifically, $|\lambda|_{\text{Ethical and Privacy}}$

$_{\text{Expectations}}$ ranged from .01 to .92 (M = .41) and $|\lambda|_{\text{Service Expectations}}$ ranged from 0 to .93 (M = .47). While majority of the items loaded highly onto their target factors, there were some cross-loadings that were suggestive of possible misspecifications. For instance, item 4 had a loading of .43 on factor two (*Service Expectations*) and a loading of .40 on factor one (*Ethical and Privacy Expectations*). Based on the content of the item (receiving regular updates based on the analysis of any educational data) and prior work (Chapter 2), item 4 was not expected to cross-load. Although not to the same degree as item 4, both item 5 and item 7 showed cross-loadings that could also be problematic (.34 and .33, respectively). Taken together, the ESEM had identified a number of misspecifications related to item loadings, which required further investigations.

Adding to the abovementioned misspecifications related item loadings, an examination of local fit further pointed to additional model problems. An assessment of the residual correlations showed there to be five absolute values that were ≥ .10 (Appendix 3.9), these items were also found to have large MI and SEPC values. The specific sources of misfit were between items 3 and 4 (-.10; MI = 12.90, SEPC = -.56), items 7 and 8 (.12; MI = 17.21, SEPC = .45), items 8 and 9 (.10; MI = 13.44, SEPC = .42), items 9 and 11 (-.11; MI = 17.26, SEPC = -.41), and items 11 and 12 (.12; MI = 26.06, SEPC = .64). The only misspecification that had previously been identified was between items 11 and 12 and it was stated that the correlation between these errors could not justified. Similarly, correlating the errors of other items that have been identified (e.g., items 7 and 8) could not be supported on conceptual grounds.

Table 3.4. Predicted Expectation Factor Loadings Obtained from the ESEM

Items	Ethical and Privacy Expectations		Service Expectations	
	Estimate	Standard Error	Estimate	Standard Error
1	.63	.06	.17	.07
2	.86	.07	-.03	.09
3	.92	.02	0	.01
4	.40	.08	.43	.08
5	.63	.07	.34	.07
6	.71	.07	.13	.08
7	.33	.08	.54	.06
8	.03	.09	.79	.07
9	.11	.09	.73	.07
10	.01	.03	.78	.04
11	-.15	.09	.80	.08
12	-.16	.09	.93	.06

3.4.5. Descriptive Statistics

Table 3.5 presents the means and standard deviations for each item across expectation types (ideal and predicted) for the Estonian student sample. Based on a comparison of mean values for each expectation type, the average responses were always higher for the ideal expectation scale than the predicted expectation scale. This adds weight to the ability of the SELAQ to differentiate between expectation types (ideal and predicted).

For those items related to the originally proposed *Ethical and Privacy Expectations* factor (items 1, 2, 3, 5, and 6), the highest average response on both the ideal (M = 6.41, SD = 1.12) and predicted (M = 5.86, SD = 1.29) expectation scales was for item 2 (*the university will ensure that all my educational data will be kept securely*). Whereas, the lowest average response on both the ideal (M = 5.81, SD = 1.41) and predicted (M = 5.05, SD = 1.57) expectation scales was 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*).

In terms of the *Service Expectations* factor (items 4, 7, 8, 9, 10, 11, and 12), item 9 was both the highest average ideal (*M* = 5.93, *SD* = 1.23) and predicted (*M* = 5.16, *SD* = 1.36) expectation item. Item 9 stated that *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*. Item 11 however, had the lowest average response for both ideal (*M* = 5.29, *SD* = 1.73) and predicted (*M* = 4.09, *SD* = 1.73) expectation types. The content of item 11 was: *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*).

Table 3.5. Descriptive Statistics for the Estonian Student Sample (n = 161)

Items	Ideal Expectations		Predicted Expectations	
	M	*SD*	*M*	*SD*
1	5.89	1.55	5.25	1.58
2	6.41	1.12	5.86	1.29
3	6.19	1.27	5.43	1.54
4	5.68	1.49	4.77	1.59
5	5.81	1.41	5.05	1.57
6	6.22	1.26	5.25	1.57
7	5.60	1.32	4.86	1.36
8	5.61	1.30	4.87	1.40
9	5.93	1.23	5.16	1.36
10	5.79	1.31	4.49	1.63
11	5.29	1.73	4.09	1.73
12	5.38	1.53	4.63	1.50

3.4.6. Discussion

While the alternative fit indices for both scales (ideal and predicted) show the two-factor model to have acceptable fit, the X^2 test remains significant, and there were a number of misspecifications that could not be ignored. For the ideal expectation scale, while items 11 and 12 loaded highly onto the target factor (*Service Expectations*), they showed weak cross-loadings onto the *Ethical and Privacy Expectations* factor. On the predicted expectation scale, however, item 4 showed a weak factor loading on both the target factor (*Service Expectations*) and non-target factor (*Ethical and Privacy Expectations*). In addition to item 4, items 5 and 7 also showed weak cross-loadings onto their non-target factors (*Service Expectations* and *Ethical and Privacy Expectations*, respectively). Thus, based on these points it is clear that the Estonian version of the SELAQ, based on the current sample, did not provide support for the purported two-factor model. Given the small sample size (n =161), it remains necessary that further work is undertaken to assess the validity of the Estonian SELAQ using larger samples. In addition, the current work has adopted a confirmatory approach in the use of ESEM, which has identified weaknesses in applying the two-factor structure to the Estonian context. The next step may be for researchers to undertaken an exploratory approach to assess whether a refinement in the items is needed or whether an alternative factor structure can be proposed.

Although sample size may be attributed to the issues within the Estonian version of the SELAQ, other explanations may be considered. 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*) refers to obtaining consent for the use of educational data. It may be that these students are accustomed to their data being readily collected, particularly attendance and grade data (Niall Sclater, 2016); thus, problems associated with item 5 may stem from students not expecting a university to undertake such steps. Item 4 may have loaded on to both factors as it is situated within a set of items referring to *Ethical and Privacy Expectations*; therefore, student responses to this may have been affected by prior item responses.

Based on the descriptive statistics presented in Table 3.5, a general view of what the sample of Estonian students expect from LA services is given. From an ethical and privacy perspective, they have strong expectations regarding the maintenance of security over any data collected. Whereas, the belief that consent should be sought before educational data is collected and analysed did elicit agreement from students, the expectation was not as strong as when compared to ensuring that all data is held securely. It may be that students were open to the university collecting data for legitimate purposes (Tsai et al., Under Review), but concerns over who has access to the collected data resulted in stronger expectations toward data security (Ifenthaler & Schumacher, 2016; Roberts et al., 2016).

The expectations toward the LA service features showed that for the Estonian student sample, they hold stronger beliefs toward receiving a learning profile. Whilst their expectations regarding the implementation of early alert systems was one of indifference. The work of Schumacher and Ifenthaler (2018) has found students to expect LA service features that updated them about their learning progress. These views have also been expressed in the work of Roberts et al. (2016), but here the students were also concerned about the loss of independence on account of the LA service being in place. Taking these aforementioned points into consideration, the findings are suggestive of students considering feedback from LA services as an important supplement to their learning, as it could allow students to evaluate their progress toward a set goal (Winne & Hadwin, 2012). Whereas, the possibility of early alert systems may undermine the agency that students exercise whilst they learn (Kruse & Pongsajapan, 2012), and LA should not remove responsibility a student has to learn (Prinsloo & Slade, 2017). This further reinforces the importance of understanding what students expect from LA services (Ferguson, 2012), as it is clear that while higher education institutions may consider some features to be useful (e.g., early alert systems), it may not coincide with student expectations.

3.5. Spanish Version of the SELAQ

3.5.1. Sample

The translated version of the SELAQ was distributed through an online system to students from a Spanish university and 543 volunteer responses were received (Females = 272). The ages of respondents ranged from 16 to 57 (*Mean* = 21.15, *Median* = 20, *SD* = 5.04). Majority of the sample was composed of undergraduate students (87%, *n* = 470), 12% were master students (*n* = 67), and 1% were PhD students (*n* = 6). Of these students, 45% were studying a subject from social and legal sciences (*n* = 244), 41% were taking an engineering subject (*n* = 224), and 14% were studying a subject from humanities, communication, and documentation (*n* = 75). In terms of student type, 93% of the sample were Spanish (*n* = 507), whilst the remaining students were international students (7%, *n* = 36). This demographic information is also presented in Table 3.6.

Table 3.6. Demographic Information for the Spanish Student Sample

Characteristic	*M*	*SD*	*N*	%
Gender				
Male			271	49.91
Female			272	50.09
Age	21.15	5.04		
Subject				
Engineering			224	41
Humanities, Communication, and Documentation			75	14
Social and Legal Sciences			244	45
Level of Study				
Undergraduate			470	87
Masters			67	12
PhD			6	1
Student Type				
Spanish			507	93
International			36	7

3.5.2. Instrument

The original 12-item SELAQ was translated into Spanish (Appendix 3.10) by a researcher who was a native Spanish speaker and who was fluent in English. Once translated, a further researcher assessed the quality of the translation to determine whether the original meaning of the SELAQ items had been preserved. If there were any identified discrepancies, the researchers made subtle changes to the translation in order to better align the item wordings with the original SELAQ. As with the original instrument, responses were 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.

3.5.3. Results of the ESEM and CFA

Ideal Expectations Scale

A marginally improved fit was obtained from the CFA ($X^2(53, n = 543) = 115.92$, $p < .001$, RMSEA = .05 (90% CI .04, .06), CFI = .98, TLI = .97) compared to the ESEM ($X^2(43, n = 543) = 109.74$, $p < .001$, RMSEA = .05 (90% CI .05, .07), CFI = .97, TLI = .96; output present in Appendix 3.11). As the CFA model was more parsimonious, the results from this model are presented.

The unstandardised and standardised estimates for the two-factor solution are presented in Table 3.7. The unstandardised estimates were all statistically significant (*ps* < .001), with a mean standardised loading of .76. The R^2 values showed the two factors to explain a moderate to large amount of the latent continuous response variance (R^2 range = .38 - .66). Both factors (*Ethical and Privacy Expectations* and *Service Expectations*) were found to strongly correlate (.53), but the correlation was at a value that did not suggest poor discriminant validity (i.e., values exceeding .85;

Brown, 2015). Moreover, the average variance extracted for the *Ethical and Privacy Expectations* (.55) and *Service Expectations* (.59) factors exceeds the squared of the correlation between the two factors (.28; Fornell & Larcker, 1981).

On the basis of alternative fit indices, the two-factor model could be regarded as having an acceptable fit, but an assessment of local fit was required due to the significant X^2 test (Kline, 2015; Ropovik, 2015). There were only two absolute residual correlation values ≥ .10 (Appendix 3.12), which were between items 2 and 5 (-.10) and items 11 and 12 (.14). MI and SEPC values also showed that the model fit could be improved by allowing the errors between items 2 and 5 (MI = 12.34, SEPC = -.36) and items 11 and 12 (MI = 27.35, SEPC = .41) to be correlated. These two sources of local misfit within the model had previously been identified (Chapter 2), but there was no justification for allowing the errors of these items to correlate. Therefore, no modifications to the model were undertaken.

Table 3.7. Standardised and Unstandardised Loadings Obtained from the Ideal Expectations CFA

Item	Latent Variable	Unstandardised Loading	Standardised Loading	Standard Error
1	Ethical and Privacy Expectations	1.00	.61	.04
2	Ethical and Privacy Expectations	1.21	.74	.04
3	Ethical and Privacy Expectations	1.28	.79	.03
5	Ethical and Privacy Expectations	1.24	.76	.03
6	Ethical and Privacy Expectations	1.31	.80	.04
4	Service Expectations	1.00	.71	.03
7	Service Expectations	1.11	.79	.02
8	Service Expectations	1.15	.82	.02
9	Service Expectations	1.12	.80	.02
10	Service Expectations	1.13	.80	.02
11	Service Expectations	.99	.71	.03
12	Service Expectations	1.08	.76	.03

Predicted Expectation Scale

A comparison between the results obtained from both the ESEM (X^2(43, n = 543) = 327.78, $p < .001$, RMSEA = .11 (90% CI .10, .12), CFI = .96, TLI = .94; output presented in Appendix 3.13) and CFA (X^2(53, n = 543) = 376.13, $p < .001$, RMSEA = .11 (90% CI.10, .12), CFI = .95, TLI = .94) showed the fits to be marginally different. Thus, a decision was made to report the results of the parsimonious CFA model.

Table 3.8 shows all unstandardised and standardised estimates from the two-factor structure. All unstandardised estimates were statistically significant (ps < .001), with a mean standardised loading of .80. The R^2 values showed the two factors to account for a large amount of the latent continuous response variance (R^2 range = .54-.75). Whilst the two factors were strongly correlated (.70), this correlation did not exceed what would be considered as poor discriminant validity (i.e., .85; Brown, 2015). In addition, the average variance extracted for both factors (.62 and .66 for *Ethical and Privacy Expectations* and *Service Expectations*, respectively) exceeded the square of the correlation (.49; Fornell & Larcker, 1981).

An assessment of the residual correlations (Appendix 3.14) showed four absolute values that are ≥ .10, which were between items 2 and 3 (.10), items 2 and 12 (.10), items 4 and 5 (.16), and items 8 and 9 (.11). MI and SEPC values were also indicative of misspecifications between items 2 and 3 (MI = 30.45, SEPC = .31), items 2 and 12 (MI = 26.04, SEPC = .31), items 4 and 5 (MI = 66.31, SEPC = .53), and items 8 and 9 (MI = 33.06, SEPC = .44). Whilst the misfit between items 2 and 3 had previously been identified in Chapter 2, the remaining sources of localised strain had not. In either case, there was no justification to re-fit the model with correlated errors between the aforementioned variable pairs.

Table 3.8. Standardised and Unstandardised Loadings Obtained from the Predicted Expectations CFA

Item	Latent Variable	Unstandardised Loading	Standardised Loading	Standard Error
1	Ethical and Privacy Expectations	1.00	.74	.02
2	Ethical and Privacy Expectations	1.03	.76	.02
3	Ethical and Privacy Expectations	1.02	.75	.02
5	Ethical and Privacy Expectations	1.12	.83	.02
6	Ethical and Privacy Expectations	1.18	.87	.02
4	Service Expectations	1.00	.78	.02
7	Service Expectations	1.07	.83	.02
8	Service Expectations	1.09	.85	.01
9	Service Expectations	1.01	.79	.02
10	Service Expectations	1.05	.82	.02
11	Service Expectations	1.02	.80	.02
12	Service Expectations	1.05	.82	.02

3.5.4. Descriptive Statistics

Table 3.9 shows the descriptive statistics for the Spanish student sample across both expectation types (ideal and predicted). Based on a comparison of mean values, it can be seen that average responses on the ideal expectation scale were higher than the predicted expectation scale. Thus, as found with the Estonian student sample, the validity of the SELAQ to differentiate between ideal and predicted expectation types is further supported.

Considering only the *Ethical and Privacy Expectation* items (items 1, 2, 3, 5, and 6), the descriptive statistics were similar to those of the Estonian student sample on both expectation types (ideal and predicted). The highest ideal (M = 6.61, SD = 1.02) and predicted (M = 5.64, SD = 1.36*)* expectation mean values were for item 2 (*the university will ensure that all my educational data will be kept securely*). Whereas, the lowest ideal (M = 6.01, SD = 1.40) and predicted (M = 4.67, SD = 1.72) expectation mean values were 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*.

Whilst the highest and lowest average responses for the *Ethical and Privacy Expectation* items (items 1, 2, 3, 5, and 6) were the same across Estonian and Spanish student samples, there were slight differences with regards to *Service Expectation* items (items 4, 7, 8, 9, 10, 11, and 12). For the Spanish student sample, item 4 (*the university will regularly update me about my learning progress based on the analysis of my educational data*) received the highest average ideal expectation (M = 6.17, SD = 1.27). Whereas, item 9 received the highest average predicted expectation response (M = 5.00, SD = 1.73). Item 9 asked to students regarding the following statement: *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*. Although the highest predicted expectation, item 9 received the lowest average response on the ideal expectation scale (*M* = 5.91, *SD* = 1.44). Similar to the Estonian student sample, item 11 had the lowest average response for the predicted expectation scale (*M* = 4.16, *SD* = 1.81). Item 11 asked whether *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*.

Table 3.9. Descriptive Statistics for the Spanish Student Sample (n = 543)

Items	Ideal Expectations		Predicted Expectations	
	M	*SD*	*M*	*SD*
1	6.28	1.24	5.14	1.62
2	6.61	1.02	5.64	1.36
3	6.35	1.23	5.13	1.62
4	6.17	1.27	4.53	1.73
5	6.01	1.40	4.67	1.72
6	6.51	1.07	5.00	1.73
7	6.16	1.22	4.93	1.54
8	6.00	1.24	4.96	1.54
9	5.91	1.44	5.00	1.58
10	6.01	1.38	4.66	1.66
11	6.04	1.49	4.16	1.81
12	6.08	1.26	4.73	1.61

3.5.5. Discussion

The alternative fit indices for the ideal expectation scale would suggest a good fitting model; whereas, the predicted scale fit could only be considered as acceptable. In order to provide a context for these fit indices, an assessment of measurement quality was also provided. This showed the mean standardised loading to be higher on the predicted expectation scale ($M = .80$) than the ideal expectation scale ($M = .76$). Thus, from a position of measurement quality, the predicted expectation scale exceeded that of the ideal expectation scale.

For both scales, the X^2 test was found to be significant; thus, an inspection of local fit was warranted. In terms of the ideal expectation scale, the sources of misfit (between items 2 and 5 and items 11 and 12) had previously been identified (Chapter 2). As stated in this prior work, while these items were to some extent related, there was no justified reason for respecifying the model to allow the errors of these items to correlate. Therefore, no steps were taken in the current study to freely correlate the item errors. A different set of localised strains for the predicted expectation scale were identified, with only a single variable pair being previously identified (misfit between items 2 and 3). In none of these cases was there a justifiable reason for respecifying the model with correlated errors between the problematic variable pairs. Taken together, it could therefore be shown that both scales showed good measurement quality, with the predicted expectation scale exceeding that of the ideal expectation scale, and the fit for each scale can at least be considered as acceptable. Nevertheless, further work on the scale is needed, particularly as the X^2 test was found to be significant.

An inspection of those descriptive statistics relating to the *Ethical Privacy Expectations* factor (Table 3.9) show the expectations of the Spanish student sample to be similar to those held by Estonian student sample. Put differently, as with the Estonian student sample, the Spanish student sample held stronger expectations, on average, toward the university ensuring all data was secure than the university seeking consent before collecting and analysing educational data. This again reiterates the view that students may be more open to their data being used for legitimate purposes (Tsai et al., Under Review), as universities regularly use such data for assessments and to monitor academic progress. Irrespective of these beliefs regarding the provision of consent for the collection and use of educational data, these Spanish students expected the university to ensure that any collected data remains secure (Ifenthaler & Schumacher, 2016; Roberts et al., 2016).

For the items of the *Service Expectations* factor, the Spanish student sample appeared to hold strong ideal expectations towards receiving regular feedback, but had higher predicted expectations towards the provision of complete learning profiles. Similar to Estonian student sample, the Spanish students were seemingly indifferent to the provision of early alert systems. Again this overview of the descriptive statistics does suggest that features aimed at supporting learner agency and self-regulated learning are expected from LA services (Schumacher & Ifenthaler, 2018). Whereas, early interventions may have unintended consequences (e.g., added pressure for students) or may even be a hindrance to independent learning (Roberts et al., 2016). These concerns could be attributed to the indifference that students expressed towards the possibility of incorporating early alert systems in LA services.

3.6. Dutch Version of the SELAQ

3.6.1. Sample

A total of 1,247 students (Females = 705) from a Dutch university completed the Dutch translated version of the 12-item SELAQ (Appendix 3.15) distributed through an online system (all responses were voluntary). Seven respondents did not provide their age or gave an incorrect age based on the demographic information of the university (e.g., 99 years of age). Of those respondents that did, their ages ranged from 18 to 82[2] (*Mean* = 44.81, *Median* = 46, *SD* = 12.14). Majority of the sample were undergraduate students (64%, *n* = 793), 36% were masters students (*n* = 450), and 4 were PhD students (.003%). Respondents were almost equally distributed across the three faculties at the university, 33% (*n* = 413) from culture and jurisprudence, 33% (*n* = 416) from management, science, and technology, and 34% (*n* = 418) from psychology and education. Majority of the sample were Dutch students (90%, *n* = 1125), 9% were European students (*n* = 106), with only 1% of respondents being overseas students (*n* = 16). This demographic information is provided in Table 3.10.

[2] The age range was also checked with the student services of the institution who confirmed the upper age limit of the students was correct.

Table 3.10. Demographic Information for the Dutch Student Sample

Characteristic	*M*	*SD*	*N*	%
Gender				
Male			542	43.46
Female			705	56.54
Age	44.81	12.14		
Subject				
Culture and Jurisprudence			413	33
Management, Science, and Technology			416	33
Psychology and Education			418	34
Level of Study				
Undergraduate			793	64
Masters			450	36
PhD			4	.003
Student Type				
Dutch			1125	90
European			106	9
Overseas			16	1

3.6.2. Instrument

The original 12-item SELAQ was translated into Dutch (Appendix 3.15). This was undertaken by a colleague whose is a native Dutch speaker. Once translated, two researchers, who are native Dutch speakers, assessed the translated survey to determine whether the original meaning of the SELAQ items had been preserved. If there were any identified discrepancies, the researchers made subtle changes to the translation in order to better align the item wordings with the original SELAQ. The translated instrument was then distributed to students through an online survey system. As with the original instrument, responses were 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.

3.6.3. Results of the ESEM and CFA

Ideal Expectation Scale

An improved fit was obtained from the ESEM (X^2(43, n = 1247) = 166.63, $p < .001$, RMSEA = .05 (90% CI .04, .06), CFI = .98, TLI = .97) than the CFA (X^2(53, n = 1247) = 288.05, $p < .001$, RMSEA = .06 (90% CI .05, .07), CFI = .96, TLI = .95; output presented in Appendix 3.16). Thus, the results of the ESEM are presented.

The results of the ESEM showed the two factors to weakly correlate (.09), with all items loaded strongly (> .40) onto their target factors (items 1, 2, 3, 5, and 6 on the *Ethical and Privacy Expectations* factor, and items 4, 7, 8, 9, 10, 11, and 12 on the *Service Expectations* factor; Table 3.11). The $|\lambda|_{\text{Ethical and Privacy Expectations}}$ ranged from 0 to .81 (M = .36) and the $|\lambda|_{\text{Service Expectations}}$ ranged from 0 to .90 (M = .51).

There were no problematic cross-loadings, but item 11 did show a weak cross-loading onto the *Ethical and Privacy Expectation* factor (λ = -.20).

An assessment of local strain in the model was required due to the significant X^2 test (Kline, 2015; Ropovik, 2015). From an inspection of the residual correlation values (Appendix 3.17), there was only one absolute value ≥ .10, which was between items 11 and 12 (.12). MI and SEPC values also pointed to a possible misspecification between items 11 and 12 (MI = 66.13, SEPC = .42). As previously stated, this misfit within the model had been identified beforehand (Chapter 2); however, there was no justified reason for allowing the errors of these items to correlate.

Table 3.11. Ideal Expectation Factor Loadings Obtained from the ESEM

Items	Ethical and Privacy Expectations		Service Expectations	
	Estimate	Standard Error	Estimate	Standard Error
1	.73	.02	-.10	.04
2	.81	.02	-.01	.02
3	.81	.02	0	.01
4	.10	.03	.78	.01
5	.70	.02	.09	.03
6	.81	.02	.07	.04
7	.07	.03	.86	.01
8	.01	.02	.90	.01
9	-.03	.03	.87	.01
10	0	.01	.86	.01
11	-.20	.03	.76	.02
12	-.06	.03	.79	.01

Predicted Expectation Scale

A marginal improvement in model fit was obtained using the ESEM (X^2(43, n = 1247) = 513.51, p < .001, RMSEA = .09 (90% CI .09, .10), CFI = .96, TLI = .93; output presented in Appendix 3.18) compared to the CFA (X^2(53, n = 1247) = 612.15, p < .001, RMSEA = .09 (90% CI = .09, .10), CFI = .95, TLI = .94). Therefore, the CFA model results are presented on the basis of it being a more parsimonious model.

Table 3.12 presents both the standardised and unstandardised estimates for the two-factor solution. All unstandardised estimates were statistically significant (*ps* < .001), with a mean standardised loading of .81. The R^2 values showed the two factors to account for a large amount of the latent continuous response variance (R^2 range .42-.79). The two factors were moderately correlated (.43), which did not suggest poor discriminant validity (i.e., did not exceed .85; Brown, 2015). In addition, the average variance extracted for the *Ethical and Privacy Expectations* factor (.69) and the *Service Expectations* factor (.63) exceeded the square of the correlation (.18).

An inspection of the residual correlations (Appendix 3.19) showed that there were eight instances of absolute values that were ≥.10. Majority of these large residual correlations were for item 11, specifically between item 1 (-.12), item 2 (-.13), item 3 (-.10), and item 12 (.13). MI and SEPC values provided further evidence of misspecification between items 1 and 11 (MI = 42.49, SEPC = -.26), items 2 and 11 (MI = 46.29, SEPC = -.30), items 3 and 11 (MI = 30.76, SEPC = -.29), and items 11 and 12 (MI = 59.39, SEPC = .38). Again, the misfit between items 11 and 12 had been identified, but there are no grounds for respecification (Chapter 2). The remaining sources of local strain (between item 11 and items 1, 2, and 3) had not been found before; thus, no respecification of the model was made, but these instances of misfit are further explored. The remaining sources of strain within the model, based on absolute residual correlation values, were between items 1 and 2 (.12; MI = 55.20, SEPC = .44), items 1 and 9 (-.10; MI = 31.13, SEPC = -.28), items 2 and 9 (-.11; MI = 32.25, SEPC = -.32), and items 4 and 5 (.18; MI = 97.86, SEPC = .54). Of these localised areas of strain, only the poor prediction between items 4 and 5 ha been identified previously (predicted expectation scale for the Spanish student sample) and there was no justification for correlated errors. For the remaining variable pairs, there are no grounds for respecifying the model.

Table 3.12. Standardised and Unstandardised Loadings Obtained from the Predicted Expectations CFA

Item	Latent Variable	Unstandardised Loading	Standardised Loading	Standard Error
1	Ethical and Privacy Expectations	1.00	.74	.02
2	Ethical and Privacy Expectations	1.09	.80	.01
3	Ethical and Privacy Expectations	1.17	.87	.01
5	Ethical and Privacy Expectations	1.14	.84	.01
6	Ethical and Privacy Expectations	1.20	.89	.01
4	Service Expectations	1.00	.73	.01
7	Service Expectations	1.18	.86	.01
8	Service Expectations	1.18	.86	.01
9	Service Expectations	1.09	.80	.01
10	Service Expectations	1.16	.85	.01
11	Service Expectations	.89	.65	.02
12	Service Expectations	1.10	.80	.01

3.6.4. Descriptive Statistics

Table 3.13 presents the mean and standard deviations for each item of the SELAQ for the Dutch student sample across expectation types (ideal and predicted). For all items, apart from item 11, the average response was always higher for ideal than predicted expectations. Item 11 asked whether *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*. An examination of item 11 for the Dutch sample showed that whilst the average responses were similar (M = 4.25 and M = 4.27 for ideal and predicted expectations, respectively), the standard deviation value for the ideal expectation was the largest across all items (SD = 2.06). Thus, for the Dutch student sample there was much variability in regards to their ideal beliefs toward teaching staff having an obligation to act under circumstances where a student may be at-risk of failing. Other than this discrepancy, the descriptive statistics were largely supportive of the Dutch translated version of the SELAQ differentiating between ideal and predicted expectations.

Considering only the *Ethical and Privacy Expectation* items, the highest ideal (M = 6.69, SD = .74) and predicted (M = 5.93, SD = 1.39) expectations, on average, was for item 2 (*the university will ensure that all my educational data will be kept securely*). Whereas, the lowest average ideal (M = 6.21, SD = 1.21) and predicted (M = 5.38, SD = 1.58) expectations was 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*.

For the *Service Expectation* items, item 8 (*the learning analytics service will show how my learning progress compares to my learning goals/the course objectives*) received the highest average response on both the ideal (M = 5.50, SD =

1.67) and predicted (M = 5.14, SD = 1.54) expectation scales. Similar to the findings from the Estonian student sample, item 11 received the lowest average response on both the ideal (M = 4.25, SD = 2.06) and predicted (M = 4.27, SD = 1.66) expectation scales. Item 11 asked whether *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.*

Table 3.13. Descriptive Statistics for the Dutch Student Sample (n = 1247)

Items	Ideal Expectations		Predicted Expectations	
	M	*SD*	*M*	*SD*
1	6.44	1.06	5.85	1.38
2	6.69	.74	5.93	1.39
3	6.56	.98	5.78	1.54
4	5.50	1.63	5.05	1.49
5	6.21	1.21	5.38	1.58
6	6.62	.99	5.64	1.66
7	5.47	1.64	5.08	1.45
8	5.50	1.67	5.14	1.54
9	4.86	1.89	4.80	1.64
10	5.29	1.70	4.75	1.57
11	4.25	2.06	4.27	1.66
12	5.00	1.76	4.68	1.55

3.6.5. Discussion

The alternative fit indices obtained from the ideal expectation scale showed the two-factor structure to have a good fit. Moreover, the improved fit was obtained from using the ESEM than the CFA. While the factor loadings presented in Table 3.11 show all items to load highly (> .40) onto their target factors, item 11 had a small but non-zero negative loading ($\lambda = -.20$) on the *Ethical and Privacy Expectations* factor; which was the largest cross-loading.

For the predicted expectation scale, the CFA model was retained due to the differences with the ESEM being marginal. While the alternative fit indices for the two-factor model were found to be acceptable, and the measurement quality was good (mean standardised loading = .81), an assessment of local fit showed there to be a number of strains in the model, particularly related to item 11. Based on the content of these variable pairs (i.e., item 11 with items 1, 2, 3, and 12), there was no justifiable reason for the respecification of the model to include correlated errors. However, focusing only on local strains between item 11 and those variables attributed to the *Ethical and Privacy Expectations* factor (items 1, 2, and 3), there may be other reasons for this misfit. While not presented, the ESEM results for the predicted expectation scale showed item 11 to have a weak negative cross-loading onto the *Ethical and Privacy Expectation* factor ($\lambda = -.18$; Appendix 3.18). Taken together, it is clear that while item 11 is strongly related to the type of service students will receive, specifically whether early interventions should be implemented, there is also an ethical element. As discussed by Prinsloo and Slade (2017), a higher education institution does share some responsibility in relation to the obligation to act, particularly from a moral basis. Thus, this may explain why item 11 weakly cross-loaded onto the *Ethical and Privacy Expectations* factor for both ideal and predicted expectation scales. In other words, students may expect that an ethical LA service would entail a right to decide if teaching staff have an obligation to act if they are deemed to be underperforming or at-risk of failing.

An assessment of local fit in the model did identify a source of strain between the variable pair of items 11 and 12, which had been identified previously (Chapter 2). Whilst this variable pair has been the most frequent source of misfit within the model, it has remained inconsistent. As shown in the Spanish student sample, the misfit between this variable pair (items 11 and 12) was only found for the ideal expectation scale; whereas, this localised strain occurred for both scales (ideal and predicted) in the Dutch and Estonian student samples. Thus, respecification of the two-factor model that included a correlated error between items 11 and 12 could not be justified on conceptual grounds, but also due to the inconsistency of this misfit.

Taking the abovementioned points into consideration, it is clear that the ideal expectation scale, based on alternative fit indices, exhibited good fit and all items loaded strongly onto their target factors, with cross-loadings being relatively small. The predicted expectation scale showed an acceptable fit, based on alternative fit indices, but the measurement quality was good. Irrespective of these findings, the X^2 test remained significant for both scales. Whilst an examination of local misfit did not highlight any variable pairs within the model whose errors could be justifiably be correlated, it remains pertinent that researchers continue to assess the validity of the Dutch version of the SELAQ.

Based on the descriptive statistics provided in Table 3.13, similarities with the Spanish and Estonian student samples can be found. In terms of the *Ethical and Privacy Expectations* factor items, the Dutch student sample appear to have strong ideal and predicted expectations toward the university ensuring that all collected data remains secure. Whereas, the weakest item, on average, for both the ideal and predicted expectation scales was for the university obtaining consent for the collection and analysis of educational data. This again shows that students may in fact be open to the university collecting and analysing specific educational data if the purpose is deemed legitimate (Tsai et al., Under Review). However, students hold stronger beliefs toward the university ensuring all collected data remain secure (Ifenthaler & Schumacher, 2016; Roberts et al., 2016).

For the *Service Expectations* factor, the highest mean value on both scales (ideal and predicted) was for students receiving feedback on how their learning is progressing in relation to a set goal. In contrast, the lowest average expectation for both scales (ideal and predicted) was for the provision of an early alert system. As with the Estonian and Spanish student sample, these descriptive statistics are suggestive of students expecting features that aim to support the regulation of their learning (Schumacher & Ifenthaler, 2018), but remain indifferent to those features that could undermine learner agency (Roberts et al., 2016).

3.7. Comparing Expectations

3.7.1. Comparisons

Figure 3.2 presents the mean value of each item of the SELAQ by country and expectation type (ideal and predicted). What can be taken away from this figure is that students across all samples seemingly have higher expectations (ideal and predicted) toward the *Ethical and Privacy Expectations* factor items (items 1, 2, 3, 5, and 6). In particular, the expectation toward the university ensuring that all data is kept secure (item 2) has the largest mean value across all items on both scales. Whereas, the expectation that the university will seek consent to collect and analyse educational data (item 5) is lowest across each country. In the case of those items related to *Service Expectations* (items 4, 7, 8, 9, 10, 11, and 12), the Spanish student sample to generally have higher expectations, on average, compared to the Estonian and Dutch student samples on the ideal expectation scale. Whereas, the mean values for the Dutch student sample on the ideal expectation scale show them to have lower expectations of LA service features. In relation to the predicted expectation scale, the average responses to the items of the *Service Expectations* factor are generally lower than responses on the ideal expectation scale. It can also be seen that item 11 receives the lowest average response for each sample.

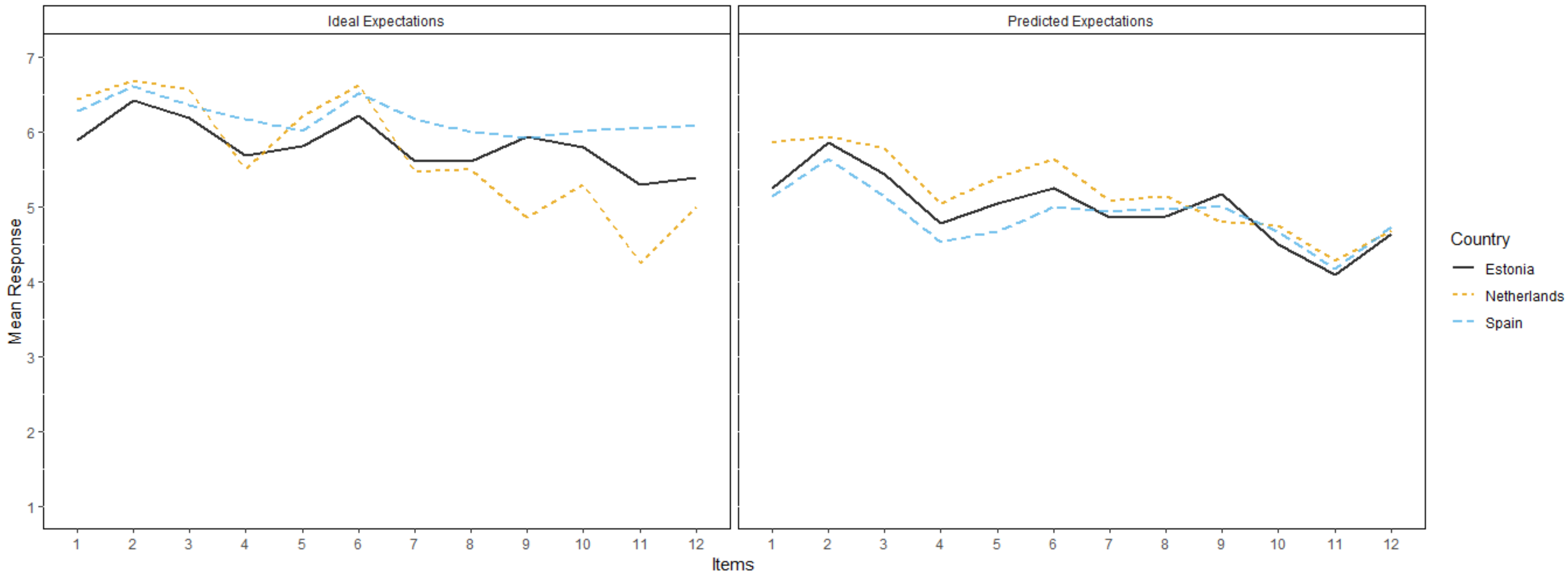

Figure 3.2. Mean Values for SELAQ Items by Country and Expectation Type (Ideal and Predicted)

3.7.2. Discussion

Using the descriptive statistics alone, preliminary insights into possible differences in student expectations of LA services can be made, as shown in Chapter 2. With regards to *Ethical and Privacy Expectations*, item 2 (*the university will ensure that all my educational data will be kept securely*) received the highest average response on both the ideal and predicted expectation scales across each sample (Estonian, Spanish, and Dutch students). This is similar to what was found with the sample of UK university students (Chapter 2). Likewise, item 5, stating that *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*, received the lowest average responses on both scales (ideal and predicted expectations) across each sample (Estonian, Spanish, and Dutch students), which was again found in Chapter 2.

From comparing highest and lowest average responses for both ideal and predicted expectation scales on the *Ethical and Service Expectation* items, there is indication of similarities across the different samples. Students hold strong beliefs toward the university securely holding all collected data (item 2), whilst the belief that a university should seek consent before the collection, use, and analysis of educational data appears to elicit the lowest average response for each sample of students (item 5). Although for the ideal expectation scale, the average responses are indicative of students strongly agreeing to item 5. For predictive expectations, responses to item 5 generally show students to be between indifference and weakly agreeing. A plausible assumption here is that it is common place for universities to collect large amounts of educational data in order to evaluate attendance and to contact students; therefore, it may be that students expect such practices to be undertaken without their consent. On the other hand, ensuring that all data remains secure may elicit higher expectations on account of students' personal data being stored by the higher education institution. Thus, whilst educational data is collected by a university, students believe that procedures should be in place that uphold privacy and confidentiality (Ifenthaler & Schumacher, 2016; Roberts et al., 2016; Slade & Prinsloo, 2014).

In relation to the *Service Expectation* items, the descriptive statistics do show variability in what features students expect from LA services. Our prior work with UK university students (Chapter 2) showed that their highest average ideal expectation response was for item 10 (*the teaching staff will be competent in incorporating analytics into the feedback and support they provide to me*), whilst for predicted expectations this was the lowest average response. The highest average predicted expectation response was for item 8 (*the learning analytics service will show how my learning progress compares to my learning goals/the course objectives*), whilst the lowest average ideal expectation response was for item 11 stating *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*.

For the Estonian student sample, they held high ideal and predicted expectations of wanting a LA service that provided them with a complete profile of their learning (item 9). As with the UK student sample (Chapter 2), the Estonian student sample had low ideal expectations toward teaching staff having an obligation to act (item 11), and this was also the lowest predicted expectation item. Likewise, the Dutch student sample was found to have the lowest average response on item 11 for both ideal and predicted expectation scales. Their (the Dutch student sample) highest average responses for both ideal and predicted expectations, however, were for LA services that show students how their learning progress compares to a set goal (item 8). In terms of the Spanish student sample, receiving a complete profile of their learning (item 9) had the lowest ideal expectation on average, but also the highest average response on the predicted expectation scale. Whereas, the highest average response for the ideal expectation scale was for receiving regular updates about their (the students') learning (item 4), and the lowest average response for the predicted expectation was for the belief about teaching staff having an obligation to act (item 11).

It appears that students do not hold strong expectations toward the use of early interventions if LA services found them to be at-risk. Similarly, Roberts et al. (2016) found students to express concern over LA services removing the ability of students to make their own independent decisions. Given the importance placed on independent learning at universities, having systems in place that are centred on the implementation of early interventions to assist underperforming or at-risk students is a contradiction to this position. In line with the view of being independent learners, students appeared to hold higher expectations of LA services that offer informative profiles about their learning, how learning is progressing with reference to a set goal, or receiving regular updates about their learning progress. Thus, students seemingly prefer an LA service that facilitates independent learning rather than one which would impede their self-determination (Schumacher & Ifenthaler, 2018).

3.8. General Discussion

Even though the SELAQ is an advantageous instrument to guide LA service implementations, it had so far only been tested in UK higher education institutions

(Chapter 2). The current work sought to address this limitation by validating the three translated versions (Estonian, Spanish, and Dutch) of the SELAQ. In doing so, this will increase the number of countries who are able to use the SELAQ in their pursuit of implementing LA services. Of the three samples (Etonian, Spanish, and Dutch students) used in this study, the findings from the Estonian student sample are not supportive of the purported two-factor model. Whereas, the results obtained from the Spanish and Dutch student samples show the translated versions of the SELAQ to have acceptable fit (based on alternative fit indices) and good measurement quality.

The problems with the Estonian version of the SELAQ can be attributed to the cross-loadings that were identified through the use of ESEM (Asparouhov & Muthén, 2009). Whilst four items showed weak cross-loadings onto their non-target factors (i.e., items 5, 7, 11, and 12), item 4 loaded weakly onto both the target and secondary factor (λ = .43 and .40, respectively) for the predicted expectation scale. Given that the current work utilised a confirmatory approach, no respecifications of the model were undertaken in order to address these problematic loadings. Nevertheless, our results highlight strains within the model that require further investigation. The next steps should then be to reassess the Estonian version of the SELAQ utilising a larger sample of students. In addition, an exploratory approach to ESEM should be undertaken as items may need to be removed or an alternative factor structure may be proposed. If continued problems are identified, it would show the SELAQ to be an inappropriate tool to be used and an alternative instrument may be required.

As for the findings obtained from the Spanish and Dutch student samples, the two-factor structure was supported. If the cut-offs proposed by Hu and Bentler

(1999) are used to assess the fit, then the ideal expectation scale appears to provide a better fit. Whilst, the RMSEA values obtained for the predicted expectation scale would be considered as acceptable or poor (MacCallum et al., 1996). As recommended by McNeish et al. (2018), alternative fit indices need to be interpreted within the context of measurement quality, particularly as it is attributed to RMSEA functioning differently. Thus, from a measurement quality, the predicted expectation scale was good, even exceeding the ideal expectation scale.

Irrespective of these results pertaining to alternative fit indices and measurement quality, the X^2 test was significant for each scale and sample (Spanish and Dutch students). It was therefore imperative to conduct an inspection of local fit, paying particular attention to the absolute residual correlation values and both MI and SEPC values. From this assessment of local fit, a number of problematic variable pairs were identified. In none of these cases did a source of misfit lead to a model respecification, which was a decision informed by both prior work (Chapter 2) and item content. For example, the misfit between items 11 and 12 had been previously identified and it was identified in all three student samples, but not all scales. More specifically, it was not identified for the predicted expectation scale for the Spanish student sample, but was found in the Dutch and Estonian student samples. Therefore, respecifying the model to allow correlated errors between these variables may equate to a capitalisation on chance (MacCallum et al., 1992), in addition to there being no justifiable reason (i.e., no overlapping content) for such modifications. Nevertheless, the significant X^2 test shows that further work on the translated versions of the SELAQ are required. It may be that an exploratory approach needs to be adopted to understand whether an alternative factor structure needs to be proposed or whether items need to be dropped.

Preliminary insights into possible differences in student expectations have also been reported. For *Ethical and Privacy Expectations*, there appeared to be similarities across the three samples (Estonian, Spanish, and Dutch students). In particular, the descriptive statistics show that, on average, students hold stronger beliefs toward the university ensuring that all data is secure (item 2) over the university seeking consent to collect and analyse educational data (item 5). In the qualitative work with students, Roberts et al. (2016) have found students to express concerns regarding the privacy of their data, particularly in relation to who has access. Similarly, Ifenthaler and Schumacher (2016) found concerns about their privacy to be an important determinant in the acceptance of potential LA services. Taken together, it appears that while students may hold particularly strong beliefs toward providing consent, the institution preserving their privacy is a pivotal expectation.

In regards to *Service Expectations*, students across all three samples seemingly expressed indifference to early interventions (item 11). Whereas, the highest average responses on these items were for LA service features that gave regular updates on their learning (item 4), showed how their learning progress compares to a goal (item 8), or receiving a complete profile of their learning (item 9). As shown by Schumacher and Ifenthaler (2018), students expect LA service features that facilitate self-regulated learning such as being able to monitor their progress.

Taking the aforementioned points into account, it provides a basic understanding of what students expect from LA services and the possible cross-cultural differences that need to be explored further. In particular, it provides an important stakeholder perspective of what students want from LA services, which is one focused on upholding independence and ensuring that all data is protected. This adds weight to the findings of Roberts et al. (2016), which found students to view LA services as potentially undermining their ability to self-direct their own learning. As discussed by Kruse and Pongsajapan (2012), LA services that predominately focus on interventions may result in a culture of passivity. Rather, students should be provided with feedback that can motivate positive changes to their learning (Gašević et al., 2015), such as engaging in self-regulation (Winne & Hadwin, 2012). What is more, features aimed at promoting more effective learning is what students expect from LA services (Roberts et al., 2017; Schumacher & Ifenthaler, 2018). Thus, the aforementioned points further reinforce the importance of gauging the expectations of students towards the LA service they want, rather than providing a service we believe they want.

3.8.1. Implications

The average responses to the *Ethical and Privacy Expectations* items provides an important perspective from the end-users of LA services, particularly in understanding their beliefs towards data handling procedures. Given the new General Data Protection Regulation[3] (GDPR) that will be put into force in Europe in May 2018, European universities will be required to apply new regulations. These will provide fundamental rights towards the data subject and the data they leave behind. Examples of these rights include: general requirements about transparency and communication, meaningful information about the algorithms involved, information about profiling, access to and rectification of personal data, and the right to erasure (Drachsler & Greller, 2016; Hoel, Griffiths, & Chen, 2017). In other words, universities will be expected to meet the *Ethical and Privacy Expectations* of the

[3] Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation)

SELAQ. From a student perspective, we can see that, on average, they have strong ideal expectations toward the university ensuring all data remains secure or controlling the access from third party companies. However, responses to the predicted expectation scale show students' beliefs to not be as strong. Therefore, while it is desirable for the university to follow such data handling procedures (e.g., asking for consent to use identifiable data), students may not expect too much from their universities, even though the GDPR demands these. The reason for these lowered predicted expectations may be the result of students' level of awareness regarding the GDPR and the implications it has for European universities.

It is also alarming that most students have low expectations of their teaching staff being able to incorporate analytics into the feedback they receive (item 10) or to intervene in circumstances of underperformance (item 11). These beliefs referring to the service students want from LA are concerning, as the GDPR forces European Universities to provide a clear purpose for their use of LA services. In addition, there is a requirement to provide an action plan on how to follow-up on the results by their staff. If there is no such purpose or staff do not possess the competencies to follow-up on the results, privacy protection officers will have to question why LA is applied at all and might just prohibit it. Put differently, if students do not expect universities to have a clear plan on how to use LA services, then intentions to introduce LA can be questioned.

3.8.2. Limitations and Future Research

The findings of the current work raise questions about the suitability of the Estonian version of the SELAQ. Given the identified problems regarding cross-loading items, it is important for researchers to follow-up this study with one that adopts an exploratory approach in conjunction with a larger sample size. It may be found that items need to be removed, an alternative factor structure is proposed, or that the SELAQ is not a viable instrument to be used in this context. If the latter position is supported, then we encourage researchers to take steps to develop and validate an alternative instrument to measure student expectations of LA services. In addition, we have discussed how the content of item 5 and the position of item 4 may have resulted in the problems identified; thus, researchers should be mindful of these when utilising the questionnaire in the future.

For the Spanish and Dutch translated versions of the SELAQ, the alternative fit indices do show the model fit to be acceptable. Whilst the RMSEA is high for the Spanish predicted expectation scale, the measurement quality is good and this is associated with the RMSEA functioning (McNeish et al., 2018). Thus, on the basis of these findings it does support the use of the SELAQ to measure student expectations within these contexts. Researchers should not be complacent, however, as the X^2 test was significant in all cases and localised strains in the model were identified. Continued assessment of the SELAQ in these contexts should therefore be undertaken.

Chapter 4: Student Expectations of Learning Analytics Services: Do they align? A multinational assessment of measurement invariance

4.1. Summary

This chapter focuses on exploring whether student expectations of learning analytics services are invariant across three samples of students (England, the Netherlands, and Spain). Through the use of measurement invariance techniques (multi-group confirmatory factor analysis and alignment), the work shows that the SELAQ (student expectations of learning analytics questionnaire) scales are invariant, but the expectations of each sample differ. These findings provide the current authors with a basis to discuss the suitability of a one size fits all approach to learning analytics policies.

4.2. Introduction

Interest in implementing learning analytics services in higher education institutions is growing (Tsai, Moreno-Marcos, et al., 2018). This has primarily been driven by claims of learning analytics services being capable of improving retention rates, allowing teaching staff to better understand students' use of learning strategies, and offering personalised support (Tsai & Gašević, 2017b). In Europe, these promises of learning analytics services are being realised, but majority of higher education institutions remain within the pre-implementation stages of adoption (e.g., preparing roll-out projects; Tsai & Gašević, 2017b). Irrespective of the possible benefits learning analytics services may bring, institutions must address the challenge of engaging with the relevant stakeholders such as students (Tsai & Gašević, 2017a; Tsai, Moreno-Marcos, et al., 2018). As shown in the technology adoption literature, failure to effectively gauge and understand the pre-adoption beliefs (i.e., expectations) of stakeholders will inevitably lead to a service that users are dissatisfied with and/or are unwilling to accept to use (Brown, Venkatesh, & Goyal, 2012, 2014; Davis & Venkatesh, 2004; Venkatesh & Goyal, 2010). Whilst measuring stakeholder expectations of learning analytics services, specifically those held by students, is a viable solution to meet the aforementioned challenge, it cannot be assumed that pre-adoption beliefs are consistent across countries. Therefore, the objective of this paper was to explore whether student expectations of learning analytics are consistent across three European countries (England, the Netherlands, and Spain).

4.2.1. Technology Acceptance Across Countries

Researchers seeking to understand post-adoption beliefs towards technology have relied extensively on the technology acceptance model (TAM; Davis, 1989; King &

He, 2006). Despite its utility in providing an understanding of those reasons that determine whether an implemented technology becomes widely used, it was recognised early on that the TAM was culturally limited (Straub, Keil, & Brenner, 1997). From the point of conception right up to the work of Straub et al. (1997), the TAM had only been applied in North American contexts without any consideration of cultural differences that may affect adoption rates. The findings of Straub et al. (1997) showed the TAM to not be supported outside its original context. The implication of this work is that variables determining the successful adoption of technology are not consistent across countries and a blanket approach to implementation cannot be expected to work.

As with the TAM, Venkatesh and Zhang (2010) similarly found the unified theory of acceptance and use of technology (UTAUT) to not be culturally consistent. In this study, the UTAUT dimension of social influence had an inconsistent effect on intentions to use a technology in a comparison between employees from the United States and China (Venkatesh & Zhang, 2010). This again reinforces the view that the results obtained from a single country cannot be used as evidence to guide implementation decisions in other countries, as certain facets of adoption may be more important than others. For the purposes of the current paper, the evidence from these technology acceptance studies show that global implementations of learning analytics services, which are guided by the findings from one country, cannot be expected to work. Rather, steps need to be taken to evaluate whether the constructs being measured are invariant and to determine whether student expectations of learning analytics services are similar.

4.2.2. Learning Analytics Across Countries

There has been little research into understanding whether student expectations of learning analytics service are homogenous across countries. The only tangible example has been the work carried out by Arnold and Sclater (2017), which compared student responses to three dichotomous items. The content of these items covered the exchange of data for early interventions or improved grades, and whether students wanted to compare performance with their peers. Results of the study are based on two samples of students from UK (United Kingdom) higher education institutions and a single American university. It was found that a larger proportion of American students (60%), in contrast to the students from UK higher education institutions (25%), would be happy to have a learning analytics service that enabled them to compare their performance with peers (Arnold & Sclater, 2017). Although these authors do not directly discuss the heterogeneity in responses obtained from these two samples, it does show that student expectations of learning analytics services may not be consistent across countries.

It is important to recognise that the interest in learning analytics is not from UK universities alone, but extends across higher education institutions in Europe and the rest of the world (Pardo et al., 2018). Thus, equally engaging with relevant stakeholders (e.g., students) in the development and implementation of learning analytics services is a challenge that will face all higher education institutions (Tsai & Gašević, 2017a). In light of the limited findings of Arnold and Sclater (2017), it is clear that the a one size fits all solution to this challenge may not be suitable, on account of the differences found between two countries. However, this work of Arnold and Sclater (2017) is not without its limitations, particularly with regards to the use of an on-the-fly scale. Without sufficient validation of the scale, it cannot then be established that the same construct is being measured across each group (measurement invariance) (Meade & Lautenschlager, 2004). Put differently, if the measurement invariance of a scale does not hold (e.g., across gender or country) then it cannot be concluded that differences are based on actual differences in the characteristics of the respondents (Horn & Mcardle, 1992). Given the methodological limitations of Arnold and Sclater's (2017) work, the current study aimed to assess the measurement invariance of the 12-item student expectations of learning analytics questionnaire (SELAQ) across three European countries (England, the Netherlands, and Spain).

4.2.3. The Student Expectations of Learning Analytics Questionnaire

In the context of learning analytics services, the current authors defined an expectation as "a belief about the likelihood that future implementation and running of learning analytics services will possess certain features" (Chapter 2, p. 46). This definition was grounded in the theoretical work on expectations (Olson & Dover, 1976), which are only distinguishable from beliefs (Ajzen, 2011; Fishbein & Ajzen, 1975) in terms of the time point the judgement refers to (Olson & Dover, 1976). Put differently, expectations are framed as beliefs about the future (Olson & Dover, 1976).

The issue with the term expectation, however, is that it is quite general and does not differentiate between levels of belief. Thus, to provide a more comprehensive understanding of what students expect from learning analytics services, the expectation decomposition presented by Thompson and Suñol (1995) was considered. In this work, Thompson and Suñol (1995) broke expectations into four types: ideal (desired outcome), predicted (realistic belief), normative (deserved service), and unformed (no expectations formed). For the purposes of understanding student expectations of learning analytics services, only the ideal and predicted expectation levels were considered (Chapter 2). This was on the basis of the work presented by Bowling et al. (2012), which found these two expectation levels to provide a useful gauge of what individuals expect from a healthcare service. More specifically, it allowed for an understanding of what is desired from the healthcare service and what is realistically expected (Bowling et al., 2012). Thus, it provides an upper reference point and realistic benchmark of service expectations. This advantage of measuring two levels of expectation has been demonstrated in the work developing and validating the SELAQ (Chapters 2 and 3).

As it stands, the developed 12-item SELAQ has been validated for use in three countries (England, the Netherlands, and Spain) and general descriptive statistics (mean response per item) have been given (Chapters 2 and 3) but no attempt at examining measurement invariance has been undertaken (Chapters 2 and 3). This is an important limitation that needs to be addressed, as without establishing that the same constructs are being measured across each country then any comparisons are not valid (Horn & Mcardle, 1992; Liu et al., 2017; Meade & Lautenschlager, 2004). Therefore, the objective of the study was to test the measurement invariance of the 12-item SELAQ across three samples of students (England, the Netherlands, and Spain). The specific research questions guiding this work are:

RQ1. Is the ideal expectation scale of the SELAQ invariant across three samples (England, the Netherlands, and Spain)?

RQ2. Is the predicted expectation scale of the SELAQ invariant across three samples (England, the Netherlands, and Spain)?

RQ3. How do student expectations of learning analytics services vary across three samples (England, the Netherlands, and Spain)?

4.3. Method

4.3.1. Sample

The study consisted of a volunteer sample of 1981 students from three countries (England, the Netherlands, and Spain; this is a re-use of the data from Chapter 2 and 3). The specific samples sizes per group were as follows: 191 for the English student sample, 1247 for the Dutch student sample, and 543 for the Spanish student sample. When reporting the output of the alignment analysis, 3-letter country abbreviations will be used (ENG = England, NLD = the Netherlands, and ESP = Spain). In addition, it is important to mention that the Dutch university was a distance learning institution; whereas, the English and Spanish universities were predominately campus-based institutions.

The average age for each of the three samples were as follows: 20.40 years for the English student sample (*SD* = 3.00, Median = 20), 21.10 years for the Spanish student sample (*SD* = 5.05, Median = 20), and 44.80 years for the Dutch student sample (*SD* = 12.10, Median = 46). It is important to note that the average age of the Dutch student sample is based on the data points of 1,240 respondents as seven were incorrectly reported. In terms of level of study, majority of the samples were made up of Undergraduate Students. For the English students, 98.40% (n = 188) identified as Undergraduate Students and only 1.57% (n = 3) were Masters Students. The Spanish student sample had a proportion of 86.60% (n = 470) for Undergraduate Students, 67% (n = 67) for Masters Students, and 1.10% (n = 6) for PhD Students. Whereas, the Dutch student sample had 63.60% (n = 793) respondents who were

Undergraduate Students, 36.10% (n = 450) who were Masters Students, and .32% (n = 4) who were PhD Students. This demographic information is also presented in Tables 4.1, 4.2, and 4.3.

Table 4.1. Demographic Information for English Student Sample

Characteristic	Mean	SD	N	%
Gender				
Male			62	32.46
Female			129	67.54
Age	20.41	3		
Subject				
Arts and Humanities			45	24
Engineering			24	13
Medicine and Health Sciences			45	24
Science			36	19
Social Sciences			41	24
Level of Study				
Undergraduate			188	98
Masters			3	.02
Student Type				
Home/EU			153	80
Overseas			38	20

Table 4.2. Demographic Information for the Dutch Student Sample

Characteristic	Mean	SD	N	%
Gender				
Male			542	43.46
Female			705	56.54
Age	44.81	12.14		
Subject				
Culture and Jurisprudence			413	33
Management, Science, and Technology			416	33
Psychology and Education			418	34
Level of Study				
Undergraduate			793	64
Masters			450	36
PhD			4	.003
Student Type				
Dutch			1125	90
European			106	9
Overseas			16	1

Table 4.3. Demographic Information for the Spanish Student Sample

Characteristic	Mean	SD	N	%
Gender				
Male			271	49.91
Female			272	50.09
Age	21.15	5.04		
Subject				
Engineering			224	41
Humanities, Communication, and Documentation			75	14
Social and Legal Sciences			244	45
Level of Study				
Undergraduate			470	87
Masters			67	12
PhD			6	1
Student Type				
Spanish			507	93
International			36	7

4.3.2. Measurements

Student expectations of learning analytics were measured using the 12-item SELAQ (Table 4.4). The items of this questionnaire cover *Ethical and Privacy Expectations* (e.g., providing consent before data is given to third party companies; factor one) and *Service Expectations* (e.g., the provision of early alert systems; factor two). Responses to each item are made on two scales that correspond to two different levels of expectation: what students ideally want from a service (ideal expectations) and what students expect to happen in reality (predicted expectations). Students responded to each of these statements using 7-point Likert scales that ranged from 'Strongly Disagree' (1) to 'Strongly Agree' (7).

Table 4.4. 12 Items of the SELAQ with Factor Key

Item Number	Factor	Item Text
1	Ethical and Privacy Expectations	The university will ask for my consent before using any identifiable data about myself (e.g., ethnicity, age, and gender)
2	Ethical and Privacy Expectations	The university will ensure that all my educational data will be kept securely
3	Ethical and Privacy Expectations	The university will ask for my consent before my educational data is outsourced for analysis by third party companies
4	Service Expectations	The university will regularly update me about my learning progress based on the analysis of my educational data
5	Ethical and Privacy Expectations	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)
6	Ethical and Privacy Expectations	The university will request further consent if my educational data is being used for a purpose different to what was originally stated
7	Service Expectations	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)
8	Service Expectations	The learning analytics service will show how my learning progress compares to my learning goals/the course objectives
9	Service Expectations	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)
10	Service Expectations	The teaching staff will be competent in incorporating analytics into the feedback and support they provide to me
11	Service Expectations	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
12	Service Expectations	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

4.3.3. Analysis Strategy

4.3.3.1. Summary of Analysis Strategy

To answer RQ1 and RQ2, the consistency of student expectations across three countries (England, the Netherlands, and Spain) were assessed using traditional multi-group confirmatory factor analysis and the alignment method (Asparouhov & Muthén, 2014b; Marsh et al., 2017). As for answering RQ3, the SELAQ factor means for *Ethical and Privacy Expectations* and *Service Expectations* were compared across each country (England, the Netherlands, and Spain), with significance being set at the 5% level.

4.3.3.2. Detailed Analysis Strategy

The approach to assessing measurement invariance of the SELAQ scales (ideal and predicted expectations), which would answer RQ1 and RQ2, followed the recommendations outlined by Marsh et al. (2017). In these recommendations, Marsh and colleagues stated that the traditional multi-group confirmatory factor analysis approach to measurement invariance should initially be pursued. If either the metric (equality of factor loadings) or scalar (equality of thresholds and loadings) models are found to be poor, then an alignment analysis should be undertaken. In the case that both metric and scalar models are good, then the traditional multi-group confirmatory factor analysis should be retained on account of parsimony. For the current study, we followed these guidelines to determine whether alignment should be pursued and to answer RQ1 and RQ2.

An examination of the response frequencies across each sample showed there to be a ceiling effect (Appendices 4.1 and 4.2). Based on this distribution of responses, the data was considered as being categorical. As the alignment method uses the maximum likelihood estimator with robust standard errors (MLR), this estimator was used for the traditional multi-group confirmatory factor analysis approach to test measurement invariance (Muthén, Muthén, & Asparouhov, 2015). When analysing categorical data with the MLR estimator, no alternative fit indices are provided such as the comparative fit index (CFI) or root mean square error (RMSEA), nor are modification indices. Thus, for the traditional multi-group confirmatory factor analysis approach to test measurement invariance the determination of whether the equality constraints placed on the loadings and thresholds degrade the models was based on the X^2 difference test. Put differently, if the X^2 difference test is found to be significant ($p < .05$) then the more restrictive model is found to be statistically worse. Other researchers have suggested that measurement invariance can be assessed using alternative fit indices, specifically CFI and RMSEA (Chen, 2007; Meade, Johnson, & Braddy, 2008), or the X^2 statistic can be improved by freeing specific parameters on the basis of modification indices (Saris et al., 2009). As previously stipulated, however, neither of these alternative fit indices or modification indices are provided with the MLR estimator and categorical variables so only the X^2 difference test is presented. It is also important to note that the X^2 difference test was calculated using the loglikelihood obtained from each model (e.g., configural, metric, and scalar models).

For the traditional multi-group confirmatory factor analysis approach to test measurement invariance, each scale (ideal and predicted expectations) was analysed in a stepwise manner using Mplus 8.1 (Muthén & Muthén, 2017). Thus, we started with the least restrictive configural model (freely estimated factor loadings and thresholds), then moved to the more restrictive metric (factor loading constrained to equality) and scalar (factor loadings and thresholds constrained to equality) models. Each model was then compared using the X^2 difference test, which if significant ($p <$ .05) is indicative of the invariance hypothesis not being supported. Typically, researchers would then carry out a step-by-step search of parameters that are not invariant in order to retain a model that is partially invariant. However, we cannot adopt this approach on account of the estimator, but also because this capitalises on chance (Flake & McCoach, 2018; Marsh et al., 2017). Instead, the alignment method would be used under such circumstances (i.e., metric or scalar invariance not being supported; Marsh et al., 2017).

The alignment method does not involve imposing a series of equality constraints to achieve metric or scalar invariance (Asparouhov & Muthén, 2014; Muthén & Asparouhov, 2013). Rather, the method starts with a configural model with equal factor numbers and zero loadings in all groups (Muthén & Muthén, 2017). A loss function is then used to estimate the degree of non-invariance across factor loadings and thresholds, which favours an optimal model with the fewest non-invariant parameters (Muthén & Muthén, 2017). Following the identification of an optimal model, the factor means and variances for each group are then estimated (Muthén & Muthén, 2017).

There are two alignment optimisations that can be run: FIXED and FREE (Asparouhov & Muthén, 2014b). The FIXED optimisation constrains the factor mean and variance for a specific group. Whilst, the FREE optimisation only constrains the factor variance, not the factor mean. The simulation studies undertaken by Asparouhov and Muthén (2014) to compare these optimisations found the FREE alignment to breakdown with only a small number of groups (e.g., two groups). However, as the number of groups increases, along with the amount of measurement non-invariance, the accuracy of parameter estimates obtained from the FREE alignment surpasses those of the FIXED alignment (Asparouhov & Muthén, 2014b). For the current study, the alignment method was initially run using the FREE optimisation. If the model was poorly identified, then the FIXED optimisation was run with the country that had factor means closest to zero being used as the reference group (i.e., factor mean constrained to 0).

With regards to the results of the alignment method, the amount of non-invariance across the loadings and thresholds should not exceed 25% in order to be considered trustworthy (Muthén & Asparouhov, 2014). Additionally, the R^2 values also reflect the degree of invariance/non-invariance, with values closer to 1 representing high invariance (Asparouhov & Muthén, 2014b); however, it may be affected by the number of groups used (Flake & McCoach, 2018). Under those circumstances where the amount of non-invariance does exceed 25%, a Monte Carlo simulation should be run to check the correlation between the estimated and population factor means. A correlation of .98 has been put forward as an indication of the estimated factor means being reliable (Muthén & Asparouhov, 2014). Irrespective of whether the amount of non-invariance fell below or exceeded 25%, the alignment method was followed up with a Monte Carlo simulation.

For the current study, the Monte Carlo simulation used the population values obtained from the alignment method, 500 replications were used, with a simulated sample size of 660 (based on the average sample size for the three groups). Along with the correlation between population and estimated factor means, researchers have also presented details regarding the recovery of specific parameters (e.g., the coverage values for factor loadings, thresholds, factor means, and factor variances; Asparouhov & Muthén, 2014b). In our study, we followed the approach taken by

Flake and McCoach (2018) and summarise the absolute relative bias, mean square error (MSE), and coverage for factor loadings, thresholds, factor means, and factor variances. The criteria for absolute relative bias states that values should not exceed .10 (10%), whilst coverage values should fall between .91 and .98 (Muthén, 2002). As for MSE, high values are indicative of the parameter estimates not accurately predicting population values (Price, Gonzalez, & Whittaker, 2018). This was used a guide to determine whether the parameters were well recovered or not.

On the basis of the alignment results being reliable, the means of each factor (*Ethical and Privacy Expectations* and *Service Expectations*) will be compared for each scale (ideal and predicted), which addresses RQ3. The output obtained from Mplus shows whether any of the groups has a factor mean that is significantly smaller at the 5% level; thus, providing an answer to RQ3

4.4. Results

4.4.1. Ideal Expectations

4.4.1.1. Summary of Results

For RQ1, results of the alignment method show the ideal expectation scale to be invariant across the three European countries (England, the Netherlands, and Spain). Those findings relating to RQ3 showed that the *Ethical and Privacy Expectations* of Dutch students were significantly higher than those of either the English or Spanish student samples. In the case of *Service Expectations*, the Dutch students had factor means significantly lower than those of both the English and Spanish student samples. Section 4.4.1.2. provides a detailed overview of the measurement invariance testing and Monte Carlo simulations.

4.4.1.2. Detailed Results

The initial analysis of the ideal expectation scale data using traditional multi-group confirmatory factor analysis resulted in a non-identified model. This was attributed to the second threshold for item 3 in the English student sample. An examination of response frequencies for all samples showed that there were five instances of categories with zero frequencies (Appendix 4.3), which may have led to the non-identification. Four of these cases were for the English student sample: item 2 (disagree category), item 3 (somewhat disagree category), item 6 (disagree category), and item 9 (disagree category). The remaining instance where there was a response frequency of zero was for item 2 (disagree category) in the Spanish student sample data. This has been identified as a common problem when using ordinal data, with one solution being to collapse adjacent categories (Liu et al., 2017). From the investigations undertaken by Grondin and Blais (2010), which explored the effects of different approaches to collapsing categories, these authors found the best results to be from collapsing the intermediate categories (somewhat and mainly). In addition, these authors found that the collapsing of categories should not applied equally across all items as it may lead to poor outcomes; instead, solutions should be applied to specific items (Grondin & Blais, 2010). Taking this into account, it was decided that the intermediate categories of ‘somewhat disagree’ and ‘disagree’ would be collapsed for the following items: item 2, item 3, item 6, and item 9. This solution would be applied across each of the three samples.

Following the collapse of the two intermediate categories (‘somewhat disagree’ and ‘disagree’) for the four items (items 2, 3, 6, and 9), the configural model was identified. Using the traditional multi-group confirmatory factor analysis approach (Table 4.5), the metric invariance model was found to not be statistically worse than the configural model ($X^2(20) = 30.947$, $p = .056$). However, scalar invariance was not supported as it was to be statistically worse than both the configural ($X^2(152) = 793.130$, $p < .001$) and metric ($X^2(132) = 781.306$, $p < .001$) models. Given that the scalar invariance model was rejected, we followed the recommendations outlined by Marsh and colleagues, which advocates the use of the alignment method under such circumstances (Marsh et al., 2017).

Table 4.5. Likelihood chi-square tests for the ideal expectations measurement invariance models

Model	Number of Parameters	Loglikelihood	
Configural	245	-27578.926	
Metric	225	-27597.711	
Scalar	93	-27973.964	
Models Compared	Chi-square	Degrees of Freedom	*P*-value
Metric vs. Configural	30.947	20	.056
Scalar vs. Configural	793.130	152	<.001
Scalar vs. Metric	781.306	132	<.001

The FIXED alignment method was used to analyse the data on account of the FREE method resulting in a non-identified model. For the FIXED approach, the Dutch student sample was used as the reference group on account of the factor means being closer to zero. The results of the alignment analysis are provided in Tables 4.6 and 4.7. All non-invariant parameters are indicated by placing the country acronyms within parentheses. For thresholds, it was found that 7.35% (n = 15) were not invariant across the three samples, whilst all loadings were invariant. Thus, the amount of non-invariance identified fell below the 25% cut-off put forward by Asparouhov and Muthén (2014), which can be indicative of the results being trustworthy, which addresses RQ1.

In addition to the percentage of non-invariant parameters, we also examined the R^2 values obtained for both thresholds and loadings. With regards to thresholds, 77.941% (n = 53) had values below .90, whilst 83.333% (n = 10) loadings had R^2 values lower than .90. The average R^2 values were found to be .552 and .589 for thresholds and loadings, respectively. These low R^2 values may be attributed to the analysis only being ran on three groups; therefore, good estimates may not be attainable (Flake & McCoach, 2018).

Table 4.6. Ideal Expectations Invariance results for aligned threshold parameters for items 1 to 12 (acronyms in parentheses show significant non-invariance)

Items	Factor	Threshold 1	Threshold 2	Threshold 3	Threshold 4	Threshold 5	Threshold 6
Item 1	Ethical and Privacy Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP
Item 2	Ethical and Privacy Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	-
Item 3	Ethical and Privacy Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	-
Item 4	Service Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG **(ESP)**
Item 5	Ethical and Privacy Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP
Item 6	Ethical and Privacy Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	-
Item 7	Service Expectations	**(NLD)** ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG **(ESP)**
Item 8	Service Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG **(ESP)**	**(NLD)** ENG ESP	NLD ENG ESP
Item 9	Service Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	**(NLD)** ENG ESP	-
Item 10	Service Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP
Item 11	Service Expectations	**(NLD)** ENG ESP	**(NLD)** ENG ESP	**(NLD)** ENG ESP	**(NLD)** ENG ESP	**(NLD)** ENG ESP	**(NLD)** ENG ESP
Item 12	Service Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	**(NLD)** ENG ESP	**(NLD)** ENG ESP	NLD ENG **(ESP)**

Table 4.7. Ideal Expectations Invariance results for aligned loadings for items 1 to 12 (acronyms in parentheses show significant non-invariance)

Items	Factor	Invariance
Item 1	Ethical and Privacy Expectations	NLD ENG ESP
Item 2	Ethical and Privacy Expectations	NLD ENG ESP
Item 3	Ethical and Privacy Expectations	NLD ENG ESP
Item 4	Service Expectations	NLD ENG ESP
Item 5	Ethical and Privacy Expectations	NLD ENG ESP
Item 6	Ethical and Privacy Expectations	NLD ENG ESP
Item 7	Service Expectations	NLD ENG ESP
Item 8	Service Expectations	NLD ENG ESP
Item 9	Service Expectations	NLD ENG ESP
Item 10	Service Expectations	NLD ENG ESP
Item 11	Service Expectations	NLD ENG ESP
Item 12	Service Expectations	NLD ENG ESP

A Monte Carlo simulation was run using the output obtained from the alignment analysis. This has been recommended as an approach to take when the amount of non-invariance exceeds 25% (Asparouhov & Muthén, 2014b). In circumstances where non-invariance is lower than 25%, the use of a Monte Carlo simulation provides additional information regarding factor mean estimation, particularly as to whether trustworthy group comparisons can be made (Muthén & Asparouhov, 2014). The factor mean correlations obtained from the Monte Carlo simulation were near perfect for both *Ethical and Privacy Expectations* (r = .984) and *Service Expectations* (r = .994), which exceeded the suggested .98 put forward by Muthén and Asparouhov (2013).

In conjunction with the correlations between population and estimated factor means, we followed the steps taken by Flake and McCoach (2018) and provide the average absolute relative bias, MSE, and coverage for all parameters (loadings, thresholds, factor means, and factor variances; Table 4.8). The average coverage values were similar to what was found by Asparouhov and Muthén (2014) in that they were above .95. None of the parameters had average absolute relative bias values that exceeded .10 (Muthén, 2002). The MSE values, however, point to problems with the thresholds (MSE = .642). This large average MSE value for thresholds appeared to be driven upwards by the English student sample, specifically the first thresholds of items 2 (MSE = 31.803), 3 (MSE = 39.314), 8 (MSE = 4.359), and 12 (MSE = 17.379). These high MSE values could be attributed to the sparseness of the data as the response frequencies for certain categories are low (Item 2: response category 1 = 1, response category 2 = 1; Item 3: response category 1 = 1, response category 2 = 1; Item 8: response category 1 = 2, response category 2

= 1; Item 12: response category 1 = 1, response category = 3). Also for the Dutch student sample, the first threshold for item 2 has a large MSE value (8.757). As with the English student sample, this could be caused by low frequencies in the lower response categories (Item 2: response category 1 = 5, response category 2 = 7).

The overview of averages found the recovery of parameter values to be good. Nevertheless, there were clear issues regarding the large MSE values obtained, which was seemingly related to the low frequency of responses with specific categories. Despite this, Muthén and Asparouhov (2013) stated that the correlation between the true and estimated factor means may be more important than individual parameter bias (Asparouhov & Muthén, 2014b). Based on the correlations observed from the Monte Carlo simulation, the alignment results can be considered as good and the factor means will be compared.

Table 4.8. Average Absolute Relative Bias, Mean Square Error, and Coverage of Loadings, Thresholds, Factor Means, and Factor Variances

Parameter Type	Absolute Relative Bias	MSE	Coverage
Loadings	.010	.064	.960
Thresholds	.021	.642	.960
Factor Means	.064	.006	.982
Factor Variances	.015	.011	.968

To answer RQ3, factor mean comparisons for the ideal expectations scales are presented in Table 4.9. The table ranks each sample by the mean and indicates in the last column as to whether the differences are significant at the 5% level. For the *Ethical and Privacy Expectations* factor, both the Spanish and English student samples had statistically smaller factor means (-.358 and -.519, respectively) than the Dutch student sample (.000). In contrast, the Dutch student sample was found to have a factor mean that was significantly smaller (.000) than both the English (.449) and Spanish (.454) student samples for the *Service Expectations* factor.

Table 4.9. Factor Means for Ideal Expectations Scale

Factor	Ranking	Group	Factor Mean	Groups with significantly smaller factor mean[a]
Ethical and Privacy Expectations	1	NLD	.000	3 2
Ethical and Privacy Expectations	2	ESP	-.358	
Ethical and Privacy Expectations	3	ENG	-.519	
Service Expectations	1	ESP	.454	1
Service Expectations	2	ENG	.449	1
Service Expectations	3	NLD	.000	

[a]NLD = Group 1, ENG = Group 2, ESP = Group 3; NLD is the reference group

4.4.2. Predicted Expectations

4.4.2.1. Summary of Results

Findings related to RQ2 showed the predicted expectation scale to be invariant across the three European countries (England, the Netherlands, and Spain). Results pertaining to RQ3 showed the Spanish student sample to have *Ethical and Privacy Expectations* that were significantly lower than those of either the English or Dutch student samples. As for *Service Expectations*, the English student sample had significantly higher factor means than those of either the Dutch or Spanish student samples. A detailed presentation of the measurement invariance testing and Monte Carlo simulation is given in Section 4.4.2.2.

4.4.2.2. Detailed Results

There were no response frequency issues that affected model identification for the predicted expectation scale (Appendix 4.4). Nevertheless, the traditional multi-group confirmatory factor analysis approach to assessing measurement invariance for the predicted expectations scale was deemed inappropriate (Table 4.10). Compared to the configural model, the metric invariance model was found to not be statistically worse ($X^2(20) = 28.079$, $p = .108$). The scalar model, however, was statistically worse than both the metric ($X^2(140) = 514.469$, $p < .001$) and configural ($X^2(160) = 529.332$, $p < .001$) models. Thus, based on the likelihood-ratio chi-square tests, the scalar model was rejected. Based on the recommendations of Marsh et al. (2017) it was therefore decided that an alignment analysis would be undertaken.

Table 4.10. Likelihood chi-square tests for the predicted expectations measurement invariance models

Model	Number of Parameters	Loglikelihood	
Configural	257	-34678.005	
Metric	237	-34696.335	
Scalar	97	-34945.667	
Models Compared	Chi-square	Degrees of Freedom	*P*-value
Metric vs. Configural	28.079	20	.108
Scalar vs. Configural	529.332	160	<.001
Scalar vs. Metric	514.469	140	<.001

Initially, the FREE alignment approach was run on the raw data, but the model was poorly identified. The analysis was then re-run using the FIXED option with the English student sample being the reference group on account of the factor means being closest to zero. The results of the FIXED alignment analysis of the three groups are provided in Tables 4.11 and 4.12. Any parameters that were not invariant are shown by placing the country acronyms in parentheses. Zero loadings were found to be non-invariant and 3.241% (n = 7) of thresholds were non-invariant. Thus, this fell below the suggested cut-off of 25% non-invariance put forward by Asparouhov and Muthén (2014), which substantiates the trustworthiness of these results and addresses RQ2.

As for the R^2 values, these did suggest that the obtained alignment results should be viewed with caution. Using the .90 rule of thumb (Flake & McCoach, 2018), there were a number of thresholds and loadings falling below this value. For the thresholds, 72.222% of the R^2 values (n = 52) were below .90 and 100% of the R^2 values for loadings did not meet this cut off (n = 12). In addition, the mean R^2 values for the thresholds and loadings were .677 and .259, respectively. Flake and McCoach (2018) did note in their simulations that using a small number of groups (e.g., three groups) may not be sufficient for obtaining good estimates for variance explained.

Table 4.11. Invariance results for aligned threshold parameters for items 1 to 12 (acronyms in parentheses show significant non-invariance)

Items	Factor	Threshold 1	Threshold 2	Threshold 3	Threshold 4	Threshold 5	Threshold 6
Item 1	Ethical and Privacy Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP
Item 2	Ethical and Privacy Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP
Item 3	Ethical and Privacy Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP
Item 4	Service Expectations	NLD ENG ESP	NLD ENG ESP	**(NLD)** ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP
Item 5	Ethical and Privacy Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP
Item 6	Ethical and Privacy Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP
Item 7	Service Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP
Item 8	Service Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	**(NLD)** ENG ESP	NLD ENG ESP
Item 9	Service Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP
Item 10	Service Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP
Item 11	Service Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	NLD **(ENG)** ESP	NLD **(ENG)** ESP	NLD **(ENG)** ESP
Item 12	Service Expectations	NLD ENG ESP	NLD ENG ESP	NLD ENG ESP	**(NLD)** ENG ESP	NLD ENG ESP	**(NLD)** ENG ESP

Table 4.12. Invariance results for aligned loadings for items 1 to 12 (acronyms in parentheses show significant non-invariance)

Items	Factor	Invariance
Item 1	Ethical and Privacy Expectations	NLD ENG ESP
Item 2	Ethical and Privacy Expectations	NLD ENG ESP
Item 3	Ethical and Privacy Expectations	NLD ENG ESP
Item 4	Service Expectations	NLD ENG ESP
Item 5	Ethical and Privacy Expectations	NLD ENG ESP
Item 6	Ethical and Privacy Expectations	NLD ENG ESP
Item 7	Service Expectations	NLD ENG ESP
Item 8	Service Expectations	NLD ENG ESP
Item 9	Service Expectations	NLD ENG ESP
Item 10	Service Expectations	NLD ENG ESP
Item 11	Service Expectations	NLD ENG ESP
Item 12	Service Expectations	NLD ENG ESP

Even though the current results were considered acceptable, based on the percentage of parameters considered non-invariant (3.241% of thresholds and 0% of loadings), a Monte Carlo simulation was run to assess the replicability of the factor means (Asparouhov & Muthén, 2014b). The results of the Monte Carlo analysis found near perfect correlations between the population and estimated factor means for both the *Ethical and Privacy Expectations* factor (r = .995) and *Service Expectations* factor (r = .985).

Table 4.13 presents the average absolute relative bias, mean square error (MSE), and coverage for loadings, thresholds, factor means, and factor variances. The average coverage values were in line with the results of Asparouhov and Muthén (2014) in that they were close to or above .95. For absolute relative bias, average values never exceeded .10 for loadings, thresholds, or factor variances (B. Muthén, 2002). The average absolute relative bias for the factor means was .335, which was associated with an incorrect estimate for the *Ethical and Privacy Expectations* factor mean in the Dutch student sample (true value = -.011, estimate = .003, bias = 1.28). The average MSE for thresholds was also found to be high (.196), which can be attributed to the first thresholds of items 1 and 2 in the English student sample (MSE values = 21.068 and 4.226, respectively). The response frequencies for items 1 and 2 are sparse for the English student sample, specifically for the first and second response categories (Item 1: response category 1 = 1, response category 2 = 3; Item 2: response category 1 = 2, response category 2 = 1).

The Monte Carlo output indicated that we should take caution in the interpretation of the alignment analysis, particularly as not all parameters were well recovered. It has, however, been suggested that the correlation between the true and estimated factor means are of greater importance than individual parameter bias

(Asparouhov & Muthén, 2014; Muthén & Asparouhov, 2013). Thus, given the correlations observed it did suggest that the alignment was good and the factor means will be compared.

Table 4.13. Average Absolute Relative Bias, Mean Square Error, and Coverage of Loadings, Thresholds, Factor Means, and Factor Variances

Parameter Type	Absolute Relative Bias	MSE	Coverage
Loadings	.015	.039	.956
Thresholds	.026	.196	.956
Factor Means	.335	.005	.959
Factor Variances	.023	.022	.937

To answer RQ3, a comparison of factor means is presented in Table 4.14. Each student sample is ordered from high to low based on the factor mean obtained, with a column also indicating whether the factor means are statistically different at the 5% level. It was found that for the *Ethical and Privacy Expectations*, the Spanish student sample had a significantly smaller factor mean (-.690) than both the sample of English (.000) and Dutch (-.011) students. As for *Service Expectations*, the Dutch and Spanish student samples had significantly smaller factor means (-.263 and -.335, respectively) than the English student sample (.000).

Table 4.14. Factor Means for Predicted Expectations Scale

Factor	Ranking	Group	Factor Mean	Groups with significantly smaller factor mean[a]
Ethical and Privacy Expectations	1	ENG	.000	3
Ethical and Privacy Expectations	2	NLD	-.011	3
Ethical and Privacy Expectations	3	ESP	-.690	
Service Expectations	1	ENG	.000	1 3
Service Expectations	2	NLD	-.263	
Service Expectations	3	ESP	-.335	

[a]NLD = Group 1, ENG = Group 2, ESP = Group 3; ENG is the reference group

4.4.3. Comparing Expectation Scales

To clarify the results pertaining to RQ3, the relative means of the *Ethical and Privacy Expectations* and *Service Expectations* factors by country are displayed in Figure 4.1 (for identification purposes, the factor mean is set to zero, with variance of one). It is important to note that for the ideal expectations scale, the Dutch student sample is the reference group; whereas, the English student sample is the reference group for the predicted expectations scale.

What can be seen from the *Ethical and Privacy Expectations* factor is that the Dutch students had the highest ideal expectations across the three samples. For predicted expectations, the English student sample were no different that the Dutch student sample, but the expectations of Spanish students were considerably lower. With regards to *Service Expectations*, Figure 4.1 shows a clear trend of students having higher ideal than predicted expectations. In contrast to *Ethical and Privacy Expectations*, Dutch students had the lowest ideal expectations regarding learning analytics service features. English students, on the other hand, had the highest *Service Expectations* across each scale (ideal and predicted expectations).

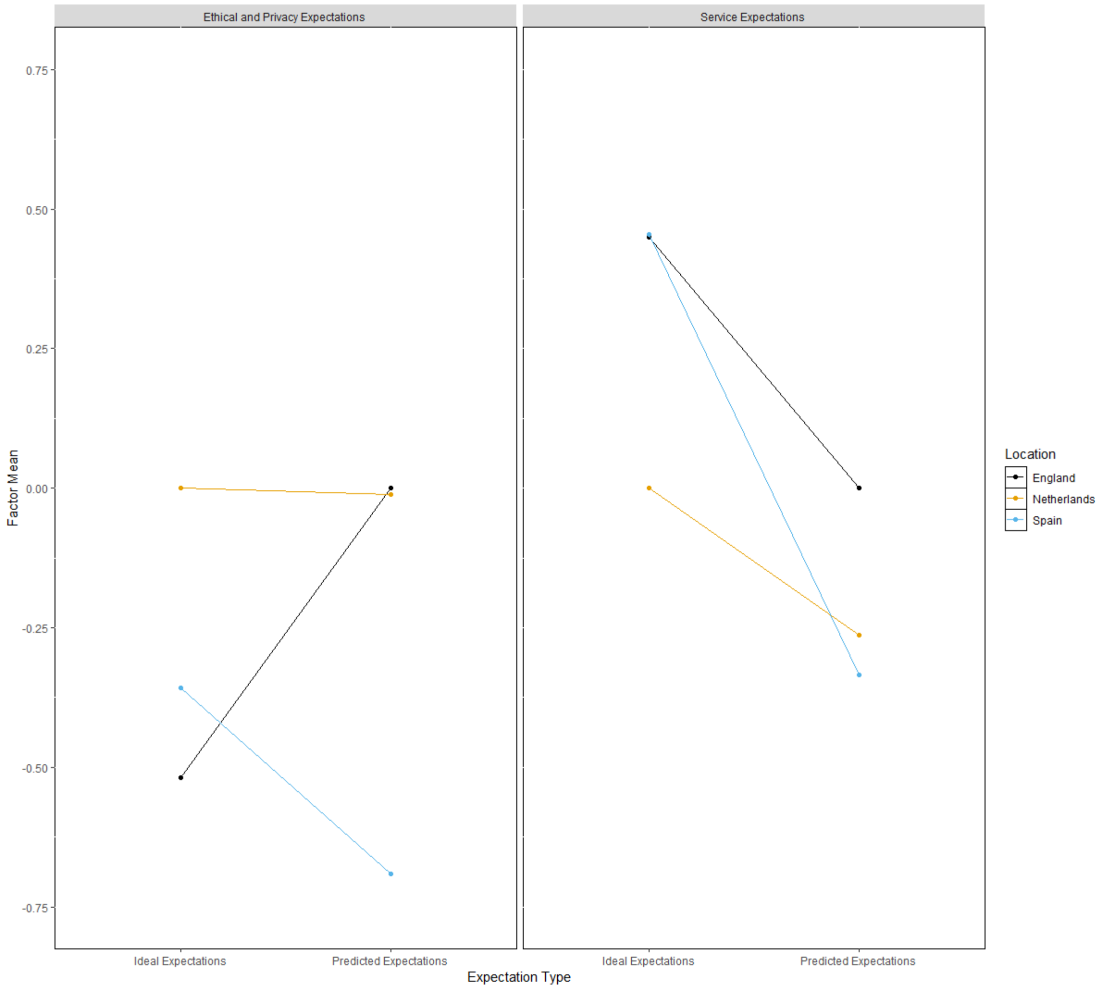

Figure 4.1. Relative Factor Means for the SELAQ constructs

4.5. Discussion

The findings of the current study provide an answer to RQ1 and RQ2 in that both the ideal and predicted expectation scales were found to be invariant across three European samples (England, the Netherlands, and Spain). As for RQ3, the results found that for the ideal expectation scale, the Dutch student sample had the highest factor mean for *Ethical and Privacy Expectations*, but the lowest factor mean for *Service Expectations*. As for the predicted expectation scale, the Spanish student sample had the lowest factor mean for *Ethical and Privacy Expectations*, whilst the English student sample had the highest factor mean for *Service Expectations*.

The identified differences with regards to the *Ethical and Privacy Expectations* could be attributed to the demographic characteristics of the three samples, particularly the students' age. For example, the Dutch student sample has a mean age of 44.80 years, compared to averages ages of 20.40 and 21.10 years for the English and Spanish samples, respectively. It has been found that older adults express greater concern towards the privacy of their information than younger adults (Laric, Pitta, & Katsanis, 2009). Based on this, it may be reasonable to assume that the high desires and realistic expectations found with the Dutch sample are associated with these students being of an older age and their propensity to have greater privacy concerns. Nevertheless, both the English and Dutch student samples had comparable factor means for *Ethical and Privacy Expectations* on the predicted expectation scale. In this case, it may be that irrespective of age, students realistically expect the university to keep data secure and to obtain consent. For the Spanish student sample, on the other hand, the low *Ethical and Privacy Expectations* may be associated with Spain's existing laws that strictly regulate personal data usage (Tsai, Gaševic, et al., 2018). In other words, the students may not hold high expectations of the university undertaking the data handling steps outlined in the SELAQ due to pre-existing laws regulating these steps.

The demographic make-up of the samples can also be considered for the *Service Expectations*, particularly in terms of the Dutch student sample. It is important to acknowledge the fact that the Dutch sample is made up of distance education students. A common issue that faces distance education students is the experience of isolation, which is attributed to students withdrawing from a course (Lake, 1999). The learning analytics service features contained in the SELAQ do not provide a solution for loneliness (e.g., more contact time with teaching staff or students). Rather, the SELAQ items are associated with students receiving feedback aimed at enabling students to monitor and regulate their learning. This may then be more appealing to students who are on-campus and want more feedback regarding their learning progress. Moreover, given the younger average ages of the English student sample (20.40 years), they may not have acquired the skills required to become independent learners (Thomas, Hockings, Ottaway, & Jones, 2015). This may then be associated with why they have significantly higher ideal and predicted expectations regarding the *Service Expectation* factors as the features offer some structure to support their transition into higher education (Leese, 2010). Whereas, distance education students are more likely to be independent learners (Bates, 2005), which may also explain why the Dutch student sample had the lowest ideal and predicted expectations for the *Service Expectation* factor.

As for the Spanish student sample, the *Service Expectation* factor mean on the ideal expectation scale was comparable to the English student sample. In this case, it may again be the case that the possibilities offered by learning analytics services are desirable as they may ease the transition into higher education, particularly on account of the pressure to be independent learners (Thomas et al., 2015). However, the Spanish student sample also had low predicted expectations that were not significantly different from the Dutch student sample. This may suggest that whilst learning analytics service features are appealing to the sample of Spanish students, they do not expect this to realistically happen. Reasons for this may refer to students wanting to remain independent learners (Roberts et al., 2016) or they may feel that the the university is not capable of providing such services.

4.5.4. Implications

To understand the findings of this current work, they need to be considered in relation to the SHEILA (Supporting Higher Education to Integrate of Learning Analytics) policy framework (Tsai, Moreno-Marcos, et al., 2018). Under this framework, institutional managers are encouraged to explore the reasons driving the implementation of a learning analytics service, identify any barriers to adoption, and establish a dialogue with key stakeholders. Through this process, the institutional manager is able to clearly delineate the expectations of a learning analytics service and the possible challenges that need to be resolved. The following paragraphs seek to illustrate how the findings obtained in this study can be used by institutional managers to identify a route to learning analytics service implementations that provides a balance between feasibility and what is expected.

For the English student sample, the current study found high expectations across the two SELAQ scales (ideal and predicted expectations) for both the *Ethical and Privacy* and *Service* dimensions. In light of this knowledge, an institutional manager knows what their student population expects from a future learning analytics in regards to data handling and service features. As a priority, the high expectations regarding ethics and privacy should be the first challenge to address, particularly as this is a requirement of the GDPR[4]. Specifically, the GDPR requires consent to be unambiguous and for the individual to have a right to withdraw consent at any time. Not all cases, however, require consent; instead, they fall within the category of legitimate interests. The latter may be considered in circumstances where the individual would expect their data to be used in a particular way (e.g., monitoring retention rates). Irrespective of whether the institution has a legitimate interest, this must be balanced against the interests of the individual. From the current findings, it is clear that the English student sample generally expect the university to seek consent and secure data. On this basis, it would appear that the university should undertake steps to obtain consent prior to any data processing. However, the English student sample also had high expectations for the service features of learning analytics implementations. Thus, it can be argued that there is a legitimate interest to collect and analyse student data as students expect to receive services aimed at supporting their learning. It is therefore clear that these students have a legitimate interest in learning analytics services based on the proposed benefits they would bring, but strong expectations regarding their data handling. The approach to adoption would then be for the institution to clearly articulate to students all steps involved in processing the data, including who has access and what data security measures are in place. In conjunction, the services made possible from processing this data should be outlined. In doing so, the university is able to justify the processing of student data for learning analytics services. If such services

[4] Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation)

features cannot be guaranteed, then it introduces questions regarding the legitimacy of processing data without first obtaining consent.

The Dutch student sample, on the other hand, were found to have low expectations towards the *Service* elements of a learning analytics implementation. In this instance, it could be argued that they do not see the institution as having a legitimate interest in the collection and analysis of their data. From the position of the institution, there is instead a need to explore ways in which they can address the *Ethical and Privacy* elements as these garnered high expectations from the students. Put differently, the institution cannot claim that there is a legitimate interest in collecting and analysing data. This could lead to the development of an engagement policy which aims to increase student interest in learning analytics services. More specifically, the Dutch student sample may not have recognised how the potential learning analytics services could be beneficial to their studies. An approach to implementation would then be to hold workshops for students that are designed to showcase prototypes of learning analytics services. Thus, these students are provided with a tangible service that they can assess whether it is beneficial support to their learning, rather than undermining student agency. As it stands, however, the current findings suggest that the Dutch university should be seeking consent from the student population on the basis of their high *Ethical and Privacy Expectations* and low *Service Expectations*. Put in a different way, whilst students cannot see a legitimate interest in processing data for the purposes of learning analytics, it is difficult to justify the undertaking of such steps in the absence of consent.

As for the Spanish student sample, they had low *Ethical and Privacy Expectations*. This suggests that these students do not expect the institution take the steps to obtain consent. In this instance, students may consider the data processing as being undertaken with legitimate interests in mind. Another way to consider this is from the view that students may consider processing educational data as important undertaking for the university, such as monitoring whether students are attending lectures or not. Thus, from the point of implementing learning analytics services, it is still important for the institution to be open about their data processing, even though students do not expect to have full control of their educational data. As for *Service* dimensions, the Spanish student sample had high desires (ideal expectations), but lower expectations of these service features realistically occurring. In this instance, it is clear that to be successful there is a need to challenge the low predicted expectations that the students hold. More importantly, as the services provided are a reflection of the legitimate interest in processing the data, the university needs to be able to justify this undertaking and demonstrate that it can implement such features. Thus, for the Spanish institution, their approach to adopting learning analytics should focus on outlining to students what services are feasible during the pre-implementation stages. This will then allow the students to determine whether the university does have a legitimate interest in processing educational data.

The SHEILA framework was designed to support the development of learning analytics with the assumption that a one size fits all approach is not feasible (Tsai et al., 2018). The findings obtained from the current work further reinforces this perspective, as student expectations of learning analytics services were not culturally consistent; therefore, strengthening the need for institution-specific policies. Moreover, it emphasises the utility of the SELAQ as a tool to support higher education institutions in their pursuit of implementing learning analytics services, but also facilitating greater student engagement.

4.5.5. Limitations

The current study tested measurement invariance across three European samples of students (England, the Netherlands, and Spain). This is problematic as it is likely to provide a biased perspective of what students expect from learning analytics services. Given the global interest in learning analytics (Pardo et al., 2018), it is therefore necessary for future research to assess the consistency of student expectations of learning analytics in countries outside of Europe. In doing so, this can provide an indication of whether student expectations of learning analytics services are consistent. This could then lead to the formulation a general policy for learning analytics that adequately meets the expectations of all higher education students.

The results from the alignment analysis were found to be trustworthy, which were substantiated by the follow-up Monte Carlo simulations. Irrespective of these outcomes, there was clear indication of sample size issues. For the ideal expectation scale, the response categories for four items had to be collapsed from 7 to 6. This was on account of the intermediate response categories being empty for certain samples, particularly the English student sample (Appendix 4.3). By collapsing the scale, it does pose problems with regards to a loss of information. However, Grondin and Blais (2010) and Liu et al. (2017) have shown this to be a good solution to a common problem that arises with ordered-categorical indicators.

A further indication of where sample size is of concern is from the alignment and Monte Carlo outputs. For the alignment, the R^2 values generally fell below the .90 cut-off put forward by Flake and McCoach (2018). As discussed in the results, Flake and McCoach (2018) found low R^2 values in their simulation results with groups of 3, 9, and 15. These authors stated that it may be the case that a larger number of groups is required in order for good estimates to be attained (Flake & McCoach, 2018). Whereas, for the Monte Carlo simulations it was found that particular parameters showed high absolute bias values (> .10; Muthén, 2002) and high MSE values. In majority of cases, these high values were associated with the English student sample, which had the smallest sample size (n = 191) and a number of response categories with zero frequencies (Appendix 4.3). Taking the aforementioned points into consideration, it is important to view the current results with caution and urge researchers to continue to test the measurement invariance of the 12-item SELAQ in larger samples.

Chapter 5: Subgroups in Learning Analytics Expectations: An Exploratory Latent Class Analysis of Student Expectations Towards Learning Analytics Services

5.1. Summary

Expectations of a service is an important determinant in whether it will be successfully adopted by the target population. The issue, however, is that expectations within a population are unlikely to be homogenous. On this basis, it cannot be assumed that all students will have the same expectations towards service features offered through learning analytics, nor how data is handled. The current chapter uses latent class analysis to provide an insight into the heterogeneity of student expectations of learning analytics services. We also discuss how higher education institutions can leverage the findings obtained from the SELAQ (student expectations of learning analytics questionnaire) to inform policy decisions related to the implementation of learning analytics services.

5.2. Introduction

Higher education institutions are collecting an unprecedented amount of data, from logs captured by the institutional virtual learning environment to library access frequency (Sclater, Peasgood, & Mullan, 2016). Behind these actions there is a belief that a better understanding of the student learning progress will emerge through the analyses undertaken, resulting in interventions designed to improve teaching and learning (Siemens, 2013). This use of learning analytics is primarily motivated by a drive to address the limited learning support and low retention rates that has come to characterise higher education (Sclater et al., 2016; Siemens & Long, 2011; Tsai & Gašević, 2017).

The advantages that learning analytics services can bring to higher education have been recognised by numerous institutions, but adoption rates remain low (Tsai & Gašević, 2017b). Despite this low adoption rate (Tsai & Gašević, 2017b), institutions recognise that successful implementation of learning analytics services requires student engagement (Ferguson et al., 2014; Tsai & Gašević, 2016, 2017a; Tsai, Moreno-Marcos, et al., 2018). As without gauging and understanding what students expect from learning analytics, future services will inadvertently create an ideological gap (Ng & Forbes, 2009; Whitelock-Wainwright et al., 2017). This is where the service offered is a reflection of management needs, but not what students expect and is associated with levels of satisfaction (Ng & Forbes, 2009). To offset this possibility of students being dissatisfied with learning analytics, researchers have begun to explore student expectations of such services (Ifenthaler & Schumacher, 2016; Roberts et al., 2017, 2016; Schumacher & Ifenthaler, 2017; Sharon Slade & Prinsloo, 2014). From this research, it has been found that students expect a learning analytics service that facilitates self-regulated learning, promotes learner agency, and respects student privacy. However, it unlikely that these student expectations towards learning analytics services are homogenous. Instead, it is possible that there is a degree of heterogeneity across the student population with regards to learning analytics service expectations. The goal of this paper is to address this current gap by exploring the heterogeneity found in student expectations of learning analytics services.

5.2.1. Stakeholder Expectations

Adoption of information systems has been extensively studied (Davis, 1989; Venkatesh & Bala, 2008; Venkatesh, Morris, Davis, & Davis, 2003), with particular emphasis on beliefs in the post-adoption phase (i.e., once the information system has been implemented). Even though this work has been fundamental in understanding the complexity of introducing new information systems, the importance of pre-adoption beliefs cannot be ignored (Karahanna, Straub, & Chervany, 1999). As early work by Davis and Venkatesh (2004) shows that expectations of an information system (i.e., pre-adoption beliefs) are valid predictors of actual system usage. More recently, Venkatesh and colleagues have demonstrated the importance of measuring user expectations of information systems, particularly in relation to technology use (Brown et al., 2012, 2014; Venkatesh & Goyal, 2010). The practical implication from this aforementioned work has been the importance for management to ensure that user expectations of information systems are at a realistic level.

When information systems do fail, it can be attributed to an organisation being unable to provide a service that aligns with stakeholder expectations (Lyytinen & Hirschheim, 1988). Put differently, it cannot be readily assumed that any newly implemented information system will succeed without first taking into account the desires and beliefs of all relevant stakeholders (Boonstra, Boddy, & Bell, 2008;

Lyytinen & Hirschheim, 1988). What is more, the level of expectation held by these stakeholders may be inflated (Jackson & Fearon, 2014). Thus, once the information system is implemented these beliefs are unlikely to be confirmed and dissatisfaction is likely to ensue (Jackson & Fearon, 2014), culminating in a lower likelihood of service usage (Venkatesh & Goyal, 2010). To avoid such system implementation failures, steps should be taken to understand the desires and expectations of technology from the users themselves (Khalifa & Liu, 2003).

Possible ways in which management can avoid services falling short of stakeholder expectations have previously been discussed (Brown et al., 2012, 2014; Davis & Venkatesh, 2004; Venkatesh & Goyal, 2010), with particular emphasis placed on strategies to be undertaken in the pre-implementation stages of development (Boonstra et al., 2008; Ginzberg, 1981; Jackson & Fearon, 2014). In the case of Davis and Venkatesh (2004), they highlight the importance of gauging stakeholder expectations early in the design process as a way of understanding attitudes toward the system in development. Likewise, Jackson and Fearon (2014) emphasise the importance of management taking a proactive stance in understanding stakeholder expectations, but also adopting approaches that avoid creating inflated expectations. In other words, if stakeholders can formulate realistic expectations toward the information system, it can mitigate against large discrepancies between beliefs and experience that are attributable to dissatisfaction (Brown et al., 2012, 2014; Venkatesh & Goyal, 2010).

5.2.2. Stakeholder Expectations of Learning Analytics

The abovementioned literature highlights the importance of gauging stakeholder expectations and this resonates with the implementation of learning analytics services, specifically with regards to future adoption. A recent survey shows that many Higher Education Institutions in Europe can be considered as being within the early stages of learning analytics service implementations (Tsai & Gašević, 2017b). This effectively equates to the pre-implementation stages of information system development, as these institutions have no learning analytics service in place, but have plans for such services in the future. It is at this point where stakeholders should be involved in design and implementation decisions to either align the service with their expectations or mitigate against inflated expectations (Jackson & Fearon, 2014). In the context of developing learning analytics services, however, it has been reported that the level of engagement from stakeholders has been insufficient (Tsai & Gašević, 2017a). A pertinent example of limited engagement with stakeholders, particularly students, has been the development of the learning analytics code of practice (Sclater, 2016). Included in this code of practice is the theme that learning analytics services should be used to benefit students, but no input from students was sought. Even though Sclater's (2016) code of practice has an important role in regulating institutional learning analytics services, it may lead to the creation of learning analytics services that are not reflective of student expectations (Whitelock-Wainwright et al., 2017). When a service is not in alignment with stakeholder expectations, this is known as an ideological gap and is associated with user dissatisfaction (Ng & Forbes, 2009).

It would be incorrect to state that learning analytics research has neglected the importance of understanding student beliefs towards possible learning analytics services. There have been developments in understanding student expectations toward learning analytics service features (Arnold & Sclater, 2017; Roberts et al., 2017; Schumacher & Ifenthaler, 2018) and student beliefs toward ethical procedures (Ifenthaler & Schumacher, 2016; Roberts et al., 2016; Slade & Prinsloo, 2014).

Across each of these studies, the authors have shown that the beliefs held by students cannot be overlooked. Moreover, they provide a valuable perspective from those whose data will eventually be used in learning analytics services, which cannot be addressed from focusing on the views of management alone. Nevertheless, gauging student expectations of learning analytics services is not an easy feat, particularly on account of the population size, which is a concern in information system implementations (Lyytinen & Hirschheim, 1988). While qualitative work has provided rich description of student beliefs toward learning analytics services (Roberts et al., 2017, 2016; Slade & Prinsloo, 2014), these may not be representative of the larger population of students. In information systems research, Szajna and Scamell (1993) have previously encouraged the development of psychometric instruments to gauge stakeholder expectations at different stages of implementations, which also offers a solution to exploring learning analytics service beliefs on a larger scale.

Therefore, to assist Higher Education institutions in their pursuit of implementing learning analytics services and to increase stakeholder engagement, the authors have developed and validated a questionnaire known as the 'Student Expectations of Learning Analytics Questionnaire' (SELAQ) (Chapters 2 and 3). The purpose of this instrument is not to replace qualitative explorations of student expectations, but as a method to accommodate a greater number of student beliefs into learning analytics service implementations. Thus, whilst the SELAQ can provide institutions with a general understanding of what a large number of students expect of learning analytics services, qualitative methods can be used in conjunction to obtain detailed insights into student beliefs.

In order to understand student expectations of learning analytics services, the authors first defined an expectation "as a belief about the likelihood that future implementation and running of learning analytics services will possess certain features" (Chapter 2, p. 46). Whilst this definition clarifies how the exploration and understanding of student expectations of learning analytics services was approached, the term expectation remained quite general. Thus, on the basis of work exploring patient expectations of health care services (Bowling et al., 2012; Thompson & Suñol, 1995), the term expectation was decomposed into ideal and predicted expectations. An ideal expectation equates to an unrealistic level of belief of the service students would like to receive. Whereas, a predicted expectation refers to a realistic level of belief of the type of service they are most likely to receive. By decomposing expectations this way, the researchers are able to gauge what students realistically expect from learning analytics services (predicted expectations), whilst also being mindful of what students desire (ideal expectations).

The SELAQ has been presented as providing researchers with a means of obtaining valid measures of student expectations towards learning analytics services (Chapters 2 and 3). However, there has yet to be an attempt at utilising the collected SELAQ data to provide a detailed exploration of how expectations of learning analytics service may vary within the student population. Given the importance of gauging and managing expectations early on in the implementation of information systems (Brown et al., 2012, 2014; Jackson & Fearon, 2014; Venkatesh & Goyal, 2010), there is a need for institutions to proactively engage in such behaviours before learning analytics services are implemented. On this basis, the current research aims to present an exploratory study of how the SELAQ can be used to understand student expectations (ideal and predicted) of future learning analytics services.

5.2.3. Segmenting Stakeholder Expectations

Gauging student expectations of learning analytics services offers institutions the possibility of offering a service that meets student expectations, or the chance to manage inflated expectations. Although progress has been made to explore student expectations of potential learning analytics services (Roberts et al., 2017; Schumacher & Ifenthaler, 2018), emphasis has been placed on viewing these beliefs as a whole. While the findings of this work have been important in emphasising the need to accommodate the student perspective in learning analytics service implementations, it cannot be assumed that all students hold similar expectations.

Expectations-based segmentation has been shown to be a useful approach in understanding what users want from a service (Diaz-Martin, Iglesias, Vazquez, & Ruiz, 2000). In doing so, it offers service providers with an opportunity to tailor a service to meet the expectations the user holds, which should increase satisfaction (Diaz-Martin et al., 2000; Webster, 1989). This approach has been applied in a Higher Education Institute where Blasco and Saura (2006) segmented students on the basis of their expectations toward elements of the service offered by a university (e.g., faculty members' level of theoretical knowledge). According to Blasco and Saura (2006), the ability to segment students by their service expectations can facilitate changes to policies that regulate the service in place. Thus, if the service provider can identify and effectively align the service with these differences in expectations, greater levels of satisfaction with the service are likely to result.

Given the value that expectation-based segmentation could have in providing a learning analytics service that aligns well with student expectations, the current case study sought to answer four research questions:

RQ1. Can students be meaningfully segmented on the basis of their ideal expectations of learning analytics services?

RQ2. Can students be meaningfully segmented on the basis of their predicted expectations of learning analytics services?

RQ3. If students can be meaningfully segmented on the basis of their ideal and predicted expectations, what covariates predict their assignment to a particular class?

RQ4. Are the class assignments given to students stable or variable across the ideal and predicted expectation scales?

5.3. Method

5.3.1. Sample

A total of 1247 responses (Females = 705, 57%) to the SELAQ were collected from a Dutch Higher Education Institute using an online system (all responses were voluntary; this is a re-use of the data collected in Chapter 3). Seven respondents provided incorrect age details (e.g., 0, 99, and 251) or omitted these details entirely. As the analysis required the data to contain no missing values, these seven respondents were omitted; the following sample descriptive statistics will pertain to the 1240 respondents (Females = 700, 56%).

Of the remaining 1240 respondents who did provide accurate age details, their ages ranged from 18 to 82[5] years of age (M_{age} = 44.81, *SD* = 12.14). The three faculties that make up the university were almost equally represented in this sample:

[5] The age range was also checked with the student services of the institution who confirmed the upper age limit of the students was correct.

33% (n = 411) were students of culture and jurisprudence, 33% (n = 413) were students of management, science, and technology, and 34% (n = 416) were students of psychology and education. Majority of the sample were composed of undergraduate students (n = 790, 64%) and masters students (n = 447, 36%); PhD students only accounted for .002% of the sample (n = 3). Due to the sample only being composed of a small number of PhD students, they were grouped with the master students to form a postgraduate category (n = 450, 36%). Finally, majority of the respondents identified themselves as being Dutch students (n = 1119, 90%), whilst only a small number of respondents stated they were either European students (n = 106, 9%) or Overseas students (n = 15, 1%). Given the small number of students who identified themselves as Overseas, any findings should be interpreted with caution. This demographic information is also presented in Table 5.1.

Table 5.1. Demographic Information for the Dutch Student Sample used in the Latent Class Analysis

Characteristic	Mean	SD	N	%
Gender				
Male			540	44
Female			700	56
Age	44.81	12.14		
Subject				
Culture and Jurisprudence			411	33
Management, Science, and Technology			413	33
Psychology and Education			416	34
Level of Study				
Undergraduate			790	64
Masters			447	36
PhD			3	.002
Student Type				
Dutch			1119	90
European			106	9
Overseas			15	1

5.3.2. Instrument

To measure student expectations of learning analytics, the SELAQ was used. It contains 12 items (Table 5.2), five of which account for Ethical and Privacy Expectations (EP1 to EP5) and seven refer to Service Expectations (S1 to S7). Responses to each item are made on two scales using seven point Likert scales (1 = Strongly Disagree, 7 = Strongly Agree). These two scales correspond to ideal (Ideally, I would like this to happen) and predicted expectations (In reality, I expect this to happen). Ideal expectations measures what students desire from a learning analytics service, whilst predicted expectations measure the learning analytics service student expect in reality. Prior work developing and validating the SELAQ has shown the scales to be reliable and valid (Chapters 2 and 3). Moreover, this scale has been translated and validated to be used in the Netherlands (Chapter 3).

Table 5.2. 12 Items of the SELAQ with Factor Key

Key	Item
EP1	The university will ask for my consent before using any identifiable data about myself (e.g., ethnicity, age, and gender)
EP2	The university will ensure that all my educational data will be kept securely
EP3	The university will ask for my consent before my educational data is outsourced for analysis by third party companies
EP4	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)
EP5	The university will request further consent if my educational data is being used for a purpose different to what was originally stated
S1	The university will regularly update me about my learning progress based on the analysis of my educational data
S2	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)
S3	The learning analytics service will show how my learning progress compares to my learning goals/the course objectives
S4	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)
S5	The teaching staff will be competent in incorporating analytics into the feedback and support they provide to me
S6	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
S7	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

5.3.3. Analysis

As an approach to segmentation, latent class analysis has been used to explore variations in patients' use of complementary medicine (Strizich et al., 2015), how attitudes toward mental health are formed (Mannarini, Boffo, Rossi, & Balottin, 2018), and stakeholder expectations toward Corporate Responsibility (Hillenbrand & Money, 2009). These latent models can also include covariates, which allow the prior probabilities of latent class assignment to vary for each respondent (Linzer & Lewis, 2011). For example, Strizich and colleagues found higher use of complementary medicines to be associated with high levels of exercise and healthier eating habits (Strizich et al., 2015). Following the approach adopted by these aforementioned studies, the current case study applied latent class analysis in an exploratory approach to gauge and segment student expectations of learning analytics services, addressing RQ1 and RQ2. Covariates were also included in the latent class model in order to gain a greater understanding of what characteristics typically define the groups identified, which answered RQ3. For RQ4, a contingency table was created to explore whether student class assignment was stable or variable across the two expectation scales (ideal and predicted).

To address research questions one (RQ1) and two (RQ2), the raw data was analysed using the three-step approach to latent class analysis (Vermunt, 2010), which was carried out in Mplus 8.1 (Muthén & Muthén, 2017). The traditional one-step method was not used as various disadvantages of this approach have been outlined (Vermunt, 2010). An example of how the one step method is disadvantageous is in relation to the number of classes to extract, as the solution changes with the inclusion or exclusion of covariates (Vermunt, 2010). To overcome these issues, Vermunt (2010) presented the three-step method to latent class analysis. This is a step-wise approach in which the latent class model is first estimated with indicator variables alone, then a most likely class variable is generated, which is then regressed onto the predictor variables (Asparouhov & Muthén, 2014a; Vermunt, 2010). Thus, the three-step method does not change the initial measurement model through the introduction of covariates, as is the case with the one-step approach (Vermunt, 2010).

For the analysis of the collected data, the ideal and predicted expectation scales were analysed separately. An assessment of the response distributions for each scale shows the data to contain ceiling effects (Appendices 5.1 and 5.2), particularly with regards to the ideal expectation scale. This is anticipated as the ideal expectation scale corresponds to a desired level of service so responses on this scale are likely to be high. Therefore, the data collected from the SELAQ was treated as categorical. As for the model covariates, the age variable was treated as continuous; whereas, the remaining variables were dummy coded. These dummy coded variables were gender (0 = male, 1 = female), management, science, and technology (0 = culture and jurisprudence, 1 = management, science, and technology), psychology and education (0 = culture and jurisprudence, 1 = psychology and education), Postgraduate Student (0 = Undergraduate Student, 1 = Postgraduate Student), European Student (0 = Dutch Student, 1 = European Student), and Overseas Student (0 = Dutch Student, 1 = Overseas Student). These covariates allowed for the exploration of whether gender, age, faculty, level of study, or student type were associated with latent class assignment.

As for the latent class model building, the steps outlined by Masyn (2013) were followed, which can be decomposed into assessments of absolute fit, relative fit, classification diagnostics, and class interpretation. When assessing absolute fit, the absolute values of standardised residuals will examined. According to Masyn (2013), values exceeding 3 are indicative of poor fitting response frequencies. Given the large number of response frequencies that are possible due to both the number of latent class indicators (n = 12 per expectation scale) and response options (n = 7), it is difficult to determine what constitutes a poor fitting model. A useful guideline was proposed by Masyn (2013), which states that large standardised residual values in “notable excess” of 5% would lead to a model being considered as poor fitting (p. 567).

With regards to the relative fit of each model, this was examined using both an inferential and information-heuristic approach (Masyn, 2013). In terms of the inferential approach, there are two tests used which compare a *K* class model to a *K* – 1 class model (e.g., compare a 3 class model to a 2 class model), which are the adjusted Lo-Mendell-Rubin likelihood ratio test (LMR-LRT; (Lo, Mendell, & Rubin, 2001) and the bootstrap likelihood ratio test (BLRT; McLachlan & Peel, 2000). In the case of either test, if the likelihood ratio difference is found to be statistically significant then the model containing a greater number of classes is considered to fit better (Masyn, 2013). As for the information heuristic approach, the Bayesian Information Criterion (BIC; Schwarz, 1978) is most commonly used to determine the best fitting model (Nylund, Asparouhov, & Muthén, 2007). This decision is usually based on the number of classes where the BIC value is lowest (Nylund et al., 2007) or form “elbow” plots (Masyn, 2013). There are other indexes that can be used such as Akaike’s Information Criterion (AIC; Akaike, 1987); however, it has been shown that the BIC is the best information criterion (Nylund et al., 2007). Therefore, only the BIC of each model was plotted and decisions regarding model selection were based on the “elbow criterion” (Masyn, 2013). If, in conjunction with the findings of the inferential approach, there was no clear contender for a model (e.g., no *K* + 1 model is rejected) then a plot of log likelihood values was also examined (Masyn, 2013). As with the BIC value plot, an “elbow” in the plot of log likelihood values can also be used to identify a candidate model (Masyn, 2013).

For assessing the classification precision, the relative entropy was one of the diagnostic statistics used (Ramaswamy, Desarbo, Reibstein, & Robinson, 1993). It is intended to provide a summary of classification accuracy across each latent class, with values lying between 0 (classification no better than chance) and 1 (classification is perfect) (Ramaswamy et al., 1993). As a means to selecting the number of classes to extract, the relative entropy should not be used as even with high values there is likely to be assignment error (Masyn, 2013). Therefore, three additional classification diagnostic statistics were examined: the average posterior class probability (AvePP), the odds of correct classification ratio (OCC), and the modal class assignment proportion (mcaP; Masyn, 2013). The AvePP provides a class-specific measure of assignment accuracy between 0 and 1, with values greater than .70 being suggestive of good accuracy (Nagin, 2005). The OCC was also used to assess both assignment accuracy and class separation, with values exceeding 5 being good (Nagin, 2005). Finally, the mcaP is the proportion of those individuals modally assigned to a specific class and this is compared to the model-estimated proportions of this class ($\hat{\pi}_k$) (Masyn, 2013). The size of the discrepancies between the mcaP and $\hat{\pi}_k$ provides an indication of whether there are errors in the class assignment, specifically when the discrepancy size is large (Masyn, 2013).

Throughout these abovementioned steps, it was necessary to consider the interpretability of the solution (Lanza & Rhoades, 2013). For instance, there may be problems regarding the local fit of the model (e.g., proportion of standardised residuals greater than 5%), which can be addressed by increasing the number of classes that are extracted. However, this additional class may not be easily interpreted; thus, based on parsimony, the *K*-1 model would be more suitable. For Lanza and Rhoades (2013), they recommend that class interpretability should be guided by a clear separation between classes, classes being easily labelled, and patterns that are logical. To assist in decisions regarding the interpretability of a solution, the step taken by Oberski (2016) was followed, which is to consult profile plots. These plots provide the estimated class means as opposed to the estimated distributions (Oberski, 2016). This is because there were seven possible response categories (1 = Strongly Disagree, 7 = Strongly Agree), which makes plots of estimated distributions difficult to read (Oberski, 2016).

To provide an overview of the steps taken in this analysis, the number of classes to extract were increased until either the solution could not be identified or the number of classes would affect the interpretability of the solution. These models were then compared on the basis of their relative fit using both the inferential and information-heuristic approaches. From this, a selection of possible models were selected and then compared on the basis of their classification accuracy and local fit. Throughout each stage, decisions regarding the selection of a candidate model were also determined by the class interpretability. Once a suitable candidate model was identified, the latent class regression was then ran, which addresses research question three (RQ3). For the purpose of this paper, the alpha level was set at 5% for determining whether an effect is considered to be statistically significant.

5.4. Results

5.4.1. Ideal Expectation Scale

5.4.1.1. Summary

Analysis of the ideal expectation using the three-step approach to latent class analysis led to the extraction of a three class solution, answering RQ1. The following labels were used to describe these classes: the *Inflated Ideal Expectation* group (Class One; n = 334, 26.94%), the *Low Ideal Service Expectation* group (Class Two; n = 306, 24.68%), and the *High Ideal Expectation* group (Class Three; n = 600, 48.39%). For this scale, the Service Expectation items (S1-S7) could be used to differentiate between the three groups. The results of the latent class regression showed that only age was associated with assignment to class one or two; thus, addressing RQ3. For a detailed presentation of these results, readers are directed to section 5.4.1.2.

5.4.1.2. Detailed Results

One to six latent class models were estimated from the data. Based on the BIC values obtained from these six models, the three class model appeared to meet the "elbow criterion" as the addition of more classes did not provide more information (Figure 5.1). It was also found that at the six class solution, the BIC value began to increase. Thus, on the BIC values alone the final model would be a three class solution.

In order to further test the suitability of this three class solution, the relative fit of this model over a two class solution was assessed using the adjusted LMR-LRT and BLRT. The results obtained from these relative fit tests did not provide clear evidence to support a three class solution over a two class solution as the adjusted LMR-LRT was not statistically significant (LMR-LRT = 2584.362, p = .763), but the BLRT was statistically significant (BLRT = 2589.332, $p < .001$). In contrast, both the LMR-LRT and BLRT were statistically significant (LMR-LRT = 3647.126, $p < .001$; BLRT = 3654.238, $p < .001$) for the comparison of a two class solution against a one class solution.

Given the discrepancies between these two evaluations of relative fit for the three class solution, it is important to also consider a plot of log likelihood values (Figure 5.1). As with the plot of BIC values, there was a clear “elbow” for the three class solution. Thus, the evidence seemingly supported the three class solution as a candidate model. However, given the non-significant LMR-LRT it was important to compare the classification diagnostics between the two and three class solutions.

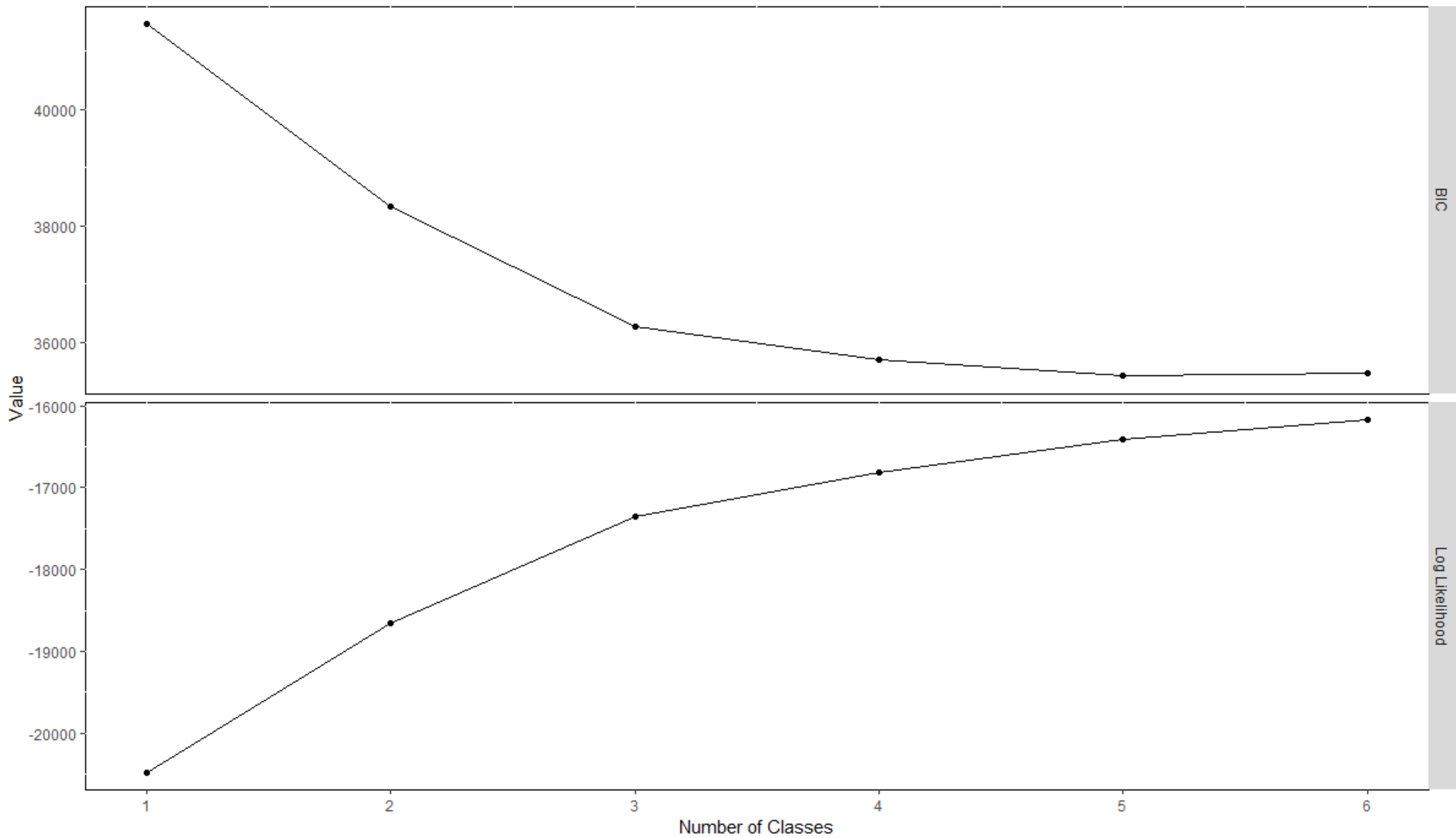

Figure 5.1. Index Values across Six Latent Class Models

To assess the classification accuracy of the two and three class solutions, the relative entropy of both models were initially compared. For the two class solution, the entropy value was .931, which was greater than the value of .919 for the three class solution. In both cases, the relative entropy values showed either solution (k = 2 and k = 3) to have good classification precision, but it should not be used to justify the selection of a candidate model. For the purpose of selecting a candidate model on the basis of classification diagnostics, the AvePP, OCC, and mcaP were used (Tables 5.3 and 5.4).

Table 5.3 shows that for the two class solution, the discrepancies between model estimated proportions for each class ($\hat{\pi}_k$) and modal class assignment proportions ($mcaP_k$) were not large (absolute difference of .004 for both class one and two). All AvePP values exceeded .70 (class one = .984; class two = .974) and both OCC values were larger than 5 (24.755 and 93.066 for class one and two, respectively).

Table 5.3. Two Class Classification Accuracy Diagnostics

Class *k*	$\hat{\pi}_k$	$mcaP_k$	$AvePP_k$	OCC_k
Class One	.713	.717	.984	24.755
Class Two	.287	.283	.974	93.066

Table 5.4 presents the classification accuracy diagnostics for the three class model. Discrepancies between model estimated proportions for each class ($\hat{\pi}_k$) and modal class assignment proportions ($mcaP_k$) were small (absolute values of .004, .002, and .007 for classes one, two, and three, respectively). AvePP values were greater than .70 (class one = .972, class two = .969, and class three = .956), and all OCC values exceeded 5 (91.980, 94.276, and 23.823 for classes one, two, and three, respectively).

Table 5.4. Three Class Classification Accuracy Diagnostics

Class *k*	$\hat{\pi}_k$	$mcaP_k$	$AvePP_k$	OCC_k
Class One	.274	.269	.972	91.980
Class Two	.249	.247	.969	94.276
Class Three	.477	.484	.956	23.823

From the classification accuracy diagnostics, it appeared that either the two or three class solutions had high classification accuracies. Therefore, it was necessary to explore the class separation of each model. To do this, the approach adopted by Oberski (2016) was used, which is to present the means of each latent class in what is known as a profile plot (Figure 5.2).

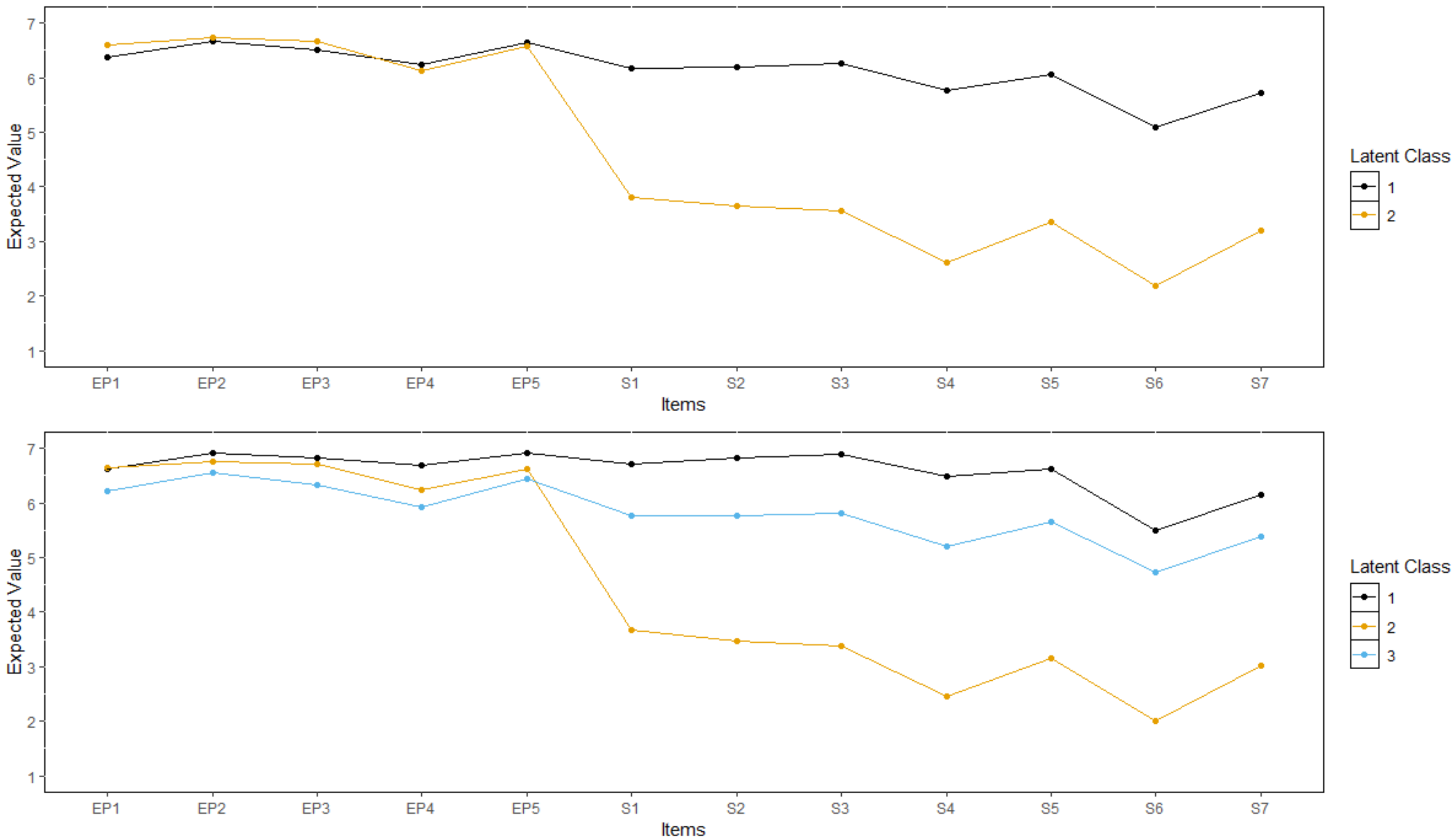

Figure 5.2. Profile Plot: Estimated Means for Ideal Expectation Items for Two and Three Class Solutions

For the two class solution (top plot in Figure 5.2), both classes were found to have high scores on the Ethical and Privacy Expectation items (EP1, EP2, EP3, EP4, and EP5). Where the two classes separated, however, were on the Service Expectations items (S1, S2, S3, S4, S5, S6, and S7). More specifically, individuals in class one had high scores across all Service Expectation items, whilst those in class two had low scores on these seven Service Expectation variables. The additional third class (bottom plot in Figure 5.2) was found to have high responses for all Ethical and Privacy Expectation items. As for the Service Expectation items, class three showed a similar response pattern to class one in that responses tended to be high. However, class one seemingly showed inflated expectations across each item, whilst the expectations of those in class three appeared to be more moderate.

A final step taken in choosing between the two and three class solutions was to assess the local fit of each model by examining the standardised residuals. For the two class solution, there were 434 of the 3234 (13.42%) absolute standardised residuals that exceeded 3; 196 (6.06%) of these were greater than 5. Improved local fit was found with the three class solution, with only 211 (6.52%) residuals exceeding 3 and 88 (2.72%) of these were greater than 5. An improved local fit would continue to be achieved if more classes were extracted (e.g., four or five classes). However, this would come at cost as the interpretability of the solution would have become increasingly difficult. Thus, on the basis of the relative fit, classification accuracy, class interpretability, and local fit the three class solution was selected as the candidate model. As noted, 6.52% of the absolute standardised residuals for this model did exceed 3, this is not excessive as in the case of the two class model (13.42% of residuals exceeding 3), but interpretation of the results was still taken with caution. For the three class solution, the following labels were given:

the *Inflated Ideal Expectation* group (Class One; n = 334, 26.94%), the *Low Ideal Service Expectation* group (Class Two; n = 306, 24.68%), and the *High Ideal Expectation* group (Class Three; n = 600, 48.39%).

The *Inflated Ideal Expectation* label was chosen for this group, on average, had scores close to 7 (Strongly Agree) across all items. The *High Ideal Expectation* label, on the other hand, was based on average responses that suggested these students generally agreed to all items, but the level of agreement was lower than those within the *Inflated Ideal Expectation* group. Finally, the *Low Ideal Service Expectation* label is based upon the average responses to the *Ethical and Privacy Expectation* items being high (i.e., the students expressed agreement), whilst the *Service Expectation* item responses were very low in comparison (i.e., the students tended to express disagreement).

The logistic regression results from the three class model are presented in Table 5.5, which used class three as the baseline group. For class one, the covariates of gender, management, science, and technology, psychology and education, Postgraduate Student, European Student, or Overseas Student were not statistically significant at the 5% level. As for those variables that were statistically significant, the results found that those in class one are more likely to be older students (p = .004). As for class two, the covariates of gender, management, science, and technology, psychology and education, Postgraduate Student, European Student, and Overseas Student were not statistically significant at the 5% level. Only age was found to be statistically significant (p = .032) in that there was more chance of being in class two with increased age.

Table 5.5. Logistic Regressions using the Three Step Method with the Three Class Solution

	Class One			Class Two		
Covariate	Estimate	Standard Error	P-Value	Estimate	Standard Error	P-Value
Gender	.028	.157	.860	.249	.165	.133
Age	.018	.006	.004	.014	.006	.032
Management, Science, and Technology	.356	.196	.069	-.113	.211	.592
Psychology and Education	.251	.190	.187	-.037	.188	.844
Postgraduate	.073	.154	.637	-.304	.174	.082
European Student	.332	.251	.186	-.033	.285	.907
Overseas Student	.059	.674	.930	.235	.636	.712

5.4.2. Predicted Expectations

5.4.2.1. Summary

Analysis of the predicted expectation scale using the three-step approach to latent class analysis led to the extraction of a four class solution, which answers RQ2. The following labels were used to describe these classes: the *High Predicted Expectation* group (Class One; n = 500, 40.32%), the *Indifferent Predicted Expectation* group (Class Two; n = 377, 30.40%), the *Inflated Predicted Expectation* group (Class Three; n = 172, 13.87%), and the *Low Predicted Service Expectation* group (Class Four; n = 191, 15.40%). It was found that only one class (the *Indifferent Predicted Expectation* group) could be differentiated on the basis of Ethical and Privacy Expectation items (EP1-EP5). Whereas, all classes could be differentiated from one another when it came to Service Expectation items (S1-S7). The latent class regression showed age to be associated with assignment to class one and two, whilst European students were less likely to be in class two, which addresses RQ3. A detailed overview of how this solution was selected is presented in Section 5.4.2.2.

5.4.2.2. Detailed Results

One to six latent class models were estimated; however, the six class solution was not identified. Therefore, only the results of the one to five class solutions will be presented. With regards to the BIC values (Figure 5.3), either a two or three class solution would be supported on the basis of the "elbow criterion".

To determine which of these two solutions (k =2 or k = 3) should be selected as a candidate model, the relative fit was assessed using the adjusted LMR-LRT and BLRT. For the two class solution, both tests showed this model to be a significant improvement over a one class solution (LMR-LRT = 3877.154, $p < .001$; BLRT =

3884.714, $p < .001$). Likewise, the fit of the three class solution was found to be a significant improvement over the two class solution (LMR-LRT = 2207.610, $p < .001$; BLRT = 2211.855, $p < .001$). At four classes, the adjusted LMR-LRT showed this solution to not provide a significantly improved fit over the three class solution (LMR-LRT = 1394.582, $p = .762$), but the BLRT output did support the four class model (BLRT = 1397.264, $p < .001$).

Taking the aforementioned evidence into consideration, it was clear that either the two or three class solution could still be selected as candidate models. The BLRT did support the four class solution, but there is a risk of this test never reaching a non-significant *p*-value. Thus, it was advisable to inspect a plot of log likelihood values for each solution and as with the BIC values, assess whether there is an "elbow". From an examination of the plot of log likelihood values in Figure 5.3, a pronounced "elbow" was found at the two class solution.

From the evaluations of relative fit, it appeared that either the two or three class solutions were permissible solutions. Extraction of further classes (e.g., a four class solution) was not supported on the basis of the BIC and log likelihood plots (Figure 5.3) or the adjusted LMR-LRT. In light of these findings, it was decided that both the two and three class solutions would be compared in regards to classification accuracy, interpretability, and local fit.

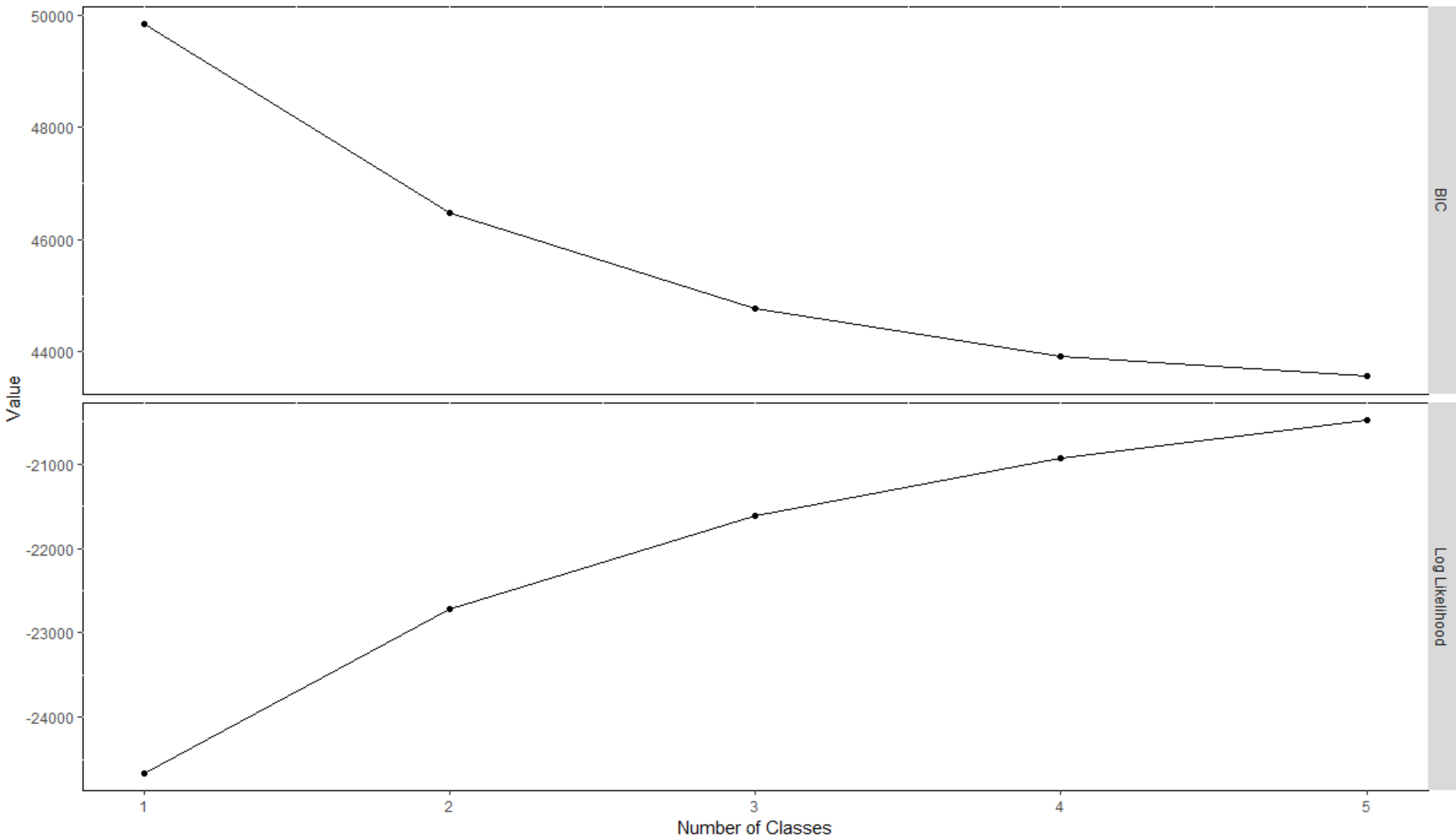

Figure 5.3. Index Values across Five Latent Class Models

The relative entropy of the two and three class solutions were found to be .887 and .901, respectively. Thus, either model was considered to have good overall classification precision. To reiterate, however, the relative entropy values are not intended to be used in decisions of model selection. Rather, such decisions should be informed by an examination of the following classification diagnostics: AvePP, OCC, and mcaP (Tables 5.6 and 5.7).

Table 5.6 presents the classification accuracy measures for the two class model. It can be seen that the average posterior class probability (AvePP) for class one and two all exceeded .70, which shows the classes to be well separated. As for the odds of correction classification ratio (OCC), both values were greater than five, which is indicative of good assignment accuracy. As for the absolute differences between modal class assignment and model estimated proportions for each class, they were small (.004 and .005 for class one and two, respectively).

Table 5.6. Two Class Classification Accuracy Diagnostics

Class k	$\hat{\pi}_k$	$mcaP_k$	$AvePP_k$	OCC_k
Class One	.472	.468	.971	37.455
Class Two	.527	.532	.966	25.501

The classification accuracy results for the three class model are presented in Table 5.7. As with the two class solution, all AvePP values exceeded .70. With regards to the OCC values, these were all greater than 5. As for the discrepancies between the mcaP and model estimated proportions for each class, these absolute values were small (.001, .002, and .001 for class one, two, and three, respectively).

Table 5.7. Three Class Classification Accuracy Diagnostics

Class k	$\hat{\pi}_k$	$mcaP_k$	$AvePP_k$	OCC_k
Class One	.436	.435	.954	26.828
Class Two	.374	.376	.950	31.802
Class Three	.190	.189	.966	121.124

Based on the classification accuracy diagnostics, either the two or three class models were found to be acceptable. Thus, the next step is to assess the interpretability and local fit of each latent class solution. The top plot in Figure 5.4 shows the two class solution, which shows class one to have high scores across all items. Class two, on the other hand, had high scores for the Ethical and Privacy Expectation items (EP1, EP2, EP3, EP4, and EP5), but for Service Expectation items (S1, S2, S3, S4, S5, S6, and S7) the scores are generally in the middle. As for the additional third class (bottom plot in Figure 5.4), this was not well differentiated from class one as it had high scores for both Ethical and Privacy Expectations and Service Expectations.

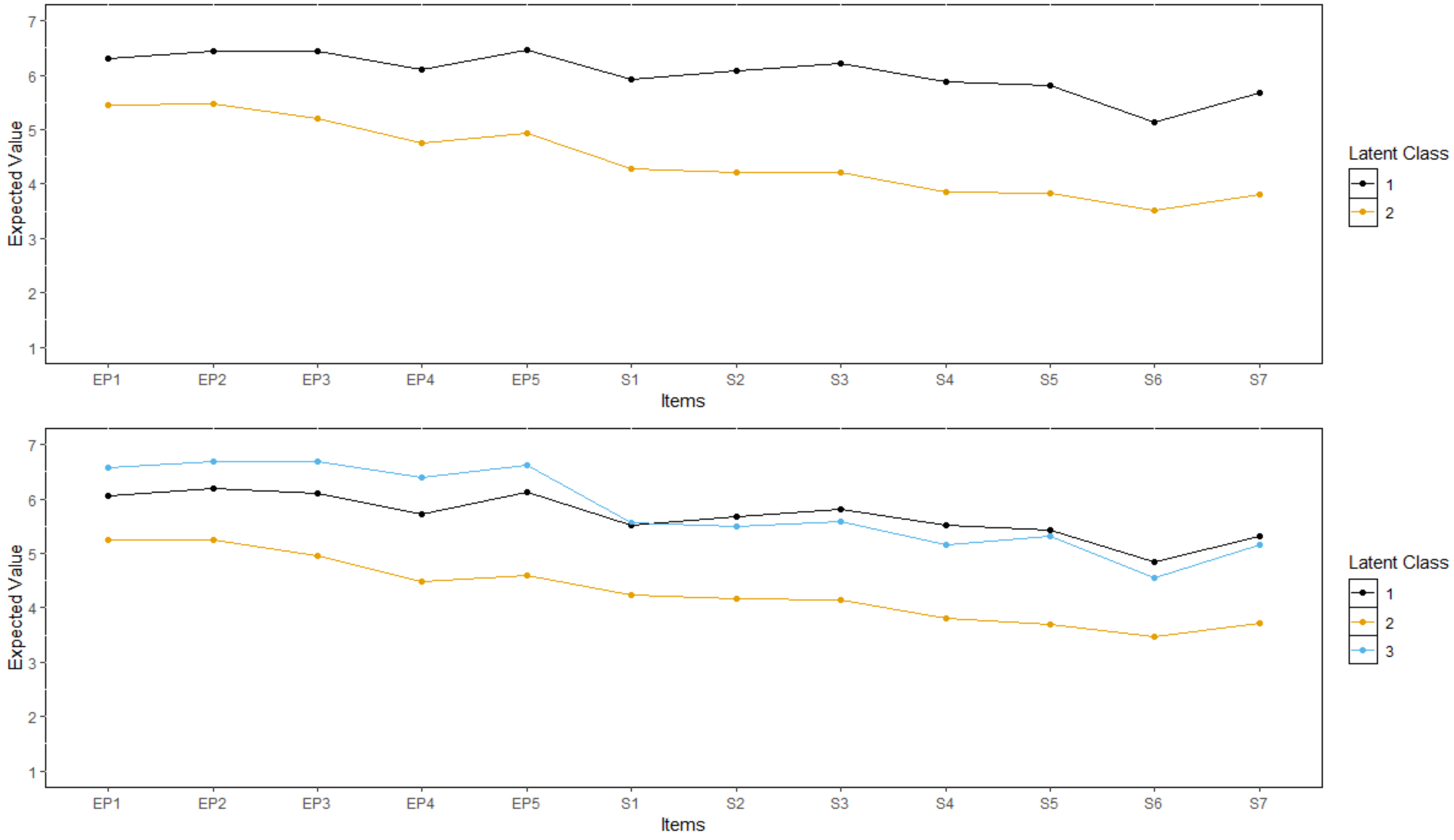

Figure 5.4. Profile Plot: Estimated Means for Ideal Expectation Items for Two and Three Class Solutions

An examination of local fit for both models (k = 2 and k = 3), however, pointed to problems on account of the large proportion of high standardised residuals. For the two class model, 17.41% (n = 563) of the absolute standardised residual values exceeded 3 and 6.65% (n = 215) were greater than 5. With the three class solution, there was an improved local fit, but 10.45% (n = 338) of absolute standardised residual values exceeded 3, with 3.74% (n = 121) of values exceeding 5. Thus, it is clear that for both models the percentage of absolute standardised residual values that were greater than 3 was in excess of 5%. Given these local fit problems with both the two and three class solutions, it was necessary to assess whether the addition of a fourth class reduces the number of high standardised residuals and whether it provides an interpretable solution.

The classification accuracy diagnostics of the four class solution are presented in Table 5.8. It was found that the four class solution had good latent class assignment accuracy, as AvePP values exceeded .70, all OCC values exceeded 5, and the discrepancies between $\hat{\pi}$ and mcaP were small (absolute values = .001, .001, .001, .003 for class one, two, three, and four, respectively).

Table 5.8. Four Class Classification Accuracy Diagnostics

Class *k*	$\hat{\pi}_k$	$mcaP_k$	$AvePP_k$	OCC_k
Class One	.402	.403	.954	30.851
Class Two	.303	.304	.948	41.937
Class Three	.138	.139	.967	183.038
Class Four	.157	.154	.957	119.501

As can be seen from Figure 5.5, the addition of a fourth class did improve the interpretability of the model. Class four is shown to have high scores for the Ethical and Privacy Expectation items (EP1, EP2, EP3, EP4, and EP5), but low scores for the Service Expectation items (S1, S2, S3, S4, S5, S6, and S7). In terms of classes one and three, they were not well differentiated in the three class model; however, the differences became clearer with the use of a four class solution. More specifically, class three is characterised by inflated scores across all items; whereas, class one are at a lower level of expectation.

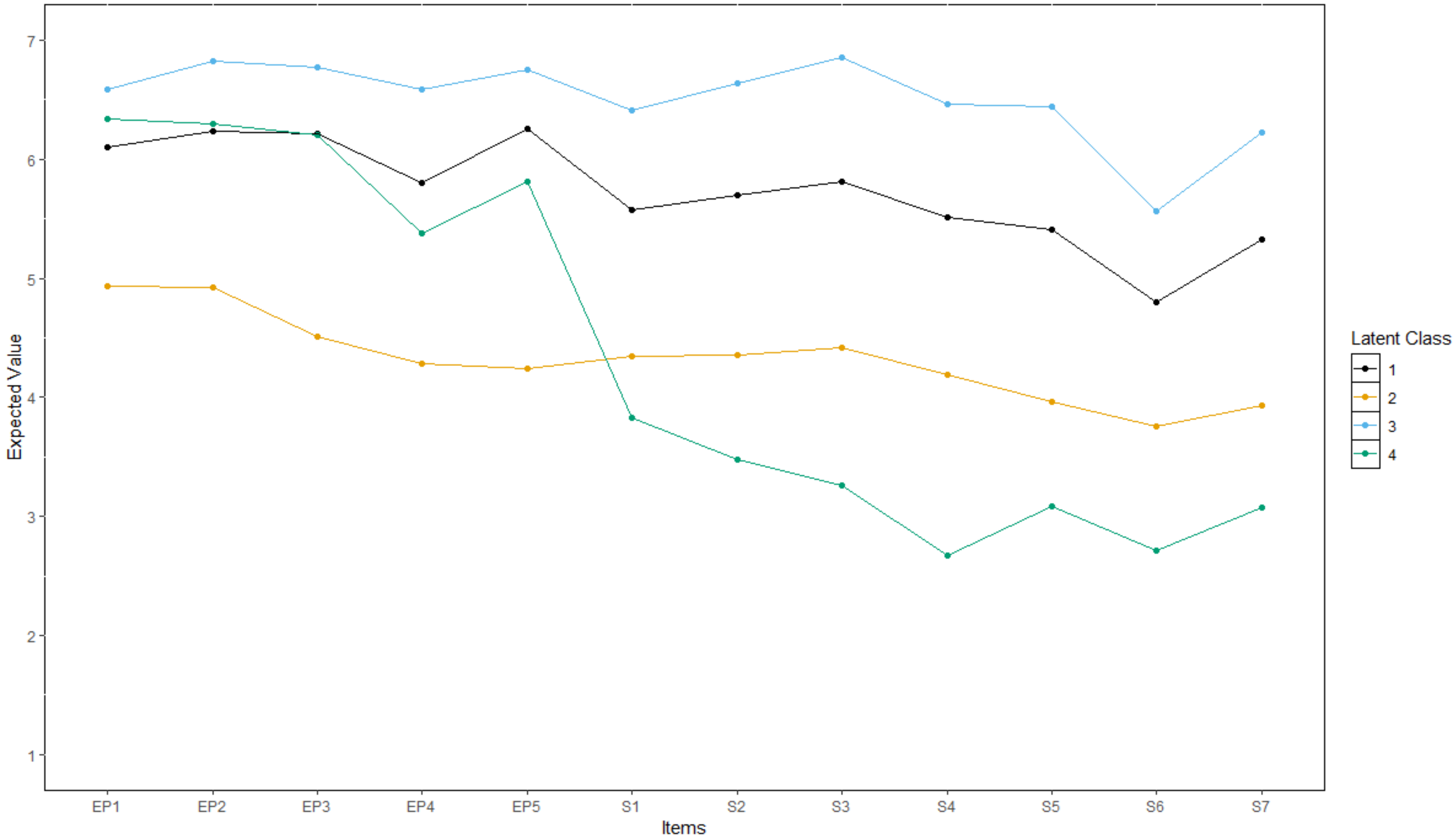

Figure 5.5. Profile Plot: Estimated Means for Ideal Expectation Items for Four Class Solutions

Along with the improved interpretability of the four class solution, the local fit was better than either the two or three class models. An examination of absolute standardised residual values shows 7.36% (n = 238) to exceed 3 and 2.54% (n = 82) to exceed 5. This showed that the addition of a fourth class did lead to a model with a better local fit. Even though the proportion of standardised residuals exceeding 3 remained greater than 5%, this is not as excessive as the proportions found for the two and three class solutions. Despite the information criteria (e.g., the BIC values) and adjusted LMR-LRT supporting either a two or three class solution, this also needs to be weighed up against the interpretability and local fit of each model. On the basis of the latter criteria, the four class model appeared more suitable and was supported by the BLRT; therefore, this was selected as the candidate model for the latent class regression. For this four class solution, the following labels were chosen: the *High Predicted Expectation* group (Class One; n = 500, 40.32%), the *Indifferent Predicted Expectation* group (Class Two; n = 377, 30.40%), the *Inflated Predicted Expectation* group (Class Three; n = 172, 13.87%), and the *Low Predicted Service Expectation* group (Class Four; n = 191, 15.40%).

As with the ideal expectation scale, the *Inflated Predicted Expectation* label was chosen for this group due to average scores across all items being close to 7 (Strongly Agree). This was differentiated from the *High Predicted Expectation* group, which was labelled on the basis that average item responses were high (students generally agreed to each item) but they were not at a comparable level to the *Inflated Predicted Expectation* group. As for the *Indifferent Predicted Expectation* group, this label was chosen as the average responses across items generally fell on the middle category (Neither Agree nor Disagree). Again, as with the ideal expectation scale, the *Low Predicted Service Expectation* group label reflected the students expressing agreement to *Ethical and Privacy Expectation* items, but generally disagreeing to *Service Expectation* items.

For the latent class regression results (Table 5.9), class four was chosen as the baseline group. Starting with class one, older students are less likely to be assigned to this class (p = .045). No other variable was found to be statistically significant at the 5% level for class one. As for class two, older students (p = .003) and students who are European (p = .015) are less likely to be assigned to this class. All remaining variables were found to not be statistically significant at the 5% level. Finally, with regards to class three, no variable was found to be statistically significant.

Table 5.9. Logistic Regressions using the Three Step Method with the Four Class Solution

	Class One			Class Two			Class Three		
Covariate	Estimate	Standard Error	P-Value	Estimate	Standard Error	P-Value	Estimate	Standard Error	P-Value
Gender	-.180	.199	.367	-.359	.211	.089	-.287	.241	.233
Age	-.015	.008	.045	-.024	.008	.003	.010	.009	.272
Management, Science, and Technology	.130	.252	.607	-.058	.267	.828	.250	.297	.401
Psychology and Education	.281	.232	.226	-.064	.243	.791	.220	.285	.440
Postgraduate	.236	.207	.256	.075	.222	.737	.083	.244	.733
European Student	-.194	.305	.524	-.927	.382	.015	.476	.337	.158
Overseas Student	.755	1.128	.503	-.189	1.307	.885	2.066	1.154	.073

5.4.3. Class Transitions

Transitions between class assignments for the ideal and predicted expectation scales are presented in Table 5.10, which addresses RQ4. It can be seen that those is the *High Expectation* and *Inflated Expectation* groups for the ideal expectation scale appeared to move to the *Low Service Expectation* group on the predicted expectation scale (n = 350 and n = 111, respectively). A large proportion of students in the *Inflated Expectation* group on the ideal expectation scale moved to the *Indifferent Expectation* group on the predicted expectation scale (n = 146). In some instances, students in the *Low Service Expectation* group for the ideal expectation scale were assigned to either the *High Expectation* or *Inflated Expectation* groups on the predicted expectation scale (n = 139 and n = 118, respectively). Finally, some students assigned to the *High Expectation* group on the ideal expectation scale were assigned to the *Inflated Expectation* group on the predicted expectation scale (n = 204).

Table 5.10. Transitions between Identified Classes based on the Ideal and Predicted Expectation Scales

		Ideal Expectation Scale		
		Low Service Expectation Group	High Expectation Group	Inflated Expectation Group
Predicted Expectation Scale	Low Service Expectation Group	39	350	111
	Indifferent Expectation Group	10	16	146
	High Expectation Group	139	30	22
	Inflated Expectation Group	118	204	55

5.5. Discussion

The aim of this exploratory paper was to gauge and segment students based on their expectations of learning analytics services using the three-step approach to latent class analysis. The findings show that for the ideal expectation scale, there are three types of response patterns within the student population. Whereas, for the predicted expectation scale, four types of responses patterns identified were identified. This is an important step as failure to gauge service user expectations is attributed to the eventual failure of information system implementations (Lyytinen & Hirschheim, 1988). Moreover, by devising ways to measure user expectations, institutions can readily identify unrealistic expectations (Jackson & Fearon, 2014). This can then lead to the creation of solutions that seek to manage these expectations early on so that eventual experience of the service does not fall short of what is expected, reducing the feelings of dissatisfaction that arise with large discrepancies (Brown et al., 2014, 2014; Venkatesh & Goyal, 2010).

5.5.1. Ideal Expectations

Based on the findings of the current study, it was found that students can be meaningfully segmented on the basis of their ideal expectations of learning analytics services (RQ1). The three classes identified from the responses to the ideal expectation are labelled as the *Inflated Ideal Expectation* group, the *High Ideal Expectation* group, and the *Low Ideal Service Expectation* group. It is important to acknowledge that where these groups become differentiated is in relation to the Service Expectation items, as average responses on the Ethical and Privacy Expectation items are similar. From this, the Ethical and Privacy Expectation items can be viewed as not being useful in differentiating these groups from one another. However, it also shows that irrespective of the services that could be offered through the university implementing learning analytics, students have strong expectations regarding the ethical and privacy elements of such a service. In other words, whilst some students may not desire features that will enable them to track their progress towards a set goal, they do desire a university to seek consent and ensure that all data is secure. This is an important point for informing the development of learning analytics policies as it shows all students have a desire for their ethical and privacy concerns to be adequately addressed (Ferguson, Hoel, Scheffel, & Drachsler, 2016; Sclater, 2016; Tsai & Gašević, 2017a; Tsai et al., 2018).

As for Service Expectations, the *Inflated Ideal Expectation* group is characterised by average item responses that were close to seven (Strongly Agree). The *High Ideal Expectation* group, on the other hand, was found to have average responses between categories five (Somewhat Agree) and six (Agree). Whereas, *the*

Low Ideal Service Expectation group has average responses below category four (Neither Agree nor Disagree), falling close to categories three (Somewhat Disagree) and two (Disagree). It is, therefore, clear that there is one group who have the strongest ideal expectations for all possible features of a learning analytics service (*Inflated Ideal Expectation* group). This may indicate that these student view such features as being useful in supporting their learning and that this is what they desire the university to implement. The same can also be said of the *High Ideal Expectation* group, but their level of desire for these features is slightly weaker.

It has been previously shown in the work of Schumacher and Ifenthaler (2018) that students desired learning analytics service features that allow for learning progress to be monitored and that provide a profile of a student's learning. Similarly, Roberts et al. (2016) found first year students to favourably view learning analytics services on account of their potential to provide some form of direction to their learning experience. This is exemplified in the series of learning analytics templates presented by Marzouk et al. (2016), which shows that learning analytics services can support autonomy (e.g., select own goals), whilst also providing the capabilities for a learner to understand the importance of externally set goals. For some students, being able to structure and monitor their learning progress may be viewed favourably, particularly given the emphasis on independent learning at university (Thomas et al., 2015). Additionally, Thomas and colleagues found students to frequently report that they struggled during their initial transition into university on account of the limited direction given by teaching staff (Thomas et al., 2015). Therefore, the prospect of learning analytics services for some students (the *Inflated Ideal Expectation* group and *High Ideal Expectation* group) may be desirable on account of its potential to assist them in their adjustment to the culture of higher education.

For the *Low Ideal Service Expectation* group, they do not express any desire to receive any of these learning analytics features. It is possible that these students, as found in the work of Roberts et al. (2016), feel that learning analytics should not remove the ability for a student to make independent decisions. Put differently, whilst a university could intervene early if a student is at-risk of failing, these students may believe that this removes their ability to become reliant upon themselves. Thus, from a policy perspective, it is clear that learning analytics cannot be a blanket implementation with all students receiving the same service.

An approach to implementation of learning analytics services, in light of these group differences, would then be to offer different forms of services that align with what students expect. This resembles a scaffolding approach, whereby the level of service offered varies in accordance with what students need. However, the possibility of students receiving regular feedback, knowing how they are progressing, or having a complete profile of their learning may not encourage the student to assume responsibility for their learning (Pol, Volman, & Beishuizen, 2010). Thus, while those in the *Inflated Ideal Expectation* group or *High Ideal Expectation* group may desire these listed learning analytics services, it is necessary for steps to be taken to avoid dependency. A solution to this would be for such support systems to gradually be faded with time (Pol et al., 2010). This would then address the challenges of first year students becoming independent learners (Thomas et al., 2015) and the concerns relating to learning analytics services undermining student responsibility for their own learning (Roberts et al., 2016). As for those in the *Low Ideal Service Expectation* group, an adaptive approach to learning analytics services could be taken where the support offered varies in accordance with a student's learning progress (Pol et al., 2010). This latter point is important, as students who may not desire for their data to be used to provide learning analytics services will become disadvantaged as they will not reap the benefits offered (Sclater, 2017). Thus, students not desiring learning analytics service features does create an additional challenge as higher education institutions must decide how to satisfy student expectations, but remain cognisant that such decisions can create further problems. A resolution to this issue has been exemplified by Nottingham Trent University, where a mandatory learning analytics service is in place that provides engagement metrics in the form of a dashboard (Nottingham Trent University, 2016; Sclater, Peasgood, & Mullan, 2016). In this case, it may be that some students may not have desired for a service to be implemented this way, but it has been associated with improvements to learner engagement and academic performance (Sclater et al., 2016). Therefore, for the *Low Ideal Service Expectation* group of students, the usefulness of learning analytics services may not become apparent until they experience the tools provided or the academic benefits are realised.

In addition to the three types of responses identified, the pattern of average responses show item S6 (the obligation to act) to be lowest for each group. In the case of the *Inflated Ideal Expectation* and *High Ideal Expectation* groups, the average responses to S6 (the obligation to act) fall between Somewhat Agree and Agree. Whilst these are positive responses, they do fall below the trends of the remaining 11 items. As for the *Low Ideal Service Expectation* group, these students, on average, appeared to express disagreement with this particular learning analytics service feature. This is important as there has been extensive discussions regarding the obligation to act, with Prinsloo and Slade (2017) stating that the both the student and institution have a shared responsibility when it comes to learning. Put differently, it is not the sole responsibility of the institution to ensure that a student is successful, the student themselves bears a responsibility to engage in the learning process (Howell, Roberts, Seaman, & Gibson, 2018).

As for the results of the latent class regression, it was found that class assignment was associated with one covariate (RQ3). More specifically, it was found that the likelihood of being either in the *Inflated Ideal Expectation* or *High Ideal Expectation* groups, compared to the *Low Ideal Service Expectation* group, increases with age. Findings have shown that mature students commonly identify family and friends as their main sources of support in higher education, whilst few sought institutional support, putting this down to being off-campus or low confidence (Heagney & Benson, 2017). It is, therefore, understandable that older students would desire the types of services that could be offered through learning analytics, as the feedback would be personalised (e.g., knowing how they are progressing in relation to a set goal) and their progress would be monitored (e.g., early alert systems). Put differently, learning analytics has the potential to change an institutional environment from one that disadvantages mature students, to one that is student-centred and improves educational outcomes for mature students.

5.5.2. Predicted Expectations

The results of the study also found that students could be meaningfully segmented on the basis of their predicted expectations of learning analytics services (RQ2). The results found that a four class solution was deemed to be suitable for the predicted expectations scale. These four groups are labelled as the *High Predicted Expectation* group, the *Indifferent Predicted Expectation* group, the *Inflated Predicted Expectation* group, and the *Low Predicted Service Expectation* group.

In contrast to the Ideal Expectation scale, these four identified groups can be differentiated on the basis of the Ethical and Privacy Expectation items (EP1 to EP5). Whilst the responses of these five items show a similar trend for classes one, two, and three, the responses for class four are considerably lower. Thus, unlike the ideal expectation scale, the Ethical and Privacy Expectation items can be used to differentiate between certain classes. Starting with the *Indifferent Predicted Expectation* group, it appears that EP1 (consent to use identifiable data) and EP2 (ensure all data is kept secure) receive the highest average responses. Whereas, expectations regarding consenting to third party usage of data (EP3), consenting to data being collected and analysed (EP4), and consenting to data being used for an alternate purpose (EP5) is met with indifference (Neither Agree nor Disagree). For these students, it appears that they do not necessarily expect the university to seek consent for collecting and analysing data, giving data to third party companies, or using data for alternative purposes. This may be on account of students being accustomed a culture where companies readily collect and analyse data day to day basis; therefore, these students may be less resistant to universities engaging in such practices (Sclater, 2016). Similarly, it has been found that some students are not concerned over the usage of data extracted from the virtual learning environment (Fisher, Valenzuela, & Whale, 2014) or university studies (Ifenthaler & Schumacher, 2016). It may, therefore, be that for those in the *Indifferent Predicted Expectation* group, there is an expectation that the use of certain data by the university and third party companies will not require them to provide consent.

Compared to the *Indifferent Predicted Expectation* group, the remaining three classes (*Low Predicted Service Expectation* group, *High Predicted Expectation* group, and *Inflated Predicted Expectation* group) have strong expectations across all Ethical and Privacy Expectation items. Again this shows that majority of students, in reality, expect for the university to clearly set out how collected data is used and who has access to this data, but for the university to also seek consent before undertaking any form of learning analytics (Slade & Prinsloo, 2014). In the work of Ifenthaler and Schumacher (2016), it was found that in some instances students were open to data being shared (e.g., pertaining to their university studies), but certain data usage drew greater concern (e.g., use of personal data). Thus, whilst it may be that there is a degree of acceptability in what data the university uses, as found by Ifenthaler and Schumacher (2016), majority of students realistically expect consent to be first sought. Given that this scale (predicted expectations) refers to what is expected of a learning analytics service in reality and the proportion of students across these three classes being high (n = 863; *Low Predicted Service Expectation* group, *High Predicted Expectation* group, and *Inflated Predicted Expectation* group), it does strengthen the view that the university takes steps to address these expectations. A solution has been outlined by Sclater (2017), which also meets the requirements of the General Data Protection Regulation[6] (GDPR). Within these guidelines, Sclater (2017) states how intuitions must inform students about any personal data collected and how it will be processed. However, if risk is minimised then consent may not be required. Even in this latter instance, the expectations of students cannot be

[6] Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation)

overlooked and it remains necessary for the institution to be transparent and clearly articulate any data handling procedures.

For Service Expectation items (S1 to S7), the *Inflated Predicted Expectation* group have average responses close to seven (Strongly Agree) for majority of the items, apart from S6 (the obligation to act). The largest identified class, the *High Predicted Expectation* group (n = 500), have average responses between five (Somewhat Agree) and six (Agree). Thus, there is some variability across the Service Expectation items with regards to the strength of the predicted expectations. For example, students from these two groups show a high average response to S3 (knowing how progress compares to a set goal), but a weaker average response to S6 (the obligation to act). As for the *Indifferent Predicted Expectation* group (Class Two), the average responses do not show much variability around response category four (Neither Agree nor Disagree). This is indicative of these students not having formulated strong expectations towards the possible learning analytics services features and whether they would or would not realistically expect them to be implemented. As for the *Low Predicted Service Expectation* group (Class Four), these students tended to display disagreement with the university being capable of offering these learning analytics service features. The item with lowest average response for this group was S4 (receiving a complete learning profile), which resonates with the findings of Howell et al. (2018). In their work, Howell and colleagues found teaching staff to express concern over the anxiety that could be created as a result of the information overload that is possible with learning analytics services (e.g., students wanting to constantly know how they are performing in relation to others). In the case of this group of students (the *Low Predicted Service Expectation* group), they may view the possibility of a university being capable of feeding such information back or coping with sheer volume of students seeking additional support to make this service unattainable. As with the ideal expectation scale, item S6 (the obligation to act) does have the lowest average response for all classes apart from class four where it is the item with the second lowest response. Given that this scale corresponds to the type of learning analytics expected in reality, it is important to recognise how responses to this item compare to the other item responses. For the *High Predicted Expectation* (Class One) and *Inflated Predicted Expectation* (Class Three) groups, features such as receiving regular updates (S1) and knowing how progress compares to set goals (S3) are expected to be implemented in reality. However, having a system in place that could place the responsibility of student success predominately with teaching staff (Howell et al., 2018; Prinsloo & Slade, 2017) does not elicit expectations that are comparable in strength. Again, this may refer to the issues previously raised in student focus groups, which refer to learning analytics services preventing students from being independent (Roberts et al., 2016). In contrast, the features in items S1 and S3 do not impede independence and can support self-regulated learning as it allows students to monitor their progress (Butler & Winne, 1995; Schumacher & Ifenthaler, 2018).

The latent class regression results found class assignment to be associated with two covariates (RQ3). More specifically, the likelihood of being in the *High Predicted Expectation* group (Class One) or the *Indifferent Predicted Expectation* group (Class Two) decreases with age, compared to *Low Predicted Service Expectation* group (Class Four). The likelihood of being or not being in the *Inflated Predicted Expectation* group (Class Three) with increased age was not statistically significant. From this it seems that the predicted expectations of older students are less likely to be high or at a level of indifference. For the ideal expectation scale, it was found that older students are more likely to be assigned to a class labelled the *Inflated Ideal Expectation* group; however, this was not found for the predicted expectation scale. Put differently, older students are not more likely to be classified in the *Inflated Predicted Expectation* group (Class Three) than *Low Predicted Service Expectation* group (Class Four).

In addition to the effect of age, it was also found that European students are less likely to be in the *Indifferent Predicted Expectation* group (Class Two) compared to Dutch students. This is important as it may be indicative of cross-cultural differences with regards to expectations of learning analytics services. It is, therefore, necessary for future research to understand whether student expectations of learning analytics services are culturally consistent or not, particularly given the global interest in learning analytics (Pardo et al., 2018).

5.5.3. Expectation Transitions

To further understand student expectations of learning analytics services, an additional step was taken to explore class transitions between the two SELAQ scales (ideal and predicted expectations). The results generally show that class assignment is not consistent across the ideal and predicted expectation scales (RQ4).

It was found that the largest proportion of students were assigned to the *High Expectation* group on the ideal expectation scale and the *Low Service Expectation* group on the predicted expectation scale (n = 350). In this instance, students may have high desires regarding learning analytics services, but do not realistically expect the university the types of services offered. This shows that the students hold quite pessimistic expectations of the university not being able to realistically implement learning analytics services. However, there have been numerous examples of universities being successful in implementing those learning analytics service features contained within the SELAQ (Sclater et al., 2016). Therefore, the university, upon knowing what student expect, can begin to challenge these expectations (Jackson & Fearon, 2014). From the perspective of cognitive dissonance, however, these expectations may not be easily challenged (Festinger, 1957). This is due to both an individual's resistance to change and the strength of the dissonance created by the university engaging in behaviours that challenge expectations (Festinger, 1957; Ngafeeson & Midha, 2014; Nov & Ye, 2008). Put differently, only when maximum dissonance is created (e.g., provide the services that are not realistically expected) can expectations of this group will be challenged (Festinger, 1957).

There are also a group of students who move from the *Low Service Expectation* group on the ideal expectation scale to either the *High Expectation* or *Inflated Expectation* group (n = 139 and n = 118, respectively). For these students, they appear to not desire any of the features of a learning analytics service, but expect that they university will implement these in reality. As previously discussed, Roberts et al. (2016) found a subset of students to express disinterest in the possibilities that learning analytics services can offer. Nevertheless, it is likely that students realise that in a society where data is regularly collected and processed, a university engaging in such practices may not be unexpected (Sclater, 2016).

5.5.4. Implications for Policy

The findings of this current work are important for the development of a learning analytics policy that accounts for the perspectives of the student stakeholder group. One of the main takeaway points from analysing the SELAQ data using latent class analysis has been the identification of heterogeneous expectations found within the student population. Some students have inflated expectations of learning analytics services, whilst others have low expectations regarding the types of features that are offered. From knowing this information, it then becomes necessary for institutions to design and implement a learning analytics service that aligns with these diverse expectations. More specifically, the university could utilise the data gathered from the SELAQ to adapt implementations to meet the expectations of individual students. In addition, it could also allow for management to intervene early and manage the expectations of students in order to mitigate the effects of inflated expectations (e.g., dissatisfaction resulting from the large discrepancies between expectations and experience; Brown et al., 2012, 2014; Jackson & Fearon, 2014; Venkatesh & Goyal, 2010). Institutions interested in implementing learning analytics services should, on the basis of these results, be encouraged to take a proactive approach by gauging student expectations early on in order to provide a service that students can be satisfied with.

The approval of the GDPR by the European Parliament has important connotations for the implementation of future learning analytics services. Part of this legal act is for businesses to ensure that all personal data is securely processed and service users must provide informed consent to data processing. As found in the current work, majority of students across all identified groups held strong expectations regarding the Ethical and Privacy Expectation items, all of which cover the main topics of the GDPR. Even in the case of the *Indifferent Predicted Expectation* group (Class Two), these students expressed slight agreement with items EP1 (consent to use personal data) and EP2 (ensuring data is secure). Therefore, the student perspectives regarding the ethical and privacy elements of a learning analytics service are in alignment with those points contained within the GDPR. On the basis of this information, it is recommended that those institutions interested in implementing learning analytics services first create a clear privacy policy that details how these ethical and privacy considerations will be addressed. These points have also been articulated by Sclater (2017), who has stated that consent must be sought for the collection and processing of sensitive data. Additionally, in the development of this document, it must also have input from stakeholders such as students so that their expectations can be gauged early on in the implementation stages (Davis & Venkatesh, 2004; Khalifa & Liu, 2003).

Under the GDPR, it is also stated that there must be a legitimate interest for processing data. In the case of learning analytics services, a university may view the potential to improve student learning as a legitimate interest for collecting and analysing data. From the findings of the current study, there were two groups who had desired and expected to receive majority of the learning analytics service features (e.g., regular updates on learning progress and receiving a completed profile of their learning). However, there were also students that were indifferent about the possible learning analytics service features and students who did not expect or desire any such features. This raises concerns regarding whether an institution does have a legitimate interest to collect and analyse student data as not all students expect these learning analytics services. Again, turning to the points raised by Sclater (2017), legitimate interest can be used to avoid seeking additional consent under circumstances where data is lawfully collected (e.g., virtual learning environment logs). It is still necessary, however, that even under these circumstances the students are aware of such steps being taken (Sclater, 2017). If universities where to process this collected data with a view of potentially intervening with students, then this falls outside of what is a legitimate interest and additional consent is required (Sclater, 2017). Taking both the current findings and data handling discussions presented by

Sclater (2017) into consideration, it is clear that whilst general processing of certain educational data by a university is permissible, there is not a consensus from students with regards to expecting or desiring learning analytics services. As stipulated in the GDPR, the interests of the individuals must be weighed up with one's own, taking into consideration how they would want their data to be used. For learning analytics services, this can easily be achieved through the use of the SELAQ and as discussed above, not all students expect their data to be used to provide such services. Therefore, there cannot be a blanket implementation of learning analytics services within universities, students must have the right to decide whether to partake in such services or not.

5.5.5. Limitations

Decisions regarding the candidate model selection were informed by the relative fit, classification accuracy, local fit, and interpretability. For both the ideal and predicted expectation scales, the proportion of absolute standardised residual values exceeding 3 was greater than the 5% guideline proposed by Masyn (2013). However, this only remains a guideline and Masyn (2013) did stipulate that if the proportion is in "notable excess" of 5% then the model fit is concerning (p. 567). In terms of the current models, it was decided that the interpretability, relative fit, and classification accuracy of the selected models were good. Therefore, seeking to meet the general guideline of 5% for local fit by increasing the number of classes extracted was deemed inappropriate. It stills remains necessary for follow-up work to be undertaken to see whether the three and four class solutions for the ideal and predicted expectation scales, respectively, are supported in additional samples.

The inclusion of class transitions is useful in showing how what students may desire from learning analytics services does not equate to what they expect in reality.

Whilst providing useful insights, there is still a need to understand why students change their expectations. As discussed in Ajzen's (2011) work, beliefs are shaped by background factors such as life values and personality. It is reasonable to extend this assertion to expectations, particularly as they are defined as beliefs about the future (Olson & Dover, 1976). Future research is therefore required to understand what shapes both the ideal and predicted expectations held. It may also be necessary to undertake additional qualitative work to provide a rich understanding of what factors lead students to fall within the identified classes reported here.

A further limitation to consider is the covariates included within the latent class regression, which only covered demographic information about the students. It is important to consider that there may be other factors that do influence the expectations that students hold (Ajzen, 2011). For example, given that learning analytics is aimed at improving learning outcomes, the expectations may vary in accordance with education factors including goal orientation. More specifically, those students with a learning goal orientation, who want to increase their understanding about a topic (Phillips & Gully, 1997), may expect learning analytics services that enable them to set and monitor their learning goals. Whereas, those students that have a performance goal orientation, who are motivated to perform well (Phillips & Gully, 1997), may expect services aimed at providing them with a complete profile of their learning. Thus, whilst the current work does show expectations to be influenced by covariates, more work is required to understand whether this extends to educationally relevant variables too.

Chapter 6: The Big Five Personality Dimensions and Student Expectations of Learning Analytics: An Exploratory Structural Equation Modelling Approach

6.1. Summary

Pre-implementation beliefs (expectations) towards an object are determined by background variables including personality (Ajzen, 2011; Oliver, 1980). Moreover, personality has been highlighted as being an important determinant in technology adoption (Devaraj, Easley, & Crant, 2008) and data privacy beliefs (Junglas, Johnson, & Spitzmüller, 2008). On this basis, it was reasonable to assume that differences in student expectations of learning analytics services may be associated with personality traits. This chapter therefore presents an exploratory structural equation model to understand how dimensions of personality are associated with student expectations of learning analytics services. The findings are discussed in relation to policy decision making with regards to the implementation of learning analytics services.

6.2. Introduction

Engaging with stakeholders (e.g., students) has been recognised as an important challenge for higher education institutions, who are interested in implementing learning analytics services, need to address (Tsai & Gašević, 2017a; Tsai, Moreno-Marcos, et al., 2018). As exemplified in the technology adoption literature, pre-adoption beliefs (expectations) towards future implementations are associated with acceptance and use (Davis & Venkatesh, 2004). According to Venkatesh and colleagues, it is advantageous to gauge expectations of a possible technology implementation as steps can be taken to manage those expectations that may be inflated (Brown, Venkatesh, & Goyal, 2012, 2014; Venkatesh & Goyal, 2010). This is on account of expectation management being a pre-implementation factor that can affect the expectations service users hold (Szajna & Scamell, 1993). However, the determinants of user expectations are not limited to the actions of the provider, but also refer to the characteristics of the individuals themselves (Oliver, 1980). This has also been discussed by Ajzen (2011), who theorised that the beliefs held by an individual are associated with a multitude of background variables, which includes personality. As previously stipulated (Chapter 2), the only discernible difference between beliefs and expectations is the reference point (i.e., expectations are beliefs about the future; Olson & Dover, 1976). This position was used to inform the framework in the development of the SELAQ (the Student Expectations of Learning Analytics Questionnaire; Chapter 2). Therefore, there is theoretical justification for undertaking an exploratory study to understand whether the background variable of personality is associated with the expectations students hold towards learning analytics services.

6.2.1. Expectations of Learning Analytics Services

There is a growing body of research that is beginning to address the challenge of engaging with students in the implementation decisions surrounding learning analytics services (Arnold & Sclater, 2017; Ifenthaler & Schumacher, 2016; Roberts et al., 2017, 2016; Schumacher & Ifenthaler, 2018; Slade & Prinsloo, 2014; Tsai & Gašević, 2017a; Tsai et al., 2018). Within this work, it has been shown that students have expectations regarding how the university should handle data (e.g., whether informed consent should be sought; Slade & Prinsloo, 2014) and what information should be fed back (e.g., metrics to monitor learning progress; Schumacher & Ifenthaler, 2018). Together, these findings represent fundamental steps towards the creation of learning analytics services that not only address what higher education institutions want (e.g., improved retention rates; Tsai & Gašević, 2017), but what students expect (Whitelock-Wainwright et al., 2017).

With regards to exploring individual differences in the expectations students have of learning analytics services, progress has been slow. Nevertheless, from a general assessment of the few studies into student expectations of learning analytics services, there is indication that the pre-adoption beliefs are not homogenous across the student population. In their qualitative study, Roberts et al. (2016) found some students to appreciate the possibilities that learning analytics services could have in providing the necessary support in their transition to university and the need to become independent learners (Thomas et al., 2015). Other students, however, expected learning analytics to not remove the ability for students to assume responsibility for their own learning (Roberts et al., 2016). Thus, even in a sample of students from the same higher education institution there are clear individual differences with regards to what is expected from learning analytics services.

Likewise, it has been shown that students can be assigned different classes based on their responses to the 12-items of the SELAQ (Chapter 5). In the latter case, it was found that some students may hold inflated expectations in that they expect the university to provide updates on how learning progress compares to set goals; whereas, other students have low expectations of the university providing such features (Chapter 5). Additionally, it was found that the assignment to a specific class was associated with certain variables (e.g., age; Chapter 5).

A further example of student expectations of learning analytics services being heterogeneous comes from Arnold and Sclater (2017). In this instance, student beliefs regarding possible learning analytics services were measured using three items, with responses being made on a dichotomous scale. The sample itself was composed of students from the United Kingdom (UK) and the United States (US), with the results showing US students being more accepting of learning analytics service features (Arnold & Sclater, 2017). A caveat of this study, which does raise questions regarding the validity of the findings, was the US students having prior experience of learning analytics services (Arnold & Sclater, 2017). Therefore, it is reasonable to assume that the expectations measured in this study undertaken by Arnold and Sclater (2017) were influenced by the amount of experience with learning analytics service. Even though Arnold and Sclater (2017) failed to discuss this latter issue, these findings are indicative of prior experience being an important background variable attributed differences in student expectations of learning analytics services.

Taking the aforementioned literature into consideration, there is evidence to suggest that student expectations of learning analytics services are not homogenous. Instead, the research does suggest that there are characteristics of the individuals that are associated with the expectations held, as proposed by Oliver (1980). On this basis, this paper aims to extend the current literature by understanding how a background variable (personality) is attributed to differences in student expectations towards learning analytics services.

6.2.2. Personality and Technology Adoption

For the purposes of this work, the Big Five model of personality was used to understand how background characteristics affect student expectations of learning analytics services. This decision was informed by both the extensive research evaluating this factor (Gosling, Rentfrow, & Swann, 2003; Rammstedt & John, 2007) and its utility in understanding individual differences in technology adoption research (Barnett, Pearson, Pearson, & Kellermanns, 2015; Devaraj et al., 2008). Under this theoretical model (the Big Five), there is a purported five factor structure that explains personality: agreeableness (characterised by trust and sympathy), conscientiousness (characterised by organisation and efficiency), extraversion (characterised by enthusiasm and energy), neuroticism (characterised by worry and anxiety), and openness (characterised by originality and curiosity) (McCrae & John, 1992). Each of these dimensions of personality will be discussed in turn, with emphasis on how it relates to technology adoption.

6.2.2.1. Agreeableness

Based on the descriptions offered by Costa and McCrae (1992), those who are high in agreeableness are more compassionate, helpful, easy going, and less inclined to be cynical. Although in the context of technology adoption, this definition of agreeableness would lead to the assumption that new technologies would be received positively by those high in this dimension. The technology adoption literature, however, shows that the effects of agreeableness are not clear. Devaraj and colleagues showed that high levels of agreeableness are positively associated with perceived usefulness (Devaraj et al., 2008). When included in the unified theory of acceptance and use of technology (UTAUT; Venkatesh, Morris, Davis, & Davis, 2003), Lakhal and Khechine (2017) only found agreeableness to be positively associated with effort expectancy (perceived ease of use). As for being a determinant of intentions to use or actual use of a new technology, agreeableness is not important (Barnett et al., 2015). Thus, with regards to how agreeableness may affect expectations of learning analytics services, it is possible that these students have higher expectations on account of being less cynical and antagonistic. Given the aforementioned mixed results, it can also be assumed that agreeableness may not affect pre-implementation beliefs (i.e., expectations).

6.2.2.2. Conscientiousness

Those individuals who are high in conscientiousness are likely to be well-organised, hardworking, and disciplined (Costa & McCrae, 1992). With regards to the effects of this personality dimension of technology adoption, it was found to moderate the effects of perceived usefulness on behavioural intentions (Devaraj et al., 2008). Put differently, individuals who are conscientious are more inclined to weigh up how a particular service would improve efficiency (Lane & Manner, 2012). The outcome would then vary the magnitude (increase or decrease) of usefulness beliefs on behavioural intentions (Devaraj et al., 2008). Additional research undertaken by Barnett et al. (2015) showed conscientiousness to be positively associated with actual usage of a technology. From a technology adoption standpoint, it can therefore be seen that conscientious individuals are more inclined to consider the productivity benefits to inform their decisions on whether to use a technology. It is important to consider that conscientiousness is also related to learning goal orientation (Payne, Youngcourt, & Beaubien, 2007), which is indirectly associated to self-regulatory behaviour such as goal setting (Phillips & Gully, 1997). Thus, with regards to education technologies, the ability to set goals and monitor progress aligns with the motivation of developing task competence as students would be able to efficiently regulate their behaviours. On this basis, it may be that conscientious students do have higher expectations of learning analytics services.

6.2.2.3. Extraversion

Extraversion embodies a variety of different traits that include joy, sociability, and optimism (Costa & McCrae, 1992; Lakhal & Khechine, 2017). As an external variable in the technology acceptance model (TAM; Davis, 1989), it was found to moderate the effects of subjective norms on behaviour intentions (Devaraj et al., 2008). As extraverted individuals are concerned with their public image, it is likely that this strengthens the effects of beliefs towards the technology that are expressed by members of their social network (Devaraj et al., 2008). Barnett et al. (2015), on the other hand, found extraversion to be negatively associated with actual use of a technology. These authors attributed this to computer usage being a solitary activity, which may lead to an extraverted individual being less inclined to use such technologies (Barnett et al., 2015). It is important to recognise, however, that technologies associated with learning analytics are guided by a view of improving learning (Siemens & Gašević, 2012). Thus, the effects of extraversion in educational research is warranted, which has shown extraversion to be positively related to having a learning goal orientation (Payne et al., 2007; Wang & Erdheim, 2007). Furthermore, it has been found that extraversion is related to goal-setting behaviours (Judge & Ilies, 2002). Given the possibility of learning analytics services being able to facilitate students' ability to monitor and regulate their behaviour (Winne, 2017), extraverted students may express high expectations.

6.2.2.4. Neuroticism

Neuroticism is associated with individuals experiencing anxiety, depression, and worry (Costa & McCrae, 1992; Lakhal & Khechine, 2017). When included in the TAM (Davis, 1989), Devaraj et al. (2008) have shown neuroticism to be negatively associated with perceived usefulness. A possible reason for this is that neurotic individuals view new technologies as stressful, which then leads to negative evaluations (Devaraj et al., 2008). This finding has been consistent, as Lakhal and Khechine (2017) have shown neuroticism to be negatively associated with the three UTAUT variables of facilitating conditions, effort expectancy, and performance expectancy (Venkatesh et al., 2003). Thus, results seem to suggest that neuroticism is associated with individuals being less inclined to adopt a technology. Given that the technology being introduced in learning analytics services are designed to "optimise learning" (Siemens & Gašević, 2012), it is important to consider the effect of neuroticism in education. For example, the research of Komarraju, Karau, and Schmeck (2009) found neurotic students to have higher grade point averages. From this, it could be argued that those students performing well in educational settings are more likely to experience anxiety, which could be attributed to wanting to be successful (Komarraju et al., 2009). In the case of learning analytics services, whilst technology adoption literature may suggest that neuroticism would result in low expectations regarding features offered, educational research would suggest the opposite. Put differently, neurotic students may have high expectations of learning analytics service features on account of their high anxiety to perform well.

6.2.2.5. Openness

Individuals who are high in openness are more likely to be curious, flexible, and non-dogmatic (Costa & McCrae, 1992; Lakhal & Khechine, 2017). As an external variable in the TAM (Davis, 1989), findings appear to suggest that openness may not be an important determinant in technology adoption. Devaraj et al. (2008) found no support for the hypothesised association between openness and perceived usefulness of a technology. Similarly, Lakhal and Khechine (2017) found no support for the effect of openness on the UTAUT construct of performance expectancy (Venkatesh et al., 2003). In addition, Barnett et al. (2015) found openness to not be related to actual use of a technology. Despite the originally hypothesised relationship between perceived usefulness and openness not being supported in the work of Devaraj et al. (2008), these authors offered an alternative model where openness had a direct effect on behavioural intentions. In this alternate model, the direct effect of openness was supported (Devaraj et al., 2008). Thus, openness may not be associated with the beliefs regarding the utility of a technology; rather, their temperament of being curious leads to greater intentions to use the technology. As for educational research findings, it has been shown that openness is related to goal-setting (Judge & Ilies, 2002). Therefore, the types of features offered through learning analytics services may align with these motivations to set and monitor goals, resulting in higher expectations.

6.2.3. Personality and Data Privacy

Considering all dimensions of the Big Five together, it has been found that agreeableness and conscientiousness are positively associated with a user’s concern for information privacy (Osatuyi, 2015). According to Osatuyi (2015) those high in agreeableness are found to be more trustworthy; therefore, they would expect the privacy of data pertaining to themselves and others to remain private. As for the conscientiousness, individuals high in this dimension are likely to be attentive to details, which would lead them to carefully assess elements of an information privacy policy (Osatuyi, 2015). Contrary to these findings of Osatuyi (2015), Junglas and colleagues found agreeableness to be negatively associated with concerns for information privacy (Junglas et al., 2008). In addition, Junglas et al. (2008) found conscientiousness and openness to be positively associated with concerns for information privacy. Thus, it can be seen that the effect of conscientiousness on concerns for information privacy has been replicated; whereas, with other dimensions of the Big Five, the effects are not clear.

The conceptualisation of student expectations towards learning analytics services was defined in Chapter 2 as "a belief about the likelihood that future implementation and running of learning analytics services will possess certain features" (p. 46). These features are not limited to the types of feedback provided to students, but cover ethical and privacy features of learning analytics services. More importantly, the SELAQ, which is based upon this abovementioned definition, contains a subscale termed *Ethical and Privacy Expectations* (Chapter 2). The dimensions of this latter factor cover expectations towards the collection of identifiable data, usage of data by third party companies, and data security. Taking both the definition and items into consideration, the possible effects of personality dimensions can be viewed in relation to the previously mentioned work on concern for information privacy. Firstly, information privacy concerns are framed as beliefs (Smith, Dinev, & Xu, 2011). Secondly, the concern for privacy instrument contains belief towards data collection, access to data that is unauthorised, and secondary data usage (Smith, Milberg, & Burke, 1996). Parallels can be then drawn with the definition of student expectations and the items of the SELAQ referring to *Ethical and Privacy Expectations*. Therefore, whilst there is no prior work exploring the effects of personality on *Ethical and Privacy Expectations* of learning analytics services, the findings from the concern for information privacy model provide a good theoretical starting point.

6.2.4. Study Aims

The aims of the current were two-fold: first, we sought to assess whether the 12-item SELAQ was valid in an additional sample of English speaking Higher Education students, which was undertaken as a means of assessing the measurement model (Kline, 2015). Second, we aimed to explore whether dimensions of personality, specifically the Big Five (agreeableness, conscientiousness, extraversion, neuroticism, and openness), were associated with the expectations that students hold towards learning analytics services. Given that the SELAQ contains two scales, which refer to ideal (a desired level of expectation) and predicted (what is expected in reality) levels of expectation, two structural regression models were ran. In other words, two structural regression models were ran to explore the effects of personality dimensions on the ideal and predicted levels of expectation. Together, this study extended prior work by exploring individual differences in students' expectations of learning analytics services. Given that there was no prior work exploring how dimensions of the Big Five are associated with student expectations towards learning analytics services, the authors of this current work made no predictions regarding the effects of the five personality dimensions (agreeableness, conscientiousness, extraversion, neuroticism, and openness) and the two expectation factors (*Ethical and Privacy Expectations* and *Service Expectations*). Instead, this exploratory research sought to answer two research questions:

RQ1. Are the purported five dimensions of personality associated with students' ideal expectations of learning analytics services?

RQ2. Are the purported five dimensions of personality associated with students' predicted expectations of learning analytics services?

6.3. Methods

6.3.1. Sample

237 respondents (Females = 80) from a Higher Education Institution in Ireland completed the questionnaire using an online system (all responses were voluntary). The age of the respondents ranged from 18 to 57 (*M* = 27.40, *SD* = 10.40). Of the sample, 82.30% were undergraduate students (n = 195), 16% were masters students (n = 38), and 1.69% were PhD students (n = 4). The Higher Education Institution contains eight faculties and the sample only represents seven (no responses from students studying a subject under the apprenticeships and trade faculty). Of those faculties that are represented, 14.30% studied a business subject (n = 34), 42.60% studied a computing subject (n = 101), 13.90% studied a creative digital media subject (n = 33), 7.59% studied an engineering subject (n = 18), 2.95% studied a horticulture subject (n = 7), 3.38% studied a sports management and coaching subject (n = 8), and 15.20% studied a humanities subject (n = 36). Finally, majority of the population identified themselves as Irish/European student (94.51%, n = 224), with 5.49% students stating they were Overseas students (n = 13). This demographic information is also presented in Table 6.1.

Table 6.1. Demographic Information for the Irish Student Sample

Characteristic	Mean	SD	N	%
Gender				
Male			157	66.24
Female			80	33.76
Age	27.40	10.40		
Subject				
Business			34	14.30
Computing			101	42.60
Creative Digital Media			33	13.90
Engineering			18	7.59
Horticulture			7	2.95
Humanities			36	15.20
Sports Management and Coaching			8	3.38
Level of Study				
Undergraduate			195	82.30
Masters			38	16
PhD			4	1.69
Student Type				
Irish/European			224	94.51
Overseas			13	5.49

6.3.2. Measures

The Big Five personality dimensions (agreeableness, conscientiousness, extraversion, neuroticism, and openness) were measured using the 10-item short version of the Big Five Inventory (Rammstedt & John, 2007; Appendix 6.1). For this questionnaire, each dimension of personality are measured using two indicators, which can be regarded as the minimum, but it does increase the susceptibility of model estimation issues (Kline, 2015). The authors' reasoning behind the use of this shortened version was on account of not overburdening respondents with questions; however, the limitations of factors with two indicators will be kept in mind and will be discussed.

As for the psychometric properties of the 10-item short version of the Big Five Inventory, Rammstedt and John (2007) found support for the originally purported five factor structure when the abbreviated set of items were factor analysed. These authors stated that target factor loadings were high (mean loading = .64), whilst non-target factor loadings were at a nominal level (mean loading = .08). Issues with the agreeableness were however found with the 10-item questionnaire, with the researchers finding the construct coverage to be lower than that of the 44-item Big Five Inventory. Thus, Rammstedt and John (2007) recommend including an additional item if researchers are particularly interested in agreeableness. For the current work, the agreeableness construct was not considered to be crucial so only the two agreeableness items were used. Thus, no changes were made to the original 10-item questionnaire (Appendix 6.1) and responses were made on a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree), as used by Rammstedt and John (2007).

To measure student expectations towards learning analytics services, the 12-item SELAQ (Chapter 2) was used (Appendix 6.2). Five of these indicators (items 1, 2, 3, 5, and 6) measure *Ethical and Privacy Expectations*, whilst the remaining seven indicators (items 4, 7, 8, 9, 10, 11, and 12) measure *Service Expectations*. For the purposes of this study, the item wording was changed from the original 'The University will' to 'The College will'. This allowed the SELAQ items to be applicable to the context in which it was used. Responses to each of these items are made on seven-point Likert scales (1 = Strongly Disagree, 7 = Strongly Agree) and on two scales, which correspond to ideal (Ideally, I would like this to happen) and predicted (In reality, I expect this to happen) expectations. Prior development and validation of this questionnaire has found the measurement quality to be good, with mean standardised factor loadings of .76 and .79 for the ideal and predicted expectation scales, respectively (Chapter 2). This prior work has also identified sources of strain within the model (e.g., absolute residual correlation values ≥ .10; Kline, 2015), but there has been no justifiable reason for allowing any form of respecification to the model (e.g., correlated errors). These details will be used in the current work to inform our decisions regarding possible model modifications, in the event that there are local misfit problems.

6.3.3. Analytic Procedures

The responses obtained from the 10-item short version of the Big Five Inventory (Rammstedt & John, 2007) did show a ceiling effect (Appendix 6.3), particularly with the second conscientiousness indicator. Similarly, both the ideal and predicted expectation scales showed ceiling effects (Appendices 6.4 and 6.5). Due to these distributions, the data was analysed using the mean-and variance-adjusted unweighted least squares (ULSMV) estimator.

The initial steps of the analysis was to assess the validity of the 12-item SELAQ. In order to do this, the raw data was analysed using confirmatory factor analysis (CFA) and exploratory structural equation modelling (ESEM), which was carried out with Mplus 8.1 (Muthén & Muthén, 2017). The approach to validation followed the recommendations outlined by Marsh, Morin, Parker, and Kaur (2014), which is to analyse the data using both CFA and ESEM then compare the obtained fits. On comparison, if the fit indices obtained from both models are similar then the CFA is selected on account of being more parsimonious. However, if obtained fit indices from both models are dissimilar then the better fitting model will be selected.

To determine how well the model fits the data, the X^2 test was the primary focus, with $p > .05$ indicating no differences between the matrix of observed covariances and model-implied covariance matrix (Ropovik, 2015). It is often the case that researchers disregard significant chi-square values and emphasise alternative fit indices; however, this overlooks the localised misspecification issues within the model (Ropovik, 2015). Therefore, if a X^2 test was found to be significant at the .05 level then an exploration of local model fit would be undertaken. This involved an inspection of the absolute residual correlation matrix, with values $\geq .10$ being indicative of a poor prediction for a particular variable pair (Goodboy & Kline, 2017; Kline, 2015). Additionally, modification index (MI) values and standardised expected parameter change (SEPC) were examined (Saris et al., 2009). Possible sources of localised strain within the models were identified by MI values ≥ 3.84 (Brown, 2015), in conjunction with SEPC values $\geq .10$ (Saris et al., 2009). Factor loadings were also examined, with target loading values $\geq .50$ being considered as practically significant (Hair, Black, Babin, & Anderson, 2010). If the factor loading values of any item fell below this criteria, or loaded higher on the non-target factor, then the suitability of this indicator was questioned.

If misspecification issues were found, it is important to reiterate that the authors' prior work developing and validating the 12-item SELAQ did identify specific sources of localised strain (e.g., between items 11 and 12); however, no justification for model respecifications were made (Chapter 2 and 3). These details were used in the current work to inform any decisions regarding model misspecifications. If, following an inspection of local model fit, there were no severe misspecifications then the model was tentatively accepted (Ropovik, 2015).

Along with the X^2 test, the authors report alternative fit indices (e.g., the Comparative Fit Index (CFI), the Tuker Lewis Index (TLI), the Root Mean Square Error of Approximation (RMSEA) with 90% confidence intervals, and the Standardised Root Mean Square Residuals (SRMR). Typically, researchers use the Hu and Bentler (1999) cut-offs for these fit indices such as .95 for CFI and TLI, .08 for SRMR, and .06 for RMSEA to determine whether a model fits well. MacCallum, Browne, and Sugawara (1996) have also suggested that RMSEA values between .08 and .10 are indicative of acceptable model fits. Irrespective of what cut-offs are used, it is important to acknowledge that these recommendations are based on analyses using the maximum likelihood estimator, not the ULSMV estimator. Moreover, Xia (2016) has expressed caution when it comes to applying these aforementioned cut-offs to instances when categorical estimators are used (e.g., ULSMV), specifically on account of their dependency on threshold symmetry. Other researchers have highlighted additional issues regarding alternative fit indices, particularly in relation to the reliability paradox (Hancock & Mueller, 2011). The latter occurs when models with poor measurement quality (e.g., low factor loadings) result in seemingly good model fits, whilst models with good measurement quality often show poor model fits (Hancock & Mueller, 2011). This has also been exemplified in the simulation work undertaken by McNeish, An, and Hancock (2018) and has shown the function of CFI, RMSEA, and SRMR to vary with measurement quality. Therefore, the recommendations of Marsh, Hau, and Wen (2004) of not overgeneralising these cut-offs were followed.

Once the validity of the 12-item SELAQ had been assessed, two measurement models were then analysed for both the ideal and predicted expectation scales. In other words, the current authors had measurement models for the five personality (agreeableness, conscientiousness, extraversion, neuroticism, and openness) and two expectation (*Ethical and Privacy Expectations* and *Service Expectations*) factors at both levels of expectations (ideal and predicted). For each measurement model, factor loadings were assessed to see whether they align with what is practically significant ($\lambda \geq .50$), along with the absolute residual correlations, and MI and SEPC values. If problems were identified, the model would then be modified (e.g., removal of a factor or indicator) and re-analysed. This process would be repeated until an acceptable measurement model was identified. At this point, a structural regression model would then be analysed with specified direct effects from the personality factors to the expectation factors, again this applied to both levels of expectation (ideal and predicted) and answers RQ1 and RQ2. Both unstandardised and standardised coefficients were recorded, along with the R^2 values. For direct effects to be considered as statistically significant, the alpha level was set at .05.

6.4. Results

6.4.1. Assessing the Validity of the SELAQ

6.4.1.1. Summary of Results

The collected data was analysed to assess the validity of the originally purported two factor structure (*Ethical and Privacy Expectations* and *Service Expectations*) across both expectation scales (ideal and predicted). Contrary to prior work, a single item (item 5; obtaining consent before collecting and analysing data) was dropped from both scales on account of failing to load onto the target factor (*Ethical and Privacy Expectations*). Despite this deviation from the original model, both expectation scales were found to be valid. A detailed description of the analysis outputs is presented in Section 6.4.1.2.

6.4.1.2. Detailed Results

6.4.1.2.1. Ideal Expectations

An improved model fit was obtained from the ESEM ($X^2(43) = 113.42$, $p < .001$, RMSEA = .08 (90% CI .07-.10), CFI = .97, TLI = .95, SRMR = .03) compared to the CFA ($X^2(53) = 155.49$, $p < .001$, RMSEA = .09 (90% CI .07-.11), CFI = .95, TLI = .94, SRMR = .05). Examining the loadings obtained from the ESEM showed that of those items that should load highly onto the *Ethical and Privacy Expectations* factor (items 1, 2, 3, 5, and 6), item 5 (The college will ask for my consent to collect, use, and analyse any of my educational data (e.g., grades, attendance, and virtual learning environment accesses) had the lowest loading ($\lambda_{\text{Ethical and Privacy Expectations}} = .47$). In addition, item 5 had a moderate loading on the non-target factor ($\lambda_{\text{Service Expectations}} = .28$), and an absolute residual correlation value ≥ .10 with item 6 (.16; MI for items 5 and 6 = 33.86, SEPC = .47). Likewise, the CFA model output also identified item 5 as being problematic with an MI value of 21.65 (SEPC = .23) for a cross-loading onto the *Service Expectations* factor. Taken together, the evidence from the ESEM showed item 5 to have a target factor loading below what is considered to be of practical significance ($\lambda \geq .50$; Hair et al., 2010), whilst both models (CFA and ESEM) showed item 5 to cross-load onto the *Service Expectations* factor.

6.4.1.2.2. Predicted Expectations

Initial analysis of the raw data found the ESEM model to outperform ($X^2(43)$ = 176.95, $p < .001$, RMSEA = .12 (90% CI .10-.13), CFI = .97, TLI = .95, SRMR = .03) the CFA ($X^2(53)$ = 362.89, $p < .001$, RMSEA = .16 (90% CI .14-.17), CFI = .92, TLI = .91, SRMR = .05). On inspection of local fit for both models, item 5 (obtaining consent before collecting and analysing data) appeared to be problematic. For the ESEM model, item 5 had a loading of .36 on the target factor (*Ethical and Privacy Expectations*) and a non-target (*Service Expectations*) loading of .56. Additionally, there was a single absolute residual correlation ≥ .10 between items 5 and 6 (.10); this variable pair also had the highest MI value of 23.63 (SEPC = .37). In the CFA model, item 5 had two absolute residual correlations ≥ .10 (.11 between items 5 and 7 and .12 between items 5 and 12). One of the largest MI values obtained from the CFA was for item 5 loading onto *Service Expectations* (MI = 160.05, SEPC = .71). Thus, this aforementioned evidence identified item 5 as being a source of localised strain within the model and suggested the need to respecify the model by removing the item.

6.4.1.2.3. Interim

The evidence obtained from both scales (ideal and predicted expectations) showed the originally purported two factor structure (*Ethical and Privacy Expectations* and

Service Expectations) to be supported. On the other hand, the results found item 5 to be problematic indicator as it had a low loading on its target factor (*Ethical and Privacy Expectations*) and contributed to multiple sources of localised strain within the model. Given these identified problems regarding item 5, the decision was taken to drop this item and re-assess the model fit. This did represent a step away from the original model, but the issues with item 5 do point to possible problems with regards to construct validity.

6.4.1.2.4. Ideal Expectations

Following the removal of item 5, the fit obtained from the ESEM ($X^2(34) = 62.53$, $p = .002$, RMSEA = .06 (90% CI .04-.08), CFI = .99, TLI = .98, SRMR = .02) showed a marked improvement over the CFA model ($X^2(43) = 122.76$, $p < .001$, RMSEA = .09 (90% CI .07-.11), CFI = .96, TLI = .95, SRMR = .04); thus, the results of the ESEM model will be presented.

Table 6.2 presents the loadings obtained from the ESEM, which shows all items to have loadings ≥ .50 on their target factors. The absolute loading values for the *Ethical and Privacy Expectations* factor ranged from 0 to .87 ($M = .30$). For the *Service Expectations* factor, the absolute loading values ranged from 0 to .90 ($M = .52$). Both factors were moderately correlated ($r = .37$, $p < .001$) and accounted for a large amount of the underlying continuous latent response variance (R^2 values range from .49 to .78).

Table 6.2. Factor Loadings for Ideal Expectations ESEM

Items	Ethical and Privacy Expectations		Service Expectations	
	Estimate	Standard Error	Estimate	Standard Error
1	.69	.05	.03	.06
2	.86	.03	0	0
3	.87	.04	-.06	.06
4	.09	.07	.66	.05
6	.57	.05	.30	.07
7	-.01	.04	.89	.03
8	-.05	.04	.90	.03
9	0	.04	.83	.03
10	.18	.06	.70	.04
11	.05	.06	.70	.04
12	0	.03	.78	.03

An inspection of residual correlations (Appendix 6.6) showed there to be no absolute values ≥ .10 and no significant MI values. While there were no absolute residual correlation values meeting this criteria, the variable pair of items 10 and 11 did have an absolute residual correlation value of .09. Based on the content of these two items, there was no justifiable reason to undertake a modification of the model. Therefore, as there were no further sources of localised strain, we tentatively accepted the model.

6.4.1.2.5. Predicted Expectations

With the removal of item 5, the ESEM model still provided a better fit to the data ($X^2(34) = 129.09$, $p < .001$, RMSEA = .11 (90% CI .09-.13), CFI = .97, TLI = .96, SRMR = .02) than the CFA model ($X^2(43) = 174.94$, $p < .001$, RMSEA = .11 (90% CI .10-.13), CFI = .96, TLI = .95, SRMR = .04). Based on the improved fit, the ESEM results will be presented.

Table 6.3 presents the factor loadings obtained from the ESEM and shows all items to have target factor loadings ≥ .50. Whilst item 6 did load highly onto the *Ethical and Privacy Expectations* factor ($\lambda_{\text{Ethical and Privacy Expectations}} = .56$), it also had the highest non-target factor loading ($\lambda_{\text{Service Expectations}} = .34$). Given that the target loading for item 6 was moderate and its non-target factor loading was below .50, the item was retained. What can also be seen from Table 6.3 is that the absolute loading values for the *Ethical and Privacy Expectations* factor ranged from 0 to .92 (M = .29). Whereas, the absolute factor loading range for the *Service Expectations* factor was from .01 to .88 (M = .55). Both factors were moderately correlated ($r = .46$, $p < .001$) and accounted for a moderate to large amount of the continuous latent response variance (R^2 values ranged from .48 to .83).

Table 6.3. Factor Loadings for Predicted Expectations ESEM

Items	Ethical and Privacy Expectations		Service Expectations	
	Estimate	Standard Error	Estimate	Standard Error
1	.70	.05	-.02	.07
2	.92	.03	-.01	.01
3	.86	.04	.02	.05
4	.05	.04	.76	.34
6	.56	.05	.34	.05
7	0	.02	.83	.02
8	-.02	.03	.88	.02
9	-.01	.03	.84	.03
10	.10	.06	.76	.04
11	-.02	.04	.84	.03
12	.03	.04	.81	.03

There were no absolute residual correlation values ≥ .10, with the highest value being between items 8 and 12 (.08; Appendix 6.7). As for the MI values, there were seven suggested modifications for the following variable pairs: items 3 and 7 (MI = 10.82, SEPC = -.36), items 7 and 8 (MI = 16.93, SEPC = .45), items 8 and 9 (MI = 14.84, SEPC = .42), items 8 and 11 (MI = 11.86, SEPC = -.38), items 10 and 11 (MI = 13.58, SEPC = .32), items 8 and 12 (MI = 18.98, SEPC = -.47), and items 11 and 12 (MI = 13.19, SEPC = .34). Based on both prior work and content of these items, no modifications to the model were made and the model was tentatively accepted.

6.4.2. Measurement Model

6.4.2.1. Summary of Results

The final measurement model for both expectation scales (ideal and predicted) was an ESEM containing two exploratory factor analysis (EFA) factors (*Ethical and Privacy Expectations* and *Service Expectations*) and two CFA factors (extraversion and neuroticism). Three personality factors were dropped (agreeableness, conscientiousness, and openness) from the measurement model, which was attributed to a non-identified model and unreliable factor indicators. The final predicted expectation model was not rejected by the exact-fit test ($p > .05$); thus, it was accepted. As for the final ideal expectation model, this did not satisfy the exact fit test ($p < .05$); however, it was tentatively accepted on the basis of the local fit of the model. A detailed reporting of these results is presented in section 6.4.2.2.

6.4.2.2. Detailed Results

The abovementioned evidence showed that for both the ideal and predicted expectation scales, the ESEM provided an improved fit over the CFA. Therefore, the ESEM was used for the measurement model exploring the association between dimensions of personality and expectations towards learning analytics services. In other words, the two separate measurement models for ideal and predicted expectations contained both EFA and CFA factors for the expectation and personality factors, respectively (Figure 6.1).

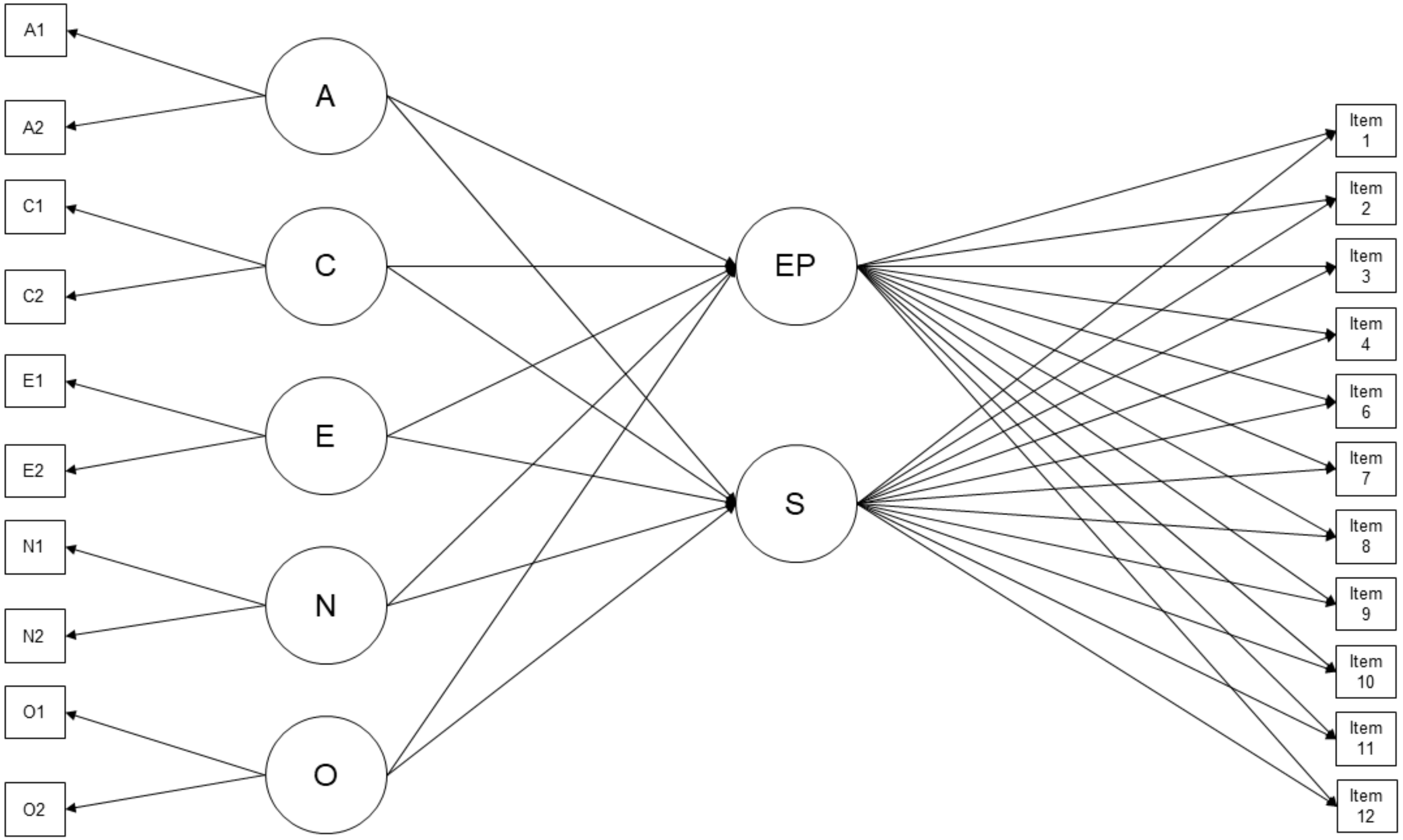

Figure 6.1. ESEM Model being tested. A, C, E, N, and O refer to Agreeableness, Conscientiousness, Extraversion, Neuroticism, and Openness, respectively. EP and S stand for Ethical and Privacy Expectations and Service Expectations, respectively. Item 5 was removed following an assessment of the SELAQ factor structure.

The raw data was submitted to Mplus 8.1 to analyse the model containing two EFA and five CFA factors. The EFA factors had 11 indicators (item 5 was removed based on the above assessment of the SELAQ) and each of the five CFA factors had two indicators each. The estimation of the standard errors could not be computed for the second openness personality item (I see myself as some who has an active imagination) in the model with predicted expectations. Similarly, for the model containing ideal expectation items, the latent variable covariance matrix was not positive definite, which was attributed to the openness factor. Thus, given these identified issues pertaining to the openness factor, it was removed from the measurement model.

With the removal of the openness factor, the ideal expectation model did show an acceptable model fit ($X^2(128) = 177.66$, $p = .002$, RMSEA = .04 (90% CI .03-.05), CFI = .97, TLI = .96, SRMR = .04). Likewise, the model for predicted expectations was found to fit the data well ($X^2(128) = 156.73$, $p = .043$, RMSEA = .03 (90% CI .01-.05), CFI = .99, TLI = .98, SRMR = .04). An inspection of standardised factor loadings, however, found there to be a problem with the second agreeableness item (I see myself as someone who tends to find fault with others) as it fell below .50 for both the ideal ($\lambda = .19$) and predicted ($\lambda = .32$) expectation models. Additional problems were also found with the two conscientiousness indicators, with the first indicator (I see myself as someone who tends to be last) having a standardised loading of .39 in the ideal expectation scale model. Whilst for the predicted expectation model, the second conscientiousness indicator (I see myself as someone who does a thorough job) had a standardised loading of .51. Even though the latter standardised loading met what we considered to be the minimum value for practical significance ($\lambda \geq .50$), the construct validity of the conscientiousness factor can be questioned. Therefore, it was decided that based on the data, the indicators for conscientiousness and agreeableness were not reliable measures of the underlying latent variables and were dropped. It was then necessary to re-run the measurement model without the agreeableness or conscientiousness factors.

The third measurement model without the agreeableness or conscientiousness factors was found to fit the data well for both the ideal ($X^2(75) = 96.77$, $p = .046$, RMSEA = .04 (90% CI .01-.05), CFI = .99, TLI = .98, SRMR = .04) and predicted ($X^2(75) = 91.90$, $p = .09$, RMSEA = .03 (90% CI 0-.05), CFI = .99, TLI = .99, SRMR = .03) expectation measurement models.

The standardised factor loadings for the ideal expectation measurement model are provided in Tables 6.4 and 6.5. For the EFA factors, the absolute loadings range from .01 to .87 for the *Ethical and Privacy Expectations* factor ($M = .29$) and from 0 to .90 for the *Service Expectations* factor ($M = .52$). As for the CFA factors, they ranged from .55 to .77 ($M = .66$); thus, they exceeded the minimum factor loading value of .50. In addition, the R^2 values ranged from .30 to .77, which showed the indicators to account for a moderate to large amount of the underlying continuous latent response variance. As for the factor intercorrelations, these ranged from -.61 to .37, and given that they do not equal or exceed .85, it does not suggest a problem with discriminant validity.

Table 6.4. Ideal Expectations Measurement Model Loadings for EFA Factors

Items	Ethical and Privacy Expectations		Service Expectations	
	Estimate	Standard Error	Estimate	Standard Error
1	.67	.05	.04	.06
2	.87	.03	0	0
3	.87	.04	-.06	.06
4	.09	.07	.68	.05
6	.57	.05	.30	.07
7	-.02	.04	.88	.03
8	-.06	.04	.90	.03
9	.01	.04	.83	.03
10	.18	.06	.70	.04
11	.05	.06	.70	.04
12	0	.03	.78	.03

Table 6.5. Ideal Expectations Measurement Model Standardised Loadings for CFA Factors

Items	Extraversion		Neuroticism	
	Estimate	Standard Error	Estimate	Standard Error
Extraversion One	.57	.09	-	-
Extraversion Two	.77	.10	-	-
Neuroticism One	-	-	.55	.08
Neuroticism Two	-	-	.75	.08

An inspection of local fit found six absolute residual correlation values to be $\geq .10$ (Appendix 6.8). These high absolute residual correlation values are all associated with the indicators of the 10-item short version of the Big Five Inventory, with the values between indicators of the SELAQ all falling below .10. The highest residual correlation, with an absolute value of .16, was between item 1 of the SELAQ (The college will ask for my consent before using any identifiable data about myself (e.g., ethnicity, age, and gender) and the first extraversion indicator (I see myself as someone who is reserved). There were three large modification indices, these were for extraversion indicator one (I see myself as someone who is reserved) being correlated with the *Ethical and Privacy Expectations* factor (MI = 12.49, SEPC = -.20), extraversion indicator two (I see myself as someone who is outgoing, sociable) and *Ethical and Privacy Expectations* (MI = 12.49, SEPC = .34), and for neuroticism indicator two (I see myself as someone who gets nervous easily) and extraversion indicator two (MI = 12.40, SEPC = .98). When assessing these identified sources of localised strain within the model, it was decided that there were no justifiable grounds to respecify the model with correlated errors. Moreover, the exact-fit hypothesis was rejected ($p < .05$), but given that there were no serious local fit issues we tentatively accept the measurement model. Nevertheless, these localised sources of strain within the model that seem to be attributed to the personality variables need to be kept in mind, particularly for the purposes of future research.

The standardised loadings for the predicted expectation measurement model are presented in Tables 6.6 and 6.7. For the EFA factors, the absolute factor loadings ranged from 0 to .92 (M = .29) for the *Ethical and Privacy Expectations* factor and from .01 to .88 (M = .55) for the *Service Expectations* factor. In terms of the CFA factors, the standardised loadings ranged from .56 to .74, which again all exceeded the minimum loading value of .50. As for the R^2 values, these ranged from .32 to .85; thus, the indicators account for a moderate to large amount of the underlying continuous latent response variance. The intercorrelations between factors ranged from -.63 to .46, which suggested discriminant validity.

Table 6.6. Predicted Expectations Measurement Model Loadings for EFA Factors

Items	Ethical and Privacy Expectations		Service Expectations	
	Estimate	Standard Error	Estimate	Standard Error
1	.69	.04	-.01	.05
2	.92	.03	-.01	.04
3	.85	.04	.03	.04
4	.05	.04	.77	.03
6	.56	.05	.34	.05
7	-.01	.03	.84	.02
8	-.01	.03	.88	.02
9	0	.02	.83	.03
10	.09	.05	.76	.04
11	-.01	.04	.83	.03
12	.03	.04	.81	.03

Table 6.7. Predicted Expectations Measurement Model Standardised Loadings for CFA Factors

Items	Extraversion		Neuroticism	
	Estimate	Standard Error	Estimate	Standard Error
Extraversion One	.60	.08	-	-
Extraversion Two	.73	.09	-	-
Neuroticism One	-	-	.56	.08
Neuroticism Two	-	-	.74	.09

There was only a single large MI value between the second neuroticism item (I see myself as someone who gets nervous easily) and the second extraversion item (I see myself as someone who is outgoing, sociable) (MI = 11.54, SEPC = .84). In addition, there was one absolute residual correlation values ≥ .10 (Appendix 6.9), which was between the second neuroticism item and the second extraversion item (.10). There was no substantive reason for making modifications to the measurement model and as the exact-fit test was not rejected (p > .05), the measurement model can be accepted.

6.4.3. Structural Models

6.4.3.1. Summary of Results

The results from the structural model pertaining to ideal expectations showed both extraversion and neuroticism to be significantly associated with *Service Expectations*, but not *Ethical and Privacy Expectations*. In the case of predicted expectations, only neuroticism was found to be significantly associated with *Service Expectations*. Together, these results address RQ1 and RQ2. A detailed presentation of these findings are presented in section 6.3.3.2.

6.4.3.2. Detailed Results

6.4.3.2.1. Structural Model for Ideal Expectations

The structural regression model had an equivalent structure to the measurement model, which is substantiated by the identical model fit ($X^2(75) = 96.77$, $p = .046$, RMSEA = .04 (90% CI .01-.05), CFI = .99, TLI = .98, SRMR = .04). For the direct effects on *Ethical and Privacy Expectations*, neither the unstandardised coefficient for the direct effect of extraversion (.14, $p = .58$) nor its standardised coefficient (.08, $p = .58$) were significant at .05 level. Similarly, the direct effect of neuroticism on *Ethical and Privacy Expectations* was not statistically significant (unstandardised coefficient: .06, $p = .81$; standardised coefficient: .03, $p = .81$). Together, these factors (extraversion and neuroticism) only accounted for .4% of the variance in *Ethical and Privacy Expectations* ($R^2 = .004$). As for the *Service Expectations* factor, both extraversion and neuroticism had significant direct effects, with unstandardised coefficients of .94 ($p = .01$; standardised coefficient: .49, $p = .01$) and .98 ($p = .02$; standardised coefficient: .49, $p = .01$), respectively. The amount of variance in *Service Expectations* that is accounted for by extraversion and neuroticism was 18% ($R^2 = .18$).

6.4.3.2.2. Structural Model for Predicted Expectations

An equivalent structure to the measurement model was used for the structural regression model, as shown by the identical model fit ($X^2(75) = 91.90$, $p = .09$, RMSEA = .03 (90% CI 0-.05), CFI = .99, TLI = .99, SRMR = .03). Unstandardised coefficients for the direct effects of extraversion (.24, $p = .29$; Standardised coefficient: .15, $p = .29$) and neuroticism (.21, $p = .41$; Standardised coefficient: .12, $p = .41$) on *Ethical and Privacy Expectations* were not statistically significant. These two factors (extraversion and neuroticism) only account for 1% of the variance in *Ethical and Privacy Expectations* ($R^2 = .01$). As for *Service Expectations*, the unstandardised coefficient for the direct effect of extraversion was not significant at the .05 level (.54, $p = .06$); however, the standardised coefficient for this effect was significant (.31, $p = .04$). An examination of the 95% confidence intervals for the latter standardised coefficient shows the interval to barely exclude zero (95% CI = .01-.61); therefore, the effect of extraversion is interpreted as non-significant. As for the direct effect of neuroticism, this was significant (Unstandardised coefficient: .75, $p = .02$; Standardised coefficient: .40, $p = .01$). Together, these factors accounted for 10% of the variance in *Service Expectations* ($R^2 = .10$).

6.5. Discussion

As for RQ1 and RQ2, it was found that the dimensions of personality were associated with student expectations of learning analytics services, specifically the *Service Expectations* factor. It is important to note that of the five originally purported dimensions in the Big Five model, only two were retained (extraversion and neuroticism). The neuroticism dimension was consistently associated with *Service Expectations* across both the ideal and predicted expectation scales; whereas, extraversion was only associated with *Service Expectations* on the ideal expectation scale. Neither of the two dimensions of the Big Five (extraversion or neuroticism) were found to be associated with the *Ethical and Privacy Expectations* factor.

6.5.1. Personality and Learning Analytics Expectations

Even though there is a growing body of literature that has sought to explore and understand student expectations of learning analytics services (Arnold & Sclater, 2017; Ifenthaler & Schumacher, 2016; Roberts, Howell, & Seaman, 2017; Roberts, Howell, Seaman, & Gibson, 2016; Schumacher & Ifenthaler, 2018; Slade & Prinsloo, 2014), little attention has been paid to the effects of background variables. As exemplified in the work of Arnold and Sclater (2017), students with prior experience of learning analytics were more accepting of potential features of future learning analytics services. Thus, there is a current gap in the learning analytics literature with regards to the effects of individual differences, which this study sought to address.

Justification for exploring individual differences in student expectations towards learning analytics services came from the model put forward by Szajna and Scamell (1993). Here the authors proposed direct effect of pre-implementation factors on expectations towards a service (Szajna & Scamell, 1993). According to Oliver (1980), one of these pre-implementation factors are individual characteristics, which includes personality. Thus, for the purposes of this current work we focused on personality as an individual characteristic that may influence the expectations students hold towards learning analytics services. This was further reinforced by the discussion presented by Ajzen (2011), which outlined the possible effects of background variables such as personality on the beliefs held by individuals. As discussed elsewhere (Chapter 2), the authors support the argument that expectations only differ from beliefs in terms of time (i.e., expectations are beliefs about the future; Olson & Dover, 1976). Together, this provided the theoretical basis for our exploration into understanding how personality (agreeableness, conscientiousness, extraversion, neuroticism, and openness) may be a determinant in the expectations students hold towards learning analytics services.

6.5.2. Personality and Service Expectations

6.5.2.1. Extraversion

The current results show extraverted students to have higher pre-implementation beliefs on the *Service Expectations* factor. This, however, only pertains to ideal expectations, not predicted expectations. To understand how extraversion may lead to higher ideal expectations regarding the *Service Expectations* factor, it is useful to consider the particular traits of extraverted individuals. More specifically, extraverted individuals are more optimistic, which is defined as being hopeful about the future (Costa & McCrae, 1992; Lakhal & Khechine, 2017). It is therefore reasonable to assume that this optimism regarding the future may lead to students holding inflated expectations with regards to the learning analytics service they desire.

To further explain these results regarding the effects of extraversion, it is also important to consider this personality dimension in the context educational research. As the meta-analytic work undertaken by Payne et al. (2007)identified an association between extraversion and learning goal orientation. Thus, the personality dimension of extraversion is associated with a learning goal orientation that predisposes students towards increasing their competence (Dweck & Leggett, 1988; Mega, Ronconi, & De Beni, 2014). Additionally, it has been found that extraversion is associated with a goal-setting motivation (Judge & Ilies, 2002). Taken together, the features offered in a learning analytics service may align with these motivations of extraverted students, as the items refer to tools designed to support self-regulated learning (e.g., students receiving a full profile of their learning progress, students knowing how their progress compares to a set goal, or students exercising agency). Therefore, given that learning analytics services may support goal setting and competency development, in addition a predisposition of being optimistic, this may explain why extraverted students have higher ideal expectations regarding the *Service Expectation* factor.

For the predicted expectation scale, however, extraversion was not associated with the *Service Expectation* factor. Thus, whilst extraversion may lead to students holding high ideal expectations towards learning analytics services, it has no effect on what they expect in reality. Turning to the technology adoption literature may help elucidate this finding. More specifically, extraversion has only been shown to moderate the effects of subjective norms on behavioural intentions (Devaraj et al., 2008). In addition, Özbek, Alnıaçık, Koc, Akkılıç, and Kaş (2014) found no support for extraversion being associated with beliefs towards the usefulness and ease of use of a technology. Taking this into consideration, it may be that whilst being more optimistic leads to higher desires (ideal expectations), there is no effect of being extraverted on a realistic level of belief (predicted expectations). It may only be in circumstances where the learning analytics services are affecting an extraverted student's public image that their predicted expectations are affected.

6.5.2.2. Neuroticism

The findings of the current research show neurotic students to have stronger pre-implementation beliefs (i.e., expectations) towards the *Service Expectations* factor on both SELAQ scales (ideal and predicted expectations). Thus, based on the technology adoption literature it would be assumed neurotic students would hold a cynical view of learning analytics services, resulting in low expectations. As shown by Devaraj et al. (2008), neurotic individuals are less likely to consider a new technology as being useful, resulting in a reduced likelihood of adoption. Instead, the opposite was found, with neurotic students expressing higher expectations.

To understand why neurotic students may express high expectations towards learning analytics services, it is again important to turn to educational research. More specifically, the work of Komarraju et al. (2009) found neuroticism to be positively associated with grade point average. This may be attributed to high performing students constantly experiencing a degree of anxiety due to a need to perform well (Komarraju et al., 2009). The possibilities of learning analytics services providing detailed feedback, updates on progress, and early interventions may therefore appeal to highly neurotic students. In other words, these students are more likely to experience anxiety related to a need to be academically successful and the learning analytics service features may provide the additional support to reduce such worries. This may then lead to these students having strong desires (high ideal expectations) towards receiving these particular learning analytics service features, as they may believe them to be instrumental in allowing them to perform well academically. In the case of what they realistically expect (predicted expectations), it may again be attributed to a need to perform well academically. However, neuroticism is characterised by depression, which in turn is associated with more realistic beliefs (Moore & Fresco, 2012). Thus, irrespective of what neurotic students desire from a learning analytics service with regards to features, they may expect such implementations irrespective of their views.

6.5.3. Personality and Ethical and Privacy Expectations

No retained personality dimension (extraversion and neuroticism) was found to be associated with *Ethical and Privacy Expectations* across both ideal and predicted expectation scales. This does partially support the findings of Osatuyi (2015), who did find extraversion to not be significantly associated with concerns for information privacy. In the case of neuroticism, Osatuyi (2015) only tested a hypothesised relationship with computer anxiety, not concerns for privacy. It is understandable that extraversion may not be associated with *Ethical and Privacy Expectations*, as it characterises someone who is sociable (Costa & McCrae, 1992; Lakhal & Khechine, 2017). The items pertaining to *Ethical and Privacy Expectations* do not refer to any social dimensions; therefore, it is reasonable to assume that being more sociable would not determine the expectations regarding expectations regarding data security and informed consent. As for neuroticism, it would be assumed that being predisposed to anxiety would lead to more concern regarding data privacy, resulting in higher *Ethical and Privacy Expectations*. The results here, however, show that a higher level of neuroticism is not associated with these expectations. Although it cannot be established on the basis of the final model, it could be that *Ethical and Privacy Expectations* do not vary as a result of personality. Put differently, the

Ethical and Privacy Expectations may be homogenous across the student population and are not affected by individual differences.

6.5.4. Implications

An important implication for the implementation of learning analytics services come from the finding of neuroticism being positively related to *Service Expectations*. It has previously been discussed that neurotic students may experience a high degree of anxiety on account of a drive to perform well academically (Komarraju et al., 2009), which could lead to a dependency on learning analytics services. This learning analytics dependency has been identified by both students (Roberts et al., 2016) and teaching staff (Howell et al., 2018). More specifically, there is a view that incorrectly implemented learning analytics services could impede students becoming self-reliant (Roberts et al., 2016) and generate greater levels of anxiety on account of the information overload (Howell et al., 2018). Thus, there is a need to take a scaffolding approach to the implementation of learning analytics wherein features are implemented and faded out in line with what students need (Pol et al., 2010). In doing so, the learning analytics service will achieve the goal of supporting student learning, but offset the possibility of creating a dependency on these tools.

The abovementioned implication refers to the findings of the ideal expectation scale. In regards to the predicted expectation scale, neuroticism was positively associated with *Service Expectations*. Again, it is possible to view such results as reflecting an anxiety to perform well academically (Komarraju et al., 2009). Nevertheless, given that neuroticism is associated with a pessimistic attitude (Oehler & Wedlich, 2018), this may lead to neurotic students to assume that the university is likely to implement learning analytics services, irrespective of what students expect.

In this case, it is important for the university to emphasise student-centred learning analytics (Kruse & Pongsajapan, 2012). In this sense, students are not forced to engage with the learning analytics service features, but rather are encouraged to use these features in a self-reflective manner (Kruse & Pongsajapan, 2012). In doing so, students may then appreciate the value, which is unlikely under circumstances where such services are framed as being mandatory.

As for the findings pertaining to the association between extraversion and the *Service Expectation* factor, it appears that this personality dimension is associated with high ideal expectations. To reiterate, extraversion is characterised by optimism (Costa & McCrae, 1992; Lakhal & Khechine, 2017) and a propensity to be motivated by learning goals (Payne et al., 2007). Thus, the types of features offered (e.g., knowing how progression compares to a set goal), may be appealing to extraverted students if they align with their goal orientations. However, this may risk students becoming dependent on metrics that are fed back through learning analytics services, as opposed to assuming responsibility for their own learning (Roberts et al., 2016). It is again necessary to consider the feasibility of an approach whereby the institution provides instruction on how to use learning analytics feedback in a self-reliant way to support goal monitoring and behavioural regulation. Again the latter could again involve scaffolding, increasing and decreasing support in relation to the needs of the student (Pol et al., 2010)

6.5.5. Limitations and Future Research

Although the originally purported two factor structure of the SELAQ (Chapter 2) was supported in an additional sample of English speaking students, there was a deviation away from the original model. More specifically, item 5 (The college will ask for my consent to collect, use, and analyse any of my educational data (e.g., grades, attendance, and virtual learning environment accesses) failed to load onto its target factor (*Ethical and Privacy Expectations*) for both scales (ideal and predicted expectations). From these results, the utility of item 5 as an indicator of *Ethical and Privacy Expectations* can be questioned. Our prior work using ESEM with the UK student sample (n = 191) did show item 5 to have the lowest factor loading and highest cross-loading for both scales (Chapter 2), with similar results being found cross-culturally (Chapter 3). In light of these findings, it is necessary for future work to assess whether this indicator continues to contribute to localised strains within the model. If this remains a consistent outcome then it is important to explore the validity of an 11-item SELAQ.

The final ideal expectation model was rejected by the exact-fit test ($p < .05$); however, the assessment of local fit did not lead to the identification of any serious misspecifications. On this basis, the model was tentatively accepted, but caution is advised with regards to the interpretations of the results. It is necessary for a follow-up study to be undertaken that seeks to replicate these presented findings to determine whether they are supported.

Even though the current authors discuss the possibility of *Ethical and Privacy Expectations* being invariant across the student population, this cannot be established on this work alone. For one reason, only two of the five personality dimensions were included in the final model; therefore, it cannot be assumed that agreeableness, conscientiousness, or openness have no effect. Additionally, personality only represents a singular background variable (Ajzen, 2011). There are other variables to consider that may be associated with the expectations have towards learning analytics services. This may include experience with prior learning analytics services (Arnold & Sclater, 2017) or even educationally relevant variables such as self-efficacy (Bandura, 1977). This can allow for a better understanding of whether those students who expect more from learning analytics vary in relation to their beliefs about their ability to meet an academic goal or whether they are motivated by a need to be more competent than other, as opposed to a need to acquire knowledge (Elliot & Thrash, 2002). In doing so, it will help guide implementation decisions with regards to whether all students need to experience the same learning analytics service, or whether it needs to be aligned to individual differences.

The development of the 10-item short version of the Big Five Inventory undertaken by Rammstedt and John (2007) did find support for the five-factor structure using EFA. These researchers also found all items to load mainly on their target factors, whilst cross-loadings were nominal. Our current work analysed the data using CFA, which Marsh et al. have shown to be overly conservative on account of all cross-loadings being constrained to zero (Marsh et al., 2014). Thus, as an additional step to assess whether the problems with the short version of the Big Five Inventory was on account of the more restrictive CFA, we analysed the 10 items using ESEM. No model fit indices were obtained due to the latent variable covariance matrix not being positive definite and the second conscientiousness indicator (I see myself as someone who does a thorough job). This further substantiates our decision to remove the conscientiousness factor from the predicted expectation measurement model. Moreover, this shows that even with a less restrictive ESEM model there are fundamental problems in using the 10-item questionnaire. Rammstedt and John (2007) do suggest that an additional agreeableness item should be added to questionnaire if this is of importance to the researchers; this is on account of the low construct coverage obtained with two agreeableness indicators. Based on our findings, however, the psychometric issues extend beyond just the agreeableness factor and highlight the need to carefully consider the validity of using such shortened questionnaires. While two indicators per factor can be considered as a minimum requirement and are advantageous for quick assessments, models do become prone to specification errors (Kline, 2015) and this has clearly been shown in our work. Therefore, follow-up work should seek to use personality measures that contain, at a minimum, three indicators per factor.

Chapter 7: Conclusions and Future Directions

7.1. Summary

The aim of this thesis was to address one of six challenges to learning analytics service implementations that higher education institutions are facing, which is the insufficient engagement of stakeholders (Tsai & Gašević, 2017a; Tsai, Moreno-Marcos, et al., 2018). Although stakeholders in learning analytics includes teaching staff, institutional managers, and researchers, the decision was made to focus on student perspectives. This was on account of students being primary users of learning analytics services and failure to understand their expectations now could lead to limited adoption of and/or dissatisfaction with learning analytics (Whitelock-Wainwright et al., 2017).

In this chapter, a summary of the main findings are presented in relation to each of the research goals and questions presented in Chapter 1 (Section 1.3). Given that this thesis forms part of the overarching SHEILA (Supporting Higher Education to Integrate Learning Analytics) project, the implications of this thesis are discussed in relation to policy decision making. Future research is also considered, with a focus on using the developed instrument globally and the need to consider the perspectives of teaching staff.

7.2. Impact of the Present Work

7.2.1. RQ1: "The Student Expectations of Learning Analytics Questionnaire"

In Chapter two, a theoretical framework of expectations was outlined along with an identification of themes within the learning analytics literature. Together, these were used to inform the development of a questionnaire designed to measure student expectation of learning analytics services. Psychometric analysis of the data collected from three roll-outs, which led to a 12-item instrument being retained, with the variance being accounted for by a two-factor solution (*Ethical and Privacy Expectations* and *Service Expectations*).

The advantage of this approach has been the ability to address the problems identified in the learning analytics literature. The latter includes the use of on-the-fly scales in the absence of a theoretical framework (Arnold & Sclater, 2017) and the exclusion of pertinent details regarding scale development (Ifenthaler & Schumacher, 2016). Put in a different way, the developed Student Expectations of Learning Analytics Questionnaire (SELAQ) is theoretically driven, valid, and allows higher education institutions to easily gauge what students expect from learning analytics services. Moreover, given the importance of pre-adoption beliefs (i.e., expectations) in the eventual adoption of technologies (Davis & Venkatesh, 2004), the SELAQ can support successful adoption of learning analytics services. This is on account of higher education institutions having the ability to readily gauge what students expect from such services and take a pro-active approach to manage expectations to offset the likelihood of service dissatisfaction (Brown et al., 2012, 2014; Venkatesh & Goyal, 2010).

Taking the aforementioned points into consideration, this thesis serves as one of the first examples of creating a psychometrically sound instrument to understand what students expect from learning analytics services. In doing so, it represents a step towards addressing the challenge of insufficient stakeholder engagement in learning analytics service development decisions.

7.2.2. RQ2: "Assessing the validity of a learning analytics expectation instrument: A multinational study"

The next contribution of the thesis was to enable higher education institutions beyond those in the United Kingdom (UK) to use the SELAQ. As shown by the submissions to the annual learning analytics and knowledge (LAK) conference, interest in learning analytics service implementations is global (Pardo et al., 2018). Therefore, the challenge of insufficient engagement of stakeholders is not unique to UK universities, but is a challenges that faces higher education institutions worldwide (Tsai & Gašević, 2017a; Tsai, Moreno-Marcos, et al., 2018).

In Chapter three, steps were then taken to translate the SELAQ for utilisation in Estonia, the Netherlands, and Spain. To ensure that each translated version of the SELAQ was psychometrically sound, steps were taken to assess the validity of the instrument in each context. Of the three translated versions of the SELAQ, the two-factor structure (*Ethical and Privacy Expectations* and *Service Expectations*) was supported in the Spanish and Dutch versions. As for the Estonian version of the SELAQ, issues with can be attributed to the small sample size. Nevertheless, these steps have allowed for the SELAQ to be used in European higher education institutions, extending our solution to the challenge of insufficient stakeholder engagement. Additionally, from the data collected through these translated versions of the SELAQ, a general assessment of cultural differences in student expectations of learning analytics services could also be undertaken.

7.2.3. RQ3: "Student Expectations of Learning Analytics Services: Do they align? A multinational assessment of measurement invariance"

Having the ability to measure student expectations of learning analytics services across cultures allows for discussions regarding the feasibility of a one size fits all solution to policy development. To ensure that this can be carried out, there was a need to assess whether the SELAQ was measuring the same constructs in each validated context. Without undertaking such assessments, comparisons of factor means cannot be considered as valid (Horn & Mcardle, 1992; Liu et al., 2017; Meade & Lautenschlager, 2004). The steps taken in Chapter four overcome this limitation by showing both scales of the SELAQ to be invariant across three countries (England, the Netherlands, and Spain). The factor comparisons from this process then allowed for a consideration of how students' expectations of learning analytics services may be attributed to the sample profiles.

The ability to compare SELAQ factor means across country allowed for a robust way of understanding whether the application of a general learning analytics policy is feasible. Prior work exploring student expectations of learning analytics services have focused only a single university (Roberts et al., 2016). Whilst this latter work has been useful in understanding the student perspective, it cannot be used to inform policy beyond a single context. This is particularly problematic, as it may lead to the codes of practice that do not account for cultural differences . The work presented in Chapter four overcomes these limitations by showing the SELAQ to be advantageous in understanding cultural differences.

7.2.4. RQ4: "Subgroups in Learning Analytics Expectations: An Exploratory Latent Class Analysis of Student Expectations Towards Learning Analytics Services"

Higher education institutions being able to measure student expectations of learning analytics is advantageous as it can offset the consequences of a service that fails to align with expectations (Jackson & Fearon, 2014). The issue here, however, is that there is an assumption that all students hold the same expectations of learning analytics services. Instead, it can be assumed that there are different groups in the student population who vary in what they desire and realistically expect from learning analytics services.

Based on this premise, Chapter four presented an expectation segmentation procedure to identify sub-groups with regards to what students expect from learning analytics services (Diaz-Martin et al., 2000). Through the use of latent class analysis, different student sub-groups were identified based on their SELAQ responses. Moreover, the inclusion of covariates allowed for an examination of whether class-assignment was associated with specific demographic variables. The findings of this exploratory analysis have important implications for learning analytics service implementation decisions. For one, they show that there are groups of students who may be at-risk of becoming dependent of such services; whereas, others, based on their low expectations, are pessimistic about such implementations. From an implementation perspective, these findings cast doubts on the feasibility of rolling out learning analytics services across all students and anticipating that it will be readily adopted. Rather, through the SELAQ demonstrated its value in being able to quantitatively identify subgroups in student expectations of learning analytics services.

7.2.5. RQ5: "The Big Five Personality Dimensions and Student Expectations of Learning Analytics: An Exploratory Structural Equation Modelling Approach"

To further our understanding of what may cause individual differences in students' expectations of learning analytics, an exploratory analysis was undertaken to investigate the effects of the Big Five personality dimensions on the two SELAQ factors (*Ethical and Privacy Expectations* and *Service Expectations*). The results of which revealed the personality dimensions of extraversion and neuroticism to be positively associated with *Service Expectations*.

One of the main contributions of this Chapter was an additional validation of the SELAQ instrument in a sample of English speaking students. Moreover, it showed that the individual differences in student expectations of learning analytics were partly associated with personality dimensions. More specifically, those students who are characterised by optimism (trait of high extraversion) and anxiety (trait of high neuroticism) have higher expectations regarding the service features. This has important implications regarding implementation decisions, particularly with regards to the neuroticism dimension, as it highlights the risk of such service creating both additional anxiety through an overload of information and dependency on feedback metrics. As for *Ethical and Privacy Expectations*, the results did not find any personality dimension to be significantly associated with this factor. This may suggest that personality does not affect the expectations students hold towards ethical and privacy elements of a learning analytics service. However, further work is required before such conclusions are drawn on account of the identified problems with the 10-item short version of the Big Five inventory (Rammstedt & John, 2007), which have been discussed in Chapter six. Nevertheless, this work highlights the possibilities that the SELAQ, in conjunction with additional self-report measures, can bring in understanding student expectations of learning analytics services.

7.3. Implications

The findings of this thesis have several implications for students, policy makers, and Higher Education Institutions. The following sections breakdown these implications for each of these groups.

7.3.1. For Students

Implementations of learning analytics services are aimed at improving student learning (Siemens & Gašević, 2012), but student input into these developments have been insufficient (Tsai, Moreno-Marcos, et al., 2018). The findings of this current work show that students hold strong expectations towards learning analytics services, which refer to both data handling procedures and the features provided. From the perspective of ethics and privacy, the work shows that students expect the university to ensure that data is kept secure and that consent is sought for identifiable data usage, for data to be outsourced to third party companies, and for when data is used for an alternative purpose. As for the service students expect, the work shows that expectations are not homogenous. It instead appears that some students may expect to have early alert systems, a complete profile of their learning, or the ability to monitor goal progress; whereas, other students do not expect this at all. For students, therefore, it is clear that dialogues need to be open when developing learning analytics services. Given that students are a main stakeholder, they should be able to express what they expect to receive from a learning analytics service, but also state what is not permissible.

7.3.2. For Policy Makers

When seeking to implement a learning analytics service, it is essential that an effective policy is in place (Tsai, Gaševic, et al., 2018). As clearly demonstrated in this work with student stakeholders, issues of ethics and privacy are of considerable importance. This assertion is based upon the little variability found in students' *Ethical and Privacy Expectations* compared to *Service Expectations*. In light of this finding, it is important for policy makers to place matters of data security, consent, and transparency above other issues. Moreover, the thesis has shown that students have clear expectations regarding their data and that they should be engaged in policy discussions. In doing so, the policy guiding the implementation of learning analytics will reflect the expectations of one of the main stakeholders.

7.3.3. For Higher Education Institutions

For those Higher Education Institutions interested in implementing learning analytics services, the work of this thesis demonstrates the need to create a user-centred service (Tsai, Gaševic, et al., 2018). Whilst the findings show *Ethical and Privacy Expectations* to vary very little within the student samples, *Service Expectations* are quite variable. In particular, it has been shown that not all students expect to have services aimed at identifying those at-risk of underperforming or failing. Whereas, other students have high expectations towards the provision of services that promote self-regulating such as being able to monitor learning progress and making self-informed decisions on the data they receive. Together, this shows that any Higher Education Institution implementing learning analytics services should consider student agency at all times and no service should undermine their ability to be self-determined learners.

7.4. Directions for Future Work

There are many avenues for future work to develop the findings of this thesis. These include translating the SELAQ for use in countries beyond those they have been developed in (England, the Netherlands, and Spain), considering the SELAQ dimensions from a network perspective, and adapting the theoretical framework to other stakeholder perspectives.

Given the global interest in learning analytics (Pardo et al., 2018), each higher education institution will face the challenge of equally engaging with stakeholders (Tsai & Gašević, 2017a; Tsai, Moreno-Marcos, et al., 2018). Therefore, it is necessary that the SELAQ is translated and validated for use in more countries than is currently possible. The SHEILA project itself has 58 associate partners, which includes countries such as the Czech Republic, France, Greece, and South Korea[7]. Each of these associate partners will have access to the SELAQ, but there it is necessary that the steps followed in Chapter 3 and 4 are followed to assess the validity of the purpose factor structure and measurement invariance across contexts. Thus, the SELAQ has the potential to provide a global solution to one of the challenges facing learning analytics service implementations.

This thesis has taken a latent variable perspective of student expectations, which assumes that changes in the measured SELAQ dimensions arise from an underlying latent variable. Although this has been an important approach for the purposes of this thesis, it does have two particular limitations (Borsboom, 2008). Firstly, the measured indicators of a latent variable must be locally independent, which means that they do not have direct causal influences on one another

[7] http://sheilaproject.eu/team/

(Borsboom, 2008). Secondly, there is exchangeability, which is the assumption that no more information can be gleaned from the addition of indicators to a questionnaire and this merely improves reliability (Borsboom, 2008). Placing this into the context of student expectations, this means that those indicators related to *Ethical and Privacy Expectations* should not have any direct causal influence on another, nor on the items pertaining to *Service Expectations*, when considered through the latent variable approach. This may appear quite limiting, particularly given accounts on how students may weight up the benefits of a learning analytics service against their privacy concerns (Ifenthaler & Schumacher, 2016). Thus, it could be assumed that higher expectations on the *Ethical and Privacy Expectation* items may result in negative associations with *Service Expectation* items. To be able to achieve such inferences, it is recommended that researchers also investigate the use of the network approach to analysing expectations. This approach has been used to study networks of attitudes towards political candidates (Dalege et al., 2016) and to understand the structure of political belief networks (Brandt, Sibley, & Osborne, 2018). As discussed in Chapter two, expectations only differ from beliefs with regards to the former being beliefs about the future (Olson & Dover, 1976). Therefore, there is justifiable grounds for adopting a network approach to understanding student expectations of learning analytics services. Moreover, in doing so can allow for the identification of central beliefs that could be important targets for expectation management.

A further recommendation for future research, which leverages the findings of the SELAQ is to incorporate them within a mixed methods approach. Current approaches to exploring student expectations of learning analytics services, including the work presented here, has taken either a quantitative or qualitative approach in isolation (Roberts et al., 2016). If the approach was mixed, however, it would allow for a more informed understand of student expectations. Put in a different way, whilst the SELAQ can be specifically used to measure expectations towards particular service features, a qualitative approach (e.g., focus groups, interviews, or group concept mapping) can add more depth by understanding why students express such expectations. For example, knowing that some students do not desire the introduction of early alert systems does not provide us with knowledge on the reasons why such views are expressed. On the other hand, knowing what a small sample of students expect from learning analytics services does not necessarily reflect the expectations of the general population of students. Therefore, for a more rounded and thorough understanding of student expectations of learning analytics services, a mixed methods approach is a necessity.

Finally, it is important to recognise that the challenge of insufficient stakeholder engagement does not specifically refer to the student population (Tsai & Gašević, 2017a; Tsai, Moreno-Marcos, et al., 2018). Rather, its ambiguity means that it can also refer to the engagement of teaching staff in the implementation of learning analytics services. Howell, Roberts, Seaman, and Gibson (2018) have explored the expectations of teaching staff towards learning analytics, which found the discussed topics to revolve around facilitating learning, ethics, student needs, the needs of teaching staff, and the need for collaboration. A specific example was that teaching staff expected learning analytics services to go beyond early intervention systems and provide details on what factors are associated with successful learning (Howell et al., 2018). Thus, whilst the SELAQ focuses solely on the expectations of students, there is a gap in measuring the expectations of teaching staff. Researchers are therefore encouraged to adapt the theoretical framework on which the SELAQ is based and devise an instrument with a specific aim of gauging the expectations of teaching staff.

7.5. Conclusions

The impetus of this work was to address one of the six challenges put forward by Tsai and colleagues, which was that the engagement with stakeholders in learning analytics has been insufficient (Tsai & Gašević, 2017a; Tsai, Moreno-Marcos, et al., 2018). To achieve this objective, the thesis was focused on developing a theoretically grounded and psychometrically sound instrument that would allow higher education institutions to increase student engagement in learning analytics service implementations. In doing so, this thesis makes several important contributions to the field of learning analytics. Firstly, a clear definition of student expectations is provided ("a belief about the likelihood that future implementation and running of LA services will possess certain features"). Secondly, a 12-item instrument (the SELAQ) is provided, which gives higher education institutions a tool to gauge student expectations of learning analytics services. Thirdly, the findings obtained from a series of analyses exploring individual differences are used to inform policy decisions. For policy makers, it is important to recognise that student expectations of learning analytics are not homogenous, nor are they restricted to ethical issues.

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Appendices

Appendix 1: Ethics Documentation

Research Ethics Application Form - 1411

Section 1: Research ethics application

Note to applicant: The following help and support is available to assist you in completing your application:

- **User guides**: Applicant User Guide | Student Applicant User Guide
- Select the **(i)** icon next to a question for question-specific help
- Select **Help** from the top of the page for a list of contacts and frequently asked questions
- **Email support** at the bottom of each section: Ethics System Support for technical issues using the system | Research ethics query for general queries relating to research ethics

1: Project titles

1.1 Project title (full title)

Supporting Higher Education to Integrate Learning Analytics

1.2 Project lay title

Supporting Higher Education to Integrate Learning Analytics

1: Investigator details

1.3 Please answer the following question:

- ○ I am a member of staff
- ◉ I am a postgraduate student
- ○ I am an undergraduate student

Note to applicant: Research ethics applications for postgraduate and undergraduate projects must be shared with the Supervisor. The Supervisor is responsible for providing guidance on, and signing off, the application. The Supervisor sign off is requested at the end of the form.

Please use the **Share** button on the left side panel to share the form with your Supervisor, ensuring that you grant full access to your Supervisor.

1.4 Have you shared the form with your Supervisor?

- ◉ Yes
- ○ No

1.5 Please indicate the type of the research project:

- ○ This is a staff project / application
- ◉ This is a postgraduate research student project
- ○ This is an undergraduate or taught postgraduate student project

1.6 Lead Student Investigator

Use the 'Search User' function above to select a Lead Student Investigator

Title	First Name	Surname
Mr	Alexander	Whitelock-Wainwright

Email: hlawainw@student.liverpool.ac.uk

Course details: PhD

1.7 Supervisor (Principal Investigator)

Use the 'Search User' function above to select a Supervisor

Title	First Name	Surname
Dr	Ricardo	Tejeiro

Department: School of Psychology (including DClinPOsych)

Telephone: 0151 794 0512

Email: tejeiro@liverpool.ac.uk

1.9 Please select the Principal Investigator's / Supervisor's School or Institute:
(for Veterinary research projects select Institute of Veterinary Science)

Institute of Life and Human Sciences - School of Psychology

1.10 Are there any University of Liverpool Co-Investigators involved in the study?

- ○ Yes
- ◉ No

1.13 Are there any other Student Investigators involved in the study?

- ○ Yes
- ◉ No

1.16 Are there any other staff not named above who will be involved in the study?

- ◉ Yes
- ○ No

1.17 Other Staff

Title	First Name	Surname
Professor	Dragan	Gasevic

Job title: Professor and the Chair in Learning Analytics and Informatics in the Schools of Education and Informatics at the University of Edinburgh

Involvement: Secondary Supervisor

Email: dragan.gasevic@ed.ac.uk

Note to applicant: Staff on honorary contracts do not automatically fall within the University's Insurance Policy. If your project involves staff on honorary contracts, please contact the University's Risk and Insurance Manager, John Stone, to arrange the appropriate insurance provisions.

1: Project details - Project dates

1.18 Proposed start date:

16/12/2016

1.19 Proposed end date:

07/06/2019

1: Project details - Project funding

1.20 Has the study received external funding or a Knowledge Exchange voucher?

- ○ Yes
- ◉ No

1: Project details - Determining whether research ethics approval is required

1.22 Please select whether your research involves:

- [x] Human participants (including owners of animals)
- [ ] Human tissue (including all samples of human material, e.g. bodily fluids)
- [ ] Personal data

Note to applicant: If you are unsure whether the data you will be processing is classified as 'personal data', please use the Information Commissioner's Office guidance on "What is personal data"

- [ ] None of the above

Thank you for completing Section 1: Project information

Please use the **Next** button on the left side panel to progress to the next section of the form.

Email support

Ethics system support | Research ethics query

Section 2: Other ethics committees

Note to applicant: If your research involves any of the following categories, it will be outside of the remit of a University ethics committee and will require review by another committee.

2.1 Does your study involve any of the following?

- [ ] Research undertaken by students studying on one of the University's online degree programmes run in partnership with Laureate
- [ ] Research that is led by Liverpool School of Tropical Medicine staff or students
- [ ] Research activities which require review by a NHS Research Ethics Committee

Note to applicant: Please use the HRA Decision Tool if you are unsure whether your research requires review by a NHS Research Ethics Committee.

- [ ] Procedures that are carried out on any living vertebrate, other than man, and any living cephalopod which are NOT considered recognised veterinary clinical practice

- [x] None of the above

2: Other ethics committees - Previous ethical review

Note to applicant: If your research has already received approval from another research ethics committee, a University of Liverpool research ethics committee will assess the review provided by the other research ethics committee. If a University of Liverpool committee rejects the review provided by the other research ethics committee, you will be asked to make an application in full to a University of Liverpool research ethics committee.

2.2 Has the study already received ethical approval from another research ethics committee?

- (•) Yes
- ( ) No

- ( ) Yes - however, a review by a University of Liverpool research ethics committee is also required

2.3 Please provide the name of the lead institution(s) which has granted approval:

The University of Edinburgh

Please upload the following documents:

Note to applicant: If you are not able to provide all the following documents, the reviewers will be unable to assess the review provided by the other institution.

If you are unable to provide all the documents below, please select the following option on question 2.2: "Yes - however, a review by a University of Liverpool research ethics committee is also required".

2.4 A copy of the approval letter from the other institution's research ethics committee

Type	Name	File Name	Date	Version	Size
Other Committee Approval Letter	ethics_ApprovalEdinburgh	ethics_ApprovalEdinburgh.pdf			274.0 KB

To add multiple documents, use the **Upload Document** button after adding the previous document

2.5 A terms of reference from the other institution's research ethics committee

Type	Name	File Name	Date	Version	Size
Other Committee Terms Of Reference	moray_House_Ethics	moray_House_Ethics.pdf			166.3 KB

To add multiple documents, use the **Upload Document** button after adding the previous document

2.6 A copy of the application form reviewed by the other institution's research ethics committee

Type	Name	File Name	Date	Version	Size
Other Committee Application Form	Ethics_Application_Form	Ethics_Application_Form.pdf	08/12/2016 12:00:00 AM	1	338.5 KB

To add multiple documents, use the **Upload Document** button after adding the previous document

2.7 Will you seek written consent from participants?

- (•) Yes
- ( ) No

2.8 Please upload a copy of the participant information sheet:

Type	Name	File Name	Date	Version	Size
Participant Information Sheet	Participant_Information_Sheet	Participant_Information_Sheet.doc	30/01/2017 12:00:00 AM	2	120.5 KB

To add multiple documents, use the **Upload Document** button after adding the previous document

2.9 Please upload a copy of the participant consent form

Type	Name	File Name	Date	Version	Size
Participant Consent Form	Consent_Form_Survey	Consent_Form_Survey.docx	08/12/2016 12:00:00 AM	1	15.2 KB
Participant Consent Form	Consent_Form_FocusGroups	Consent_Form_FocusGroups.docx	08/12/2016 12:00:00 AM	1	16.6 KB

To add multiple documents, use the **Upload Document** button after adding the previous document

2.11 Will the research be conducted outside the UK?

- ○ Yes
- ◉ No

2.13 Please provide a brief summary of the research:

Learning analytics (LA) has provided a much needed resolution to higher education's slow response to analysing the proliferation of student data that is collected (e.g., the frequency and intensity of virtual learning environment usage, attendance, grades). Through the use of data-mining and statistics, LA can provide additional educational services to students that are aimed at supporting them during their learning (e.g., provide visualisations on how they are performing in relation to their peers).

LA services are still in their infancy, but the adoption rates are steadily increasing in higher education institutes as they become more aware of the benefits that analytics offers. Even though the uptake remains within the early stages of adoption, there is a impending need for the LA community to work with relevant stakeholders (e.g., students, teaching staff, etc.) to develop a policy framework that allows for such future services to be successful. To date, the initatives taken by the LA community have been driven by the opinions and ideas of researchers within the field. Even though important for the foundational stages of LA, it fails to acknowledge the input from those most likely to reap the benefits of LA services (e.g., students).

This research forms part of the SHEILA project (http://sheilaproject.eu/) that aims to incoporate the direct engagement of stakeholders into the development of a policy framework for future LA adoption in higher education. For this project, we are attemtping to understand students' expectations of a university collecting, handling, and analysing educational data. To achieve this, a questionnaire will be developed using students from the University of Liverpool and the University of Edinburgh. This questionnaire will explore themes pertaining to ethical and legal issues (e.g., third party use of educational data), the importance of data accuracy, and how they would like this data to be used (e.g., to improve the curriculum or feedback). Each item on the questionnaire will contain two subscales: what students desire from a learning analytics services, and what is the minimum service they expect.

Results from this study will be important for the LA community as there has yet to be a full exploration into what students expect from the collection and analysis of their educational data. As these findings will also be used to build a LA policy, the future LA services offered will be reflective of student opinions which should lead to higher levels of satisfaction and usage from the students themselves.

The first stage of this research will involve the development of a questionnaire to explore student expectations towards LA. The pilot questionnaire will be distributed to only a group of students from the University of Edinburgh through an online system. Alongside this, a focus group will be ran with only students from the University of Edinburgh - the aim of this method is to gain a better understanding of student views towards LA. To clarify, the focus group is not being carried out by either Mr Alexander Whitelock-Wainwright or Dr Ricardo Tejeiro - this part of the study is being ran by a member of the University of Edinburgh. No students from the University of Liverpool will be asked to take part in the focus group.

The second stage of the research will be the distribution of the final questionnaire. The number of items on this final questionnaire will be smaller as the results from the pilot questionnaire will be used to remove unclear questions, so should take students less time to complete. The student survey team for the University of Liverpool has granted us permission to distribute this to all first and second year undergraduate students at the University of Liverpool through the online questionnaire system (see attached). As stated in the University of Edinburgh's ethics (see attached), we intend to include 600 students from Edinburgh - this will be the number of participants included at the University of Liverpool.

Thank you for completing Section 2: Other research ethics committees

Please use the **Next** button on the left side panel to progress to the next section of the form.

Email support

Ethics system support | Research ethics query

Section 24: Other Governance Permissions

24.1 Will the research involve Sensitive IT Usage?

Note to applicant: If you are unsure what constitutes 'Sensitive IT usage' please see the help text, or contact the University's Information Security Officer, Mr David Hill, for confirmation.

- [ ] Yes
- [x] No

24: Other Governance Permissions - Health and Safety

24.2 Is the research activity covered by a Health and Safety risk assessment?

- [x] Yes
- [ ] No

24: Other Governance Permissions - Sponsorship

24.3 Does your research:

- [ ] Involve patients and users of the NHS including use of their data, tissue or other bodily material
- [ ] Involve relatives or carers of NHS patients
- [ ] Use NHS premises or resources
- [ ] Involve a Clinical Trial of an Investigational Medicinal Product (CTIMP)

Note to applicant: It is a criminal offence to conduct any CTIMP without a sponsor.

- [x] None of the above

24: Other Governance Permissions - Identifiable personal health information

24.4 Will this project hold fully identifiable personal health information about individuals?

- ( ) Yes
- (•) No

Thank you for completing Section 24: Other governance permissions

Please use the **Next** button on the left side panel to progress to the next section of the form.

Email support

Ethics system support | Research ethics query

Section 25: Declaration and Submission

25.1 Are there any additional ethical issues you would like to discuss that are not mentioned elsewhere in the form?

- ( ) Yes
- (•) No

25: Declaration and Submission - Training

25.3 Please provide details of your most recent training in research ethics

Ethics in Educational Research (26/11/2015). Centre for Lifelong Learning, The University of Liverpool..

25: Declaration and Submission - Peer review

25.4 Has the study undergone peer review?

- ( ) Yes
- (•) No

25.6 Please describe whether there are any plans to ensure the project undergoes peer review:

The questionnaire will discussed as part of the Learning Analytics and Knowledge conference next year, which enable the researchers to receive feedback from members of the learning analytics community to provide suggestions for improvements.

25: Declaration and Submission - Research tools

25.7 Are there any additional research tools or attachments that you would like to upload?

- (•) Yes
- ( ) No

25.8 Please upload the document:

Type	Name	File Name	Date	Version	Size
Research Tools	Questionnaire_Final	Questionnaire_Final.pdf	08/12/2016 12:00:00 AM	1	384.9 KB
Research Tools	student_Survey_Approval	student_Survey_Approval.docx	30/01/2017 12:00:00 AM	1	33.9 KB

To add multiple documents, use the **Upload Document** button after adding the previous document

25: Declaration and Submission - Feedback

25.9 Would you like to leave feedback on the online system?

- ○ Yes
- ◉ No

25: Declaration and Submission - Declarations

25.11 Are there any declarations of interest to disclose?

Note to applicant: All University staff and students are required to recognise and disclose activities that might give rise to conflicts of interest or the perception of conflicts and to ensure that such conflicts are seen to be properly managed or avoided.

Further information can be found in the University of Liverpool Statement of Policy and Procedure on Disclosure of Interest.

- ○ Yes
- ◉ No

25: Declaration and Submission - Sign Off

Note to applicant: You must agree to the following:

The information in this form is accurate to the best of my knowledge and belief. I understand that the information and conditions contained in this application apply to all co-applicants and other investigators - and that it is my responsibility to ensure they abide by them. I undertake to adhere to the terms of the application and any conditions set by the Committee.

- ☑ I agree

I understand that I am responsible for notifying the Committee of any changes to the terms of the ethical approval through the amendment procedure. I understand that I am responsible for monitoring the research at all times. I understand that I am responsible for immediately stopping the research and alerting the Committee of any serious adverse events within 24 hours of the occurrence.

- ☑ I agree

I have read and understand the University's Policy on Research Ethics. I have read and understand the Concordat to Support Research Integrity. I undertake to abide by the ethical principles laid down by relevant professional societies.

☑ I agree

Please sign here:

Signed: This form was signed by Mr Alexander Whitelock-Wainwright (hlawainw@student.liverpool.ac.uk) on 02/02/2017 10:40

This is the end of the application form.

Please press the **Submit** button on the left side panel. Your form will be validated prior to submission for missing answers.

25: Declaration and Submission - Authorisation

Note to applicant: To get your application signed off by your supervisor, select **Request Signature** below. This will lock the form while your supervisor assesses the content of the application. If you would like to unlock the form to make further changes, please select the **Unlock** button from the left side panel. Once the form is signed off by your supervisor, it will be automatically submitted for review, therefore no further changes can be made.

Please select Request Signature to request sign off from your Supervisor

Signed: This form was signed by Dr Ricardo Tejeiro (tejeiro@liverpool.ac.uk) on 02/02/2017 14:57

This is the end of the application form.

After your signature request has been authorised by your supervisor, you will receive an email to confirm the form has been submitted.

Email support

Ethics system support | Research ethics query

UNIVERSITY OF LIVERPOOL

Research Integrity and Ethics

21 February 2017

Dear Dr Tejeiro,

We are pleased to inform you that your application for research ethics approval has been approved. Details and conditions of the approval can be found below:

Reference:	1411
Project Title:	Supporting Higher Education to Integrate Learning Analytics
Principal Investigator/Supervisor:	Dr Ricardo Tejeiro
Co-Investigator(s):	Mr Alexander Whitelock-Wainwright
Lead Student Investigator:	-
Department:	School of Psychology (including DClinPOsych)
Reviewers:	Prof Elizabeth Perkins
Approval Date:	21/02/2017
Approval Expiry Date:	Five years from the approval date listed above

The application was **APPROVED** subject to the following conditions:

Conditions

- All serious adverse events must be reported via the Research Integrity and Ethics Team (ethics@liverpool.ac.uk) within 24 hours of their occurrence.
- If you wish to extend the duration of the study beyond the research ethics approval expiry date listed above, a new application should be submitted.
- If you wish to make an amendment to the research, please create and submit an amendment form using the research ethics system.
- If the named Principal Investigator or Supervisor leaves the employment of the University during the course of this approval, the approval will lapse. Therefore it will be necessary to create and submit an amendment form using the research ethics system.
- It is the responsibility of the Principal Investigator/Supervisor to inform all the investigators of the terms of the approval.

Kind regards,

Research Integrity and Ethics 0151-794-8290
0151-795-8355

Research Ethics Amendment Form - 1411

Section 1: Project Details from original application (information only)

Note to applicant: This section is drawn from the original application and is for information only and cannot be amended. Please use the **Next** button on the left side panel to progress to the next section of the form.

1.1 Project lay title

Supporting Higher Education to Integrate Learning Analytics

1.5 Please indicate the type of the research project:

- ( ) This is an undergraduate student project
- ( ) This is a taught postgraduate student project (for example: MA, MRes, MSc, MBA, LLM student projects)
- (•) This is a postgraduate research student project (for example: PhD student projects)
- ( ) This is a staff project
- ( ) This is a staff application to cover a collection of student projects

1.5 Lead Student Investigator

Use the 'Search User' function above to select a Lead Student Investigator

Title	First Name	Surname
Mr	Alexander	Whitelock-Wainwright

Email: hlawainw@student.liverpool.ac.uk

1.6 Supervisor (Principal Investigator)

Use the 'Search User' function above to select a Supervisor

Title	First Name	Surname
Dr	Ricardo	Tejeiro

Department: School of Psychology (including DClinPOsych)

Telephone: 0151 794 0512

Email: tejeiro@liverpool.ac.uk

1.16 Other Staff

Title	First Name	Surname
Professor	Dragan	Gasevic

Job title	Professor and the Chair in Learning Analytics and Informatics in the Schools of Education and Informatics at the University of Edinburgh
Involvement	Secondary Supervisor
Email	dragan.gasevic@ed.ac.uk

1.9 Please select the Principal Investigator's / Supervisor's School or Institute:
(for Veterinary research projects select Institute of Veterinary Science)

Institute of Life and Human Sciences - School of Psychology

1.18 Proposed end date:

07/06/2019

You have reached the end of Section 1: Project details

Please use the **Next** button on the left side panel to progress to the next section of the form.

Section 2: Type of amendment

Note to applicant: If you are requesting for the approval to be extended past the original five years, this cannot be done via the amendment procedure - a new full application form must be submitted.

2.1 Please select the committee which granted approval to the original application (found on the approval letter):

Health and Life Sciences Research Ethics Committee
(Psychology, Health and Society)

2.2 Is this an amendment to:

- [x] Information supplied in the original University Research Ethics Approval application form
- [ ] Participant information sheets and participant consent forms or other documentation received by participants
- [x] Other supporting documentation

2.3 Please upload the updated documentation:

Type	Name	File Name	Date	Version	Size
Default	ethics_Approval_07_11_2017	ethics_Approval_07_11_2017.pdf	07/11/2017 12:00:00 AM	1	214.6 KB
Default	ethics_Amendment_31_10_2017	ethics_Amendment_31_10_2017.pdf	07/11/2017 12:00:00 AM	1	268.3 KB
Default	SHEILA_University_Contract	SHEILA_University_Contract.docx	07/11/2017 12:00:00 AM	1	17.0 KB

2.4 Is the amendment likely to significantly affect any of the following:

- [ ] The safety or physical or mental integrity of study participants
- [ ] The conduct or management of the study
- [ ] The purpose or design of a study (including the procedures used)
- [ ] The study population (i.e. numbers, age range, inclusion/exclusion criteria)
- [ ] The documentation received by participants (such as participant information sheet or consent form)
- [x] The data that is collected from participants
- [x] The research sites

- [ ] The amendment will not significantly affect any of the above

2: Details of Amendment

2.5 Please summarise the details of the amendment in language comprehensible to a lay person, including what measurements have been put in place for any additional ethical issues that may arise as a result of the amendment(s):

Firstly, we would like to add Dr Kate Bennett as principal investigator (School of Psychology at the University of Liverpool; k.m.bennett@liverpool.ac.uk) to the ethics forms.

Secondly, we have received confirmation from the ethics committee at the University of Edinburgh to distribute the student expectation survey to multiple universities (see attached document 'ethics_Approval_07_11_2017'). The ethics committee required the researchers to introduce a quality control system to deal with the large numbers of interested universities. To meet this requirement, we have created a generic document (see attached 'SHEILA_University_Contract') that outlines the purpose of the questionnaire and research, the procedures involved, an outline of how data will remain secure and confidential, and an agreement that data will be given back to the participating university at the end of collection. The document requires the interested university to sign and agree to the terms of the research before the creation of an online survey specific for that university. We have also attached two additional questionnaires to use alongside the student expectation questionnaire, these are a 10-item personality questionnaire and a locus of control scale. You can find details of these questionnaires in the file titled 'ethics_Amendment_31_10_2017' under section 6.1, along with student consent forms, and the student expectation questionnaire. No ethical issues will arise from these amendments, the SHEILA project has been setup to increase the student voice in the implementation of institutional learning analytics systems. Their opinions are valuable and will be used to create a learning analytics system that is ethical and reflects the views of the student population.

Thank you for completing Section 2: Details of Amendment

Please press the **Submit** button on the left side panel. Your form will be validated prior to submission for missing answers.

Central University Research Ethics Committees

23 November 2017

Dear Dr Tejeiro,

I am pleased to inform you that the amendment to your study has been approved. Amendment details and conditions of approval can be found below. If applicable, Appendix A contains a list of documents approved by the Committee.

Amendment details

Reference: 1411 (amendment)
Project Title: Supporting Higher Education to Integrate Learning Analytics
Principal Investigator: Dr Ricardo Tejeiro
Co-Investigator(s): Mr Alexander Whitelock-Wainwright Student Investigator(s): -
Department: School of Psychology (including DClinPOsych) Approval Date: 23/11/2017

The amendment was **APPROVED** subject to the following conditions:

Conditions of approval

- All serious adverse events must be reported to the Committee within 24 hours of their occurrence, via the Research Integrity and Ethics Officer (ethics@liv.ac.uk).
- If it is proposed to make further amendments to the research, you should notify the Committee by following the Notice of Amendment procedure.
- If the named Principal Investigator or Supervisor leaves the employment of the University during the course of this approval, the approval will lapse. Therefore please contact the Committee (details below) in order to notify them of a change in Principal Investigator or Supervisor.

Kind regards,

Central University

Research Ethics

Committees

ethics@liverpool.

ac.uk

794-8290

Appendix - Approved documents

If applicable, the final document set reviewed and approved by the committee is listed below:

Document Type	File Name	Date	Version
Default	ethics_Approval_07_11_2017	07/11/2017	1
Default	ethics_Amendment_31_10_2017	07/11/2017	1
Default	SHEILA_University_Contract	07/11/2017	1

Appendix 2: The Student Expectations of Learning Analytics Questionnaire

Appendix 2.1. Introductory Paragraph for the SELAQ

Student Expectations of Learning Analytics

In the forth-coming years, learning analytics will be increasingly prevalent in higher education. Learning analytics involves the collection of educational data, such as grades, lecture attendance, or number of accesses to online resources from various learning environments to better inform how students learn and engage in their studies. The educational data is used to implement support services that are used to aid student learning such as the development of early alert systems for those who may be at-risk of failing a course or dropping out, personalised learning environments, and improving student feedback processes. For example, the collection of a student's online learning environment data (e.g., hours spent online) can be used by a learning analytics service to determine whether a student is above or below the average level of engagement for the course/module. If the service detects that the student is below the average level of engagement required for a course, it may alert their personal tutor for providing relevant feedback and support. The learning analytics service provides timely information so that the tutor can contact the student to identify any problems, and provide support before these problems jeopardise the student's learning.

As students will be the main beneficiaries from learning analytics, it is important for their opinions and expectations are accommodated into the design and implementation of any developed services. You have been asked to participate in this survey to investigate your expectations towards a learning analytics service and the use of your educational data by the university. These expectation questions have been formatted to understand what you desire from a learning analytics service (e.g., what you ideally hope for) and what is the minimum standard that you expect from the service (e.g., what you expect to happen in reality). By completing this survey, you will be providing critical information on student expectations regarding learning analytics. The findings from the survey will inform how future services are developed to ensure they reflect, and meet, yours and your peers' expectations and needs.

The results of this survey will be used to inform the development of the learning analytics policy at the (University Name).

Appendix 2.2. 79-Item Student Expectations of Learning Analytics Services Questionnaire

Based on the information provided to me about learning analytics, I expect…	**Retained?**	**Reason for Removal**
1. the university to provide me with guidance on when and how often I should consult the analysis of my educational data	Yes	
2. the analytics will be not used to allow future cohorts to benefits from improvements to educational content	No	Unclear Item
3. the university to encourage my peers to support one another as part of the analytic process	No	Unclear Item
4. the analytics to not promote student decision making	Yes	
5. the university to not ask for my consent for any interventions that are carried out based upon the analysis of my educational data	Yes	
6. the university to ignore personal circumstances when analysing my educational data	Yes	
7. the university to warn me if withdrawing from analytic processes will lead to a negative impact on my academic progress	Yes	

Based on the information provided to me about learning analytics, I expect…	**Retained?**	**Reason for Removal**
8. to not be reassured that analytics are collecting and presenting data that is accurate	Yes	
9. the university to explain all analytics processes as clearly as possible (e.g., the collection and analysis of my educational data)	Yes	
10. the analytics to relate to my learning goals	Yes	
11. the university to ask for my consent for using any sensitive data about myself (e.g., ethnicity, religion, etc.)	Yes	
12. the university to make me aware of who can view my educational data	Yes	
13 .the university to not use the analysis of my educational data for only its own benefits	Yes	
14. the teaching staff to not be trained with analytics in order to provide feedback and support	Yes	
15. the analytics to not be in an easy read format	Yes	
16. to not have the right to decide how analytics will be used in my learning	No	Content Overlap

Based on the information provided to me about learning analytics, I expect…	**Retained?**	**Reason for Removal**
17. the university to not have a transparent policy of who has access to my educational data	No	Content Overlap
18. the university will use the analysis of educational data for quality assurance and improvement	No	Content Overlap
19. the university to carry out real-time interventions based on the analyses of my educational data	Yes	
20. the university to reassure me that all my educational data will be kept securely and used properly	Yes	
21. the university to use the analysis of my educational data to improve future students' overall experience	No	Content Overlap
22. the university to not make me aware of their ability to monitor my actions as a result of collecting my educational data	No	Content Overlap
23. the feedback guided by analytics to promote skill development (e.g., essay writing, referencing, etc.)	Yes	

Based on the information provided to me about learning analytics, I expect…	**Retained?**	**Reason for Removal**
24. the analytics to not be used to improve quality of feedback and assessment	No	Content Overlap
25. the university to not ask for my consent for any of my educational data being outsourced to third party companies	Yes	
26. the output from analytics will not be given to me through text (e.g., emails)	Yes	
27. the analytics to clearly show how my performance stands in comparison to my peers	Yes	
28. the university to not protect my privacy while collecting and using my educational data	Yes	
29. the analytics to integrate educational data for the benefit of students	No	Content Overlap
30. the analytics to be used to improve timeliness of feedback and assessment	No	Content Overlap

Based on the information provided to me about learning analytics, I expect…	**Retained?**	**Reason for Removal**
31. the university to not inform me about the uses of my educational data in any analytics	No	Content Overlap
32. the feedback guided by analytics will be aimed at providing support for my well-being	No	Content Overlap
33. the analytics will not be used to improve the educational experience in a module/course/programme	Yes	
34. the analytics will allow for timely marking of my work	No	Content Overlap
35. the teaching staff to not have an obligation to act if I am at-risk of failing , underperforming, or if I could improve my learning	Yes	
36. the analytics will allow me to receive continual feedback as I progress through my studies	Yes	
37. the university to contact me frequently about my learning progress based on the analysis of my educational data	Yes	

Based on the information provided to me about learning analytics, I expect…	Retained?	Reason for Removal
38. that I will not have the opportunity to draw my own conclusions from the analytic outputs received	No	Content Overlap
39. the university to not ask for my consent for the collection and use of any of my educational data used in the analytics	Yes	
40. all analytics to be meaningful and accessible for me	No	Content Overlap
41. the university to not release analyses of my educational data in real-time	No	Content Overlap
42. the analytics will not allow for a student-focused provision of higher education	No	Unclear Item
43. the university to not give me the right to opt-out of data collection and analysis	Yes	
44. the output from analytics to be given to me in person (e.g., by teachers, supervisors, advisors, or personal tutors)	Yes	

Based on the information provided to me about learning analytics, I expect…	**Retained?**	**Reason for Removal**
45. the analytics will show me what is the optimum pathway through my studies	Yes	
46. the university to not demonstrate how they work ethically in collecting and analysing my educational data	No	Content Overlap
47. analytics to be used for the benefit of the students	No	Content Overlap
48. the university to not inform me about my educational data being used for analytics	No	Content Overlap
49. the university to keep my educational data within secured servers used by the university	No	Content Overlap
50. the analytics will not be used to build better relationships between myself and teaching staff	Yes	
51. to not be reassured that analytics are collecting and presenting data that is beneficial for my academic success, learning experience, and/or well-being	No	Content Overlap

Based on the information provided to me about learning analytics, I expect…	**Retained?**	**Reason for Removal**
52. the analytics will not guide me through necessary learning resources	No	Content Overlap
53. the teaching staff to be proactive about the results of my analytics (e.g., if I was underperforming, at-risk of failing, or if I could improve my learning)	No	Content Overlap
54. the analytics to not provide me with information of how my learning progress compares to my peers	No	Content Overlap
55. the analytics to present myself with a complete profile of my learning across every module	Yes	
56. the university to inform me about any algorithms and any labels inferred by the use of these algorithms	No	Content Overlap
57. the analytics to not notify my teachers early if I am underperforming, at-risk of failing, or if I could improve my learning in a module/degree programme	Yes	

Based on the information provided to me about learning analytics, I expect…	**Retained?**	**Reason for Removal**
58. the university to ask for my consent again if any of my educational data is being used for a different purpose than originally stated	Yes	
59. all components of my learning activities carried out on the university's virtual learning environment to not be represented by the analytics	No	Content Overlap
60. the analytic notifications to not provide me with a full breakdown of a my learning progress	No	Content Overlap
61. the analytics to be used to improve my learning experience and my overall well-being	Yes	
62. all data inaccuracies in the results produced by analytics to be minimised	No	Content Overlap
63. the analytics will allow me to monitor my own learning progress	No	Content Overlap
64. the analytics to not provide me with information on what is needed to meet my learning goals	Yes	

Based on the information provided to me about learning analytics, I expect…	**Retained?**	**Reason for Removal**
65. the university to make me aware of any third party involvement in the analysis process of my educational data	No	Content Overlap
66. the university to only hold my collected educational data for a limited time before it is destroyed	Yes	
67. the analytics to not provide me with clear guidance on how to improve my learning	No	Content Overlap
68. the university will not give me the right to withdraw from the collection of my educational data when consent is given	No	Content Overlap
69. the analytics to be user friendly and complete	No	Content Overlap
70. the university will not use the analysis of my educational data to improve future students’ academic success	No	Content Overlap

Based on the information provided to me about learning analytics, I expect…	Retained?	Reason for Removal
71. the university to let me have a say on what data is collected and how it will be used	No	Content Overlap
72. the university to provide a reference frame of how my analytics align with the learning objectives of a module	No	Content Overlap
73. to not be made aware of course objectives in order to fully understand analytics	No	Content Overlap
74. the amount of incomplete educational data to be minimised for the use in analytics	No	Content Overlap
75. to not be informed about what analytics are actually measuring	No	Content Overlap
76. the university to release analyses of my educational data weekly to prevent me from being overwhelmed	Yes	

Based on the information provided to me about learning analytics, I expect…	**Retained?**	**Reason for Removal**
77. the analytics will provide more detailed information on my learning progress	No	Content Overlap
78. to not have the right to decide when and often I consult my analytics	No	Content Overlap
79. the university will not use the analysis of my educational data to demonstrate compliance with quality assurance arrangements	No	Unclear Item

Note: Following peer review, amendments to the wording of the retained items were made in order to improve the clarity and understanding. An additional item was also introduced based on the feedback of the learning analytics experts, which was ‘The feedback from analytics will be presented as a visualisation (e.g., in the form of a dashboard)’ (Item 37, Appendix 2.3).

Appendix 2.3. 37-Item Student Expectations of Learning Analytics Services Questionnaire used in Study One

The university will:	Retained?	Reason for Removal
1. Provide me with guidance on when and how often I should consult the analysis of my educational data	Yes	
2. Ask for my consent before offering support (e.g., tutor advice or counselling) based upon the analysis of my educational data	No	Did not load onto a factor
3. Take into my account personal circumstances (e.g., health, financial status) when analysing my educational data	No	Did not load onto a factor
4. Warn me if withdrawing from the analytic process will lead to a negative impact on my academic progress (e.g., grades)	No	Did not load onto a factor
5. Explain all analytic processes as clearly as possible (e.g., how my educational data is collected, analysed, and used)	Yes	
6. Ask for my consent before using any sensitive data about myself (e.g., ethnicity, religion, etc.)	Yes	

The university will:	Retained?	Reason for Removal
7. Make me aware of who can view my educational data (e.g., teaching staff, third party companies)	No	Highly correlated with other items.
8. Not use the analysis of my educational data for only its own benefits (e.g., higher education service quality assurance)	No	Did not load onto a factor
9. Provide real-time support (e.g., advice from tutors) based on the analyses of my educational data	Yes	
10. Reassure me that all my educational data will be kept securely and used properly	Yes	
11. Ask for my consent before my educational data is to be outsourced to third party companies	Yes	
12. Protect my privacy while collecting and using my educational data	No	Highly correlated with other items.
13. Regularly contact me about my learning progress based on the analysis of my educational data	Yes	
14. Ask for my explicit consent for the collection, use, and analysis of any of my educational data (e.g., grades, attendance, virtual learning environment accesses, etc.)	Yes	

The university will:	Retained?	Reason for Removal
15. Give me the right to opt-out of data collection and analysis	Yes	
16. Only hold my collected educational data for a limited time before it is destroyed	No	Low Cronbach's Alpha Value
17. Ask for my consent again if my educational data is being used for a different purpose than originally stated	Yes	
The analytics will:	**Retained?**	**Reason for Removal**
18. Promote student decision making (e.g., encouraging you to adjust your set learning goals based upon the feedback provided to you, draw your own conclusions from the outputs received, etc.)	Yes	
19. Collect and present data that is accurate (i.e., free from inaccuracies, such as incorrect grades)	Yes	
20. Clearly link my data to my progression towards my learning goals	Yes	
21. Be presented in a format that is both understandable and easy to read	Yes	

The analytics will:	Retained?	Reason for Removal
22. Be used to improve the educational experience in a module/course/programme (e.g., identifying problems in the feedback, assessments, learning activities, etc.)	Yes	
23. Clearly show how my learning performance/progress compares to that of my peers	No	Low Cronbach's Alpha Value
24. Provide me with regularly update feedback as I progress through my studies	No	Highly correlated with other items.
25. Show me what is the optimum pathway through my studies (e.g., guide me through the necessary learning resources to achieve my learning goals)	No	Highly correlated with other items.
26. Present me with a complete profile of my learning across every module (e.g., number of accesses to online material, attendance, etc.)	Yes	
27. Notify my teachers early on if I am underperforming, at-risk of failing, or if I could improve my learning in a module/degree programme	No	Highly correlated with other items.

The analytics will:	**Retained?**	**Reason for Removal**
28. Be used to improve my learning experience and my overall well-being	No	Highly correlated with other items.
29. Be used to build better relationships between myself and teaching staff (i.e., teaching staff should have a better understanding of my learning performance)	No	Highly correlated with other items.
The teaching staff will:	**Retained?**	**Reason for Removal**
30. Be competent in incorporating analytics in the feedback and support they provide to me	Yes	
31. 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	Yes	
32. Make me aware of how the analytics align with the learning objectives of the module	No	Highly correlated with other items.
The feedback from analytics will:	**Retained?**	**Reason for Removal**
33. Be used to promote skill development (e.g., essay writing, referencing, etc.)	Yes	

The feedback from analytics will:	Retained?	Reason for Removal
34. Be presented to me through text (e.g., emails)	No	Low Cronbach's Alpha Value
35. Be given to me in person (e.g., by teachers, supervisors, advisors, or personal tutors)	No	Low Cronbach's Alpha Value
36. Be released at fixed intervals (e.g., weekly) to prevent me from being overwhelmed by information	No	Low Cronbach's Alpha Value
37. Be presented as a visualisation (e.g., in the form of a dashboard)	No	Did not load onto a factor

Appendix 2.4. Factor Loadings Obtained from Study One for 19-Item Desired Expectations Scale

Item	Service Expectations	Ethical and Privacy Expectations	Communalities
20. The analytics will clearly link my data to my progression towards my learning goals	.76		.63
31. 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		.53
33. The feedback from analytics will be used to promote skill development (e.g., essay writing, referencing, etc.)	.71		.47
26. The analytics will present me with a complete profile of my learning across every module (e.g., number of accesses to online material, attendance, etc.)	.70		.50
30. The teaching staff will be competent in incorporating analytics in the feedback and support they provide to me	.70		.47
9. The university will provide real-time support (e.g., advice from tutors) based on the analyses of my educational data	.66		.48
13. The university will regularly contact me about my learning progress based on the analysis of my educational data	.59		.37
22. The analytics will be used to improve the educational experience in a module/course/programme (e.g., identifying problems in the feedback, assessments, learning activities, etc.)	.55		.38
18. The analytics will promote student decision making (e.g., encouraging you to adjust your set learning goals based upon the feedback provided to you, draw your own conclusions from the outputs received, etc.)	.49		.34
1. The university will provide me with guidance on when and how often I should consult the analysis of my educational data	.46		.28
17 The university will ask for my consent again if my educational data is being used for a different purpose than originally stated		.74	.55
10. The university will reassure me that all my educational data will be kept securely and used properly		.67	.49

Appendix 2.4. Factor Loadings Obtained from Study One for 19-Item Desired Expectations Scale

Item	Service Expectations	Ethical and Privacy Expectations	Communalities
11. The university will ask for my consent before my educational data is to be outsourced to third party companies		.65	.40
6. The university will ask for my consent before using any sensitive data about myself (e.g., ethnicity, religion, etc.)		.62	.36
15. The university will give me the right to opt-out of data collection and analysis		.61	.34
5. The university will explain all analytic processes as clearly as possible (e.g., how my educational data is collected, analysed, and used)		.56	.33
14. The university will ask for my explicit consent for the collection, use, and analysis of any of my educational data (e.g., grades, attendance, virtual learning environment accesses, etc.)		.53	.26
21. The analytics will be presented in a format that is both understandable and easy to read		.50	.50
19. The analytics will collect and present data that is accurate (i.e., free from inaccuracies, such as incorrect grades)		.43	.29

Appendix 2.5. Factor Loadings Obtained from Study One for 19-Item Predicted Expectations Scale

Item	Service Expectations	Ethical and Privacy Expectations	Communalities
31. 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	.75		.48
26. The analytics will present me with a complete profile of my learning across every module (e.g., number of accesses to online material, attendance, etc.)	.69		.43
20. The analytics will clearly link my data to my progression towards my learning goals	.68		.48
30. The teaching staff will be competent in incorporating analytics in the feedback and support they provide to me	.67		.58
33. The feedback from analytics will be used to promote skill development (e.g., essay writing, referencing, etc.)	.65		.46
9. The university will provide real-time support (e.g., advice from tutors) based on the analyses of my educational data	.65		.44
13. The university will regularly contact me about my learning progress based on the analysis of my educational data	.59		.39
1. The university will provide me with guidance on when and how often I should consult the analysis of my educational data	.57		.36
18. The analytics will promote student decision making (e.g., encouraging you to adjust your set learning goals based upon the feedback provided to you, draw your own conclusions from the outputs received, etc.)	.53		.32
22. The analytics will be used to improve the educational experience in a module/course/programme (e.g., identifying problems in the feedback, assessments, learning activities, etc.)	.44		.40
17. The university will ask for my consent again if my educational data is being used for a different purpose than originally stated		.76	.58
6. The university will ask for my consent before using any sensitive data about myself (e.g., ethnicity, religion, etc.)		.72	.47

Appendix 2.5. Factor Loadings Obtained from Study One for 19-Item Predicted Expectations Scale (Continued)

Item	Service Expectations	Ethical and Privacy Expectations	Communalities
11. The university will ask for my consent before my educational data is to be outsourced to third party companies		.70	.47
15. The university will give me the right to opt-out of data collection and analysis		.67	.40
10. The university will reassure me that all my educational data will be kept securely and used properly		.62	.41
14. The university will ask for my explicit consent for the collection, use, and analysis of any of my educational data (e.g., grades, attendance, virtual learning environment accesses, etc.)		.57	.42
5. The university will explain all analytic processes as clearly as possible (e.g., how my educational data is collected, analysed, and used)		.48	.38
21. The analytics will be presented in a format that is both understandable and easy to read		.47	.51
19. The analytics will collect and present data that is accurate (i.e., free from inaccuracies, such as incorrect grades)		.47	.34

Appendix 2.6. 19-Item Student Expectations of Learning Analytics Services Questionnaire used in Study Two

Items	Retained?	Reason for Removal
1. The university will provide me with guidance on how to access the analysis of my educational data	No	Did not load onto a factor
2. 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)	No	Did not load onto a factor
3. The university will ask for my consent before using any identifiable data about myself (e.g., ethnicity, age, and gender)	Yes	
4. The university will provide support (e.g., advice from personal tutors) as soon as possible if the analysis of my educational data suggests I may be having some difficulty or problem (e.g., I am underperforming or at-risk of failing)	No	Item cross-loads
5. The university will ensure that all my educational data will be kept securely	Yes	

Items	**Retained?**	**Reason for Removal**
6. The university will ask for my consent before my educational data is outsourced for analysis by third party companies	Yes	
7. The university will regularly update me about my learning progress based on the analysis of my educational data	Yes	
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)	Yes	
9. The university will give me the right to opt-out of data collection and analysis even if the action reduces the opportunities to provide me with personal support	No	Did not load onto a factor
10. The university will request further consent if my educational data is being used for a purpose different to what was originally stated	Yes	

Items	Retained?	Reason for Removal
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)	Yes	
12. The learning analytics service will collect and present data that is accurate (i.e., free from inaccuracies such as incorrect grades)	No	Did not load onto a factor
13. The learning analytics service will show how my learning progress compares to my learning goals/the course objectives	Yes	
14. The feedback from the learning analytics service will be presented in a format that is both understandable and easy to read	No	Did not load onto a factor

Items	Retained?	Reason for Removal
15. The feedback from the learning analytics service will be used to improve the educational experience in a module/course/programme (e.g., identifying problems in the feedback, assessments, and learning activities)	No	Item cross-loads
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)	Yes	
17. The teaching staff will be competent in incorporating analytics into the feedback and support they provide to me	Yes	
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	Yes	
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	Yes	

Changes to item wordings of the 37-item instrument used in study one based on feedback from students and learning analytics experts:

Item 1 – In the 37-item instrument this item was 'The University will provide me with guidance on when and how often I should consult the analysis of my educational data', this was changed to 'The University will provide me with guidance on how to access the analysis of my educational data'.

Item 2 – In the 37-item instrument this item was 'The University will explain all analytic processes as clearly as possible (e.g., how my educational data is collected, analysed, and used)', this was changed to '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)'.

Item 3 – In the 37-item instrument this item was 'The University will ask for my consent before using any sensitive data about myself (e.g., ethnicity, religion, etc.)', this was changed to 'The University will ask for my consent before using any identifiable data about myself (e.g., ethnicity, age, and gender)'.

Item 4 – In the 37-item instrument this item was 'The University will provide real-time support (e.g., advice from tutors) based on the analyses of my educational data', this was changed to 'The university will provide support (e.g., advice from personal tutors) as soon as possible if the analysis of my educational data suggests I may be having some difficulty or problem (e.g., I am underperforming or at-risk of failing)'.

Item 5 – In the 37-item instrument this item was 'The University will reassure me that all my educational data will be kept securely and used properly', this was changed to 'The University will ensure that all my educational data will be kept securely'.

Item 6 – No changes made to item wording.

Item 7 – In the 37-item instrument this item was 'The University will regularly contact me about my learning progress based on the analysis of my educational data', this was changed to 'The University will regularly update me about my learning progress based on the analysis of my educational data'.

Item 8 – In the 37-item instrument this item was 'The University will ask for my explicit consent for the collection, use, and analysis of any of my educational data (e.g., grades, attendance, virtual learning environment accesses, etc.)', this was changed to '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)'.

Item 9 – In the 37-item instrument this item was 'The University will give me the right to opt-out of data collection and analysis', this was changed to 'The University will give me the right to opt-out of data collection and analysis even if the action reduces the opportunities to provide me with personal support'.

Item 10 – In the 37-item instrument this item was 'The University will ask for my consent again if my educational data is being used for a different purpose than originally stated', this was changed to 'The University will request further consent if my educational data is being used for a purpose different to what was originally stated'.

Item 11 – In the 37-item version of the instrument this item was 'The analytics will promote student decision making (e.g., encouraging you to adjust your set learning goals based upon the feedback provided to you, draw your own conclusions from the outputs received, etc.)', this was changed to '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)'.

Item 12 – In the 37-item instrument this item was 'The analytics will collect and present data that is accurate (i.e., free from inaccuracies, such as incorrect grades)', this was changed to 'The learning analytics service will collect and present data that is accurate (i.e., free from inaccuracies such as incorrect grades)'.

Item 13 – In the 37-item instrument this item was 'The analytics will clearly link my data to my progression towards my learning goals', this was changed to 'The learning analytics service will show how my learning progress compares to my learning goals/the course objectives'.

Item 14 – In the 37-item instrument this item was 'The analytics will be presented in a format that is both understandable and easy to read', this was changed to 'The feedback from the learning analytics service will be presented in a format that is both understandable and easy to read'.

Item 15 – In the 37-item instrument this item was 'The analytics will be used to improve the educational experience in a module/course/programme (e.g., identifying problems in the feedback, assessments, learning activities, etc.)', this was changed to 'The feedback from the learning analytics service will be used to improve the educational experience in a module/course/programme (e.g., identifying problems in the feedback, assessments, and learning activities)'.

Item 16 – In the 37-item instrument this item was 'The analytics will present me with a complete profile of my learning across every module (e.g., number of accesses to online material, attendance, etc.)', this was changed to '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)'.

Item 17 – In the 37-item instrument this item was 'The teaching staff will be competent in incorporating analytics in the feedback and support they provide to me', this was changed to 'The teaching staff will be competent in incorporating analytics into the feedback and support they provide to me'.

Item 18 – No changes to item wording.

Item 19 – In the 37-item instrument this item was 'The feedback from analytics will be used to promote skill development (e.g., essay writing, referencing, etc.)', this was changed to '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'.

Appendix 2.7. 12-Item Student Expectations of Learning Analytics Services Questionnaire used in Study Three

Factor Key	Items
E1	1. The university will ask for my consent before using any identifiable data about myself (e.g., ethnicity, age, and gender)
E2	2. The university will ensure that all my educational data will be kept securely
E3	3. The university will ask for my consent before my educational data is outsourced for analysis by third party companies
S1	4. The university will regularly update me about my learning progress based on the analysis of my educational data
E4	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)
E5	6. The university will request further consent if my educational data is being used for a purpose different to what was originally stated

Factor Key	Items
S2	7. 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)
S3	8. The learning analytics service will show how my learning progress compares to my learning goals/the course objectives
S4	9. 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)
S5	10. The teaching staff will be competent in incorporating analytics into the feedback and support they provide to me
S6	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
S7	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

Appendix 2.8. Exploratory Structural Equation Model Factor Loadings for the Ideal Expectation Scale

Items	Factor One		Factor Two	
	Estimate	Standard Error	Estimate	Standard Error
1	.69	.05	-.01	.02
2	.70	.07	.04	.08
3	.79	.06	-.03	.07
4	.04	.08	.66	.06
5	.53	.07	.19	.07
6	.71	.06	.10	.08
7	.13	.07	.74	.05
8	-.06	.07	.90	.04
9	-.004	.006	.76	.03
10	.05	.09	.80	.05
11	.02	.08	.65	.06
12	-.13	.09	.86	.06

Appendix 2.9. Residual Correlations for the Ideal Expectation Scale Confirmatory Factor Analysis

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12
Q1	-											
Q2	0.14	-										
Q3	0	0.08	-									
Q4	-0.1	-0.01	0.01	-								
Q5	0.05	-0.19	0	0.09	-							
Q6	-0.06	0.01	0.04	0.08	-0.04	-						
Q7	0.02	-0.06	0.05	-0.02	0.13	0.12	-					
Q8	-0.08	0	-0.06	0.04	-0.01	-0.02	0.08	-				
Q9	-0.06	0	-0.05	-0.06	0.07	0	0.03	0.04	-			
Q10	0.02	-0.06	0	0.02	0.05	0.06	-0.08	-0.03	-0.01	-		
Q11	0.04	0.09	-0.05	-0.07	0.04	-0.05	-0.11	-0.05	0.01	0.02	-	
Q12	-0.04	0.01	-0.1	0.03	-0.05	-0.12	-0.05	0	-0.01	0.05	0.17	-

Appendix 2.10. Exploratory Structural Equation Model Factor Loadings for the Predicted Expectation Scale

Items	Factor One		Factor Two	
	Estimate	Standard Error	Estimate	Standard Error
1	.66	.07	.13	.08
2	.79	.06	-.05	.07
3	.83	.03	-.006	.006
4	.21	.08	.64	.06
5	.56	.06	.21	.07
6	.77	.05	.11	.07
7	.09	.08	.79	.05
8	-.06	.07	.94	.04
9	-.003	.004	.81	.03
10	.11	.08	.77	.05
11	.15	.08	.66	.06
12	-.09	.07	.82	.05

Appendix 2.11. Residual Correlations for the Predicted Expectation Scale Confirmatory Factor Analysis

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12
Q1	-											
Q2	0.11	-										
Q3	-0.02	0.12	-									
Q4	0.1	0.04	-0.03	-								
Q5	-0.05	-0.12	-0.03	0.13	-							
Q6	-0.11	0.03	0.06	0.08	0.02	-						
Q7	0.07	-0.04	-0.01	-0.01	0.05	-0.02	-					
Q8	-0.03	-0.08	-0.09	-0.02	-0.02	-0.02	0.08	-				
Q9	-0.06	-0.05	-0.02	-0.02	0.02	-0.02	0.01	0.11	-			
Q10	0.03	-0.05	0.01	-0.04	0.1	0.01	-0.04	-0.01	-0.01	-		
Q11	0.07	0.04	0.04	-0.08	0	0.03	-0.07	-0.04	-0.08	0.03	-	
Q12	-0.05	-0.1	-0.09	-0.04	-0.03	-0.05	-0.01	0.03	0.04	0.01	0.15	-

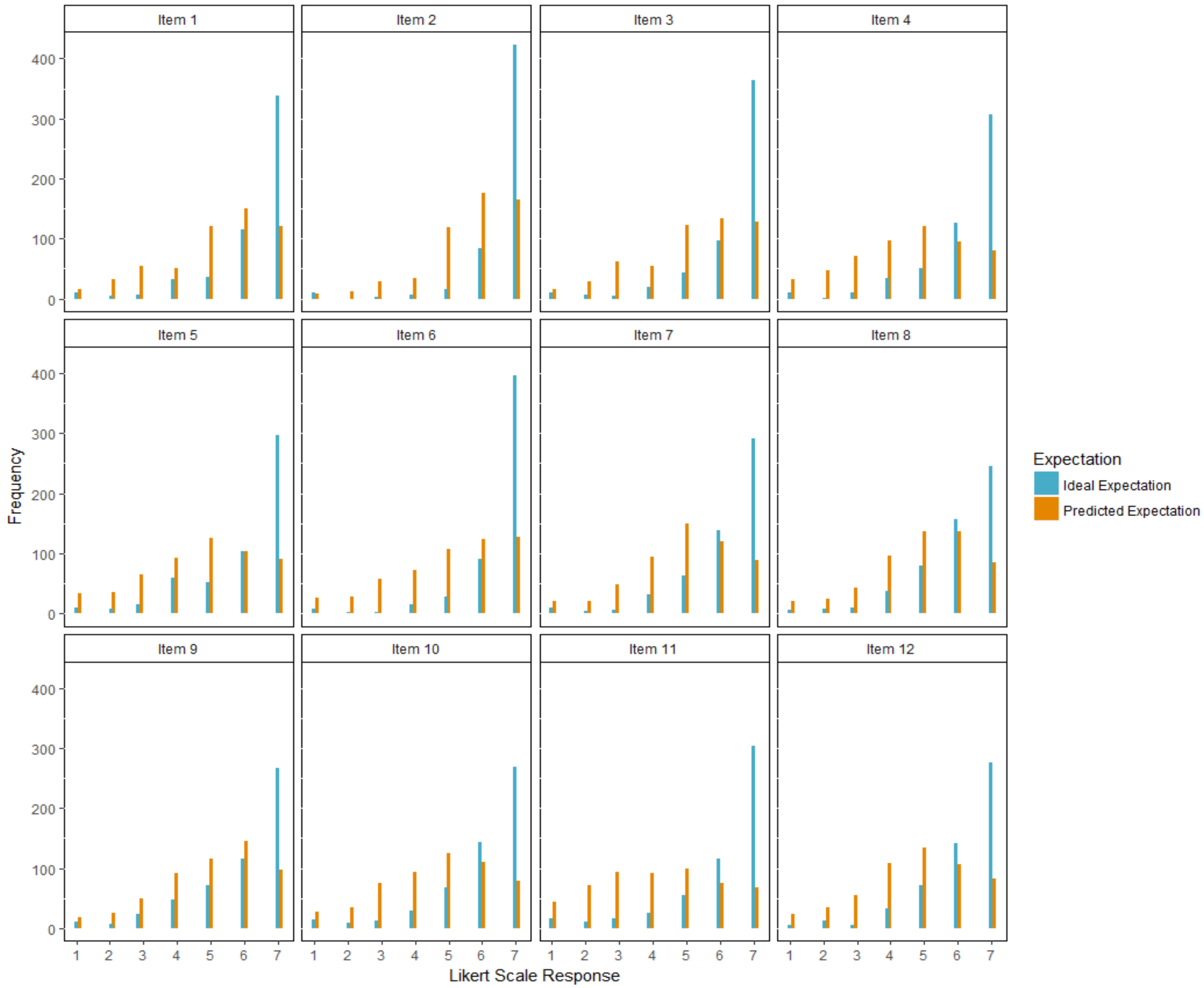
Appendix 3: Assessing the validity of a learning analytics expectation instrument: A multinational study

Appendix 3.1. Original Version of the SELAQ.

Factor	Items
Ethical and Privacy Expectations	1. The university will ask for my consent before using any identifiable data about myself (e.g., ethnicity, age, and gender)
Ethical and Privacy Expectations	2. The university will ensure that all my educational data will be kept securely
Ethical and Privacy Expectations	3. The university will ask for my consent before my educational data is outsourced for analysis by third party companies
Service Expectations	4. The university will regularly update me about my learning progress based on the analysis of my educational data
Ethical and Privacy Expectations	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)
Ethical and Privacy Expectations	6. The university will request further consent if my educational data is being used for a purpose different to what was originally stated
Service Expectations	7. 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)
Service Expectations	8. The learning analytics service will show how my learning progress compares to my learning goals/the course objectives
Service Expectations	9. 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)
Service Expectations	10. The teaching staff will be competent in incorporating analytics into the feedback and support they provide to me
Service Expectations	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
Service Expectations	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

Appendix 3.2. Estonian Student Sample Item Response Distributions for Each Scale

Appendix 3.3. Spanish Student Sample Item Response Distributions for Each Scale



Appendix 3.4. Dutch Student Sample Item Response Distributions for Each Scale

Appendix 3.5. Estonian Version of the SELAQ

1. Ülikool küsib minu nõusolekut enne minu kohta käivate identifitseeritavate andmete kasutamist
2. Ülikool tagab, et minu hariduslikke andmeid hoitakse turvaliselt
3. Ülikool küsib eelnevalt minu nõusolekut, kui jagab välja minu hariduslikke andmeid kolmandatele osapooltele analüüsimise eesmärkidel
4. Ülikool hoiab mind regulaarselt kursis minu arenguga õppetöös tuginedes minu hariduslike andmete analüüsimisele
5. Ülikool küsib minu nõusolekut, et koguda, kasutada ja analüüsida minu hariduslikke andmeid (nt: hinded, õppetöös osalemine, veebipõhise õpikeskkonna kasutamine)
6. Ülikool küsib minult täiendavat nõusolekut, kui minu hariduslikke andmeid kasutatakse muul eesmärgil, kui algselt märgitud
7. Õpianalüütika teenust kasutatakse õppijate otsustusprotsesside toetamiseks (nt oma õpieesmärkide sõnastamise julgustamine tuginedes tagasisidele, mida õppija on saanud; järelduste tegemine lähtuvalt õpitulemustest)
8. Õpianalüütika teenus näitab mulle, kuidas minu areng kursuse jooksul suhestub kursuse eesmärkidega ning enda poolt seatud õpieesmärkidega
9. Õpianalüütika teenus näitab mulle täielikku profiili minu õppimisest moodulite ja kursuste üleselt (nt. veebipõhiste õppematerjalidele ligipääs, kursustel kohalkäimine)
10. Õppejõud on pädevad, et integreerida õpianalüütika tulemused tagasisidesse ja toetusesse, mida nad mulle kursusel annavad
11. Õppejõud on kohustatud tegutsema (nt mind toetama), kui analüütika näitab, et ma olen läbikukkumise ohus, alasoorituses või kui võiksin parendada oma õppimist
12. Tagasisidet, mida õpianalüütika teenus annab, kasutatakse akadeemiliste ja professionaalsete oskuste arendamiseks (essee kirjutamine, viitamine) minu tulevaseks tööalaseks vajaduseks.

Ideal Expectation Scale: Ideaalis ma loodan, et nii juhtub

Predicted Expectation Scale: Ma eeldan, et reaalselt nii juhtub

Appendix 3.6. Tallinn Student Sample: Standardised and Unstandardised Loadings Obtained from the Ideal Expectations CFA

Item	Latent Variable	Unstandardised Loading	Standardised Loading	Standard Error
1	Ethical and Privacy Expectations	1.00	.73	.05
2	Ethical and Privacy Expectations	1.04	.77	.05
3	Ethical and Privacy Expectations	1.11	.81	.04
5	Ethical and Privacy Expectations	1.13	.83	.04
6	Ethical and Privacy Expectations	1.13	.83	.04
4	Service Expectations	1.00	.74	.04
7	Service Expectations	1.01	.75	.04
8	Service Expectations	1.11	.83	.03
9	Service Expectations	1.15	.85	.03
10	Service Expectations	1.00	.74	.04
11	Service Expectations	.61	.45	.06
12	Service Expectations	.86	.64	.05

Appendix 3.7. Tallinn Student Sample: Residual Correlations from the ESEM for the Ideal Expectation Scale

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12
Q1	-											
Q2	.10	-										
Q3	.01	.02	-									
Q4	-.08	-.01	-.04	-								
Q5	-.03	-.04	-.01	.10	-							
Q6	-.05	-.02	.03	.04	.05	-						
Q7	-.04	-.06	.02	.04	-.01	-.02	-					
Q8	.01	-.05	0	-.06	.03	-.04	.12	-				
Q9	0	-.01	-.06	-.02	-.01	.02	.10	.04	-			
Q10	.10	.03	-.02	-.01	-.07	-.04	-.03	0	.03	-		
Q11	-.01	.10	.04	.06	-.02	-.04	-.08	-.05	-.06	-.03	-	
Q12	.01	-.01	.03	-.01	-.01	.06	-.10	-.02	-.06	.03	.13	-

Appendix 3.8. Tallinn Student Sample: Standardised and Unstandardised Loadings Obtained from the Predicted Expectations CFA

Item	Latent Variable	Unstandardised Loading	Standardised Loading	Standard Error
1	Ethical and Privacy Expectations	1.00	.77	.04
2	Ethical and Privacy Expectations	1.01	.78	.04
3	Ethical and Privacy Expectations	1.11	.86	.03
5	Ethical and Privacy Expectations	1.21	.93	.02
6	Ethical and Privacy Expectations	1.04	.80	.03
4	Service Expectations	1.00	.79	.04
7	Service Expectations	1.06	.83	.03
8	Service Expectations	1.00	.79	.03
9	Service Expectations	1.02	.80	.03
10	Service Expectations	.97	.77	.04
11	Service Expectations	.80	.63	.05
12	Service Expectations	.93	.73	.04

Appendix 3.9. Tallinn Student Sample: Residual Correlations from the ESEM for the Predicted Expectation Scale

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12
Q1	-											
Q2	-.02	-										
Q3	.02	.05	-									
Q4	0	-.02	-.10	-								
Q5	.04	-.04	-.03	.09	-							
Q6	-.05	.02	.01	.05	0	-						
Q7	.01	-.02	.03	.02	-.05	-.01	-					
Q8	-.02	.02	-.01	-.07	-.03	-.01	.12	-				
Q9	.01	-.01	-.02	0	.04	-.04	.02	.10	-			
Q10	.01	-.02	0	.04	.02	0	-.01	-.05	0	-		
Q11	0	.05	.02	-.01	-.04	.01	-.03	-.04	-.11	.04	-	
Q12	-.01	.01	.04	-.02	0	.02	-.08	-.02	-.02	-.02	.12	-

Appendix 3.10. Spanish Version of the SELAQ

1. La universidad solicitará mi consentimiento antes de utilizar cualquier dato de carácter personal (por ejemplo, etnia, edad o género)
2. La universidad se asegurará de mantener seguros mis datos educativos
3. La universidad solicitará mi consentimiento antes de compartir mis datos educativos con otras instituciones o empresas
4. La universidad me informará regularmente sobre mi progreso de aprendizaje, en base al análisis de mis datos educativos
5. La universidad solicitará mi consentimiento para recopilar, utilizar y analizar cualquiera de mis datos educativos (por ejemplo, calificaciones, datos de asistencia o accesos a entornos de aprendizaje electrónico)
6. La universidad solicitará un nuevo consentimiento si mis datos educativos se van a utilizar para un propósito diferente del original
7. Los servicios asociados a la analítica del aprendizaje se utilizarán para promover la toma de decisiones por parte de los estudiantes (por ejemplo, animando al estudiante a ajustar sus propios objetivos de aprendizaje mediante la información de realimentación que se le proporciona, o animándole a que saque sus propias conclusiones en base a los resultados obtenidos)
8. Los servicios asociados a la analítica del aprendizaje compararán mi progreso con respecto a mis objetivos de aprendizaje, o con respecto a los objetivos del curso
9. Los servicios asociados a la analítica del aprendizaje me mostrarán un perfil completo de mi aprendizaje en cada uno de los módulos (por ejemplo, número de accesos a un recurso electrónico o datos de asistencia)
10. El personal docente será capaz de incorporar los resultados, obtenidos a través del análisis de mis datos educativos, en la información y en la ayuda que se me proporcionará
11. El personal docente tendrá la obligación de actuar (es decir, de ayudarme) si los resultados muestran que estoy en riesgo de suspender, si muestran que mi rendimiento está por debajo de la media, o si muestran que puedo mejorar mi aprendizaje
12. La información obtenida a través de los servicios asociados a la analítica del aprendizaje, se utilizará para promover el desarrollo de habilidades académicas y profesionales (por ejemplo, la redacción de ensayos) útiles para mi futura empleabilidad

Ideal Expectation Scale: Idealmente, me gustaría que sucediera

Predicted Expectation Scale: En la realidad, creo que sucederá

Appendix 3.11. Spanish Student Sample: Ideal Expectations Scale Factor Loadings Obtained from the ESEM

Items	Ethical and Privacy Expectations		Service Expectations	
	Estimate	Standard Error	Estimate	Standard Error
1	.67	.05	-.06	.05
2	.66	.05	.08	.06
3	.85	.04	-.06	.05
4	.13	.05	.62	.04
5	.75	.03	.01	.03
6	.79	.04	.02	.03
7	.09	.05	.72	.04
8	0	.02	.82	.02
9	.02	.04	.79	.03
10	-.03	.04	.83	.03
11	-.08	.05	.78	.04
12	.01	.03	.76	.03

Appendix 3.12. Spanish Student Sample: Residual Correlations from the CFA for the Ideal Expectation Scale

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12
Q1	-											
Q2	-.05	-										
Q3	.06	.04	-									
Q4	-.01	.05	.06	-								
Q5	.05	-.10	.02	.06	-							
Q6	.01	0	-.04	.05	.02	-						
Q7	.02	.04	-.01	0	.03	.06	-					
Q8	-.07	.05	-.02	.02	-.02	-.01	.06	-				
Q9	-.06	.04	-.04	-.04	-.01	.06	-.03	.02	-			
Q10	-.01	.02	-.02	-.02	-.05	-.04	-.04	-.01	.06	-		
Q11	-.05	-.03	-.07	-.03	.01	-.07	-.01	-.02	-.03	.06	-	
Q12	.03	.01	-.04	-.05	.03	-.02	-.05	-.04	.02	0	.14	-

Appendix 3.13. Spanish Student Sample: Predicted Expectations Scale Factor Loadings Obtained from the ESEM

Items	Ethical and Privacy Expectations		Service Expectations	
	Estimate	Standard Error	Estimate	Standard Error
1	.77	.02	0	0
2	.75	.04	.04	.05
3	.92	.04	-.11	.05
4	.07	.04	.72	.04
5	.59	.04	.24	.04
6	.68	.04	.20	.05
7	0	.01	.84	.02
8	-.06	.03	.91	.02
9	-.05	.04	.84	.03
10	.02	.04	.81	.03
11	.05	.04	.76	.03
12	.16	.04	.69	.03

Appendix 3.14. Spanish Student Sample: Residual Correlations from the CFA for the Predicted Expectation Scale

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12
Q1	-											
Q2	.06	-										
Q3	.09	.10	-									
Q4	-.03	-.05	-.01	-								
Q5	-.02	-.09	-.01	.16	-							
Q6	-.04	-.04	.02	.04	-.05	-						
Q7	-.01	-.01	-.07	.02	.04	.02	-					
Q8	-.05	-.04	-.06	0	.01	.01	.09	-				
Q9	-.03	-.04	-.07	.01	.02	.02	.04	.11	-			
Q10	-.01	0	-.05	-.03	-.01	.01	-.04	-.03	.01	-		
Q11	-.02	.01	-.04	-.01	.02	.02	-.05	-.05	-.04	.09	-	
Q12	.02	.10	.03	-.08	0	.03	-.04	-.04	-.06	.04	.06	-

Appendix 3.15. Dutch Version of the SELAQ

1. De universiteit zal mijn toestemming vragen voordat identificeerbare persoonlijke gegevens worden gebruikt (bijv. etniciteit, leeftijd en geslacht)
2. De universiteit zal ervoor zorgen dat al mijn educatieve gegevens/data veilig worden bewaard
3. De Universiteit zal mijn toestemming vragen voordat mijn educatieve gegevens/data voor analyse beschikbaar wordt gesteld aan derden
4. De universiteit zal mij regelmatig op de hoogte houden van mijn leerprogressie, gebaseerd op de analyses van mijn educatieve gegevens/data
5. De universiteit zal mijn toestemming vragen voor het verzamelen, gebruiken en analyseren van mijn educatieve gegevens/data (bijv. cijfers, aanwezigheid en toegang tot virtuele leeromgevingen)
6. De Universiteit zal mijn verdere toestemming vragen als mijn educatieve gegevens/data gebruikt wordt voor een ander doel dan waar oorspronkelijk toestemming voor is gegeven.
7. De learning analytics dienst zal worden gebruikt om de besluitvorming van studenten te bevorderen (bijv. aanmoedigen dat uw leerdoelen aangepast worden op de terugkoppeling die aan u wordt gegeven en uw eigen conclusies trekken uit de output die u ontvangt)
8. De learning analytics dienst zal mij inzicht verschaffen in hoe mijn voortgang zich verhoud tot mijn leerdoelen/de leerdoelen van de cursus
9. De learning analytics dienst zal me een compleet profiel verschaffen m.b.t. mijn leren binnen elke module (bijv. het aantal keren dat ik toegang heb gehad tot online materiaal en aanwezigheid)
10. Het onderwijzend personeel zal in staat zijn om learning analytics te integreren in de terugkoppeling en ondersteuning die zij mij geven
11. Het onderwijzend personeel heeft de verplichting om in te grijpen als learning analytics aantonen dat ik een cursus niet dreig af te maken, slecht presteer, of als ik mijn leren zou kunnen verbeteren
12. De terugkoppeling van de learning analytics dienst zal worden gebruikt om de ontwikkeling van academische en professionele vaardigheden voor mijn toekomstige inzetbaarheid te bevorderen (zoals het schrijven van essays en het aanhalen van referenties) te bevorderen

Ideal Expectation Scale: In een ideale situatie wil ik dat dit gebeurt

Predicted Expectation Scale: Ik verwacht dat dit in werkelijkheid gebeurt

Appendix 3.16. Dutch Student Sample: Standardised and Unstandardised Loadings Obtained from the Ideal Expectations CFA

Item	Latent Variable	Unstandardised Loading	Standardised Loading	Standard Error
1	Ethical and Privacy Expectations	1.00	.69	.02
2	Ethical and Privacy Expectations	1.17	.81	.02
3	Ethical and Privacy Expectations	1.17	.81	.02
5	Ethical and Privacy Expectations	1.06	.73	.02
6	Ethical and Privacy Expectations	1.20	.83	.02
4	Service Expectations	1.00	.79	.01
7	Service Expectations	1.10	.87	.01
8	Service Expectations	1.14	.90	.01
9	Service Expectations	1.09	.87	.01
10	Service Expectations	1.09	.86	.01
11	Service Expectations	.92	.73	.01
12	Service Expectations	.98	.78	.01

Appendix 3.17. Dutch Student Sample: Residual Correlations from the ESEM for the Ideal Expectation Scale

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12
Q1	-											
Q2	.04	-										
Q3	-.01	.02	-									
Q4	0	-.01	0	-								
Q5	0	-.04	-.01	.01	-							
Q6	-.03	-.02	0	0	.06	-						
Q7	-.02	-.01	.01	.04	0	0	-					
Q8	.01	.01	-.02	.01	-.02	0	.05	-				
Q9	-.01	-.02	.01	0	.02	-.01	-.01	.02	-			
Q10	.02	.02	-.02	-.02	-.02	.01	-.02	-.02	.02	-		
Q11	0	-.01	.01	0	.02	-.01	-.02	-.06	-.03	.02	-	
Q12	0	.03	.02	-.04	.02	.01	-.05	-.01	-.02	.01	.12	-

Appendix 3.18. Dutch Student Sample: Predicted Expectations Scale Factor Loadings Obtained from the ESEM

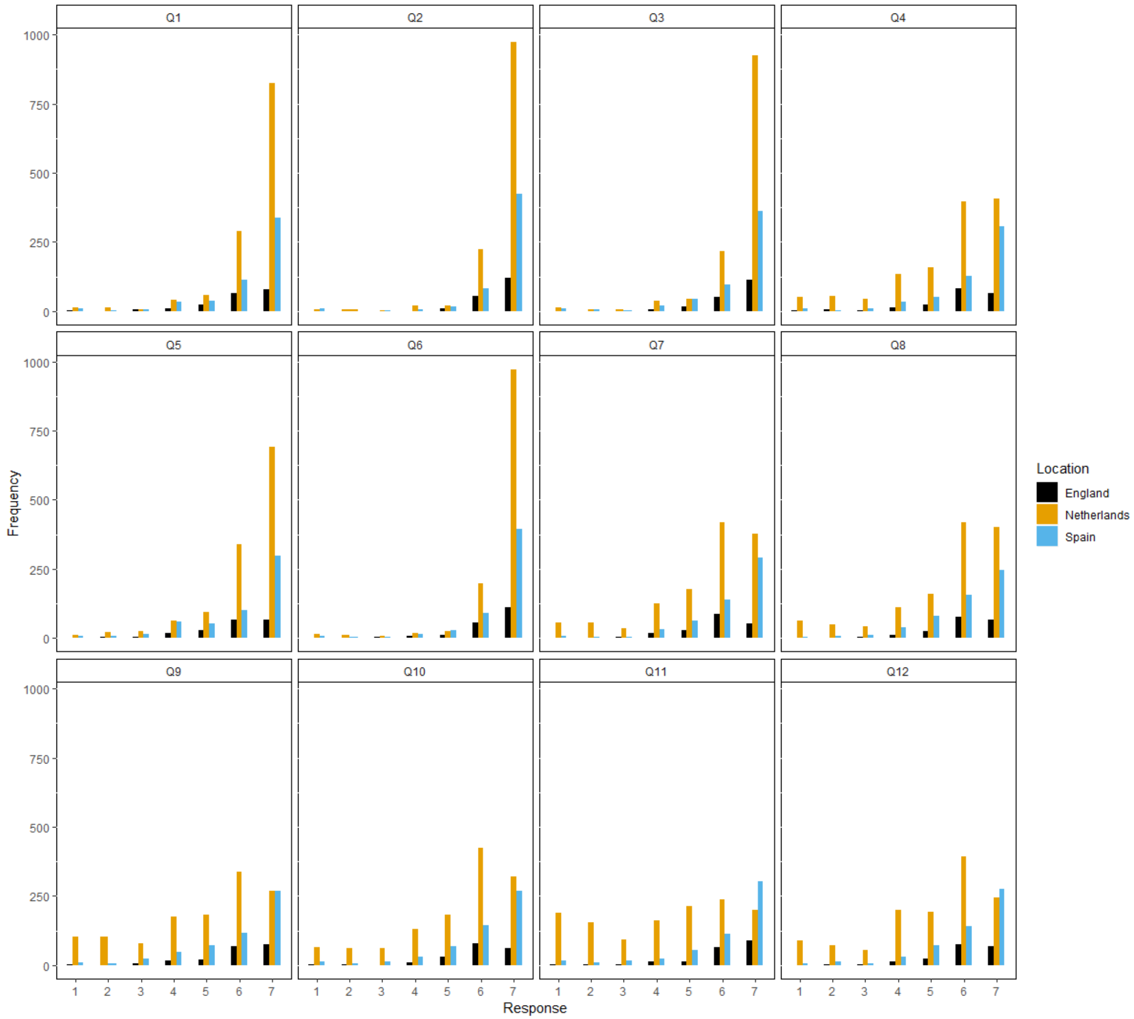
Items	Ethical and Privacy Expectations		Service Expectations	
	Estimate	Standard Error	Estimate	Standard Error
1	.81	.02	-.05	.02
2	.86	.01	-.03	.02
3	.88	.01	.01	0
4	.07	.03	.68	.02
5	.72	.02	.14	.02
6	.81	.01	.10	.02
7	.03	.02	.83	.01
8	0	.01	.85	.01
9	-.13	.02	.88	.01
10	.02	.02	.83	.01
11	-.18	.03	.77	.02
12	0	.01	.80	.01

Appendix 3.19. Dutch Student Sample: Residual Correlations from the CFA for the Predicted Expectation Scale

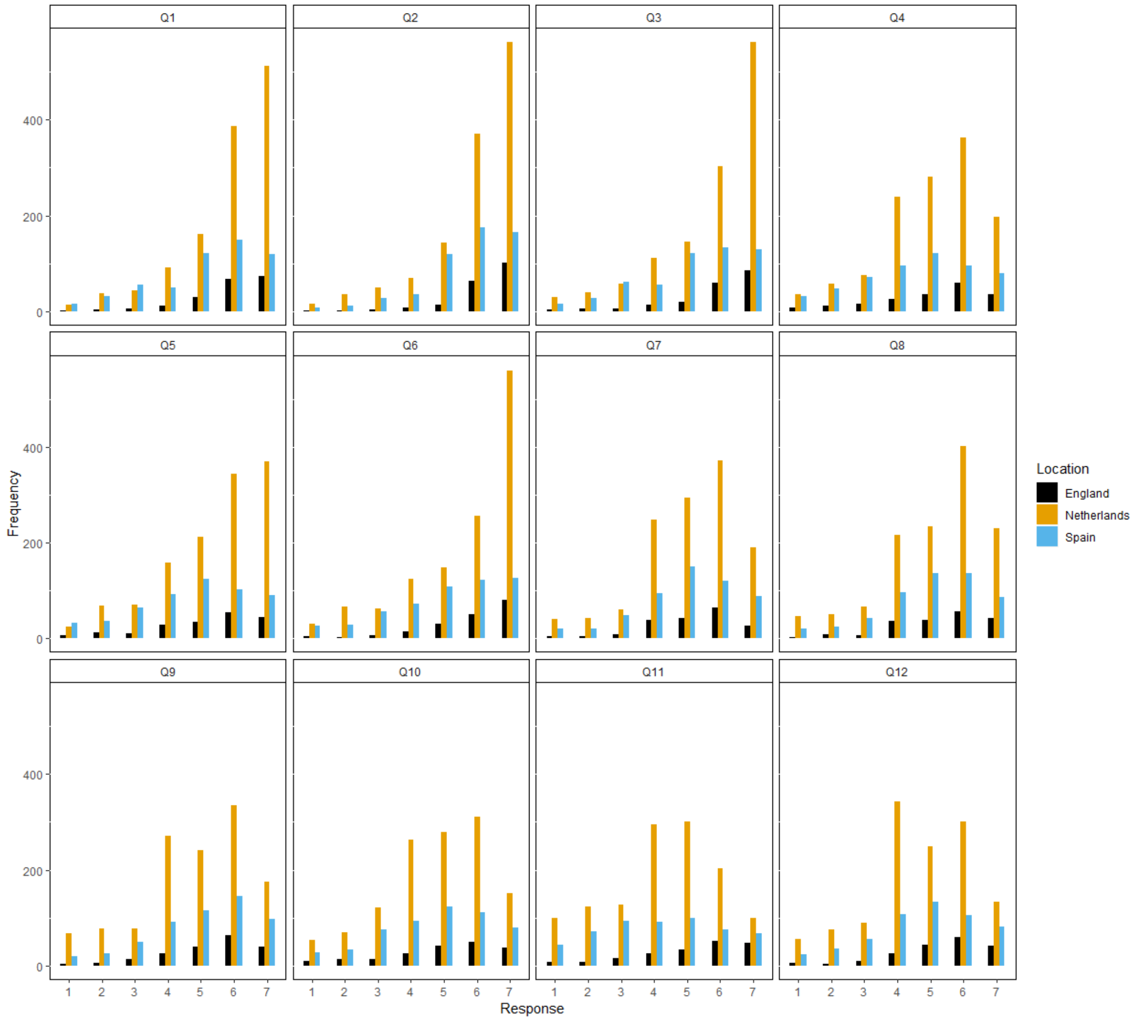
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12
Q1	-											
Q2	.12	-										
Q3	.04	.07	-									
Q4	.02	0	.02	-								
Q5	0	-.07	-.05	.18	-							
Q6	-.04	-.02	0	.06	-.03	-						
Q7	-.01	-.02	0	.01	.08	.08	-					
Q8	-.03	0	-.01	-.02	.05	.03	.04	-				
Q9	-.10	-.10	-.06	.01	0	-.03	.01	.05	-			
Q10	-.02	.02	.01	-.07	.05	.06	-.05	-.03	.02	-		
Q11	-.12	-.13	-.10	.02	-.05	-.08	-.02	-.04	.06	.06	-	
Q12	-.02	.01	0	-.06	.03	.04	-.06	-.03	-.01	.02	.13	-

Appendix 4: Student Expectations of Learning Analytics Services: Do they align? A multinational assessment of measurement invariance

Appendix 4.1. Response Distributions for the Ideal Expectation Scale



Appendix 4.2. Response Distributions for the Predicted Expectation Scale



Appendix 4.3. Response Frequencies for the Ideal Expectation Scale

Location	Item	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
The Netherlands	1	13	14	6	41	59	291	823
The Netherlands	2	5	5	2	19	19	223	974
The Netherlands	3	13	5	8	37	43	216	925
The Netherlands	4	51	54	43	134	160	397	408
The Netherlands	5	10	23	24	64	95	338	693
The Netherlands	6	14	12	8	19	25	197	972
The Netherlands	7	56	57	36	126	176	419	377
The Netherlands	8	65	50	41	110	160	418	403
The Netherlands	9	102	103	79	176	181	336	270
The Netherlands	10	66	63	60	132	182	424	320
The Netherlands	11	190	154	92	160	214	239	198
The Netherlands	12	90	71	53	201	194	393	245
England	1	4	1	5	11	25	65	80
England	2	1	0	1	1	10	56	122
England	3	1	1	0	6	17	53	113
England	4	2	5	2	12	22	83	65
England	5	2	6	4	18	28	67	66
England	6	2	0	3	9	10	56	111
England	7	2	1	5	17	28	86	52
England	8	2	1	6	13	26	77	66
England	9	3	0	6	18	21	68	75
England	10	4	4	1	9	31	80	62
England	11	3	4	4	12	14	65	89
England	12	1	3	2	15	25	76	69
Spain	1	10	4	6	33	37	115	338

Appendix 4.3. Response Frequencies for the Ideal Expectation Scale (Continued)

Location	Item	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
Spain	2	11	0	3	6	16	84	423
Spain	3	11	6	4	19	43	97	363
Spain	4	11	2	10	35	51	127	307
Spain	5	9	7	16	59	52	103	297
Spain	6	8	3	3	15	28	90	396
Spain	7	9	4	6	32	63	138	291
Spain	8	6	7	10	38	80	157	245
Spain	9	11	7	23	47	72	116	267
Spain	10	14	8	12	29	68	143	269
Spain	11	17	10	17	25	55	115	304
Spain	12	6	12	6	32	71	141	275

Appendix 4.4. Response Frequencies for the Predicted Expectation Scale

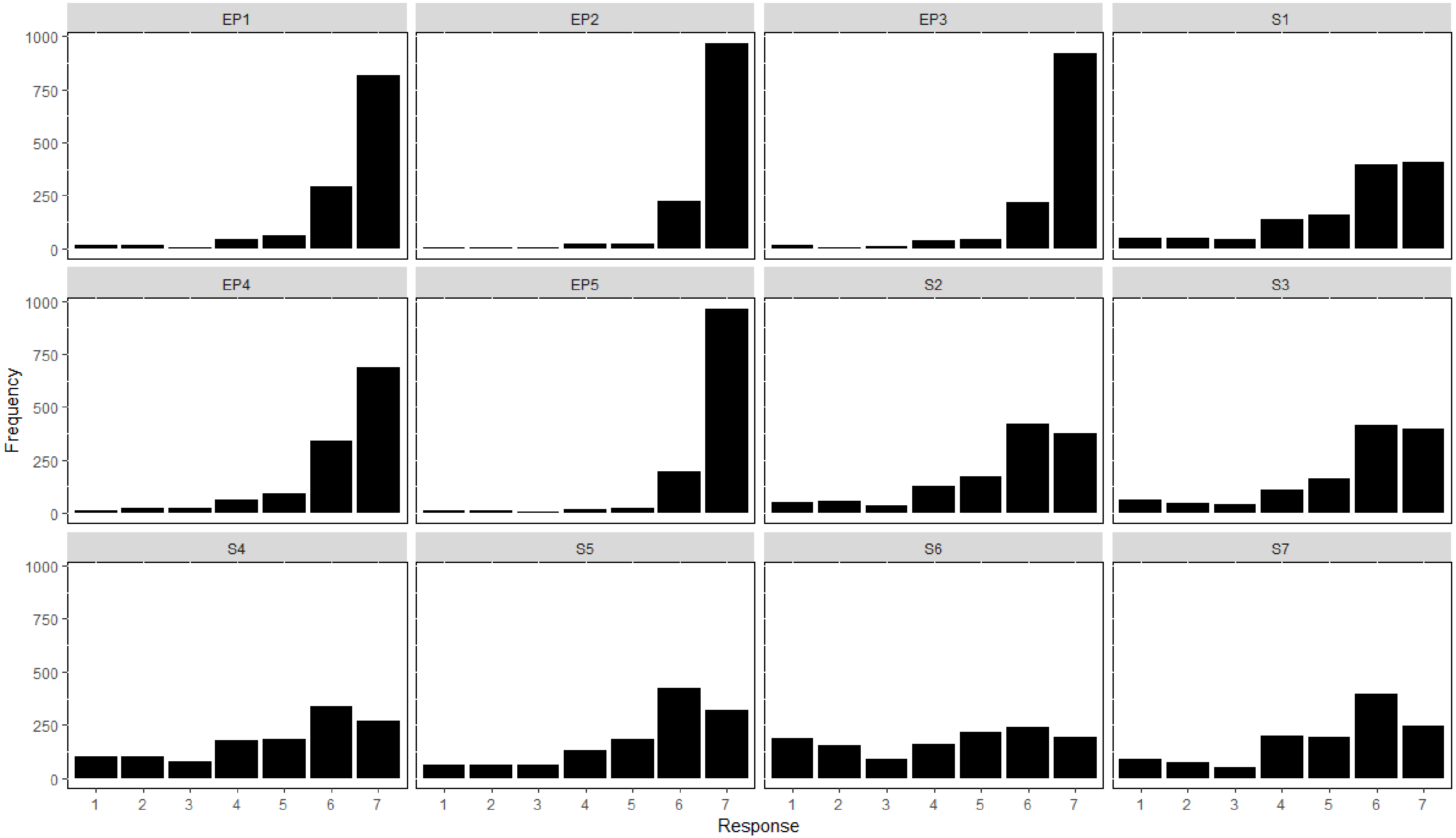
Location	Item	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
The Netherlands	1	14	38	43	91	162	387	512
The Netherlands	2	16	36	49	69	144	370	563
The Netherlands	3	29	40	57	111	145	302	563
The Netherlands	4	35	57	75	239	281	362	198
The Netherlands	5	25	68	71	159	212	343	369
The Netherlands	6	31	66	63	124	148	256	559
The Netherlands	7	40	42	61	249	294	371	190
The Netherlands	8	46	50	67	217	235	401	231
The Netherlands	9	68	78	77	271	242	335	176
The Netherlands	10	53	70	121	263	278	311	151
The Netherlands	11	100	123	127	294	300	204	99
The Netherlands	12	56	75	89	343	249	301	134
England	1	1	3	6	11	29	67	74
England	2	2	1	3	7	13	64	101
England	3	3	5	5	13	20	60	85
England	4	7	12	16	25	36	59	36
England	5	6	12	10	28	35	55	45
England	6	4	3	6	15	31	51	81
England	7	4	5	9	39	43	64	27
England	8	3	8	7	36	39	56	42
England	9	3	6	14	25	40	63	40
England	10	9	14	14	25	42	50	37
England	11	7	8	16	26	34	52	48
England	12	5	4	10	26	44	60	42
Spain	1	15	32	55	50	121	150	120

Appendix 4.4. Response Frequencies for the Predicted Expectation Scale (Continued)

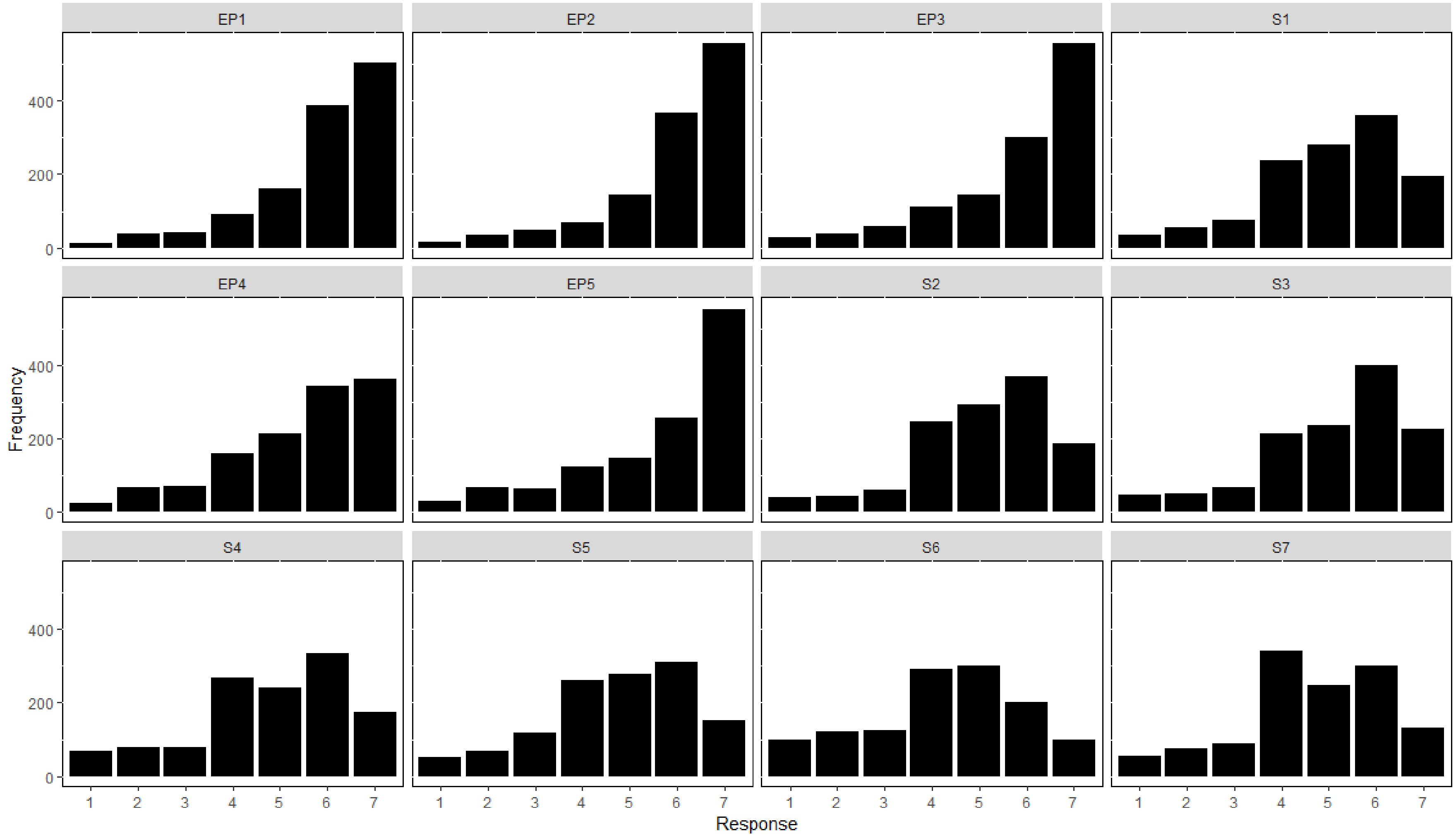
Location	Item	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
Spain	2	8	12	28	35	119	176	165
Spain	3	15	28	61	55	122	133	129
Spain	4	32	48	71	96	121	95	80
Spain	6	27	28	57	73	108	123	127
Spain	7	21	21	48	94	150	121	88
Spain	8	20	24	42	97	137	137	86
Spain	9	19	25	50	91	115	146	97
Spain	10	27	34	75	93	124	111	79
Spain	11	44	72	93	91	99	76	68
Spain	12	23	35	55	108	134	106	82

Appendix 5: Subgroups in Learning Analytics Expectations: An Exploratory Latent Class Analysis of Student Expectations Towards Learning Analytics Services

Appendix 5.1. Distribution Plots for Ideal Expectation Scale



Appendix 5.2. Distribution Plots for Predicted Expectation Scale



Appendix 6: The Big Five Personality Dimensions and Student Expectations of Learning Analytics: An Exploratory Structural Equation Modelling Approach

Appendix 6.1. 10-Item Short Version of the Big Five Inventory (Rammstedt & John, 2007)

Factor Indicator	Wording
Extraversion One*	I see myself as someone who is reserved
Agreeableness One	I see myself as someone who is generally trusting
Conscientiousness One*	I see myself as someone who tends to be lazy
Neuroticism One*	I see myself as someone who is relaxed, handles stress well
Openness One*	I see myself as someone who has few artistic interests
Extraversion Two	I see myself as someone who is outgoing, sociable
Agreeableness Two*	I see myself as someone who tends to find fault with others
Conscientiousness Two	I see myself as someone who does a thorough job
Neuroticism Two	I see myself as someone who gets nervous easily
Openness Two	I see myself as someone who has an active imagination

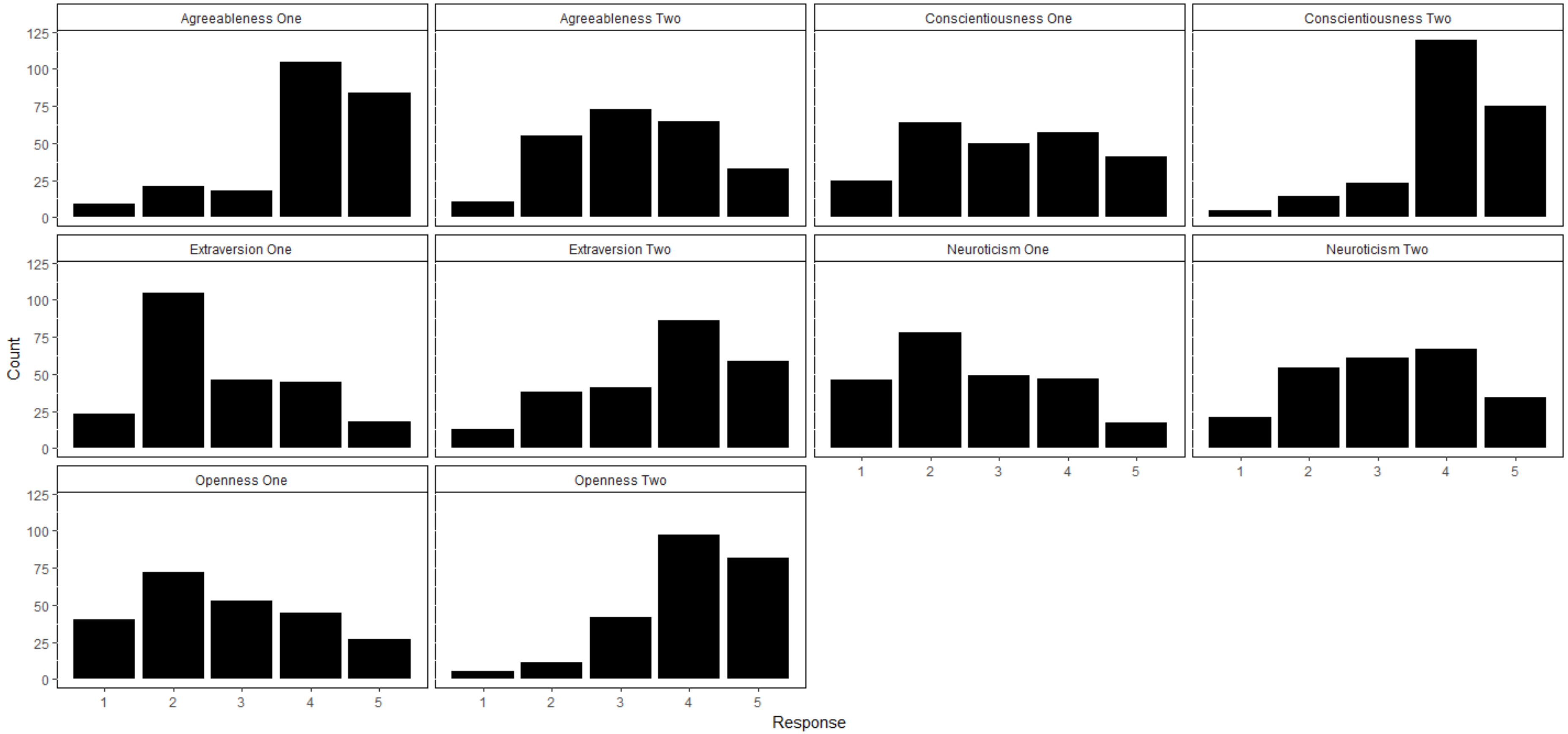
*Indicates a reversed Item

Appendix 6.2. 12-Item Student Expectations of Learning Analytics Questionnaire (SELAQ)

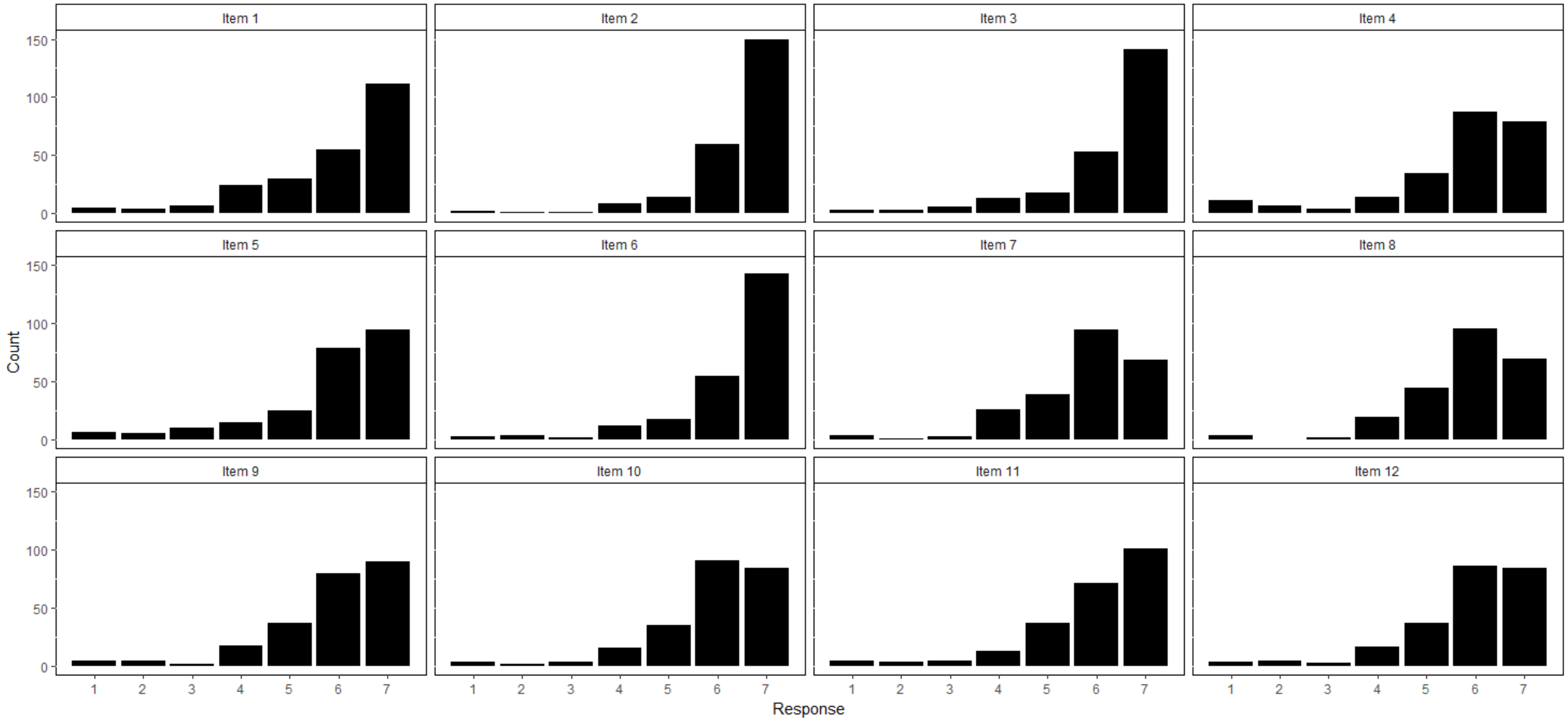
Item Number	Factor	Wording
1	Ethical and Privacy Expectations	The college will ask for my consent before using any identifiable data about myself (e.g., ethnicity, age, and gender)
2	Ethical and Privacy Expectations	The college will ensure that all my educational data will be kept securely
3	Ethical and Privacy Expectations	The college will ask for my consent before my educational data is outsourced for analysis by third party companies
4	Service Expectations	The college will ask for my consent to collect, use, and analyse any of my educational data (e.g., grades, attendance, and virtual learning environment accesses)
5	Ethical and Privacy Expectations	The college will request further consent if my educational data is being used for a purpose different to what was originally state
6	Ethical and Privacy Expectations	The college will regularly update me about my learning progress based on the analysis of my educational data
7	Service Expectations	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)
8	Service Expectations	The learning analytics service will show how my learning progress compares to my learning goals/the course objectives

Item Number	Factor	Wording
9	Service Expectations	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)
10	Service Expectations	The teaching staff will be competent in incorporating analytics into the feedback and support they provide to me
11	Service Expectations	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
12	Service Expectations	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

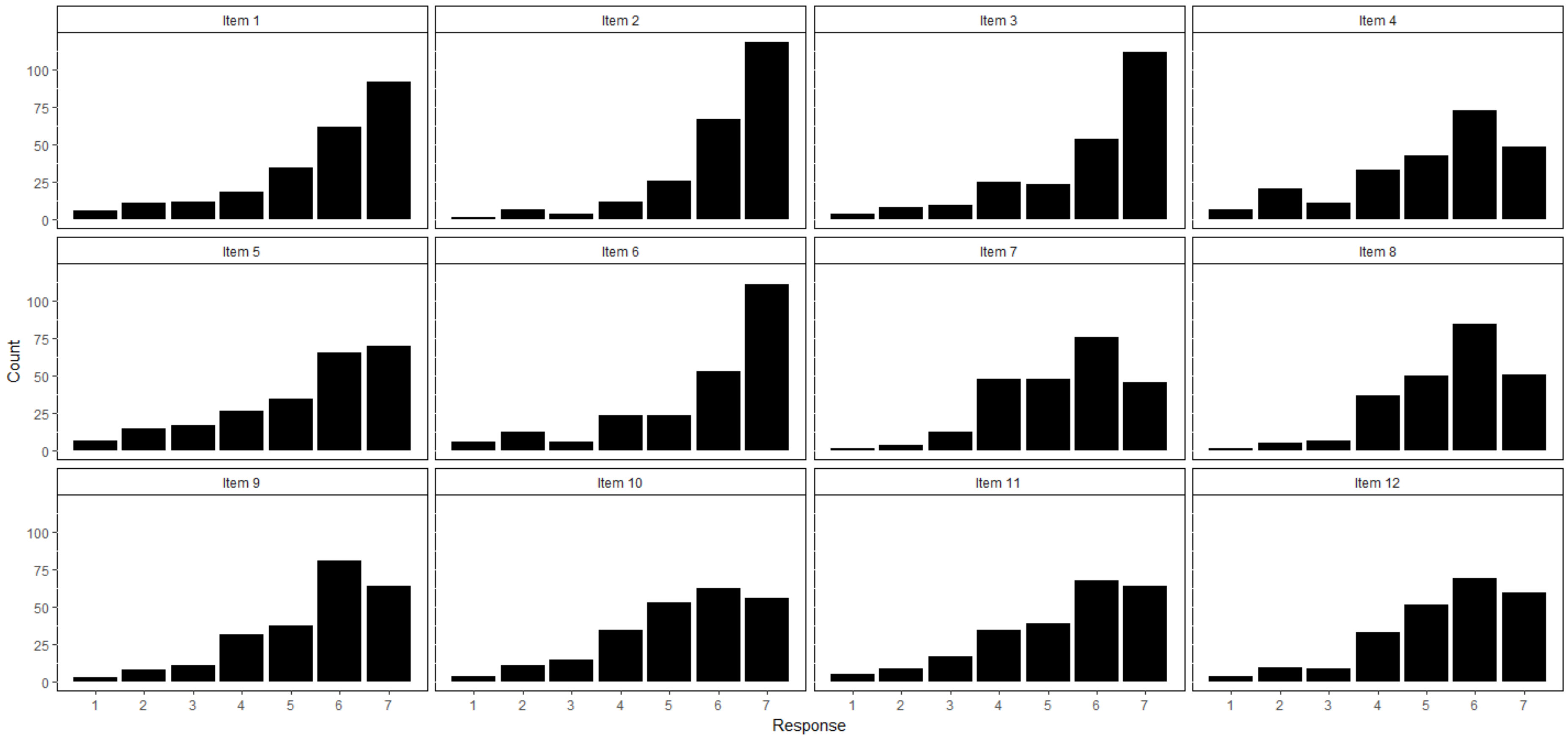
Appendix 6.3. Response Distributions for the 10-Item Short Version of the Big Five Inventory



Appendix 6.4. Response Distributions for the Ideal Expectation Scale



Appendix 6.5. Response Distributions for the Predicted Expectation Scale



Appendix 6.6. Residual Correlations for the Ideal Expectations ESEM

	Item 1	Item 2	Item 3	Item 4	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Item 12
Item 1	-										
Item 2	.03	-									
Item 3	-.02	-.01	-								
Item 4	-.05	-.02	.06	-							
Item 6	.01	-.01	.01	0	-						
Item 7	.06	-.05	0	.01	.02	-					
Item 8	.05	.02	-.04	.03	-.02	.03	-				
Item 9	-.05	.04	-.03	.01	.05	0	.03	-			
Item 10	-.03	-.01	.03	-.03	-.01	-.02	-.03	-.01	-		
Item 11	-.03	-.02	.05	0	-.03	-.03	-.05	-.03	.09	-	
Item 12	.02	.03	-.04	-.02	0	0	-.02	-.03	.02	.06	-

Appendix 6.7. Residual Correlations for the Predicted Expectations ESEM

	Item 1	Item 2	Item 3	Item 4	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Item 12
Item 1	-										
Item 2	.01	-									
Item 3	-.01	0	-								
Item 4	-.06	.01	.02	-							
Item 6	-.01	-.01	.01	.04	-						
Item 7	.03	.03	-.06	.01	0	-					
Item 8	0	0	-.01	.02	.04	.08	-				
Item 9	.04	0	-.01	-.01	-.04	-.02	.07	-			
Item 10	0	-.03	.02	-.02	.03	-.02	-.05	-.04	-		
Item 11	-.04	.01	.03	0	-.04	-.05	-.06	0	.07	-	
Item 12	.02	-.02	.02	-.01	-.03	0	-.08	0	.04	.07	-

Appendix 6.8. Residual Correlations for the Ideal Expectations Measurement Model

	E One	E Two	N One	N Two	Item 1	Item 2	Item 3	Item 4	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Item 12
E One	-														
E Two	.02	-													
N One	0	-.09	-												
N Two	-.08	0	.11	-											
Item 1	-.16	.09	.05	.14	-										
Item 2	-.02	-.08	.14	-.06	.04	-									
Item 3	-.08	0	.04	-.04	-.01	-.02	-								
Item 4	0	-.02	.07	.10	-.05	-.01	.06	-							
Item 6	-.10	-.07	.01	.04	.01	-.02	.01	0	-						
Item 7	-.03	-.04	0	.02	.05	-.05	0	0	.02	-					
Item 8	-.02	-.01	.02	.02	.04	.03	-.04	.02	-.02	.03	-				
Item 9	.07	-.05	.03	-.05	-.05	.04	-.03	0	.05	0	.03	-			
Item 10	-.02	-.03	-.06	.04	-.03	-.01	.03	-.03	-.01	-.02	-.02	-.01	-		
Item 11	-.04	.01	-.01	.03	-.04	-.02	.05	-.01	-.03	-.03	-.05	-.03	.09	-	
Item 12	-.02	-.08	.03	.02	.01	.03	-.04	-.03	0	0	-.02	-.02	.02	.06	-

E One and E Two = Extraversion Indicators One and Two; N One and N Two = Neuroticism Indicators One and Two

Appendix 6.9. Residual Correlations for the Predicted Expectations Measurement Model

	E One	E Two	N One	N Two	Item 1	Item 2	Item 3	Item 4	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Item 12
E One	-														
E Two	.04	-													
N One	0	-.09	-												
N Two	-.06	0	.10	-											
Item 1	-.01	.05	.03	.07	-										
Item 2	-.03	-.04	.04	-.04	.01	-									
Item 3	-.03	.05	.02	-.03	0	-.01	-								
Item 4	-.06	-.03	.07	.09	-.06	.01	.02	-							
Item 6	-.06	-.05	.01	.02	0	-.01	.01	.04	-						
Item 7	-.06	.01	.01	.07	.03	.04	-.06	0	0	-					
Item 8	.02	-.01	.08	0	-.01	0	-.02	.02	.04	.07	-				
Item 9	.09	-.03	.07	-.02	.04	0	-.01	-.01	-.04	-.02	.07	-			
Item 10	-.04	-.04	-.07	.02	0	-.03	.02	-.02	.03	-.02	-.05	-.03	-		
Item 11	-.05	-.02	0	-.04	-.04	.01	.03	0	-.04	-.05	-.06	0	.08	-	
Item 12	-.08	-.03	-.02	0	.02	-.02	.02	-.02	-.03	0	-.08	.01	.05	.07	-

E One and E Two = Extraversion Indicators One and Two; N One and N Two = Neuroticism Indicators One and Two