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# An Exploratory Latent Class Analysis of Student Expectations Towards Learning Analytics Services

--Manuscript Draft--

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| **Abstract:** | For service implementations to be widely adopted, it is necessary for the expectations of the key stakeholders to be considered. Failure to do so may lead to services reflecting ideological gaps, which will inadvertently create dissatisfaction amongst its users. Learning analytics research has begun to recognise the importance of understanding the student perspective towards the services that could be potentially offered; however, student engagement remains low. Furthermore, there has been no attempt to explore whether students can be segmented into different groups based on their expectations towards learning analytics services. In doing so, it allows for a greater understanding of what is and is not expected from learning analytics services within a sample of students. The current exploratory work addresses this limitation by using the three-step approach to latent class analysis to understand whether student expectations of learning analytics services can clearly be segmented, using self-report data obtained from a sample of students at an Open University in the Netherlands. The findings show that student expectations regarding ethical and privacy elements of a learning analytics service are consistent across all groups; however, those expectations of service features are quite variable. These results are discussed in relation to previous work on student stakeholder perspectives, policy development, and the European General Data Protection Regulation (GDPR). |
| **Suggested Reviewers:** | |
| **Response to Reviewers:** | |

# Supplementary Material (SM)

## Contents

## SM 1. Detailed Analysis Steps

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 scale (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 will change 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, 2014; 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 (SM 4 and 5), 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) will be 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 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 from “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 will be plotted and decisions regarding model selection will be based on the “elbow criterion” (Masyn, 2013). If, in conjunction with the findings of the inferential approach, there is no clear contender for a model (e.g., no $K + 1$ model is rejected) then a plot of log likelihood values will also be 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 will be 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 will be examined: the average posterior class probability (AvePP), the odds of correct classification ratio (OCC), and the modal class assignment proportion (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 is 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 is necessary that the interpretability of the solution needs to be considered (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, we will follow the step taken by Oberski (2016) and use profile plots. These plots provide the estimated class means as opposed to the estimated distributions (Oberski, 2016). This is because there are seven possible categories (1 = Strongly Disagree, 7 = Strongly Agree), which makes plots of estimated distributions difficult to read (Oberski, 2016).

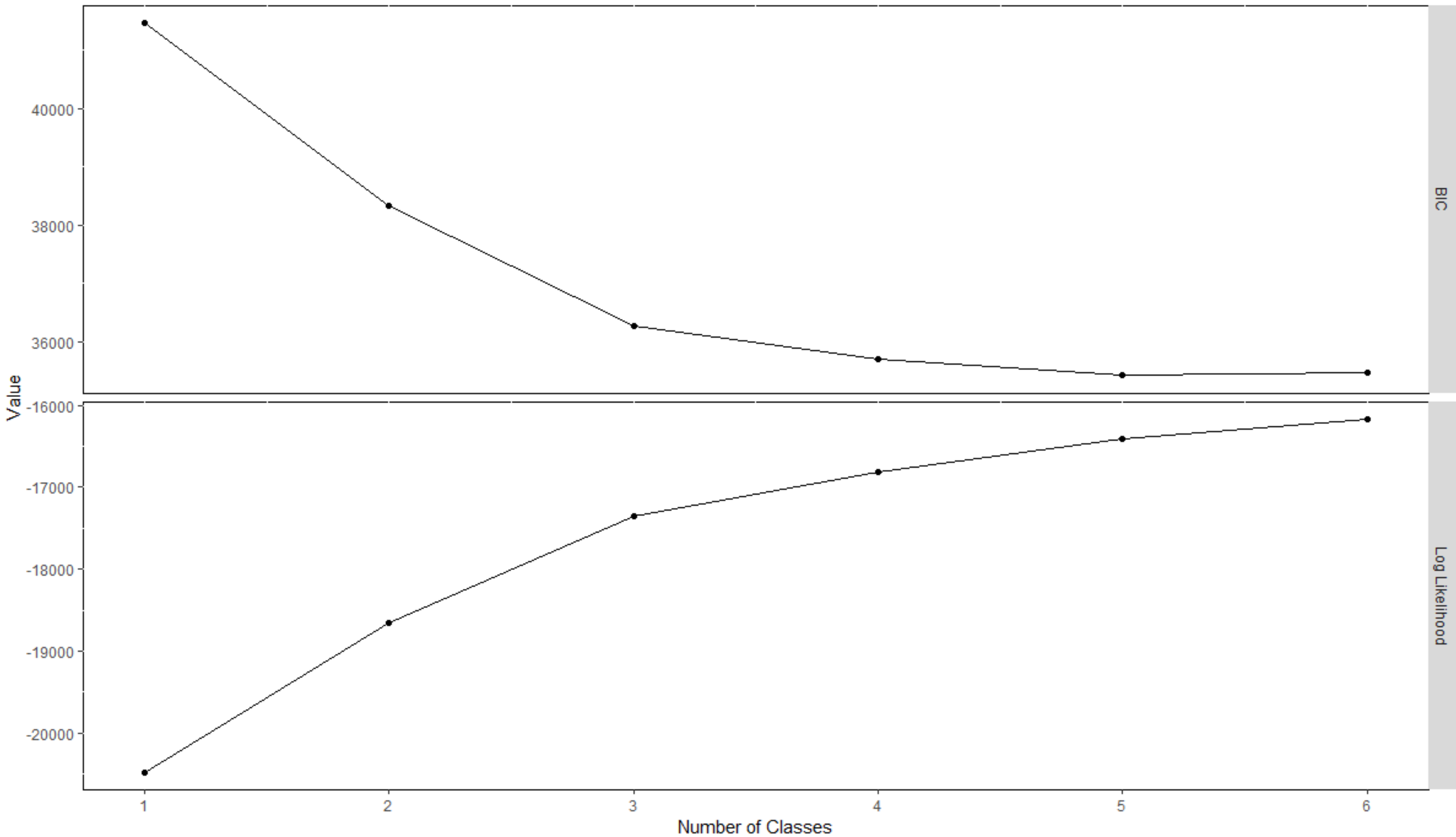
Thus, to provide an overview of the steps taken in this analysis, we increased the number of classes to extract until either the solution could not be identified or the number of classes would affect the interpretability of the solution. These models would then be compared on the basis of their relative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

**SM 2. Detailed Results for the Ideal Expectation Scale**

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 (SM Figure 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 (SM Figure 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.




**SM Figure 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 (SM Tables 1 and 2).

SM Table 1 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).

**SM Table 1.** Two Class Classification Accuracy Diagnostics

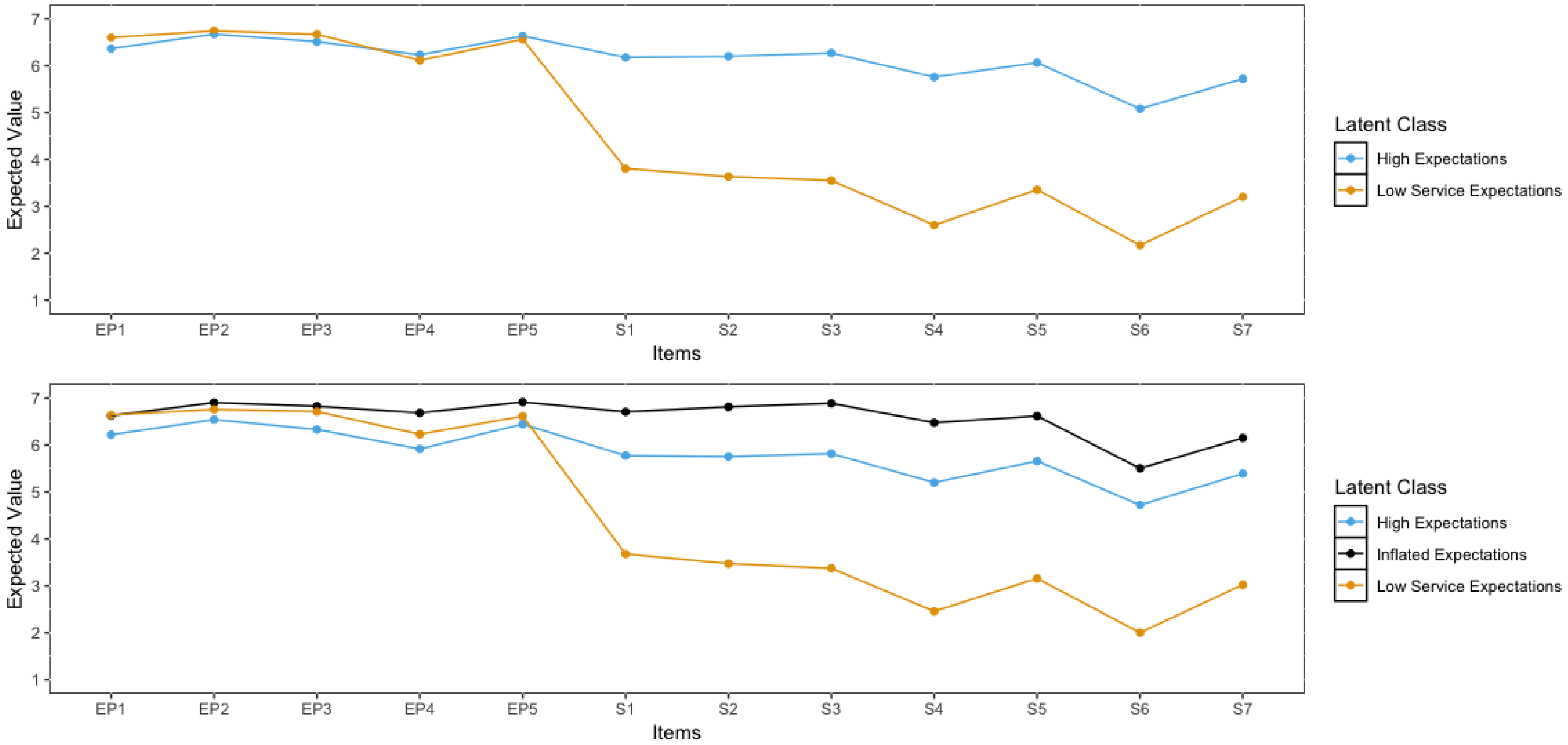
| Class $k$ | $\hat{\pi}_k$ | $mcaP_k$ | $AvePP_k$ | $OCC_k$ |
|---|---|---|---|---|
| Class One | .713 | .717 | .984 | 24.755 |
| Class Two | .287 | .283 | .974 | 93.066 |

SM Table 2 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).

**SM Table 2.** 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 (SM Figure 2).




**SM Figure 2.** Profile Plot: Estimated Means for Ideal Expectation Items for Two and Three Class Solutions

For the two class solution (top plot in SM Figure 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 SM Figure 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 logistic regression results from the three class model are presented in SM Table 3, 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.

**SM Table 3.** 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 |

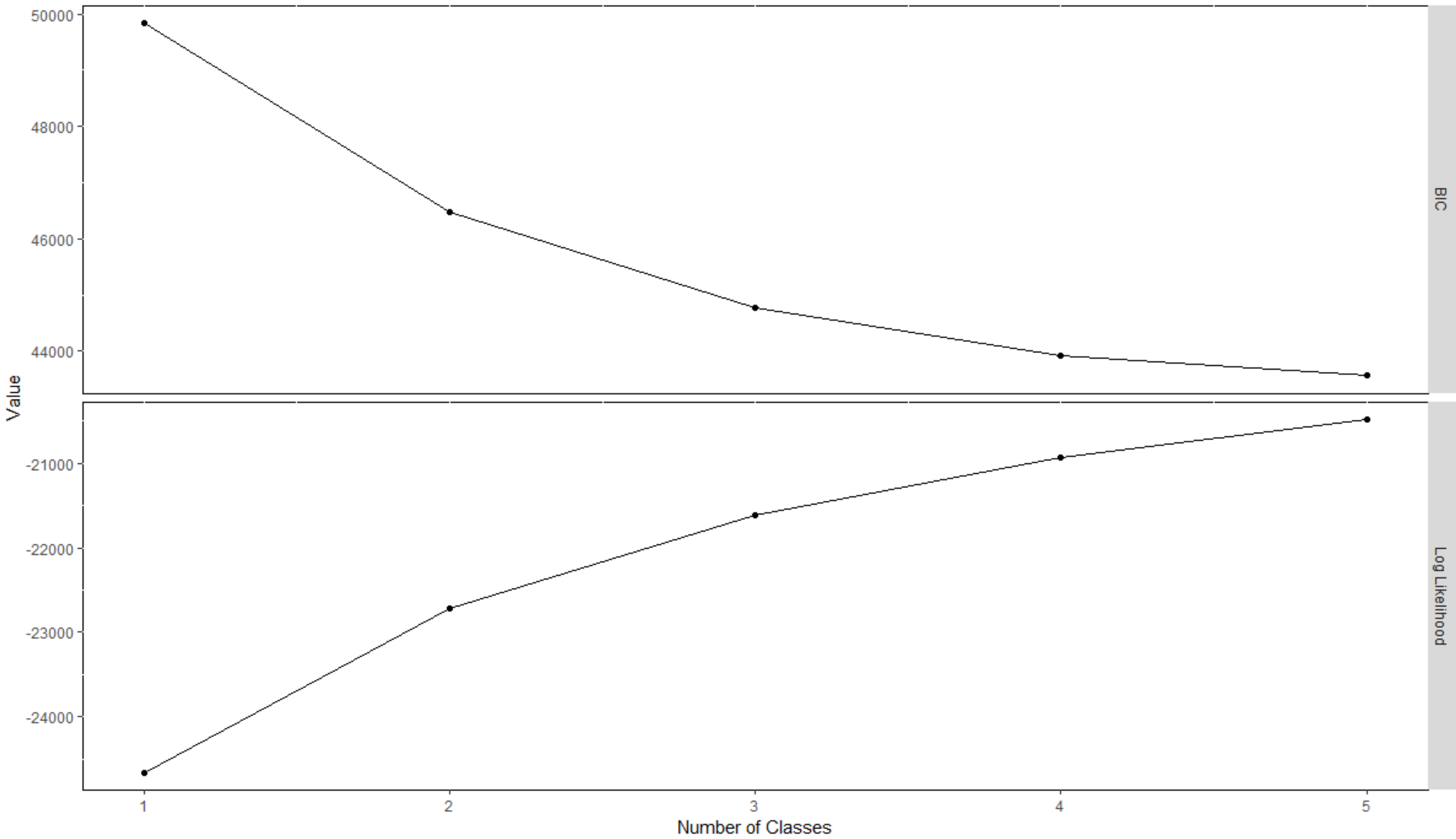
**SM 3. Detailed Results for the Predicted Expectation Scale**

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 (SM Figure 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 SM Figure 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 (SM Figure 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.




**SM Figure 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 (SM Tables 4 and 5).

SM Table 4 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).

**SM Table 4.** Two Class Classification Accuracy Diagnostics

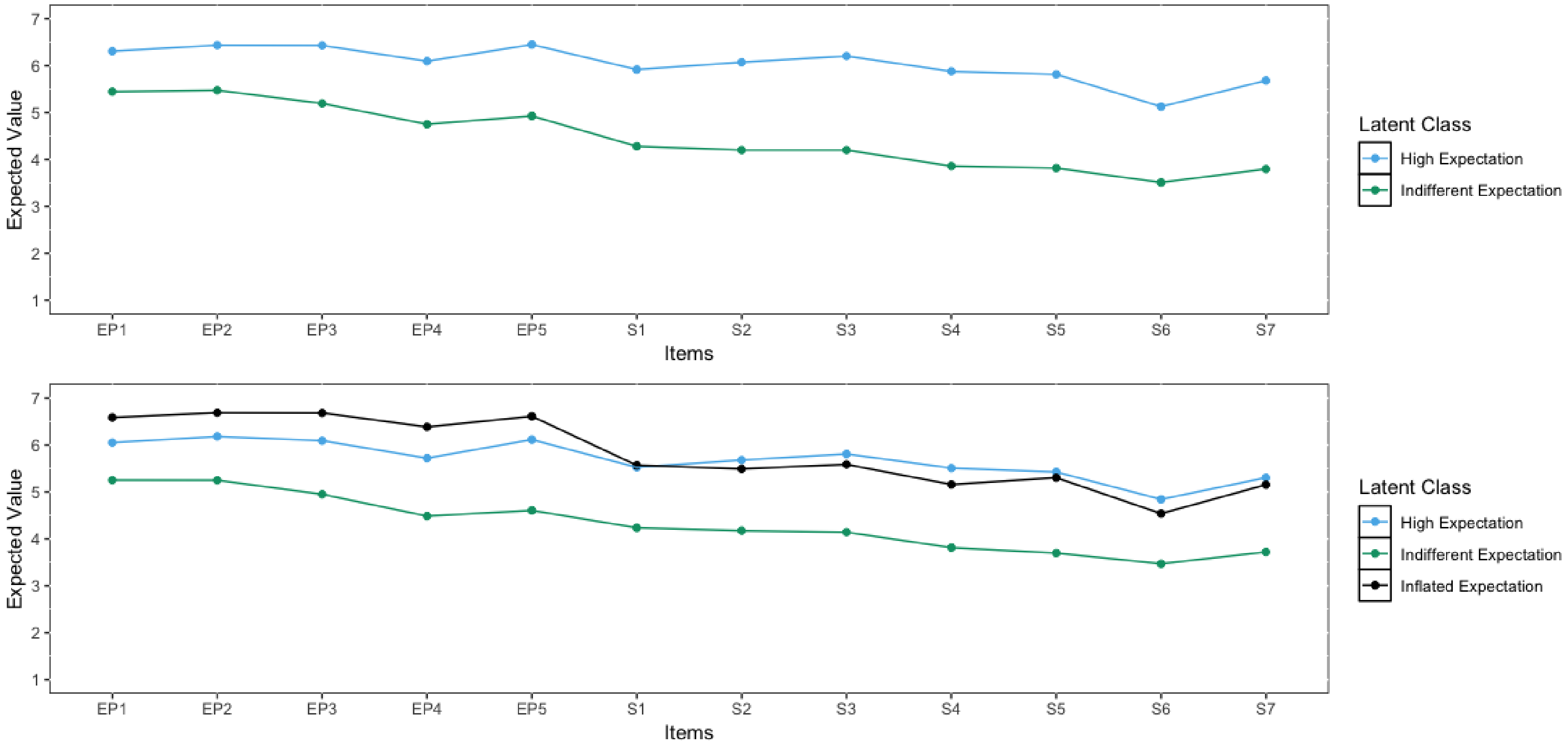
| Class $k$ | $\hat{\pi}_k$ | $mcaP_k$ | $AvePP_k$ | $OCC_k$ |
|---|---|---|---|---|
| Class One | .472 | .468 | .971 | 37.455 |
| Class Two | .527 | .532 | .966 | 25.501 |

The classification accuracy results for the three class model are presented in SM Table 5. 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).

**SM Table 5.** 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 SM Figure 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 SM Figure 4), this was not well differentiated from class one as it had high scores for both Ethical and Privacy Expectations and Service Expectations.




**SM Figure 4.** Profile Plot: Estimated Means for Ideal Expectation Items for Two and Three Class Solutions

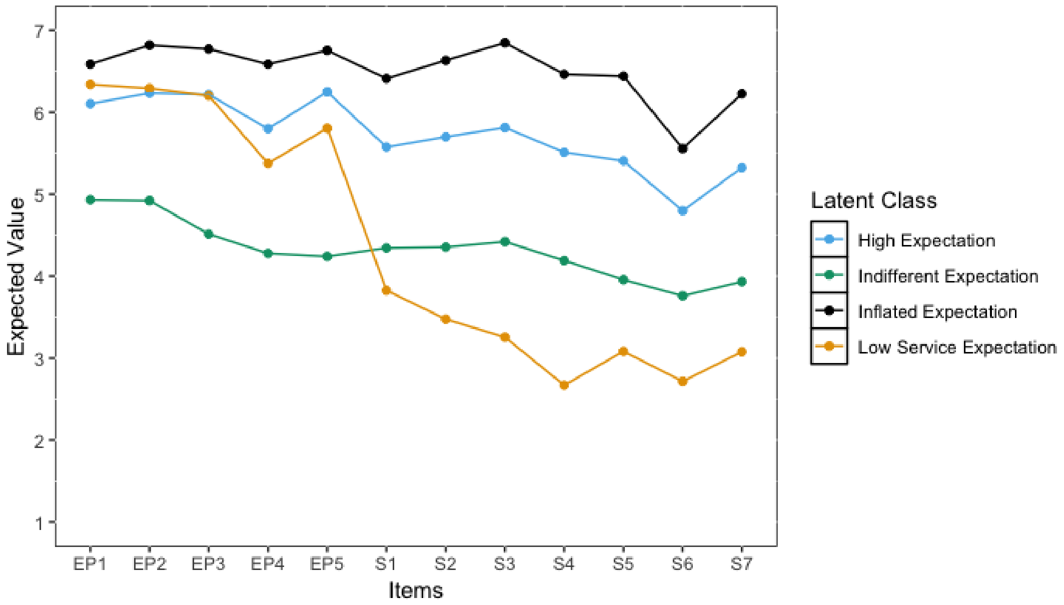
An examination of local fit for both models (k = 2 and k = 3), however, pointed to problems on account of the large proportion of high standardised residuals. For the two class model, 17.41% (n = 563) of the absolute standardised residual values exceeded 3 and 6.65% (n = 215) were greater than 5. With 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 SM Table 6. 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).

**SM Table 6.** 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 SM Figure 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.




**SM Figure 5.** Profile Plot: Estimated Means for Ideal Expectation Items for Four Class Solutions

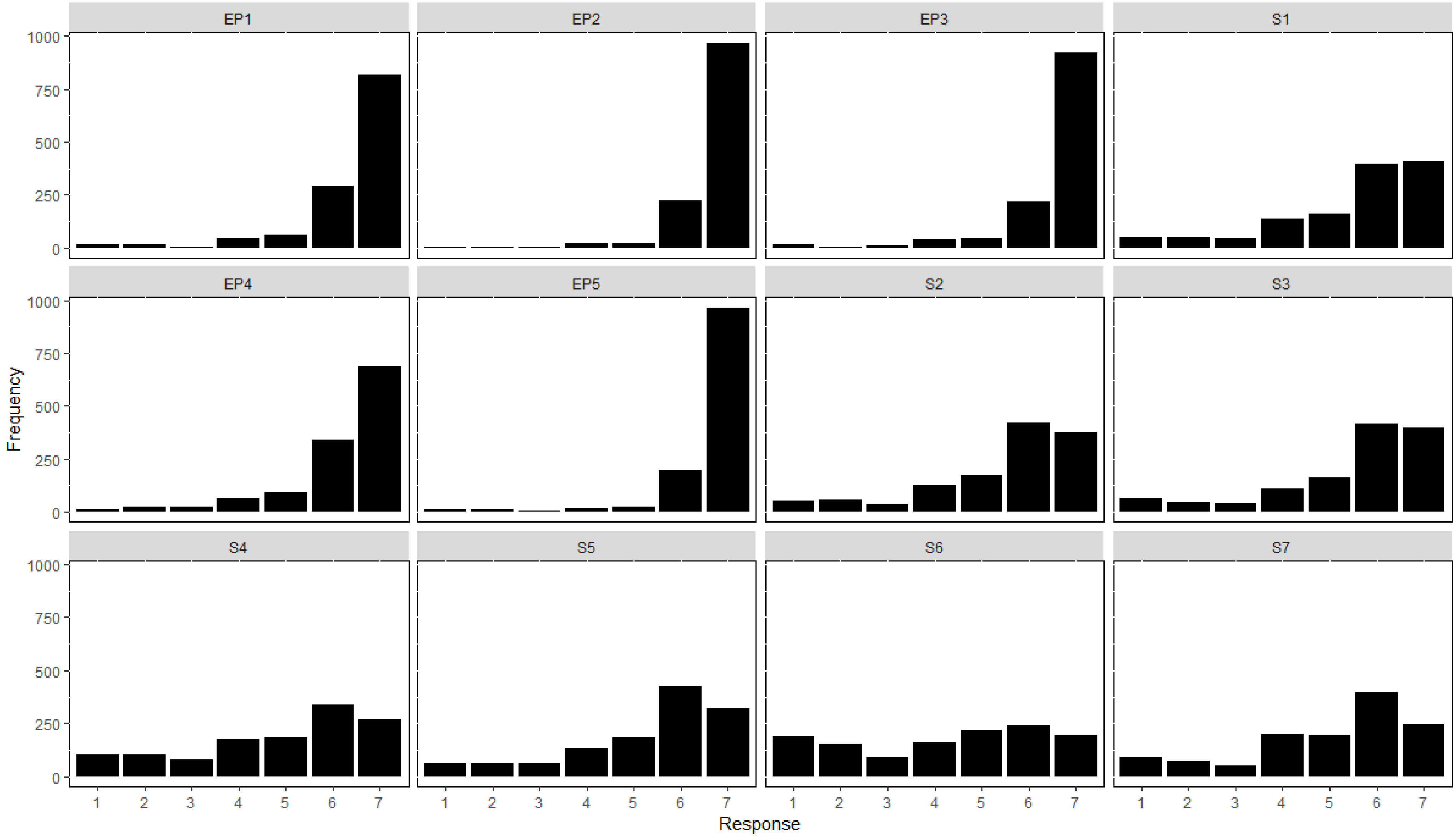
Along with the improved interpretability of the four class solution, the local fit was better than either the two or three class models. An examination of absolute standardised residual values shows 7.36% (n = 238) to exceed 3 and 2.54% (n = 82) to exceed 5. This showed that the addition of a fourth 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%).

For the latent class regression results (SM Table 7), 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.

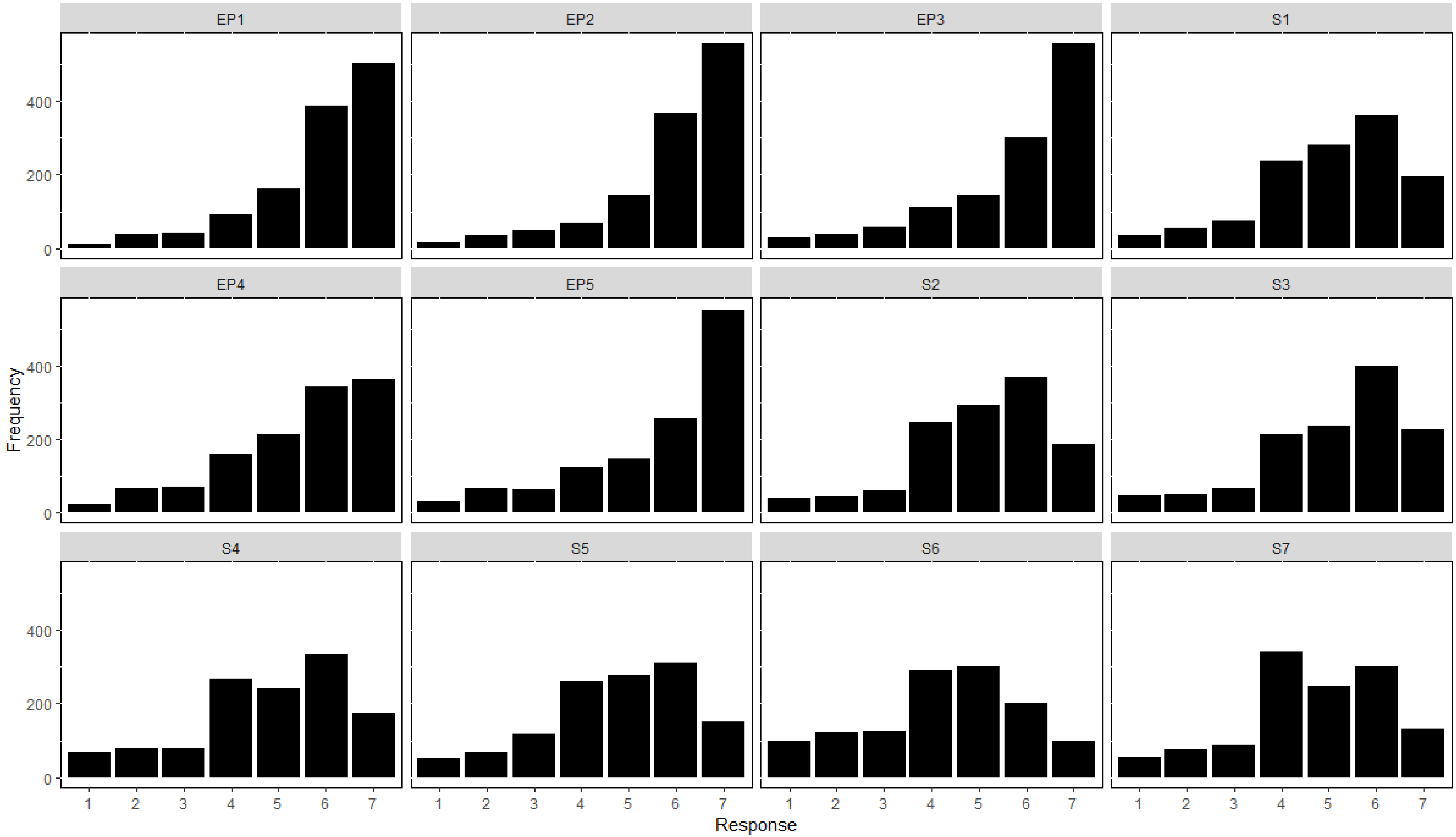
**SM Table 7.** Logistic Regressions using the Three Step Method with the Four Class Solution

| | 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 |

**SM 4. Distribution Plots for Ideal Expectation Scale**



## SM 5. Distribution Plots for Predicted Expectation Scale



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**Responses to reviews**

Dear editor and reviewers,

Many thanks for your kind consideration of our manuscript and sharing your thoughtful feedback. We have given our best to address all your suggestions.

Kind regards,
The authors

***Reviewer #1***

Thank you for the opportunity to review this revised manuscript focused on exploratory latent class analysis to segment students' expectations on learning analytics for policymaking and implementations of such services.

The manuscript has the potential to inform the field of learning analytics services. The topics and methods used are of interest to the journal. And the revisions were made. However, I still have the following comments and concerns.

→ We would like to thank Reviewer 1 for taking time to carefully review this manuscript again. We have tried to respond to each of the comments, explained below and highlighted in blue.

Again, the second paragraph, changes was made from "From this research" to "From this cited research" which research? Five STUDIES have been cited in a previous sentence (Ifenthaler & Schumacher, 2016; Roberts et al., 2017, 2016; Schumacher & Ifenthaler, 2018; Slade & Prinsloo, 2014), which of THESE STUDIES found "students expect a learning analytics service that facilitates self-regulated learning, promotes learner agency, and respects student privacy?"

→ These points are a summary of the cited references. To clarify, we replaced “From this cited research, it has been found that students expect...” by “The studies cited above suggest that students expect….”

"The focus of these research questions is on the exploration of whether expectations towards learning analytics services are homogenous within a sample of students." But the hypothesis and justification was: "We cannot assume that these student expectations towards learning analytics services are homogenous across the population, rather there is likely to be a degree of heterogeneity (Authors, 2020)." Would it be more straightforward to state that the study is trying to see "whether expectations towards learning analytics services are HETEROGENEOUS within a sample of students?" This indicates the direction of the hypothesis; or otherwise stated clearly whether it is the null hypothesis or alternative. Although the following sentences explained more, this stood out to me, and was distracting.

→ To clarify, we have rephrased this sentence as “student expectations towards learning analytics services should not be assumed to be homogenous across the population ; rather there is likely to be a degree of heterogeneity (Authors, 2020).”

Following my previous comments regarding the gap and the review of relevant theories and literature, this manuscript is not situated in justifiable literature and theories, although the problem of conducting this study has been reiterated in the introduction. The backgrounds of RQ1 and RQ2 were discussed (i.e., ideal and predicted expectations classified based on health care services), but can be improved regarding a stronger theoretical underpinnings. For example, in the SELAQ (Author, 2019) paper, it discussed the importance of expectations related to human cognition. It also backed up by Bandura's theory.

→ We have revised Section 1 by adding two paragraphs before the last one to address this comment.

To be specific, the logic of the current introduction did not well-situated this manuscript in a strong theoretical background. I would suggest to reduce the space for the section of 1.1, or combine it with section 1.2. Because, first, sections 1.1 and 1.2 seem to be redundant to me; second, "stakeholder expectations" is really not the focus of this manuscript but the Stakeholder Expectations of LEARNING ANALYTICS (and "stakeholder expectations" takes one double-spaced page, if your response to the reviewer stated that the space is limited, you would want to keep the most important arguments in the manuscript). By doing so, there will be space to discuss the variables/ covariates and the current state of LEARNING ANALYTICS in HIGHER EDUCATION or learning at large. I understand the emphasis on the exploratory nature for this manuscript, but still, for a journal paper, it is important to have a stronger theoretical underpinnings (especially when it is lacking in introduction to align with research questions, findings, discussion and implications). That is, RQ3: the hypothesis of students being heterogenous was discussed. What covariates (e.g., age, discipline, nationality/ culture) were discussed in the literature? The development of SELAQ paper (Author, 2019) did not discuss the potential covariates, thus we don't know the importance of collecting and reporting the portion of the data (e.g., age, nationality, discipline). Especially when the two covariates found to be predictive are very specific to the specific context (age in an open university with older adults; European students in an European university); that said, what are the contributions of the related findings to the field?

→ As stated in the introduction, the study aimed to explore the heterogeneity in student expectations of learning analytics services using latent class analysis. It was thus a research design decision to include a number of demographic questions commonly used to characterise student populations. As there is currently a lack of research investigating this topic, we are not able to include a literature review on covariates of student traits on expectations of learning analytics. In the revised manuscript (third paragraph, Section 1), we have however cited and introduced other relevant literature that justifies the reasons for the introduction of the covariates.  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) is an exploratory question and our analysis identified age to be a key covariate in ideal expectations. In order to interpret this observation, we reflected on the university context; that is, an open university has a student population of a wider range of age, and mature students expressed higher expectations of learning analytics services so as to better manage their studies and receive support while being outside of the campus. Similarly, the identification of European students being more likely to be in the Indifferent Predicted Expectation group than Dutch students implicates the importance to consider different trends in expectations of university services, such as learning analytics, between home students and European students. Both findings are important contributions to university-level strategic planning when it comes to investing in the right analytics infrastructure and ways to implement learning analytics that meet the needs of different student bodies. To clarify, we added a line (shown in bold and underlined below) at the end of the literature review where we introduced the research questions:

"The focus of these research questions is on the exploration of whether expectations towards learning analytics services are homogenous within a sample of students…. **<u>To this end, we conducted a latent class analysis to segment respondents based on their expectations, and further explored the demographic characteristics of the groups identified</u>**."

We have also added two extra paragraphs in Section 1 (the two paragraphs are added before the last one just before Heading 1.1).

Finally, we have added additional theoretical information about expectations and expectations from learning analytics services in Section 1.1.

Specifically, the contribution and implication of age as a predictor were also not discussed, thus, I questioned the contribution to the current state of the literature for RQ3 (as well as why it is an worthwhile question to investigate based on the literature).

→ To clarify the contribution, we rephrased the final line in Section 4.1 from “Put differently, learning analytics has the potential to change an institutional environment for mature students by increasing the offering of support, even though they may not be based on campus” to “Put differently, learning analytics can be used strategically to strengthen the existing support infrastructure for distance-learning students, thus cultivating a sense of belonging among students and providing information that can help students better manage their studies and achieve learning goals”.

"The two response scales correspond to ideal (Ideally, I would like this to happen) and predicted expectations (In reality, I expect this to happen)." What are those in the parenthesis? Direct quotes of the example item? Or a random example? What does "this" mean in "Ideally, I would like this to happen?"

→ For each of the 12 survey items, participants were invited to use a seven-point Likert scale to indicate their ideal and predicted expectations. The wording in the parenthesis was used in the survey.

I assume that the readers can find the information of the reliability and validity of the translated survey in the cited work Author, 2020.

→ We will unblind the reference in a later stage.

I know dummy codes are commonly used concept in statistics. I don't understand why there are two dummy codes regarding the nationality of the students. That is "European Student (0 = Dutch Student, 1 = European Student), and Overseas Student (0 = Dutch Student, 1 = Overseas Student)." European students are those students from European countries besides Dutch students. Overseas students are all students except the ones in Europe including Dutch students? If the codes for overseas student is 1, Dutch student is 0 in "overseas student" did you code European students 0 or 1? Then what is the difference between "European Student" and "Overseas Student"? or did you remove the data of European students in "overseas student" codes? As far as I know, if you have k groups, the dummy code would be k-1. Great comparison between the data and the university distribution for the age. How about Dutch/ European/ Overseas students?

→ There are three options regarding this survey question: Dutch students, European students, and Overseas students. We used Dutch students as the baseline group, coded as 0. The group that we compared against the baseline group is coded as 1. Thus, when we compared the responses of European students against those of Dutch students, the former group is coded as 1 and the latter as 0. Similarly, when comparing the responses of

Overseas students against those of Dutch students, the former group is coded as 1 and the latter as 0.

Masyn (2013) was cited for model building, Vermunt, 2010 was cited for three-step approach to latent class analysis. Oberski, 2016 was cited to discuss "too many categories makes the plots of estimated distributions difficult to read," but how the following solutions of the analysis being supported by rigorous statistical technique?

→ Section 2.3, paragraph 3 already cites Lanza and Rhoades (2013) to explain what is meant by interpretability.

No citation was given: "we increased the number of classes to extract until either the solution could not be identified, or the number of classes would affect the interpretability of the solution."

→ Hagenaars & McCutcheon (2002) are cited now.

In the limitations, "In terms of the current models, it was decided that the interpretability, relative fit, and classification accuracy of the selected models were good." What does it mean by "it was decided?" who decided? The statistical procedures? Or the authors decided by themselves? With all these questionable areas, I would also suggest: make it explicit to the readers why Latent Class Analysis is a reasonable approach to answer the research questions instead of cluster analysis, factor analysis among others.

→ Section 2.3, paragraph 3 defines what is meant by interpretability, absolute fit, relative fit, and classification diagnostics, i.e., accuracy (as measured by relative entropy) by drawing on the well-known literature on LCA. We have now clarified that classification diagnostics is accuracy in Section 2.3 and it is measured by relative entropy. We have also updated the paragraph in the limitation section to improve clarity.

Were the assumptions checked and met? The current organization/ writing of the method is not convincing that the method and analysis were appropriate.

→ The only assumption is that the data are categorical as it was the case in our study (Hagenaars & McCutcheon, 2002). Latent class analysis does not make any assumptions related to linearity, normal distribution, homogeneity or any other assumptions. We have stated these basic assumptions, or the lack of thereof, about LCA now in Section 2.3.

"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)," it seems that this is focused on addressing "stakeholder expectations." However, I wonder were findings on learning analytics expectations not presented in recent literature? From this sentence, it seems since 1988, this issue has not been addressed, but is this true?

→ The first two paragraphs introduced relevant conceptual background on expectations from information systems. Lyytinen & Hirschheim (1988) wrote a seminal paper that stressed the role of stakeholder expectations in technology adoption. Thus, we prefer to keep this important work. We have however restructured Section 1.1 by reducing the parts related to general literature on technology adoption and expectations and also expanded (new last paragraph) that talks about the definition of expectations in learning analytics.

"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)." "A solution has been outlined by Sclater (2017), which also meets the requirements of the General Data Protection Regulation (GDPR)." Solutions have been proposed and implemented previously, what this study has to inform the field? And this contradicts to the necessity of "exploratory" of this study since people already have solutions.

→ Our study calls for institutions to consider heterogeneity in student expectations of learning analytics services and to recognise that there is no one-size-fits all solution. The examples that we provided from Nottingham Trent University (2016) and Sclater (2017) are to demonstrate possible ways institutions may consider following when addressing the phenomenon of heterogeneous expectations of learning analytics. Please note that the gap that our study set out to address is the need to engage students in successful implementation of learning analytics services. The way we fill in the gap is by conducting a student survey widely to explore possible differences in expectations among students. However, we appreciate the reviewer for pointing out the places where our expressions may have caused confusions. We have thus removed the use of the word 'solution', and rephrased the text about the Nottingham Trent University case as follows:

"One possible approach to tackle this issue could be introducing a mandatory learning analytics service that provides engagement metrics in the form of a dashboard, as already implemented at Nottingham Trent University (Nottingham Trent University, 2016; Sclater, Peasgood, & Mullan, 2016). In this way, students who have initially expressed low interest in learning analytics may change their expectations due to the exposure to or perceptions of the way their peers benefit from using the services (Sclater et al., 2016)."

We also rephrased the text where we cited Sclater's (2016) suggestion about the way universities should approach student data under GDPR as follows:

“In particular, under the governance of the General Data Protection Regulation (GDPR), universities do have the legal responsibility to inform students about any personal data collected and how it will be processed (Sclater, 2017).”

In the discussion, some items were taken out or highlighted for discussions, however, they were not reported in the results section, for example, "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." This reads like a findings and should be reported in the results. In the discussion, the manuscript should present and interpret the meaning of this finding. Not adding this in the discussion. This is an alignment issue. I know figures were presented in the results section, but findings of the items were not highlighted in text (for example, unusual items such as S6). This is just an example, I see several items discussed in the discussions but not reported/ highlighted in the results.

→ The observation about responses to S6 is presented in Figure 1. To add clarity, we have included a cross inference in a bracket in this sentence. Moreover, we included a line to explain the figure in Section 3.1: “Among these items, Item S6 (obligation to act) received the lowest average rating across all the groups.”

In the highlights before the abstract: "Student expectations of learning analytics can be segmented based on service items." I simply don't understand what does "service terms" mean. You may want to just write/ repeat the major takeway mentioned in the manuscript.

→ Unfortunately, we could not locate this sentence in the manuscript and would appreciate if the reviewer could point us precisely where this sentence is in the manuscript. As for the service items from SELAQ, they include those whose item numbers have prefix ‘S’ - i.e., items S1-7.

There are still distracting writing issues in the manuscript. "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 avoid dependency." What do you mean by "To be taken avoid dependency?" Do you mean "To be taken TO avoid dependency?" I also see some inconsistency of using the word "toward" or "towards;" "but the exposure to and perceived benefits from using the services may facilitate lead to a change in expectations:" "may FACILITATE LEAD to a change in expectations" is not clear to me. I am just throwing out some examples, a close edit of the entire manuscript is STRONGLY suggested.

→ Thank you for pointing these out. We corrected the first sentence as “it is necessary for steps to be taken **to** avoid dependency”. We have addressed the inconsistency issue with the use of ‘towards’. We also deleted ‘facilitate’ in the second sentence. We have also double checked the whole article.

Please also fix the reference, for example, Sclater, N, Peasgood, A., & Mullan, J. (2016). Learning Analytics in Higher Education: A Review of UK and International Practice. Jisc. https://www.jisc.ac.uk/sites/default/files/learning-analytics- in-he-v2_0.pdf
This link brought me to a "Page not found." This is just an example, examine all.

→ Thank you for pointing these out. We have addressed the issue.

Again, thank you for the opportunity to review this manuscript.

Reviewer #2: Thank you for the opportunity to review the manuscript again. Most of the issues were resolved after revision. However, there are still some issues to be solved.

→ We would like to thank Reviewer 2 for reviewing this manuscript again and providing valuable feedback. We respond to each of the comments below and highlight our response in blue.

- There are some problems with citations in the text. I think, using the Mendeley software most of the resources were cited in the text. So, the studies with 3 or more authors were cited with the last name of the first author (e.g. Sclater et al., 2016). However, this standard citation was not followed in some citations (e.g. Ferguson, Hoel, Scheffel, & Drachsler, 2016; Sclater, 2016; Sclater, Peasgood, & Mullan, 2016; Tsai, Moreno-Marcos, Tammets, Kollom, & Gašević, 2018). Please address them.

→ We have checked this and addressed it to the best of our ability.

- The authors have developed and validated the SELAQ in a different study. The aim of the study is to segment the students' expectations towards LA services, not to discuss how SELAQ can be used to understand student expectations. Hence, the 3rd and 5th paragraphs which are not directly related to the aim of the study are needed to be moved to the instrument section and would be used to improve this section.

→ We have moved the two paragraphs to the Methods section, i.e., Section 2.2.

- The respondents of the study were selected through opportunity sampling. However, opportunity sampling is often viewed as the weakest form of sample selection. It is also regarded by some as being less demanding on researchers, in terms of resources or expertise, than other methods of sampling. Hence, the results should be discussed with this limitation, and this limitation should be stated in the limitation section of the study.

→ The survey to the entire student population (~16,000) of the university where the study was conducted and the response rate was about 8% which is a similar rate to those reported in the literature. We can not say that the sample was opportunistic as the survey was intended to understand student expectations in the given institution. What we can claim is that generalizability of our findings should be further investigated and this limitation has been reinforced in the Limitations section of the revised manuscript.

- The introduction and results parts utilized the related previous work. However, some of the resources in discussion are different than in the introduction part (e.g. Ferguson, Hoel, Scheffel, & Drachsler, 2016; Thomas et al., 2015; Pol e al., 2010; etc). This difference points out that the introduction and the results are discussed in different ways with different resources. In the opposite, the statement of the problem and the results are needed to be discussed with the same resources. The integrity of the study should be satisfied by using the same resources in the statement of the problem and the discussion.

→ We have addressed this by making sure that the relevant background information is brought up in the introduction section now. Specifically, we have revised section 1 by adding two new paragraphs and also slightly revising the rest of the subsections of the Introduction.

- Last sentence before 4.3. is related to the future studies. It should be moved to the end of the limitations section. In addition, the last sentence of the conclusion belongs to the future research.

→ Thank you for pointing these out. We rephrased the ending sentence in Section 4.2 as "It is, therefore, necessary for **decision makers in higher education** 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)." We have also rephrased the conclusion section title to include 'future work'.

- Please do not forget to add the references of Authors (2019 and 2020).

→ Thank you for the reminder. We will make sure that the blinded references are unblinded once the paper is accepted.

Highlights:

Student expectations of learning analytics can be segmented based on service items

Ethical and privacy expectations were relatively consistent across the sample

Provides a discussion on how to integrate findings into institutional policies on learning analytics implementations

Title: An Exploratory Latent Class Analysis of Student Expectations Towards Learning Analytics Services

Authors:

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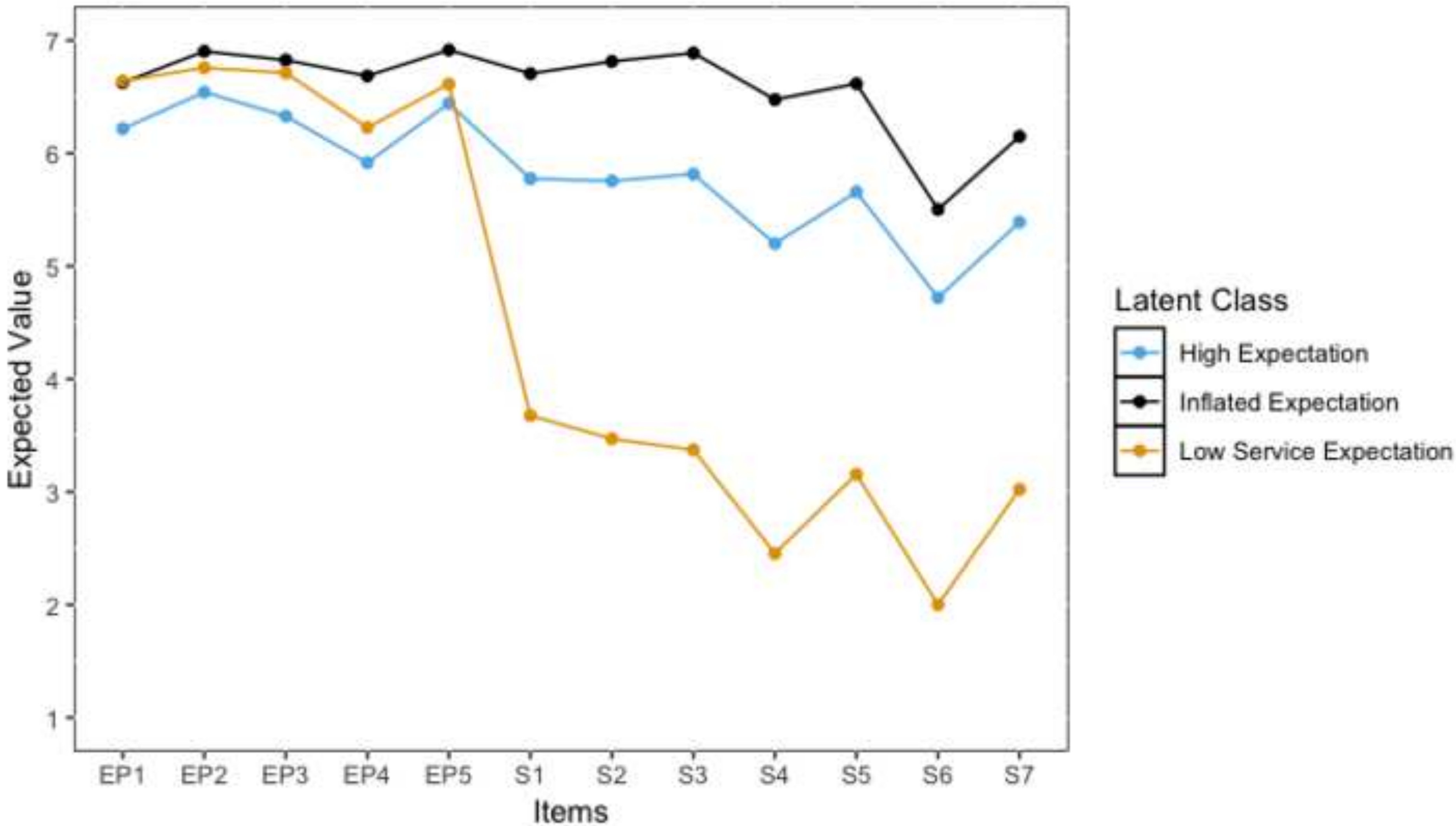
Figure

Click here to download Figure figure_1.png



Figure

Click here to download Figure figure_2.png

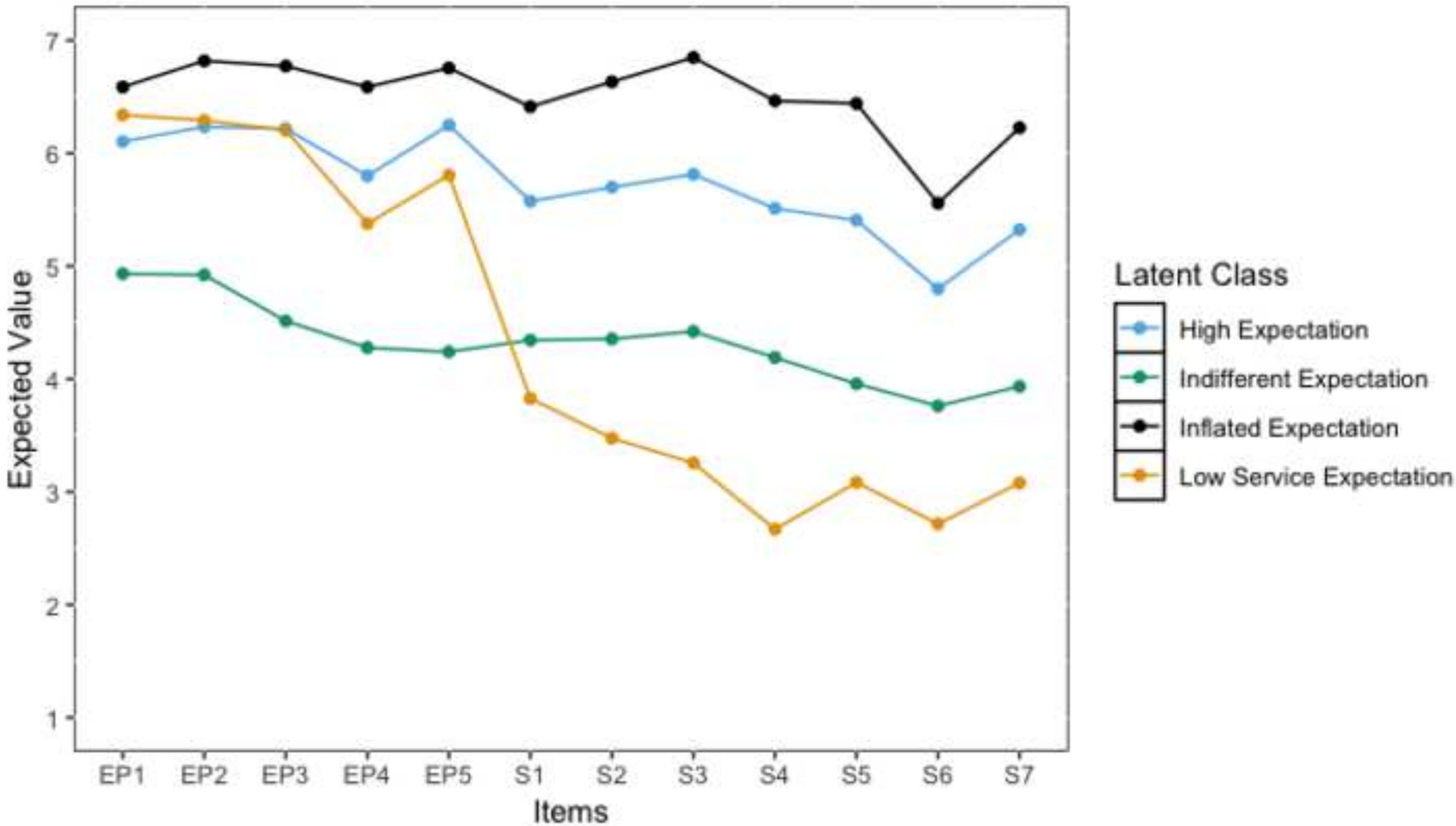


**Table 1.** 12 Items of the SELAQ with Factor Key

| 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 |

**Table 2.** 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 |

**Table 3.** 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 |

**Table 4.** 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 |

**Abstract**

For service implementations to be widely adopted, it is necessary for the expectations of the key stakeholders to be considered. Failure to do so may lead to services reflecting ideological gaps, which will inadvertently create dissatisfaction amongst its users. Learning analytics research has begun to recognise the importance of understanding the student perspective towards the services that could be potentially offered; however, student engagement remains low. Furthermore, there has been no attempt to explore whether students can be segmented into different groups based on their expectations towards learning analytics services. In doing so, it allows for a greater understanding of what is and is not expected from learning analytics services within a sample of students. The current exploratory work addresses this limitation by using the three-step approach to latent class analysis to understand whether student expectations of learning analytics services can clearly be segmented, using self-report data obtained from a sample of students at an Open University in the Netherlands. The findings show that student expectations regarding ethical and privacy elements of a learning analytics service are consistent across all groups; however, those expectations of service features are quite variable. These results are discussed in relation to previous work on student stakeholder perspectives, policy development, and the European General Data Protection Regulation (GDPR).

# 1 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 through the analyses undertaken, resulting in interventions designed to improve teaching and learning (Dawson et al., 2019; Gašević et al., 2017; Siemens, 2013). This use of learning analytics is primarily motivated by a drive to address the limited learning support and low retention rates that are key performance indicators of higher education (Sclater et al., 2016; Siemens & Long, 2011; Tsai & Gašević, 2017b).

The advantages that learning analytics services can bring to higher education have been recognised by numerous institutions, but adoption rates remain low (Tsai, Rates, et al., 2020; Tsai & Gašević, 2017a; Viberg et al., 2018). Nevertheless, institutions recognise that successful implementation of learning analytics services requires student engagement (Buckingham Shum et al., 2019; Ferguson et al., 2014; Jivet et al., 2020; Tsai et al., 2018; Tsai & Gašević, 2016, 2017b). 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 (Ng & Forbes, 2009). Dissatisfaction becomes a likely outcome that occurs in these instances where expectations of the primary stakeholder are not met (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., 2016, 2017; Schumacher & Ifenthaler, 2018; Slade & Prinsloo, 2014; Tsai, Perrotta, et al., 2020; Tsai, Whitelock-Wainwright, et al., 2020). The studies cited above suggest that students expect a learning analytics service that facilitates self-regulated learning (Lim et al., 2020; Roberts et al., 2016; Schumacher & Ifenthaler, 2018) and promotes learner agency (Roberts et al., 2016; Tsai, Perrotta, et al., 2020). The existing studies also showed that students are open to the idea of their data being used for these purposes  (Fisher et al., 2014) provided their privacy is protected (Ifenthaler & Schumacher, 2016; Slade & Prinsloo, 2014; Tsai, Whitelock-Wainwright, et al., 2020) and informed consent obtained in advance (Slade & Prinsloo, 2014; Sun et al., 2019) as now mandated by the General Data Protection Regulation[1] (GDPR) in the European Union (Sclater, 2017).

Student expectations towards learning analytics services should not be assumed to be homogenous across the population; rather there is likely to be a degree of heterogeneity (Authors, 2020). This heterogeneity assumption is support by several accounts. *First*, the literature demonstrates that students who have just commenced their studies in higher education require more direction and support from higher education institutions to become independent learners than students who have already spent some time in higher education institutions (Thomas et al., 2015). *Second*, mature students often depended on family and friends as the main sources of support in higher education with limited expectation for institutional support (Heagney & Benson, 2017). *Third*, learning analytic services can be considered as a form of feedback (Matcha et al., 2020). However, providing regular feedback may not be necessary for all students given the development of their skills to monitor and control (i.e., self-regulate) their learning (Pol et al., 2010; Winne, 2017). *Finally*, demographic and academic information of students can play a significant role in types of supports students may need from higher education institutions (Gašević et al., 2016).

[1] 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)

Common examples of such information used in the learning analytics literature are subject matter (Gašević et al., 2016; Morris & Finnegan, 2009), student origin (e.g., domestic vs international) (Dawson et al., 2017; Gašević et al., 2016; Tempelaar et al., 2017), and genders of the students. Consideration of subject matter is predicated on the assumption of different pedagogies followed across different subject domains (Gašević et al., 2016; Morris & Finnegan, 2009). Consideration of student origin is justified by student differences in academic background (Tempelaar et al., 2017) or in needs for support services (Glew et al., 2019) of domestic students in comparison to international students. Gender is commonly used in education literature to study differences in academic characteristics and outcomes (Sheard, 2009).

Obliged to act based on the results of learning analytics and who is responsible for student success by acting upon learning analytics are essential issues that need to be carefully considered in connection with student expectations. Some institutions such as Nottingham Trent University implemented a mandatory learning analytics service as part of their strategy that rests on the assumption that the university is obliged to act based on learning analytics for the sake of student support (Nottingham Trent University, 2016; Sclater, Peasgood, & Mullan, 2016). In many institutions however teaching staff say they are often seen as responsible for student success and thus will be tasks to communicate the results of learning analytics with students (Howell et al., 2018). Related research in learning analytics however suggests that institutions and students should share the responsibility for student learning (Prinsloo & Slade, 2017), which is well aligned with the objectives for students to become independent learners (Thomas et al., 2015) who can control their own learning (Pol et al., 2010). As not all learners can be ready to independently learning immediately upon commencement of their studies, it is essential for higher education institutions to understand needs and expectations of different student subpopulations for effective implementation of a learning analytics service. Unfortunately, the existing literature has offered limited empirical accounts about student subpopulations and their different expectations of learning analytics services.

The goal of this paper is to therefore address this current gap by exploring the heterogeneity found in student expectations of learning analytics services using latent class analysis.

## 1.1 Definition of Stakeholder Expectations

Adoption of information systems has been extensively studied (Davis, 1989; Venkatesh & Bala, 2008; Venkatesh et al., 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 et al., 1999). As early work by Davis and Venkatesh (2004) shows, 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 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). 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 towards 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 towards 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).

In this study, we follow the definition of expectations that has previously been used in the learning analytics literature (Authors, 2019). Specifically, an expectation is defined as a belief about "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). Accordingly, an expectation in learning are defined as "as a belief about the likelihood that future implementation and running of learning analytics services will possess certain features" (Authors, 2019, p. xx). For example, a learner's perceived likelihood that LA service will provide feedback on how the learner is progressing towards their set goals. Expectations are significance for human cognition (Roese & Sherman, 2007). Expectations influence how an individual manages their behaviours and motivation in a particular context (Bandura, 1977, 1982; Elliot & Church, 1997). Expectations are also used as reference points for assessing our actual experiences (Christiaens et al., 2008; Festinger, 1957) and for estimating how hard some expectations can change (Ngafeeson & Midha, 2014; Nov & Ye, 2008). According to Thompson & Suñol (1995), expectations can be divided into four types: ideal, predicted, normative, and unformed. An *ideal* expectation represent wanted outcomes, or what an individual wants would like to have in a service (Leung et al., 2009). A *predicted* (or realistic) expectation what an individual realistically expects the service is the most likely to be. Indeed, the existing literature supports the distinction between ideal and realistic expectations as two different subtypes (Askari et al., 2010; David et al., 2004; Dowling & Rickwood, 2016). The other two expectation subtypes are about what service an individual believes is justified to have (*normative* expectation) and the situations where the individual is unable to form expectations from a service (*unformed* expectations). In learning analytics, predicted and ideal expectations have been studied as this distinction allows the researchers and practitioners to gauge what students realistically expect from learning analytics services (predicted expectations), whilst also being mindful of what students' desire (ideal expectations). This distinction between predicted and realistic expectations is used as a foundation of the construction of the Student Expectations from Learning Analytics Questionnaire (SELAQ) (Authors, 2019), which has been used in the analysis of several higher education institutions in Europe and Latin America (Hilliger et al., 2020; Kollom et al., 2021).

## 1.2 Prior Studies on 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, Rates, et al., 2020). 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 (Buckingham Shum et al., 2019; 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 unequal (Tsai & Gašević, 2017b).  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, input from students came from a single representative of the National Union of Students. 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 towards learning analytics service features (Arnold & Sclater, 2017; Jivet et al., 2020; Roberts et al., 2017; Schumacher & Ifenthaler, 2017) and student beliefs towards ethical procedures (Ifenthaler & Schumacher, 2016; Jones et al., 2020; Roberts et al., 2016; Slade et al., 2019; Slade & Prinsloo, 2014; Tsai, Whitelock-Wainwright, et al., 2020). 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 towards learning analytics services (Roberts et al., 2016, 2017;

Slade & Prinsloo, 2014), these tend to focus on relatively small samples. 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. Such instrument has recently been developed and validated to measure expectations of students from learning analytics services (Authors, 2019) as outlined in Section 2.2. While this instrument has been used across several international contexts (Authors, 2020; Authors, 2021), there has not been any prior research that attempted to understand if student expectations for learning analytics services can be meaningful segmented to enable higher education institutions to serve to the specific expectations of different student subpopulations.

## 1.3 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 (Jivet et al., 2020; Roberts et al., 2017; Schumacher & Ifenthaler, 2017), emphasis has been placed on viewing these beliefs on the population level. 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 (Roberts et al., 2017; Teasley, 2017).

Expectations-based segmentation has been shown to be a useful approach in understanding what users want from a service (Diaz-Martin et al., 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 based on their expectations towards 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 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?

The focus of these research questions is on the exploration of whether expectations towards learning analytics services are homogenous within a sample of students. It is motivated by the view that not all students will hold the same expectations towards learning analytics and in order to maximise uptake, we need to understand whether a one size fits all solution is a viable solution. To this end, we conducted a latent class analysis to segment respondents based on their expectations, and further explored the demographic characteristics of the groups identified.

# 2 Method

## 2.1 Sample

The survey was distributed to the entire student population (~16,000) at the Open University of the Netherlands and a total of 1247 responses (Females = 705, 57%) to the SELAQ were collected. 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 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 years of age ($M_{age}$ = 44.81, *SD* = 12.14). The average age of the sample is in line with the student population, who are typically older adults seeking to develop skills during their career. The three faculties that make up the university were almost equally represented in this sample: 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 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 from the Dutch students (*n* = 1119, 90%), whilst only a small number of respondents stated they were either European students (i.e., students who were from other European countries other than the Netherlands, *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.

## 2.2 Instrument

To measure student expectations of learning analytics, the SELAQ was used. We have developed and validated SELAQ (Authors, 2019) to assist higher education institutions in their pursuit of implementing learning analytics services and to increase stakeholder engagement. 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 in conjunction to obtain detailed insights into student beliefs.

The SELAQ has been presented as providing researchers with a means of obtaining valid measures of student expectations towards learning analytics services (Authors, 2019). Items cover various service features that have previously been discussed in the literature, specifically on self-regulated learning (Lim et al., 2020; Roberts et al., 2016; Schumacher & Ifenthaler, 2018) and linkages with the learning sciences (Marzouk et al., 2016). 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 seeks to present an exploratory study of how the SELAQ can be used to understand student expectations (ideal and predicted) of future learning analytics services.

The questionnaire hosted on the Qualtrics platform; an invitation to participate was distributed to all students at the university. The questionnaire itself contains 12 items (Table

1), 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). Development of these items required careful consideration of the limited applications of learning analytics in higher education; thus, items are phrased quite generally to maximise participant understanding (Authors, 2019). The two response 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. As a result, it has been shown that response distributions on the ideal expectation scale elicit stronger responses than the predicted expectation scale (Authors, 2019, 2020; see supplementary material). Prior work developing and validating the SELAQ has shown the scales to be reliable and valid (Authors, 2019, 2020). Initial development of the scale was carried out across three samples of higher education students in the United Kingdom, wherein survey responses and item feedback were used to refine the number of items and the item wordings. Both scales (ideal and predicted) were found to have good composite reliability values (.94 and .95, respectively). Since then, this scale has been translated and validated to be used in the Netherlands and Spain (Authors, 2020), wherein the originally proposed two-factor model was supported. The instrument has also been used in several Latin American higher education institutions (Authors, 2020).

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Insert Table 1 about here

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## 2.3 Analysis

The current study applied latent class analysis (LCA) 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).

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 only assumption LCA has is that the data are categorical as it was the case in our study (i.e., seven-point Likert scales). LCA does not make any assumptions related to linearity, normal distribution or homogeneity (Hagenaars & McCutcheon, 2002). LCA is a form of finite mixture model allows for soft-clustering method that calculates probabilities of group assignment (Hagenaars & McCutcheon, 2002), unlike hard clustering algorithms that assign each instance to exactly one group. That is, instead of finding clusters with an arbitrary distance measure as commonly done in cluster analysis, an LCA model identifies a distribution of the data and gauges probabilities that certain cases are members of certain latent classes. Since an LCA produces a statistical model based on the data used in analysis, it can also assess goodness of fit (e.g., Akaike Information Criterion), unlike commonly used cluster analysis methods. While a cluster analysis can only assign individual cases to clusters, LCA can also include co-variates that predict membership of cases in latent classes.

For the analysis of the collected data, we analysed the ideal and predicted expectation scales separately. An assessment of the response distributions for each scale shows the data to contain ceiling effects (Supplementary Material), 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 origin were associated with latent class assignment.

As for the latent class model building, we followed the steps outlined by Masyn (2013), which can be decomposed into assessments of absolute fit (standardised residuals), relative fit (e.g., the Bayesian Information Criterion), and classification diagnostics (i.e., accuracy as measured by relative entropy). Throughout the latent class model building, it is necessary that the interpretability of the solution needs to be considered (Lanza & Rhoades, 2013). 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, we followed the step taken by Oberski (2016) and use profile plots. These plots provide the estimated class means as opposed to the estimated distributions (Oberski, 2016). This is because there are seven possible categories (1 = Strongly Disagree, 7 = Strongly Agree), which makes plots of estimated distributions difficult to read (Oberski, 2016).

Thus, to provide an overview of the steps taken in this analysis, we increased the number of classes to extract until either the solution could not be identified, or the number of classes would affect the interpretability of the solution (Hagenaars & McCutcheon, 2002).

These models would then be compared on the basis of their relative fit. Throughout each stage, decisions regarding the selection of a candidate model were also determined by the class interpretability. Once a suitable candidate model had been identified, the latent class regression was then ran. For the purpose of this paper, the alpha level was set at 5% for determining whether an effect is considered to be statistically significant. A detailed presentation of the analysis steps are presented in the supplementary materials.

# 3 Results

The results presentation that follows is a summarised account of the model building steps, which led to a three-class and a four-class solution being retained for the ideal and predicted expectation scales, respectively. Additionally, the results of the logistic regressions for each scale are presented. For a detailed account of the results, readers are directed to the supplementary materials.

## 3.1 Ideal Expectation Scale

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 and RQ3. 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 (Figure 1). Among these items, Item S6 (obligation to act) received the lowest average rating across all the groups. The results of the latent class regression showed that only age was associated with assignment to class one or two (Table 2); thus, addressing RQ3.

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Insert Figure 1 about here

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## 3.2 Predicted Expectations

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 and RQ3. 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; Figure 2). 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 (Table 3), which addresses RQ3.

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Insert Figure 2 about here

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Insert Table 3 about here

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**3.3. Class Transitions**

Transitions between class assignments for the ideal and predicted expectation scales are presented in Table 4, which addresses RQ4. Those in 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).

# 4 Discussion

This exploratory paper sought to gauge and segment students based on their expectations of learning analytics services using 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 were identified. Segmentation of student expectations 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). In the following sections, the research questions are fleshed out with a focus on describing the results and using prior findings to facilitate the interpretations made.

## 4.1 Ideal Expectations

Based on the findings of the current study, it was found that students can be meaningfully segmented based on 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, aligning with previous findings (Ifenthaler & Schumacher, 2016; Jones et al., 2020; Slade et al., 2019; Slade & Prinsloo, 2014; Tsai, Whitelock-Wainwright, et al., 2020). Previous works are cited from this point onwards to help with additional interpretations of the data.

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 students 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, learning analytics cannot be a blanket implementation with all students receiving the same service. This has previously been hypothesised by Teasley (2017) and Roberts et al. (2017) who proposed a need for personalised or customisable learning analytic services. However, the hypothesis by Teasley was mostly based on a narrative review of the literature, while the proposition by Roberts et al. was based on a qualitative study with relatively small sample. Our study is the first to offer evidence in support these previous hypotheses and demonstrate differences in student expectations from learning analytics services.

An approach to implementation of learning analytics services, considering 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 et al., 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. One possible approach to tackle this issue could be introducing a mandatory learning analytics service that provides engagement metrics in the form of a dashboard, as already implemented at Nottingham Trent University (Nottingham Trent University, 2016; Sclater, Peasgood, & Mullan, 2016). In this way, students who have initially expressed low interest in learning analytics may change their expectations due to the exposure to or perceptions of the way their peers benefit from using the services (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 shows item S6 (the obligation to act) to be lowest for each group (as shown in Figure 1). In the case of the *Inflated Ideal Expectation* and *High Ideal Expectation* groups, the average responses to S6 (the obligation to act) fall between five (Somewhat Agree) and six (Agree). Whilst these are positive responses, they do fall below the trends for 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 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, but the student themselves bears a responsibility to engage in the learning process (Howell et al., 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. Studies 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 can be used strategically to strengthen the existing support infrastructure for distance-learning students, thus cultivating a sense of belonging among students and providing information that can help students better manage their studies and achieve learning goals.

## 4.2 Predicted Expectations

The results of the study also found that students could be meaningfully segmented based on 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. Below, the identified are described in further detail, with previous findings being used as a lens to facilitate interpretations.

In contrast to the Ideal Expectation scale, these four identified groups can be differentiated based on 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) received 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) was met with indifference (Neither Agree nor Disagree (4)). For these students, it appears that they did 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 to 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 et al., 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), a 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. In particular, under the governance of the GDPR[1], universities in the European Union do have the legal responsibility to inform students about any personal data collected and how it will be processed (Sclater, 2017). Thus, in conjunction with the expectations of students presented here, 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. Put differently, S6 appears to be a feature that students generally do not expect a university to implement, but other items receive positive responses. For the *High Predicted Expectation* (Class One) and *Inflated Predicted Expectation* (Class Three) groups, features that include, but are not limited to, 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 (Lim et al., 2020; Roberts et al., 2017; Schumacher & Ifenthaler, 2017).

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 no 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 were 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 decision makers in higher education 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).

## 4.3 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). Previous literature on student stakeholder perspectives of learning analytics services is again used to offer additional interpretations from the descriptions of the data.

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 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) on the predicted expectation scale. For these students, they appear to not desire any of the features of a learning analytics service but they do expect the university will implement such services. 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).

## 4.4 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. 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, a 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, as research has shown this area to be the most important aspect of a policy that governs the use of learning analytics (Scheffel et al., 2019). 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) and used (e.g., creating and sending personalised emails), whereas Cormack (2016) suggests that under this premise, consent-seeking is necessary only prior to actioning interventions. It is still necessary, however, that even under these circumstances the students are aware of such steps being taken (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 no 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 your 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 blanket implementation of learning analytics services within universities, students must have the right to decide whether to partake in such services or not.

## 4.5 Limitations

Our decisions regarding the candidate model selection were informed by the relative fit, classification diagnostics, local fit, and interpretability as introduced in Section 2.3. 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, our analysis showed that the interpretability, relative fit, and classification accuracy of the selected models were good. Therefore, we concluded that seeking to meet the general guideline of 5% for absolute fit by increasing the number of classes extracted was inappropriate. It 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 desires 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 underdtake additional qualitative work to provide a rich understanding of what factors lead students to fall within the identified classes reported here.

The study was conducted at a single higher education institution with specific educational, political, and cultural context. Therefore, this study should be replicated in other contexts before any generalisability claims can be substantiated.

# 5 Conclusion and Future Work

The current work has provided answers to the four proposed research questions, and identified a need for higher education institutions to develop approaches to the implementation of learning analytics that cater to the expectations of different student subpopulations. Specifically, the work has shown that student expectations of learning analytics can be segmented through the application of latent class analysis. Each identified group shows a distinct profile of what is expected from a learning analytics service. The majority of the respondents expected the university to act ethically in the use of student data central to any service, whilst the expectations towards learning analytics services are not consistent. There is a need for follow up work to understand the reasons behind students holding contrasting expectations towards the types of learning analytics features that could be offered.

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