



# Exploring students' expectations of learning analytics: A person-centered approach

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## Abstract

In order to successfully implement learning analytics (LA), we need a better understanding of student expectations of such services. Yet, there is still a limited body of research about students' expectations across countries. Student expectations of LA have been predominantly examined from a view that perceives students as a group of individuals representing homogenous views. This study examines students' ideal (i.e., representing their wanted outcomes) and predicted expectations (i.e., unveiling what they realistically expect the LA service is most likely to be) of LA by employing a person-centered approach that allows exploring the heterogeneity that may be found in student expectations. We collected data from 132 students in the setting of Swedish higher education by means of an online survey. Descriptive statistics and Latent Class Analysis (LCA) were used for the analysis. Our findings show that students' ideal expectations of LA were considerably higher compared to their predicted expectations. The results of the LCA exhibit that the Swedish students' expectations of LA were heterogeneous, both regarding their privacy concerns and their expectations of LA services. The findings of this study can be seen as a baseline of students' expectations or a cross-sectional average, and be used to inform student-centered implementation of LA in higher education.

**Keywords** Students' expectations · Learning analytics · Person-centered approach · Higher education · Latent class analysis · Impact

## 1 Introduction

The potential of learning analytics (LA) and the advantages that LA services can offer to higher education have been acknowledged by researchers and practitioners worldwide, but their adoption still remains low (Viberg & Grönlund, 2021; Tsai et al., 2020; Cuzmán-Valenzuela et al., 2021). LA is defined as “the measurement, collection, analysis and reporting of data about learners and their contexts for purposes

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of understanding and optimizing learning and the environments in which it occurs” (Long & Siemens, 2011, p. 34). To be able to effectively implement any information system (e.g., a LA service) at scale, stakeholders’ expectations of it is a vital and valid predictor of actual system use (Davis & Venkatesh, 2004). Furthermore, it has been argued that it is important to consider these expectations thoroughly at the early stages of design, since the stakeholder “expectations gauged at this early stage could provide valuable insights into subsequent acceptability of the software product [e.g., a student-facing learning dashboard] to be developed” (Davis & Venkatesh, 2004, p. 44).

One of the key stakeholders of LA – aiming at improved student learning and the contexts in which it occurs (Long & Siemens, 2011) - are students (West et al., 2020). Consequently, the examination of students’ expectations of LA (i.e., what they expect from LA services in terms of functionality and effectiveness) and their related ethical and privacy expectations of LA (i.e., in relation to the responsible use of their data; Whitelock-Wainwright et al., 2019), is a crucial first step that can facilitate the adoption of LA in higher education. However, considering the importance of students’ expectations for design and implementation of LA in practice, they are so far not well explored across countries, with some exceptions (e.g., Schumacher & Ifenthaler, 2018; Hilliger et al., 2020; West et al., 2020; Tsai et al., 2020; Whitelock-Wainwright et al., 2021). Moreover, researchers stress that students’ engagement in the design of LA services has hitherto been largely low (Viberg et al., 2018; Jivet, 2021). All this may have underpinned a slow adoption of LA in practice worldwide, including Sweden, a highly digitalized country (European Commission, 2019), in which there have hitherto been very scarce, largely small-scale attempts to implement LA (Ifenthaler et al., 2019; Nouri et al., 2019). In the present study, we focus on the examination of Swedish students’ expectations towards LA.

Taking into account the fact that individual students’ preferences and expectations of LA may differ not only across countries and cultures, but also within a homogenous sample of students, there have yet been rare attempts to divide or segment them into different subpopulations (Whitelock-Wainwright et al., 2021). This is important for a higher adoption rate of LA among different student groups in higher education. Researchers in other fields, for example, in social sciences have emphasized that inadequate attention to the heterogeneity aspect in the complexity of human social activity has resulted in a number of important phenomena in regard to individual differences left largely unexplored (Scotto Rosato & Baer, 2012). A considerable part of the learning process can similarly be seen as a human social activity that needs to be carefully explored.

LA scholars argue the heterogeneity assumption can be supported by several accounts, including the following: 1. students who have just started their studies in higher education require more support from higher education institutions to better (self-) regulate their learning process compared to the students who have already been enrolled in higher education studies for some time; 2. LA services can be seen as a form of feedback; yet, this feedback may vary depending on the students’ needs and skills (e.g., in terms of self-regulation in their studies), and 3. students’ demographic and academic information (e.g., grades) – that usually varies considerably – can play a significant role in forms of support students need from higher education institutions (Whitelock-Wainwright et al., 2021).

Consequently, the differentiation of students' expectations towards LA is critical since its results can offer a sound ground for designing more effective student - oriented LA services that would: 1. adequately consider students' characteristics (e.g., their level of motivation and/or their level of self-regulation in their studies), and 2. meet their preferences (e.g., towards LA services' functionality and privacy settings) and needs (e.g., in relation to their learning progress), ultimately leading to improved learning. Here, it is important to stress that any design of a LA tool can only lead to improved conditions for students' learning, because learning cannot be designed directly (Viberg & Grönlund, 2017).

An attention to the differentiation of students' expectations towards LA is in turn supported by an increasingly growing interest in shifting research focus in technology-supported learning environments from group (e.g., a group of students representing a certain culture or institution) differences and measurement instruments towards learners' multivariate profiles and changes over time (Jang et al., 2017). Researchers refer to such more individual-oriented approaches as *person-oriented* approaches that “focus on how specific variables or characteristics group within individual learners” (Jang et al., 2017, p. 555; for more, see Background). These *person-centered* approaches align well with a recent call for a human-centered LA approach which suggests that the design of effective LA extends beyond sound technical and pedagogical principles; it needs “to take into account a range of human factors, including why and how they will be used” by individual learners (Buckingham Shum et al., 2019, p. 1). Yet, the current literature does offer only limited empirical insights about students' subpopulations (or classes) and their varied expectations of LA (Whitelock-Wainwright et al., 2021) across countries. Consequently, this study aims to build on the recent related research efforts (e.g., Whitelock-Wainwright et al., 2021) by investigating the heterogeneity that may be found in students' expectations, as compared to the students' general expectations of LA in the context of Swedish higher education.

In order to examine heterogeneity, we draw on Whitelock-Wainwright et al. (2021), who employed latent class analysis to segment a heterogeneous student group into classes. In particular, this study aims to answer the following research question: *Are students' expectations of learning analytics heterogeneous, and if so, what are the main classes that can be identified?* To be able to demonstrate how they differ from students' overall expectations, this study also briefly examines their overall expectations, which are in detail presented in Engström et al. (2022). Further, the exploration of students' expectations of LA focuses on the differentiation between their *ideal* and *predicted* expectations, further explained in the next section.

## 2 Background

### 2.1 Stakeholders' expectations of information systems

Ochoa et al. (2020) highlight that “[w]e, as a field, have failed to bridge the adoption chasm to put these [learning analytics] tools into the hands of instructors and learners” (p.1). One of the reasons behind this failure can be linked to the limited body of knowledge in terms of key stakeholders' expectations of LA. Researchers posit that when an information system (e.g., a LA system) fails, “one cause may be its inability

to meet the expectations of its stakeholder groups” (Szajna & Scamell, 1993, p.493), namely students and teachers in the context of LA. Sanders (1984) stresses that user expectations are situated between pre-implementation factors (i.e., those variables that could have an impact on the realism of user expectations) and two indicators of information system success, namely user perceptions (i.e., satisfaction) and user performance (i.e., decision quality). Also, scholars underline that while user expectations are significant, the realism of them is potentially a factor of its success and failure (Szajna & Scamell, 1993). Ginzberg (1981) for example, showed that the realism of user expectation was significantly correlated with user attitudes and usage of the information system, and explained the success or failure of an information system better than several other pre-implementation factors (e.g., user involvement). Others (Venkatesh & Goyal, 2010; Venkatesh et al., 2003) have similarly emphasized that the user expectations of information systems should be at a realistic level. Users’ unrealistic expectations can lead to users showing low satisfaction and usage (Szajna & Scamell, 1993; Sackl et al., 2017). But what do we mean by the term *expectations*?

Definitions of the term *expectations* have been offered by researchers in different fields, including social psychology, organizational behavior, and information systems (Shackle, 1952; Vroom, 1964). In these definitions, researchers focus on two key components of expectations: 1. a future time perspective, and 2. a degree of uncertainty (Szajna & Scamell, 1993). Based on that, scholars defined *user expectations* of an information system (e.g., a LA service) as “a set of beliefs held by the targeted users of an information system associated with the eventual performance of the IS [information system] and with their performance using the system” (Szajna & Scamell, 1993, p. 494). This definition has been adopted for the purposes of this study.

Also, scholars differ between *ideal* expectations (i.e., representing stakeholders’ wanted outcomes) and *predicted* or realistic ones (i.e., unveiling what a person realistically expects the service is most likely to be; David et al., 2004; Dowling & Rickwood, 2016). In the setting of LA, stakeholders’ ideal and predicted expectations have been recently compared (e.g., Whitelock-Wainwright et al., 2019, 2021; Hilliger et al., 2020; Kollom et al., 2021). The differentiation between them allows researchers and practitioners to better understand what students realistically expect from LA services (e.g., in terms of the functionality of the system and potential privacy concerns), whilst also being attentive to what students prefer (Whitelock-Wainwright et al., 2021).

## 2.2 Students’ expectations of LA

Students’ expectations of LA are critical for any successful adoption of them in everyday teaching and learning practices. However, there has been a limited – in different ways (e.g., in terms of the limited sample size, the contexts examined, and the methods of analysis employed) – body of research that uncovers students’ views (Braunack-Mayer et al., 2020; West et al., 2020), including their related expectations of LA services, in LA decision-making, and few studies that empower students to be co-creators of LA services (e.g., Ifenthaler & Schumacher, 2016; de Quincey et al., 2019; West et al., 2020). Yet, as stressed by Whitelock-Wainwright et al. (2021), LA researchers have made some relevant

research attempts in this direction (e.g., Arnold & Sclater, 2017; Ifenthaler & Schumacher, 2016; Schumacher & Ifenthaler, 2018; Tsai et al., 2020; West et al., 2020; Whitelock-Wainwright et al., 2021).

The results of the conducted studies demonstrate that despite the students' overall lack of awareness of what constitutes LA (West et al., 2020), students in higher education overall exhibit positive attitudes towards and expectations of LA (see e.g., Arnold & Sclater, 2017; Ifenthaler & Schumacher, 2016; Hilliger et al., 2020; Schumacher & Ifenthaler, 2018; Whitelock-Wainwright et al., 2021). Hilliger et al. (2020) for example, through a mixed-method approach (i.e., focus groups interviews and surveys) investigated students' needs, among others, for LA adoption in Latin American universities. The findings showed that students need quality feedback (i.e., timely and individualized feedback beyond the grading as a form of formative evaluation) and data-driven support from teaching staff to improve their learning results; most students (88%) expected their educational data to be used to inform support interventions. West et al. (2020) investigated students' expectations of the collection and use of student data for LA in the context of Australian higher education. The results exhibit that while students are overall comfortable with the use of their data, they are concerned with the use of demographic data, location data and data collected from wireless networks, social media and mobile applications; the findings have also stressed the need for transparency to support informed consent and personal-professional boundary being critical.

Whereas the prevailing part of the studies examining students' expectations toward LA have approached their samples as homogenous student populations, scholars posit that we cannot assume that all students have similar expectations (see e.g., Jivet, 2021; Schumacher & Ifenthaler, 2018; Teasley, 2017). Their expectations may differ based on their level of self-regulation in studies and their level of motivation, as well as their cultural values (e.g., Tsiligiris et al., 2021). Overall, expectations-grounded segmentation has been proved to be a useful approach in better understanding what users (e.g., students who are using LA tools) want from a service (Webster, 1989). Whereas there are some related studies in education settings (e.g., Blasco & Saura, 2006), such attempts in LA research have hitherto been limited. In a recent study, Whitelock-Wainwright et al. (2021) explored students' expectations of LA services in the setting of the Dutch higher education. In that study, a three-step approach to latent class analysis to understand whether students' expectations of LA services can be segmented has been employed. Their findings reveal that students' expectations of ethical and privacy elements of a LA service are consistent across all identified student groups, but their expectations of the LA service vary. This in turn suggests that there is a need for higher education institutions to develop granular approaches to the implementation of LA that cater to the expectations of different student subpopulations.

### 2.3 Person-centered approaches

The majority of the performed studies focusing on student expectations of LA approached their respondents as homogenous groups. Scholars stress that the two key limitations of variable-centered methods refer to their inability: 1. to deal with heterogeneity within and between individuals, and 2. to accurately characterize

non-linear and interactive patterns (Hickendorff et al., 2018). In contrast, *person-centered approaches* can model heterogeneity; they emphasize the individual to be able to account for heterogeneous patterns of variable interactions (Hickendorff et al., 2018). The aim of the use of these approaches in learning research is to discover and illustrate general – in contrast to single individual's – patterns of learning behavior, learning pathways (Hickendorff et al., 2018), as well as students' expectations of targeted technology-enhanced learning activities (e.g., LA tools), since they can directly predict their future learning behavior, assisted by the use of selected technologies (e.g., Whitelock-Wainwright et al., 2021).

In particular, variable-oriented methods aim at exploring the relationships between variables, e.g., how and to what extent engagement can be correlated to students' performance in a course, or how students' expectations of LA service features correlated with their privacy concerns in this regard. These methods are informative of what a group of individuals can do 'on average' (Hickendorff et al., 2018; Scotto Rosato & Baer, 2012). However, scholars posit that such methods are an overgeneralization (Hickendorff et al., 2018), based on the assumptions that students are a homogenous group, while in fact, there are several variations and dissimilarities that are basic to human nature leading to heterogeneity within any human behavior. Person-centered methods aim at capturing such heterogeneity by discovering subgroups that have similar behavior (homogenous clusters) and represent a distinct subpopulation. These methods have been increasingly popular in social sciences and education since they allow researchers to account for the heterogeneous and multidimensional nature of learning and learners' behavior (Goodman, 1974; Hickendorff et al., 2018; McCutcheon, 1987; Scotto Rosato & Baer, 2012). For instance, Quirk et al. (2013) used such methods to discover distinct subgroups of students' readiness to schools. Carroll and White (2017) employed the methods to discover students' distinct profiles of online learning behaviour. Others used similar methods to classify profiles of students' learning strategies (Mirriahi et al., 2018).

Latent Class Analysis (LCA) – employed in this study – is one of the frequently employed person-based methods that allows the discovery of such heterogeneity of the data by finding 'hidden' groups or latent classes within the data (Hickendorff et al., 2018). LCA uses study participants' responses to categorical indicator variables (Weller et al., 2020). It does not require the data to be normally distributed, and entails no linearity or homogeneity allowing for the study of several types of data and contexts (Hickendorff et al., 2018; Scotto Rosato & Baer, 2012). Such flexibility of LCA has made it popular among educational researchers to explore students' profiles and distinct subpopulations (e.g., Carroll & White, 2017; Jang et al., 2017; Parpala et al., 2010).

### 3 Method

#### 3.1 Data collection

In this study, we have adopted a survey instrument called *Student Expectations of Learning Analytics Questionnaire* (SELAQ; Table 1; Whitelock-Wainwright et al.,

2019, 2021). SELAQ does not aim to replace qualitative explorations of student expectations, but rather to be used as a quantitative instrument that can be employed to “accommodate a greater number of student beliefs into learning analytics service implementation” (Whitelock-Wainwright et al., 2021, p.4). The instrument has been earlier validated in several higher education settings (Whitelock-Wainwright et al., 2019), and used to measure students’ expectations of LA in different higher education settings (e.g., Garcia et al., 2021; Whitelock-Wainwright et al., 2021). It consists of two parts: 1. the first part (items 1–5) focuses on the understanding of students’ privacy and ethical expectations of LA, and the second one (items 6–12) – on their expectations in terms of LA services, which refer to a “belief about the likelihood that future implementation and running of LA services will possess certain features” (Whitelock-Wainwright et al., 2019, p. 4). Moreover, considering the fact that the term *expectation* is problematic and much inclusive (see e.g., Szajna & Scamell, 1993; Thompson & Sunol, 1995), students’ expectations in the SELAQ are measured in terms of their *ideal* expectations and their *predicted* expectations. That is,

**Table 1** Student Expectation of Learning Analytics Questionnaire (SELAQ; adopted from Whitelock-Wainwright et al., 2020)

Factor	Items
Ethical and Privacy Expectations	
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 analyze 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
Service Feature Expectations	
S1	The university will regularly update me about my learning progress based on the analytics of my education 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

students have been asked to provide their response twice to the same item ( $n = 12$ ) focusing on 1. their ideal expectations and 2. their predicted expectations of LA.

The following developments to the original version of SELAQ were made. First, to better understand the characteristics of the examined sample we have added demographic questions regarding the respondents' age, gender, educational program and year of study (at the university). Second, to ensure that the respondents who are likely not aware of what LA refer to understand the content of all the survey items adequately and provide relevant responses, we have included a short introductory text to LA, with a definition of LA and some concrete examples of LA tools or services, at the beginning of the survey. We have also chosen to use a 5-point Likert scale (1 – 'totally disagree' > 5 – 'totally agree') instead of the originally used 7-point scale, because the use of the latter was earlier found to yield data of lower quality (Revilla et al., 2014). The questionnaire was then translated into Swedish. The translated version of the adopted SELAQ was piloted among two students by means of a think-aloud method. Based on that, several smaller text improvements were made before the survey was distributed online to the students of the three courses at Anonymized (Sweden) in March 2021. The choice of the courses was based on convenience sampling. In this study, we have approached several course responsible coordinators, and three of them have agreed on distributing the survey in their courses. The respondents' participation in the study was anonymous. They were also asked to fill out the informed consent to participate in the study.

### 3.2 Data analysis

The data were analyzed using Latent Class Analysis (LCA) implemented in the R! software package PolCA (Linzer & Lewis, 2011). Since the survey instrument consists of two distinctive parts (i.e., 1. students' predicted expectations of LA and 2. their ideal expectations of LA), both of which contain the same questions, each part was analyzed separately. Also, each of these parts focuses on the two distinctive aspects of students' expectations of LA (their expectations towards: 1. privacy and ethics, and 2. LA services; they were also analyzed separately; Item 1–5 for the X scale and Items 6–12 for the Y scale. This decision was underpinned by the results of the preliminary analysis, the results of which have shown that based on our data a full-scale model failed to fit.

We used an Analytic Hierarchy Process (AHP) to determine the suitable number of classes (Akogul & Erişoğlu, 2017; Saaty, 1990). The AHP method allows decision making from multiple factors through a structured process (Saaty, 1990). Our method for the choice of the best number of clusters followed Akogul and Erisoglu's (2016, 2017) implementation of AHP to select the best model based on multiple cluster fit indices. First, we calculated several fit indices for each model with different numbers of classes, namely Akaike's Information Criterion (AIC), Approximate Weight of Evidence (AWE), Bayesian Information Criterion (BIC), Classification Likelihood Criterion (CLC), and Kullback Information Criterion (KIC). For each of the fit indices, we calculated the magnitude of support of each of the models compared to the other models. The magnitude of support for each model was used to construct a priority vector



for each model. Then a weighted average of the priorities was calculated based on each index ability to contribute to recovering the accurate number of clusters (Akogul & Erişoğlu, 2016, 2017). The number of clusters is selected based on the highest weighted priority (Akogul & Erişoğlu, 2017; Saaty, 1990). This approach allows for a non-subjective rigorous way of finding the best number of classes.

We created four models – and therefore, the process was performed for each model. The input for the first model was the students' ideal expectations in terms of privacy and ethics (EP1-EP5, Table 1). In the analysis, these items are labeled as IDL1 - IDL5. The second model focuses on their related predicted expectations (Table 1), labeled as EXP1 - EXP5. The third model focuses on their ideal expectations of the LA service (S1-S7, Table 1), labeled as IDL 6-IDL12 in the analysis, and the fourth one – on their predicted expectations in this regard (EXP6-EXP12). Table 1 presents the complete list of items. The full conceptual, mathematical details and process are detailed in Akogul and Erişoğlu (2016, 2017).

### 3.3 Limitations

This study has several limitations that should be taken into consideration while interpreting the results. First, our data were collected from the students from a technical university; these students may have a higher data literacy compared to students who study, for example, humanistic programs. Second, our sample size was limited, and the generalization of results may need to be confirmed by the results from further similar studies. However, given the explorative nature of the present study and the limited insights about student expectations of LA representing different countries and cultures, we believe that our results are valuable for LA researchers, teachers and learning designers who aim to scale up LA efforts in higher education. Moreover, the existing guidance on the optimal number of a sample size is inconclusive and far from informative; several studies and guidelines stress different numbers of clusters, covariates, and parameters (see e.g., Hua et al., 2004). Some scholars (e.g., Dziak et al., 2014) have suggested that a reasonable statistical power can be achieved with a sample size slightly above 100 (similar to ours). Since our data and models were simple i.e., had no covariates and limited number of parameters and clusters, we believe that the number of observations is reasonable to support the conclusions of the study.

## 4 Results

### 4.1 Participants

A total of 132 students participated in this study, with a 46% response rate. 64% were men and 35% women. Two participants have chosen the “other/does not want to answer” option. The participants' age varied between 19 and 34 years old; the median age was 22 (SD=2.57). In regard to the year of study, 39% of the respondents were first year students, 34% - Year 2 students, and 27% - Year 3 students.

## 4.2 Students' general expectations towards LA

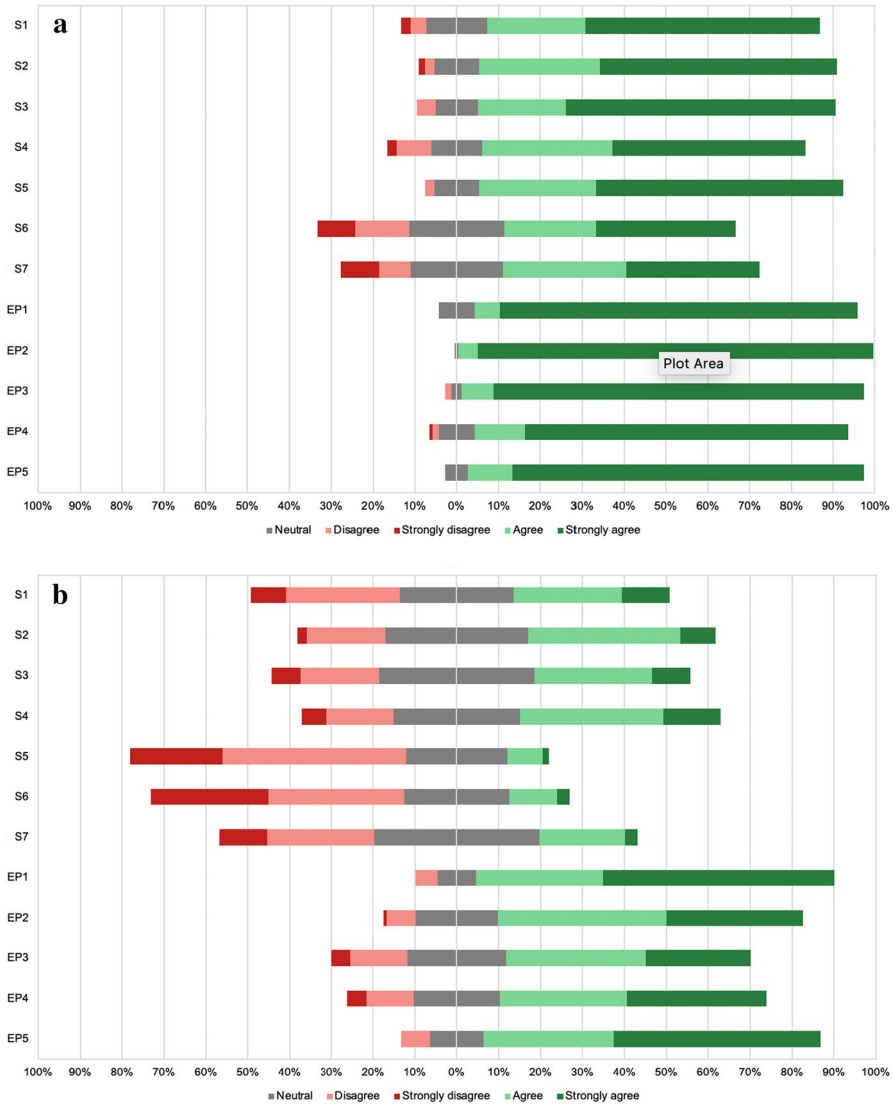
The results showed a clear discrepancy between students' ideal and predicted expectations (Fig. 1a, b). It was most noticeable with respect to the students' expectations toward privacy and ethics (EP1–5). Their related ideal expectations (Fig. 1a) are very high: the mean agreement of privacy items was 95% compared to their predicted expectations which mean was at 50% only (Fig. 1b). In particular, the majority of students (89%) have agreed that ideally (vs 50% predicted) the university will ask for informed consent before collecting data; 92% have agreed that the university will ideally ask for their consent before using identifying information (vs 39% predicted). Similarly, 97% have agreed that ideally (vs 56% predicted) the university will ask for consent before outsourcing data, and 95% have agreed that ideally (vs 44% predicted) they will be asked for further consent if the data will be used for other purposes. Finally, all the students have agreed that ideally (vs 60% predicted) university will make data secure.

The found discrepancy regards also the students' expectations focusing on the teaching staff. The majority of students (87%) have expressed high expectations that ideally (vs 32% predicted) the teaching staff will be competent in using LA for support and feedback (S5). Interestingly, the students' lowest ideal expectations concern their expectations of teachers who should act on LA data (55% ideal vs 36% predicted; S6). Also, the respondents have reported their uncertain or 'neutral' predicted expectations in regard to: 1 the need of on the part of the teacher's competency to integrate LA into the feedback and the provided support (S5), and 2. the university will update them about their learning progress (S1).

Overall, students' ideal and predicted expectations were more concordant regarding the LA services (S1 - S7), where 86% of students have agreed that ideally (vs 70% predicted) LA services will be used for decision making (S2). 77% have agreed that ideally (vs 64% predicted) LA will present a complete profile of learning across modules (S4), and 85% have expressed that ideally (vs 65% predicted) LA services will show their individual learning progress in relation to the set learning goals (S3).

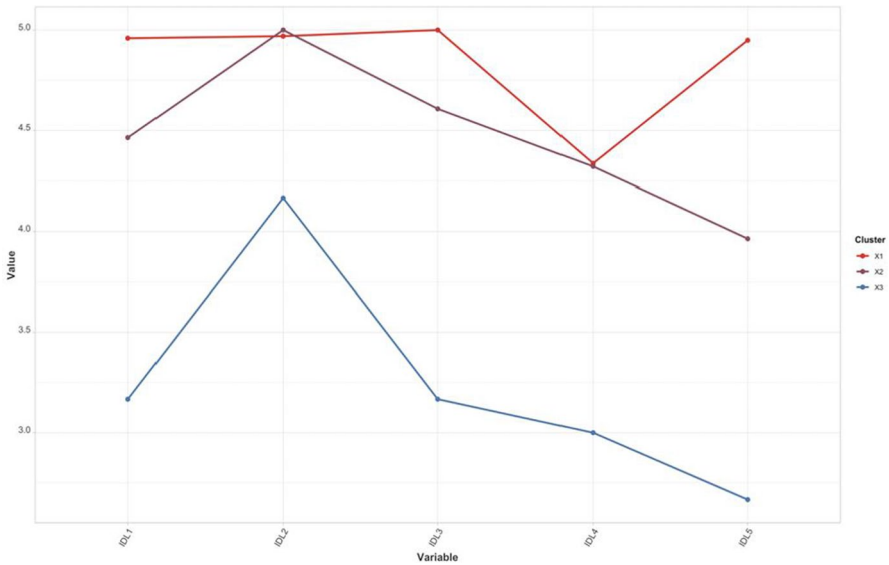
## 4.3 Ideal expectations: Ethics and privacy

The results of the LCA demonstrate the students can be classified into three subpopulations or classes according to their *ideal* privacy and ethical expectations of LA services (Fig. 2). These classes have been labeled as 1. *Ideal Privacy Perfectionists* (71%), 2. *High Ideal Privacy Anticipators* (25%), and 3. *Low Ideal Privacy Anticipators* (5%). Class 1 (×1, Fig.2) represents a group of students who have the highest expectations in four out of five statements (IDL 1–3, 5). In particular, these students – who represent the largest subpopulation – would ideally expect HE institutions to ask for their consent before using any identifiable information about themselves (e.g., gender and age) and before their educational data is outsourced for analysis by third party services, as well as to ensure that all their educational data will be kept securely. Finally, they have high expectations that the university will request further consent if their educational data is being used for a purpose different from what was originally stated. In this subgroup,



**Fig. 1** **a** Students' general ideal expectations of LA (see Table 1). **b**: Students' general predicted expectations of LA (see Table 1)

the students' expectations of whether the university would ask for their consent to collect, use, and analyze their educational data (e.g., grades and attendance) or not were a bit lower (Fig. 2). Class 2 represents the expectations of a smaller group of students (25%) who have also rather high expectations in terms of the HE institutions' responsible use of their educational data, especially in the first three items (IDL 1–3, Fig. 2). However, their expectations of whether the university would ask for their consent to collect, use and analyze their educational



**Fig. 2** Profile plot - estimated means for ideal privacy expectation items for the three-class solution

data or not (IDL 4), and that it would request further consent if their educational data is being used for a purpose different to what was originally used or not (IDL 5) have been reported to be slightly lower. Finally, Class 3 depicts the smallest subgroup (5%; Fig. 2) who have overall reported their low and indefinite ideal expectations in relation to the university's responsible management of their educational data. The only item that they have scored highly at relates to their expectation that the university would ensure that all their educational data would be kept securely (IDL2). Also, the results of our analysis display that the predicted class membership will be slightly higher for the first class compared to the estimated numbers (i.e., Class 1–74%), the same for Class 2 (i.e., 21%), and Class 3 (5%), suggesting that overall, students will have very high and high expectations in terms of responsible use of their data.

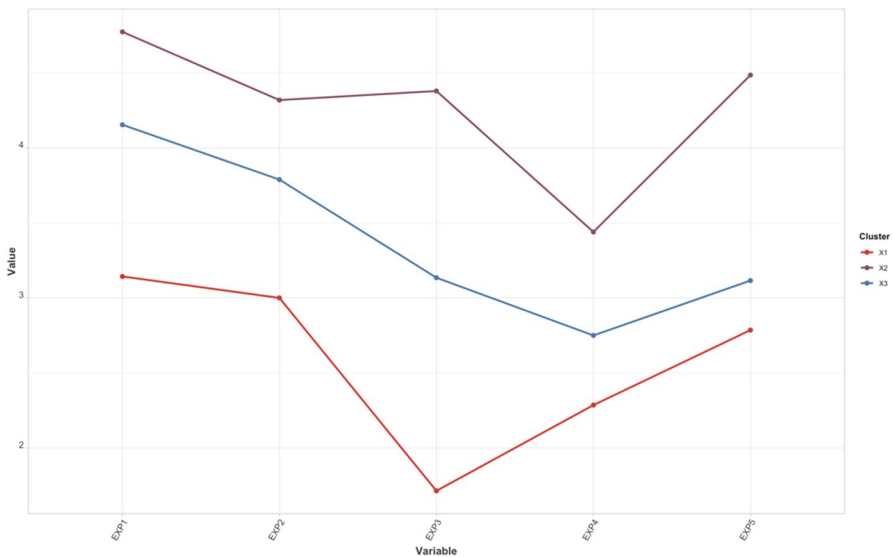
#### 4.4 Predicted expectations: Ethics and privacy

The students' *predicted* or in other words, their more realistic expectations of the responsible collection, use and analysis of their educational data on the part of the university are overall lower compared to their related ideal expectations (Fig. 1b). The results of the LCA have also revealed that there is a degree of heterogeneity in their expectations in this regard. That is, the three distinctive classes have been identified. Class 1 – *Low Predicted Privacy Anticipators* (11%) – consists of the students who have low (EXP 3–4; Fig. 3) or indefinite expectations (EXP1–2, 5) in relation to the responsible LA. These students have specifically reported very low expectations towards the two assumptions: 1. the university would ask for their consent before their educational data is outsourced for analysis by third party companies

(EXP 3) and 2. that it would ask for a consent to collect, use and analyze any of their educational data (EXP 4). The second extracted of students (Class 2) represents the largest (51%) class and is called *High Predicted Privacy Anticipators* (Fig.3). These students have exhibited their very high and high expectations in the four examined assumptions (EXP1–3, 5). Yet, they have expressed somewhat lower and uncertain expectations of whether the university would ask for their consent to collect, use and analyse any of their educational data or not. Finally, Class (3) represents *Moderate Predicted Privacy Anticipators* (38%, Fig.3). These students have exposed somewhat higher expectations in terms of that the university would: 1. ask for their consent before using any identifiable data about them (EXP1) and 2. ensure that all their educational data would be kept securely (EXP2). Similar to the other two classes, students in this group have demonstrated the lowest expectations in terms of whether the university would ask them for their consent to collect, use and analyze their educational data, including grades, attendance and virtual learning setting accesses (e.g., through a learning management system). The predicted class membership is close to the estimated one: Class 1–11%, Class 2–50%, and Class 3–39%.

#### 4.5 Students' ideal expectations: LA service

Analysis of the students' ideal expectations of LA service has resulted in the identification of three, similar in their size subpopulations or classes: Class 1 (36%) - *High Ideal Service Anticipators*, Class 2 (35%) - *Ideal Service Perfectionists*, and Class 3 (29%) - *Moderate Ideal Service Anticipators* (Fig. 4). In all classes, the students reported very high expectations (i.e., strongly agree) of that the university would regularly update them about their learning progress, based on the analysis of their educational data (IDL 6). The students representing Class 2 have similarly expressed their highest



**Fig. 3** Profile plot - estimated means for predicted privacy expectation items for the three-class solution

expectations in terms of that the LA service would: 1. be used to promote their decision-making during the learning process (IDL 7); 2. show how their individual learning progress relates to their learning goals/course objectives (IDL 8); and 3. present a student with her complete profile of her learning across every module (IDL 9). Also, these students reported high expectations that the teaching staff will be competent enough to incorporate analytics into the feedback and the provided to them support (IDL 10). In this class, the students have scored slightly lower but still high, in relation to their expectations of the educators' obligation to act or support them based on the analytics' results (IDL 11), and their expectations of the assumption of that the feedback from the LA service would be used to promote academic and professional skill development for their future employability (IDL 12). Class 1 consists of students who have high ideal expectations towards the LA service (IDL 6–10) and slightly indifferent expectations ('neither agree nor disagree') of the last two items (IDL 11–12). Finally, Class 3 represents students who have either indifferent expectations of the LA service (IDL 7–10) or low expectations towards the teacher's obligation to act as well as that the feedback from the LA service will be used to promote their academic and professional skill development (IDL 11–12, Fig. 4). The predicted class membership is similar to the estimated one: Class 1 (36%), Class 2 (35%), and Class 3 (29%).

#### 4.6 Students' predicted expectations: LA service

The findings illustrate that the students' *predicted* expectations are lower compared to their ideal expectations of LA services to support their learning process (Fig. 1). Moreover, the findings of the LCA display that the students in our sample can be clustered into two distinctive classes: *Moderate Predicted LA Service Expectation*

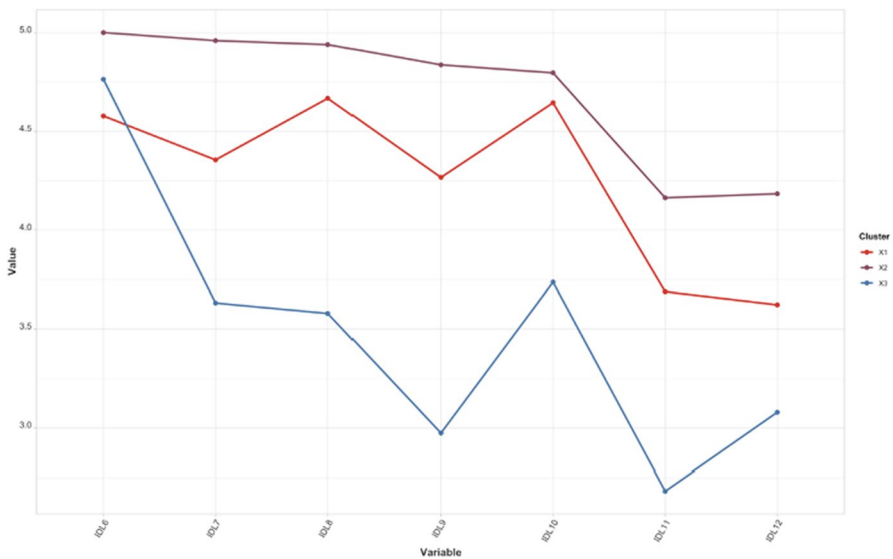
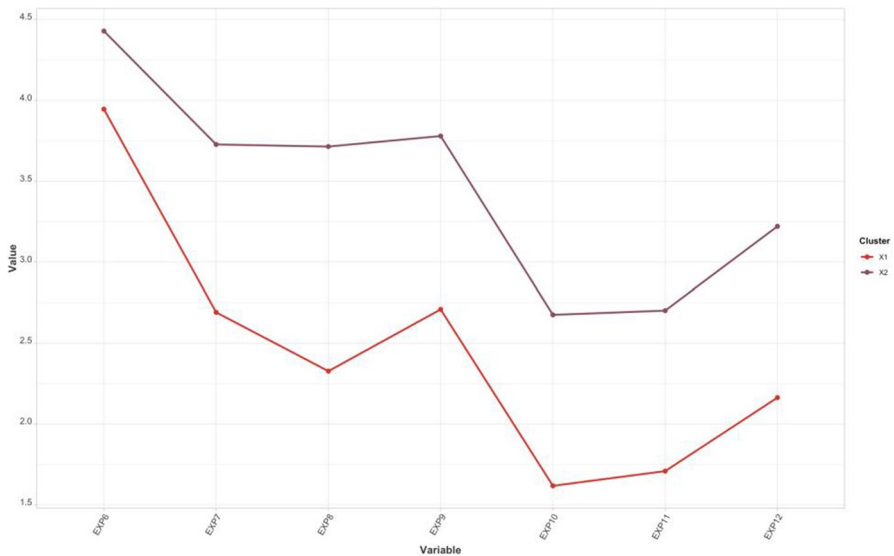


Fig. 4 Profile plot - estimated means for ideal LA service expectation items for the three-class solution

group (Class 1; 55%; Fig. 5) and *Low Predicted LA Service Expectation* group (Class 2; 45%). Yet, it is important to stress that the students in both classes have exhibited their high predicted expectations in regard to the assumption that the university would regularly update them on their learning progress based on the analysis of the educational data (EXP6, Fig. 5). Class 2 students reported overall somewhat low expectations regarding the following three assumptions, i.e., the LA service will: 1. be used to support their decision making (EXP7), 2. show their learning progress compared to the learning goals or course objectives (EXP8), and finally, 3. present them with a complete profile of their learning across educational modules (EXP9). Also, their predicted expectations of the educators' actions and related skills needed to integrate the results of analytics in their teaching practice in order to improve students' conditions for learning (EXP 10, 11) were reported to be very low. The *Moderate Predicted LA Service Expectation* group (Class 1) represents students largely having somewhat indifferent expectations of the actions and skills needed on the part of the educator to facilitate their decision-making for improved learning (EXP10–12), and higher expectations towards the assumptions related to the LA service features (EXP7–10). The predicted class membership is close to the estimated one (Class 1–58%, Class 2–42%).

## 5 Discussion and conclusions

This study has explored the Swedish students' expectations of LA using a *person-centered* approach. It aimed at unveiling not only their general expectations, but also to examine whether they could be clustered into different classes in order to provide



**Fig. 5** Profile plot - estimated means for predicted LA service expectation items for the two-class solution

more individual student- oriented LA services in the future, compared to seeing students as one group that represents homogenous views. Such an understanding is critical to be able to facilitate the adoption of LA services across HE institutions.

The results show that in general students' ideal expectations of privacy and ethical issues related to the implementation of LA systems were uncompromisingly higher (mean 95%) compared to their predicted expectations (50%). This is an interesting but not a surprising finding that suggests the ideally LA designers, researchers and practitioners should carefully consider the students' predicted expectations in this regard. Earlier research has stressed that the stakeholders' predicted expectations are more important to consider in the first hand in terms of the realistic implementation of the information system (e.g., the adoption of LA services by students) in practice (Szajna & Scamell, 1993). That is, if we just pay attention to their very high ideal expectations, there is a risk that the adoption of the LA services will be delayed since these expectations may lead to their dissatisfaction with the system use in practice. For example, the high expected functionality of the LA service and the related privacy-protection mechanisms can be often enabled after some time of the use of the tool/service, when several improvements have to be continuously made, based on the users' preferences, individual differences, and the context in which the tool is used. As stressed by Szajna & Scamell, 1993), "when the users are dissatisfied with an information system and the use of the system is voluntary [which can be a common case for the implementation of a LA service (e.g., a student-oriented dashboard)], the users may discontinue their use of the system" (p. 510). This is important to consider for several reasons, including the fact the LA systems (at scale) can be expensive and they can consume substantial organizational resources. For LA researchers and practitioners, it is important not only to study the performance of an LA service, but also the students' perceptions of its performance.

Another possible explanation for the fact that the students have lower predicted expectations of the related privacy and ethical approaches to LA (compared to the ideal ones) relates to the assumption that they have a low trust in the university's present ability to deal with ethical and privacy concerns in this regard. Consequently, higher education institutions may need to improve such student privacy - enhancing practices that would protect students' privacy and enable their agency in higher education.

Students with ideal expectations can still get an accurate picture of the LA service as they interact with it. This may account for the tendency of unrealistic expectations to "wear off" over time (Szajna & Scamell, 1993, p. 510). To assure an accurate picture of a LA service among students, there is a need for facilitated communication between students and developers (e.g., in terms of how student data are collected, stored, secured and handled) and the promotion of the students' involvement in the development process, for example through participatory design approaches. Also, it is crucial to help the student to create an accurate picture of the LA service by not promising what cannot be delivered in practice. In general, assessing students' expectations at different stages of the design process can assist designers and developers to detect and deal with the problem (e.g., related to students' privacy concerns, see Mutimukwe et al., 2021) areas before they become implemented in the system.



The results of the LCA illustrated that the students' expectations of LA privacy and ethics are heterogeneous, which is not in line with the earlier recent research findings that have demonstrated the homogeneity of the students' expectations in this regard (Whitelock-Wainwright et al., 2021). This finding can be supported by several facts. First, privacy concerns and problems are context-specific (Xu et al., 2011). Second, students from different cultures may represent different cultural values (e.g., in terms of power distance), which were earlier found to have a significant influence on the users' (of information systems) information privacy concerns across cultures (Milberg et al., 2000).

Students' ideal expectations of LA service features were also high (mean = 76%) with lower predicted expectations (mean = 54%). Interestingly, the difference between their ideal and predicted expectations in this regard is not that distinct compared to the expectations in terms of privacy and ethics. The students' predicted expectations were shown to be heterogeneous and overall, at the moderate and low expectations' levels, except of their high expectation of the university to regularly update them about their learning progress based on the analysis of the educational data (Fig. 5). This is an interesting finding that suggests that universities should start considering how to develop relevant data-driven support mechanisms that would continuously support students in their learning process. In this process, it is critical to take into account not only the technical side of such development (e.g., pertaining to the data collection, analysis and use) but also consider students' individual differences and preferences. The results also demonstrated students with the low predicted expectations (Class 2, Fig. 2) of the LA service do not expect it to be used to support their decision making and show their learning progress. This can be explained by several reasons, including their incomplete understanding of LA, which aligns well with earlier research (e.g., West et al., 2020), and their uncertainty about the university's ability to act based on analysis of their educational data.

Interestingly, the students in both classes have reported very low and low expectations of the teacher to obtain relevant skills and also to act based on the data-driven analysis of their educational data, which is in line with earlier recent findings (Whitelock-Wainwright et al., 2021). This can suggest that students may still want to have teacher guidance that cannot be easily substituted by a LA service. Another explanation is that the students do not believe that teachers have enough competence to improve their teaching based on the LA analyses. To understand this deeper, there is a need to complement the survey findings with for example, interviews' results.

The application of person-oriented methods usually leaves researchers with various decisions during the modeling process (including a decision about a number of classes to include in the model). This can in future be overcome by validating the findings through, for example, the examination of whether the found classes show theoretically expected relations with external variables. This stresses a need for more theory-driven studies in this regard.

Overall, this study extends the recent work on heterogeneity in students' expectations of LA (Whitelock-Wainwright et al., 2021) and continues the work that has explored the phenomenon in other educational dispositions (e.g., Quirk et al., 2013; Mirriahi et al., 2018). Our findings indicate the heterogeneity within the Swedish students' expectations of LA, both in terms of their privacy and ethics expectations,

as well as their expectations of the LA service. These results can be seen as a baseline of students' expectations or a cross-sectional average. However, such exceptions are also dynamic and are expected to change according to students' use of LA tools, experience, knowledge, and environment. Therefore, future research could explore the changes in students' expectations, or more importantly, what factors in students' expectations that can be modeled so that students will be more likely to adopt and endorse the use of LA. Future research is also needed to increase our understanding of the causes of high ideal or unrealistic expectations of LA. From a practical view, the primary focus should be on the development of suitable approaches and LA services to avoid unrealistic expectations. This will increase the adoption of LA at scale.

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## Declarations

**Conflict of interest** None.

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