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Students' expectations of Learning Analytics across Europe

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Abstract

Background: Learning Analytics (LA) is an emerging field concerned with measuring, collecting, and analysing data about learners and their contexts to gain insights into learning processes. As the technology of Learning Analytics is evolving, many systems are being implemented. In this context, it is essential to understand stakeholders' expectations of LA across Higher Education Institutions (HEIs) for large-scale implementations that take their needs into account.

Objectives: This study aims to contribute to knowledge about individual LA expectations of European higher education students. It may facilitate the strategy of stakeholder buy-in, the transfer of LA insights across HEIs, and the development of international best practices and guidelines.

Methods: To this end, the study employs a 'Student Expectations of Learning Analytics Questionnaire' (SELAQ) survey of 417 students at the Goethe University Frankfurt (Germany) Based on this data, Multiple Linear Regressions are applied to determine how these students position themselves compared to students from Madrid (Spain), Edinburgh (United Kingdom) and the Netherlands, where SELAQ had already been implemented at HEIs.

Results and Conclusions: The results show that students' expectations at Goethe University Frankfurt are rather homogeneous regarding 'LA Ethics and Privacy' and 'LA Service Features'. Furthermore, we found that European students generally show a consistent pattern of expectations of LA with a high degree of similarity across the HEIs examined. European HEIs face challenges more similar than anticipated. The HEI experience with implementing LA can be more easily transferred to other HEIs, suggesting standardized LA rather than tailor-made solutions designed from scratch.

KEYWORDS

comparison, Europe, higher education, Learning Analytics, SELAQ, students' expectations

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1 | INTRODUCTION

Learning Analytics is concerned with measuring, collecting and analyzing data about learners and their contexts to gain insights into learning processes (Greller & Drachsler, 2012). As a relatively new technology, Learning Analytics (LA) is a promising approach to improving learning and teaching (Hernández-de-Menéndez et al., 2022; Long et al., 2011). However, given a field of research that has been practiced for over a decade, the implementation of LA has remained still in its infancy (Viberg et al., 2018). While students and teachers continue to see benefits in the introduction of LA, for example, the possibility to provide early interventions (Sun et al., 2019) or to identify at-risk students (Kollom et al., 2021), systematic adoptions are not yet widely seen (Gasevic et al., 2019), and little LA research is undertaken at the level of study programs or institutions (Dawson et al., 2019). Initiatives such as LACE (Drachsler & Greller, 2016) or SHEILA (Tsai, Gašević, et al., 2018) have been launched to facilitate the adoption in Europe by providing solutions to existing adoption barriers and supporting institutions to make LA a key component of their didactics. Both initiatives addressed transverse topics of action like ethics and privacy, technical standards, and policy-making for adopting LA in higher education. Results have shown that the design and implementation of LA in Higher Education Institutions (HEIs) is non-trivial due to its infrastructural and practical impacts (Gašević et al., 2016; Schmitz et al., 2017a). Furthermore, three main challenges have been identified, that is technical, educational and social challenges. Technical challenges are concerned with handling privacy concerns (Drachsler & Greller, 2016; Pardo & Siemens, 2014; Tsai, Whitelock-Wainwright, & Gašević, 2020) or designing large-scale learning applications (Ciordas-Hertel et al., 2019; Sclater et al., 2015). Educational challenges are concerned with a higher degree of applicability (Baker, 2019), higher reliability (Kitto et al., 2018; Larrabee Sønderlund et al., 2019; Mahmoud et al., 2020; Scheffel et al., 2017), or better connections to learning science (Ahmad et al., 2022; Ferguson, 2012; Jivet et al., 2017). In this paper, our primary focus lies on investigating means of addressing a social challenge: The development of LA systems that take the interests of learners, teachers, and education administrators into account (Francis et al., 2020; Tsai, Moreno-Marcos, et al., 2018).

This so-called stakeholder buy-in is vital to LA success (Alzahrani et al., 2022), as incorporating stakeholder opinions and interests may facilitate or impede technological adoption (Tsai et al., 2019). Scientists have recommended particularly involving students and teachers in the LA development process (Sun et al., 2019), as it is essential for LA uptake (Drachsler & Greller, 2012) and critical to the success of LA adoptions (Ferguson et al., 2014). To identify students' expectations, researchers employ interviews, questionnaires, focus groups, surveys, and experiments (Mahmoud et al., 2020). To our best knowledge, the instrument most mature and widely used at the time of running this study is the 'Student Expectations of Learning Analytics Questionnaire' (SELAQ) (Whitelock-Wainwright et al., 2019) that was developed in the SHEILA project.[1] SELAQ is intended to help HEIs identify students' expectations (Whitelock-Wainwright et al., 2020), while its scales have been grounded in a theoretical framework focusing on ideal expectations (hopes) and predicted expectations (realistic beliefs). SELAQ has been applied by different European HEIs, such as the University of Edinburgh, the Open University of the Netherlands, and the University Carlos III of Madrid, which can be regarded as important benchmarks and enable comparisons under standardized conditions. Especially in Europe, these comparisons are of interest, as knowledge exchange on LA-related challenges is constrained by the heterogeneity of educational systems, even at a sub-country level and becomes visible in performance differences of higher education students in international large-scale assessments such as PIAAC.[2]

Therefore, this study aims to contribute to knowledge about individual LA expectations of European higher education students and the transfer of LA insights in-between European HEIs. For this, we applied SELAQ to identify the expectations of students from Goethe University in Frankfurt, Germany. We selected the Goethe University Frankfurt (GU) students for this study, as Germans have turned out to be concerned about privacy regarding data collections (Schomakers et al., 2019), and GU administrators are currently faced with the question of whether to build their own LA systems from scratch or adopting existing solutions. Moreover, we compared our findings with the expectations found in aforementioned SELAQ studies to identify how students' expectations can be generalized across countries and institutions. We thus aim to address the need for research on individual perceptions of privacy principles across countries (Botnevik et al., 2020) and to explore how LA implementation guidelines (Scheffel et al., 2022) and best practices can successfully be transferred to other HEIs. Several factors, such as a focus on distance learning, private or public funding, and different historical background in terms of privacy (Griths, 2020), distinguish these HEIs and make their students unique. We argue that these factors might influence students' expectations of LA, whose differences need to be considered. Therefore, we chose the following research questions:

RQ1. What are the expectations of Goethe University Frankfurt students for LA?

RQ2. How do these expectations compare to students from other HEIs in Europe?

2 | RELATED WORK

The pursuit of institutional-level LA services is of growing interest for many universities, motivated by a need to improve teaching and learning practices (Gibson & Ifenthaler, 2020). LA is expected to enhance a student's educational experience by analyzing interactions within learning systems and raising awareness of students' learning processes (Ferguson, 2012). Even with such anticipated benefits from LA, successful implementations are rare. Early stages of LA implementations are reported from many regions around the globe, which often come along with suggestions to incorporate stakeholders' needs

[1] https://sheilaproject.eu.

[2] https://www.oecd.org/skills/piaac/.

better (Leitner et al., 2019). For example, studies comparing LA development in Latin American countries showed that the progress of applying LA is not uniform at a premature level (Cechinel et al., 2020). At the same time, LA services could be improved by fulfilling the needs of teachers, managers, and students (Hilliger et al., 2020). In the context of LA uptake in Malaysia, a similar conclusion was derived by pointing out that implementations are somewhat limited and indicating that institutions could benefit from a more supportive, ethical and system-integrated culture which takes all stakeholders' needs into account (West et al., 2018).

2.1 | Learning Analytics in Europe

In Europe, the early stage of LA uptake was inferred from relatively small-scale implementations (Dawson et al., 2018; Ifenthaler & Yau, 2020; Nouri et al., 2019), a short period of experience, and the rare usage of dedicated strategies, policies or evaluation frameworks (Ifenthaler & Yau, 2019; Tsai, Rates, et al., 2020), while a persisting demand for LA has been indicated (Kollom et al., 2021) and students were indicated as key stakeholders (Tsai, Rates, et al., 2020). To resolve these hurdles of implementing LA in Europe, the SHEILA project ('Supporting Higher Education to Integrate LA') was initiated (Tsai, Gašević, et al., 2018). At a general level, the SHEILA project sought to offer an adaptable framework to guide HEIs in developing LA policies and strategies (Tsai, Moreno-Marcos, et al., 2018). This framework was based on the results of a series of empirical studies that sought to incorporate different stakeholder perspectives, for example, LA experts (Scheffel et al., 2019), decision-makers (Tsai, Moreno-Marcos, et al., 2018), or students (Whitelock-Wainwright et al., 2019).

The SHEILA framework can be considered important to European LA capacity building. Although LA adoption has been reported to suffer from cross-institutional barriers (Tsai, Rates, et al., 2020), the exchange of experiences on LA adoptions is limited even beyond obvious language barriers. In fact, the European education landscape consists of many smaller and bigger subsystems with different educational approaches for historical, organizational or pedagogical reasons. Despite significant efforts, such as the Bologna Process (Zahavi & Friedman, 2019), European higher education remains little standardized. In this context, the OECD Programme for the International Assessment of Adult Competencies (PIAAC) revealed differences in literacy, numeracy, and problem-solving in technology-rich environments (De La Rica & Gortazar, 2016; Vera-Toscano et al., 2017). At the same time, studies found differences between HEIs regarding internationalization strategies (Seeber et al., 2020) and the students' views of higher education (Brooks et al., 2021). In addition, cultural differences are reflected in local regulations that HEIs have to comply with. Data protection guidelines, for example, are country-specific regulations regardless of the introduction of the GDPR.

To contribute to a European understanding of LA adoptions, a cross-country comparison of European countries regarding expectations of academic staff (Kollom et al., 2021) was conducted. It revealed that there is great potential in general for LA by enabling early interventions, supporting students' decision-making, and giving feedback about the learning progress.

The comparison indicated that expectations of academic staff vary across countries. While teaching staff in the UK have lower expectations than in other countries, technical issues seem to be more critically observed in the Netherlands. As students' expectations of LA may vary in terms of ethics and privacy across countries (Arnold & Sclater, 2017), a European cross-country comparison of students' LA expectations is of interest. Such a comparison could support the development of shared adoption strategies, build knowledge of European student expectations and help to overcome common barriers to institutional adoption, which result from a lack of resources, ethics and privacy compliance, stakeholder buy-in, or a lack of capabilities (Tsai, Rates, et al., 2020).

2.2 | Student Voices in Learning Analytics

To systematically incorporate the diverse voices of LA stakeholders into a common adaptation strategy for HEIs, the SHEILA framework was developed. It is based on the idea of overcoming three adoption barriers, named (1) the demand for resources, (2) issues of ethics and privacy, and (3) stakeholder engagement and buy-in. While solutions to each of these adoption barriers are essential to successful LA implementations, the current work focuses mainly on the adoption barrier of student stakeholder engagement owing to what has been identified as an oversight when creating LA services: the inclusion of the student perspective both in the development of institutional implementation approaches (Tsai & Gasevic, 2017) and the design of LA tools (Buckingham Shum et al., 2019).

Researchers have addressed this limitation through qualitative (Roberts et al., 2016, 2017) and quantitative methodologies (Schumacher & Ifenthaler, 2018). Findings from both methodologies have shown that students have expectations regarding data security and transparency, about which LA features should be offered, and whether LA should promote student agency. Beyond the specifics of what students expect, such work has clearly illustrated that student stakeholders can articulate the expectations of LA. Informed by the research mentioned above, the SHEILA project consortium developed and validated the Student Expectations of Learning Analytics Questionnaire (SELAQ; Whitelock-Wainwright et al., 2019, 2020) to explore student expectations regarding aspects of services, ethics, and privacy. The need to explore what student stakeholders wanted from LA services triggered SELAQ, using items that were accessible, irrespective of educational level. Recent developments indicate that incorporating students' voices into LA services has gained importance. Examples are implementations which encourage students to create their own LA (Jivet et al., 2021) or involve them in creative processes of learning designs (Schmitz et al., 2017b).

3 | METHOD

To explore students' expectations regarding LA features and draw relations to their peers from other European HEIs, expectations of Goethe University Frankfurt students were collected using the SELAQ (Whitelock-Wainwright et al., 2019) and compared with the responses from students of the University Carlos III of Madrid, the University of

Edinburgh and the Open University of the Netherlands as previously obtained in the SHEILA project. Although the SHEILA project also collected responses from students in Estonia, these were not taken into account due to the relatively small sample size. To report more concisely on the expectations of students from different HEIs, we refer to students according to the location of their university. Unlike the other students, the Open University of the Netherlands students cannot be assigned to a particular place because it is a distance education university. We therefore refer to these students the country - the Netherlands.

3.1 | SELAQ

Instruments used to identify stakeholders' expectations of LA were presented in a recent literature review (Mahmoud et al., 2020), which points to 16 publications concerned with students' expectations. According to the literature review, 12 studies applied interviews and focus groups, seven used questionnaires or surveys, two conducted experiments, and one constructed a framework to determine students' expectations. Besides two individual non-validated scales, the questionnaires mentioned are the Student Expectations of Learning Analytics Questionnaire (SELAQ), the questionnaire by Okkonen et al. (Okkonen et al., 2020), and the questionnaire by Schumacher and Ifenthaler (Schumacher & Ifenthaler, 2018). SELAQ is the only questionnaire which was found to be applied multiple times. In addition to this, we identified other instruments in the literature that deal with students' perceptions of LA, such as psychometric instruments (Szajna & Scamell, 1993), the institute's readiness for LA (Oster et al., 2016), or the students' perceptions of data handling (Arnold & Sclater, 2017). However, these approaches have their constraints in being not validated, requiring students to have direct experience with LA or observing them while LA is being implemented. Taking these constraints into account, we selected SELAQ in this study, which has been shown to measure students' anticipations regarding LA by drawing a picture of future applications. SELAQ is therefore incorporating students into the design process of the implementation of LA services even if students have no direct experience with LA (Whitelock-Wainwright et al., 2019). Moreover, it has been applied in different institutions since 2017 and thus offers validated points of comparison for our study.

The SELAQ structure consists of 12 items that measure two factors (Whitelock-Wainwright et al., 2019): LA Ethics and Privacy (E) and LA Service Features (S) (see Table 1). Each item is measured on two expectation scales: (1) ideal, measuring what students desire from an LA service, and (2) predicted, which concerns the students' predictions regarding implementing LA services. This results in a total of four scales, referred to as LA Ethics and Privacy of an ideal implementation (E_ideal), LA Ethics and Privacy of an anticipated prediction (E_pred), LA Service Features of an ideal implementation (S_ideal), and LA Service Features of an anticipated prediction (S_pred). SELAQ items were derived in three steps: The first step consisted of a literature review identifying 79 items which were used before to measure students' expectations of LA. In the second step, a scale purification was conducted through an exploratory factor analysis, resulting in 19 items. Finally, the items were validated using an exploratory structural equation modelling and a confirmatory factor analysis resulting in 12 items (Whitelock-Wainwright et al., 2019). Responses to these items are measured using 7-point Likert scales ranging from 1 (strongly disagree) to 7 (strongly agree). The items were created to be accessible, irrespective of educational level. This is supported in two ways: items are framed, so they focus on general-level details of LA services, and items are framed as expectations. The reasoning behind general-level items is based on a view that students would have little understanding of LA service specifics due to limited HEI implementations, HEI LA service implementations not being consistent, and student knowledge of a LA service intricacies being somewhat limited. Expectations are adopted as the framework of choice for a similar reason: students are unlikely to perceive an actual LA service implementation. The general term of expectations was also deconstructed into ideal expectations, that is, what individuals desire, and predicted expectations, that is,

TABLE 1 SELAQ items— LA Ethics and Privacy factor (E1–E5) and LA Service Features factor (S1–S7).

ID	Item
E1	The university will ask for my consent before using any identifiable data about myself (e.g., ethnicity, age, and gender)
E2	The university will ensure that all my educational data will be kept securely
E3	The university will ask for my consent before my educational data are outsourced for analysis by third-party companies
E4	The university will ask for my consent to collect, use, and analyse any of my educational data (e.g., grades, attendance, and virtual learning environment accesses)
E5	The university will request further consent if my educational data are 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 and under performing 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

what individuals realistically expect. Breaking down expectations in this way leads to a more nuanced understanding of what students expect from LA services. We can thus differentiate between what students may find appealing and what they may, for various reasons, not expect to happen in reality (Whitelock-Wainwright et al., 2019, 2020). Finally, SELAQ determined a student's confidence in realizing their LA expectations by measuring a discrepancy between these ideal expectations and predicted expectations.

3.2 | Materials and participants

For all four samples, the SELAQ was presented as an online survey. Besides the SELAQ items, demographic items such as participants' gender, age, study course, and current semester (year of study) were included in the online survey. Participants were informed and contacted through mailing lists, social media posts, publicly available paper notices and listings in survey tools. Participants could email further questions and were informed that participation in the survey was pseudonymous and would have no impact on any assessment of their coursework.

For the sample collected in Frankfurt, survey items were translated from English into German. The translation process involved three independent steps: (1) translation of items, (2) reverse translation of translated items, and (3) validation. Step 1 was done using the DeepL Neural Network translator,[3] which is known for precise translations. Step 2 was done by a professional translator. The translation was then manually checked by a team of LA researchers and the process was repeated until the conclusion was reached that a high degree of accuracy had been achieved. Participants had the choice to answer either in German or English language. In Frankfurt, we collected the answers from 417 students. In total, 251 (60.2%) were male, 160 (38.4%) female, and 6 (1.4%) non-binary gender. The age structure was divided into five buckets, with 68 (16.3%) participants aged up to 19 years, the majority with 227 (54.4%) participants from 20 to 24 years, 95 (22.8%) participants from 25 to 29 years, 18 (4.3%) participants from 30 to 39 years and 9 (2.2%) participants were at least 40 years old.

For the sample collected in Madrid, a similar translation process from the English language into Spanish was applied. Steps 1 and 3 were done by a researcher active in the LA domain, and step 2 was done by another senior research expert in LA. Participants had to answer the items in Spanish. Within the Madrid sample, 543 students participated in total, with 271 (50%) male and 272 (50%) female students and an age range from 16 to 57 years ($M = 21.2$; $SD = 5.0$).

For the sample collected in Edinburgh, 674 students, 245 (36.4%) male and 429 (63.6%) female at an age range from 17 to 72 ($M = 24.4$; $SD = 7.9$), participated. A translation of survey items was not needed, as the primary language of this HEI is English.

Given the sample collected in the Netherlands, 1242 students participated, 537 (43.2%) male and 705 (56.8%) female at an age range from 18 to 82 ($M = 44.8$; $SD = 12.4$). The translation process was iteratively carried out by a native Dutch speaker, whose translation was repeatedly assessed for accuracy by two native Dutch-speaking researchers. In contrast to the other samples, participants in this sample were primarily distance education learners.

3.3 | Procedure

All four data samples invited students to participate voluntarily in an online survey. The Frankfurt survey was conducted from 1st November 2020 to 31st January 2021. All participants could enter a draw at the end of the survey to win one of ten 25 EUR vouchers. The Edinburgh survey was conducted from 30th March 2017 to 9th April 2017. All participants could enter a draw at the end of the survey to win one of five 50 GBP vouchers. The Madrid survey was conducted from 11th September 2017 to 30th September 2017. Students did not receive any rewards for participation. The Netherlands survey was conducted from 1st July to 15th September 2017. All participants could enter a draw at the end of the survey to win one of ten 20 EUR vouchers.

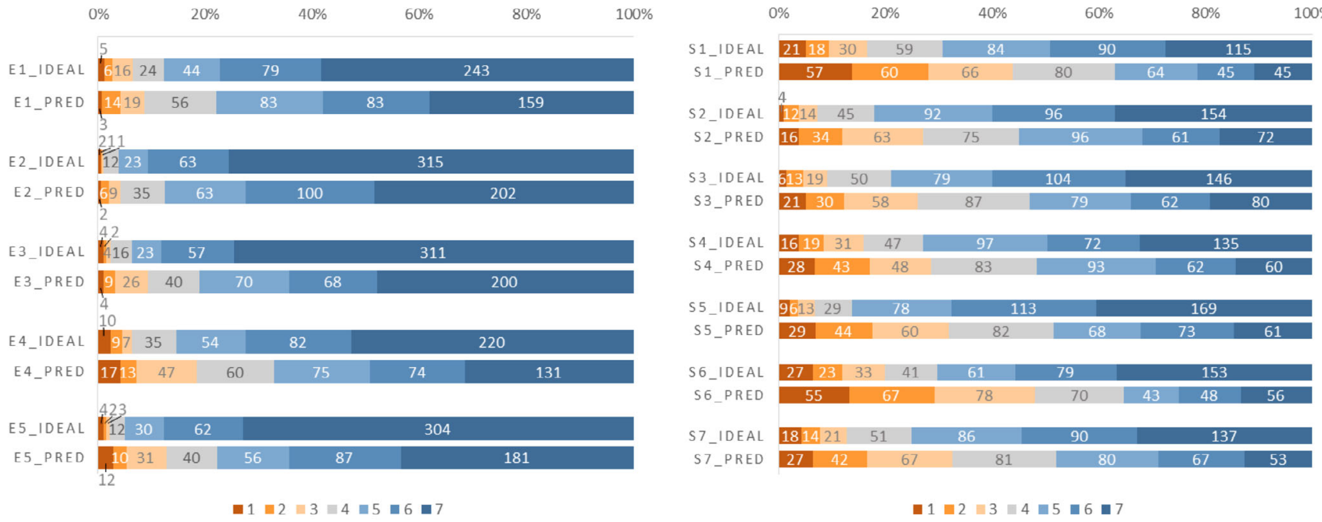
3.4 | Analysis

The SELAQ responses are compared using Multiple Linear Regression (MLR) supported by descriptive statistics. The mean of the SELAQ scales and the differences between the ideal and predicted scales were selected as the dependent variables, whilst the HEI affiliations were chosen as independent variables. These independent variables were determined through dummy coding of three HEI-specific codes so that the Frankfurt survey was the baseline (0) to compare differences to the Madrid, Edinburgh, and Netherlands samples, coded as (1) on their HEI- specific codes. The MLR, therefore, directly calculates an overall model with Frankfurt as baseline and residuals to Madrid, Edinburgh, and the Netherlands. We also analyzed the variance between these separated samples. In our case, the use of MLR works well as we wanted to compare the Frankfurt survey to other countries and not run a pairwise comparison among countries. Furthermore, no post hoc test was needed, as our comparison used the Frankfurt survey as a reference class. The underlying assumptions are that all SELAQ scales have a linear relationship between dependent and independent variables. The independent variables may not be highly correlated, and each residual's variance has to be constant. This is given due to the chosen dummy coding. The multivariate normality of the samples was checked through Q–Q plots. Finally, the required independence of observations is given to separately surveying different HEIs in Europe.

4 | RESULTS

Before exploring responses across data samples (Frankfurt, Madrid, Edinburgh, and the Netherlands), the results of the Frankfurt sample

[3]Accessible through: http://www.deepl.com/.



(a) LA Ethics and Privacy Expectations responses

(b) LA Service Feature Expectations responses

FIGURE 1 Likert-type item responses of the Frankfurt survey (7: strongly agree | 1: strongly disagree).

are presented in detail. After that, the comparison of the individual surveys is first described in detail and finally underpinned by the results of the MLR.

4.1 | Responses to the Frankfurt survey

The findings for the Frankfurt survey (Figure 1) show the familiar pattern already known from other surveys: Items that ask for an opinion on the ideal LA implementation are, on average, clearly more highly supported than items that ask for an anticipated prediction of the LA implementation.

To answer RQ1, a paired samples *t*-test was conducted to compare the mean expectation scores of students on LA Ethics and Privacy of an ideal implementation (E_ideal) and an anticipated prediction (E_pred). There was a significant difference in the scores for expectations on LA Ethics and Privacy of an ideal implementation ($M = 6.35$, $SD = 0.83$) and an anticipated prediction ($M = 5.65$, $SD = 1.14$); $t(416) = 12.6$, $p < 0.001$, two-tailed. The difference of 0.7 scale units (scale range: 1–7; Cohen's $d = 0.62$) indicated a medium effect and suggested medium confidence in the realization of LA Ethics and Privacy expectations.

Another paired samples *t*-test was conducted to compare the mean expectation scores of students on LA Service Features of an ideal implementation (S_ideal) and an anticipated prediction (S_pred). There was a significant difference in the scores for expectations on LA Service Features of an ideal implementation ($M = 5.45$, $SD = 1.18$) and an anticipated prediction ($M = 4.30$, $SD = 1.41$); $t(416) = 17.6$, $p < 0.001$, two-tailed. The difference of 1.15 scale units (scale range: 1–7; Cohen's $d = 0.86$) indicated a strong effect and suggested low confidence in the realization of LA Ethics and Privacy expectations.

Moreover, items that ask about LA Ethics and Privacy (Figure 1a) are clearly more supported than items that ask about LA Service Features (Figure 1b). The response pattern within the LA Ethics and Privacy scale and the LA Service Feature scale is largely homogeneous and shows no particularly deviating item responses. By calculating the differences between the E_ideal and E_pred scales (in the following as Diff_E), as well as of S_ideal and S_pred scales (in the following as Diff_S), another known response pattern can be recognized: The absolute value of the difference in the LA Ethics and Privacy scales ($M_{Diff\_E} = -0.70$, $SD = 1.13$) is on average a smaller than the one of the LA Service Features scales ($M_{Diff\_S} = -1.15$, $SD = 1.34$).

Additional investigations to distinguish groups of students within the data set and identify divergent opinions regarding their individual expectations (Table 2) led to only one significant result. In particular, an independent samples *t*-test was conducted to compare the mean expectations scores of male and female students on LA Service Features of an ideal implementation. There was a significant difference in the scores of male ($M = 5.59$; $SD = 1.07$) and female students ($M = 5.22$, $SD = 1.30$); $t(409) = -3.19$, $p = 0.002$, two-tailed. The difference of -0.37 scale units (scale range: 1–7; Cohen's $d = -0.32$) indicated a small effect and suggested that female students have slightly fewer expectations in terms of LA Service Features for an ideal implementation. The remaining differences examined between male and female participants (E_ideal, E_pred, S_pred) and the differences between students of STEM and Social Sciences subjects turned out to be insignificant.

4.2 | Sample comparison results

The responses were contrasted with six scales to compare the four HEI samples. Figure 2 presents the distributions of responses for each of the SELAQ scales (E_ideal, E_pred, S_ideal, S_pred, Diff_E, and Diff_S) across all samples (Frankfurt, Madrid, Edinburgh and the

TABLE 2 Responses of male and female, as well as of STEM and Social Sciences students within the Frankfurt data set.

	LA Ethics and Privacy		LA Service Features	
	Ideal	Predicted	Ideal	Predicted
Male	$M = 6.36$; $SD = 0.80$	$M = 5.62$; $SD = 1.17$	$M = 5.59$; $SD = 1.07$	$M = 4.38$; $SD = 1.41$
Female	$M = 6.30$; $SD = 0.88$	$M = 5.70$; $SD = 1.10$	$M = 5.22$; $SD = 1.30$	$M = 4.18$; $SD = 1.41$
STEM	$M = 6.38$; $SD = 0.64$	$M = 5.70$; $SD = 1.06$	$M = 5.31$; $SD = 1.07$	$M = 4.35$; $SD = 1.35$
Social Sciences	$M = 6.32$; $SD = 0.98$	$M = 5.66$; $SD = 1.21$	$M = 5.50$; $SD = 1.29$	$M = 4.27$; $SD = 1.47$

Netherlands). On average, responses to items on the "ideal" scale are higher than those made on the "predicted" scale. Looking at the distributions more closely, students appear to have high ideal expectations but mixed responses when asked about predictions. This general pattern applies to all samples, but there are also some notable differences among sub-samples.

Similar variances can be observed on the LA Ethics and Privacy scales. Answers to E_ideal (Figure 2a) and E_pred (Figure 2b) hardly show any major difference across the surveys. In the E_ideal scale, distributions, medians, and means seem highly comparable between surveys. The responses are predominantly located at the upper end of the scale, while the Netherlands survey seems to have the highest mean. In E_pred, responses to the Madrid survey seem to show an offset related to a relatively homogeneous response pattern in Edinburgh, Frankfurt and the Netherlands. Although the Madrid survey has slightly lower response values on this scale, its mean and median values still fall in the interquartile ranges of the other surveys. Looking at the difference between E_ideal and E_pred, shown in Figure 2e, a comparable pattern can be seen within the surveys of Edinburgh, Frankfurt and the Netherlands. Due to the offset of Madrid in E_pred there is an offset of the Madrid survey on this differential scale. As with E_pred, this offset is limited in that the mean of Madrid responses still falls within the interquartile ranges of the other surveys.

The scales S_ideal (Figure 2c) and S_pred (Figure 2d) concerned with LA Service Features are, on average, rated lower than the LA Ethics and Privacy scale counterparts. At the same time, these scales show a greater variation between the surveys. The variations are limited to overlapping interquartile ranges. The S_ideal scale shows varying variances between the surveys, with a lower variance for the Edinburgh and Madrid surveys and higher variances for the Frankfurt and the Netherlands surveys. The S_pred scale, by contrast, shows relatively stable variances of the individual surveys, while the means and medians of Edinburgh, Madrid and the Netherlands seem comparable. The Frankfurt survey appears to have an offset, showing a lower mean and median. A sequence of means can be recognized by looking at the differences between S_ideal and S_pred, shown in Figure 2f. In this sequence, the Netherlands survey is the highest-rated, followed by the Edinburgh, Frankfurt and Madrid surveys. Regarding the variance, it seems like the same sequence seems to apply from a low variance for the Netherlands survey to a higher variance for the Madrid survey.

4.3 | Multiple linear regression

To answer RQ2, where we aim to look for differences in students' expectations among HEIs, we conducted Multiple Linear Regression (MLR) models over SELAQ results. The MLR is a statistical method that uses a regression model to determine the effect of multiple independent variables on one dependent variable. For the analysis of SELAQ responses, the SELAQ scales and the differential scales of Diff_E and Diff_S were selected as dependent variables. The independent variables were determined through dummy coding of the participants' HEI affiliations.

In the following, we examine the MLR models separately to underline and quantify findings for each SELAQ scale. In the same step, we will present the model fit measures, including the effect sizes. The identified effect sizes relating HEI environments to students' LA expectations are generally relatively small (Table 3), while a rather large sample size (Section 3.2) led to significant MLRs in all cases. The MLR coefficients, which represent the difference between the Frankfurt survey baseline to other surveys, show a diverse picture of significant and insignificant deviations across the surveys (Tables 4 and 5). While deviations on the S_ideal, S_pred, and Diff_S models are significant across all surveys, deviations on the E_ideal, E_pred and Diff_E models show little variation.

In particular, an MLR was calculated to predict participants' expectations on the E_ideal scale based on their HEI affiliation. A significant regression equation was found (F (3, 2877) $= 6.58$, $p < 0.001$) with an R^2 of 0.0068. Participants' predicted expectations on the E_ideal scale is equal to $6.35 + 0.05$ (Edinburgh) $+ 0.01$ (Madrid) $+ 0.15$ (Netherlands) scale units (scale range: 1–7), where a Frankfurt affiliation is the baseline and Edinburgh, Madrid, and the Netherlands affiliations are coded as $0 =$ not affiliated, $1 =$ affiliated. Participant's expectations on the E_ideal scale increased by 0.05 scale units through an Edinburgh affiliation, 0.01 scale units through a Madrid affiliation, and 0.15 scale units through a Netherlands affiliation. The only significant predictor for expectations on the E_ideal scale was a Netherlands affiliation, while Edinburgh and Madrid affiliations were found to be insignificant. In other words, students' expectations of ideally realized LA Ethics and Privacy hardly differ across the surveys examined, while the students' HEI affiliations examined to account for just 0.68% of the variance. The Edinburgh and Madrid survey coefficients were not statistically significant, indicating higher similarities across the Frankfurt, Edinburgh and Madrid students' expectations.

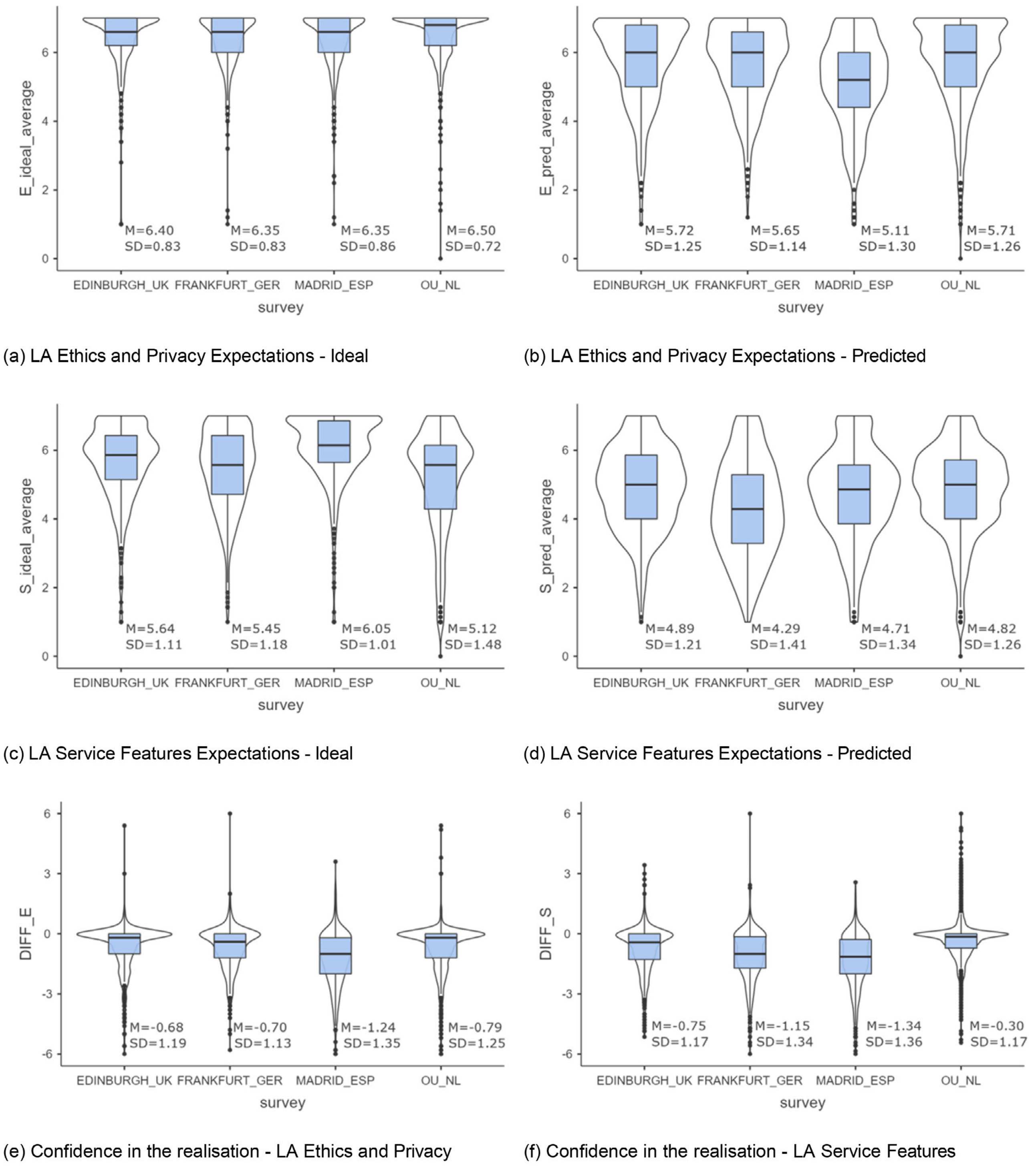


FIGURE 2 Violin chart comparison of samples.

A second MLR was calculated to predict participants' expectations on the E_pred scale based on their HEI affiliation. A significant regression equation was found (F (3, 2877) = 32.9, p < 0.001) with an R^2 of 0.0331. Participants' predicted expectations on the E_pred scale is equal to 5.65 + 0.07 (Edinburgh) − 0.54 (Madrid) + 0.06 (Netherlands) scale units (scale range: 1–7), where a Frankfurt affiliation is the baseline and Edinburgh, Madrid, and the Netherlands affiliations are coded as 0 = not affiliated, 1 = affiliated. Participant's expectations on the E_pred scale increased by 0.07 scale units through an Edinburgh affiliation, decreased by 0.54 scale units through a Madrid affiliation, and increased by 0.06 scale units through a Netherlands affiliation. The only significant predictor for expectations on the E_pred scale was a Madrid affiliation, while Edinburgh and the Netherlands affiliations were found to be insignificant. In

TABLE 3 Model fit measures for MLR models.[a]

Model	R	R^2	Adjusted R^2	RMSE	F	p
E ideal	0.083	0.0068	0.0058	0.789	6.58	<0.001
E pred	0.182	0.0331	0.0321	1.25	32.9	<0.001
S ideal	0.266	0.0706	0.0697	1.28	72.9	<0.001
S pred	0.147	0.0217	0.0207	1.29	21.3	<0.001
Diff E	0.159	0.0252	0.0242	1.24	24.8	<0.001
Diff S	0.323	0.1040	0.1030	1.23	112	<0.001

[a]df1 = 3; df2 = 2877.

TABLE 4 Results of MLR analysis—ideal and predicted scales.

Predictor	Estimate	SE	t	p
Model coefficients—LA Ethics and Privacy—ideal (E ideal)				
Intercept[a]	6.34676	0.0387	164.089	<0.001
Edinburgh (UK)	0.05472	0.0492	1.112	0.266
Madrid (ESP)	0.00536	0.0514	0.104	0.917
Open Univ. (NL)	0.15043	0.0447	3.367	<0.001
Model coefficients—LA Ethics and Privacy—predicted (E pred)				
Intercept[a]	5.6499	0.0611	92.407	<0.001
Edinburgh (UK)	0.0691	0.0778	0.888	0.374
Madrid (ESP)	−0.5350	0.0813	−6.580	<0.001
Open Univ. (NL)	0.0617	0.0706	0.874	0.382
Model coefficients—LA Service Features—ideal (S ideal)				
Intercept[a]	5.445	0.0626	87.02	<0.001
Edinburgh (UK)	0.194	0.0796	2.44	0.015
Madrid (ESP)	0.608	0.0832	7.30	<0.001
Open Univ. (NL)	−0.326	0.0723	−4.50	<0.001
Model coefficients—LA Service Features—predicted (S pred)				
Intercept[a]	4.295	0.0631	68.09	<0.001
Edinburgh (UK)	0.594	0.0803	7.40	<0.001
Madrid (ESP)	0.414	0.0839	4.93	<0.001
Open Univ. (NL)	0.524	0.0729	7.19	<0.001

[a]Represents a reference level, defined by the Frankfurt (GER) data set.

other words, students' expectations of an anticipated prediction on LA Ethics and Privacy only differ with a small to negligible effect size for the surveys examined, and the students' HEI affiliations examined account for just 3.31% of the variance. The Edinburgh and the Netherlands survey coefficients were not statistically significant, indicating higher similarities across the Frankfurt, Edinburgh and Netherlands expectations.

A third MLR was calculated to predict participants' expectations on the S_ideal scale based on their HEI affiliation. A significant regression equation was found (F (3, 2877) = 72.9, p < 0.001) with an R^2 of 0.0706. Participants' predicted expectations on the S_ideal scale is equal to 5.45 + 0.19 (Edinburgh) + 0.61 (Madrid) − 0.33 (Netherlands) scale units (scale range: 1–7), where a Frankfurt affiliation is the baseline and Edinburgh, Madrid, and the Netherlands affiliations are coded as 0 = not affiliated, 1 = affiliated. Participant's expectations on the S_ideal scale increased by 0.19 scale units through an Edinburgh affiliation, increased by 0.61 scale units through a Madrid affiliation, and decreased by 0.33 scale units through a Netherlands affiliation. All HEI affiliations were significant predictors for expectations on the S_ideal scale. In other words, students' expectations of ideally realized LA Service Features differ with a small but notable effect size across the surveys examined, while the students' HEI affiliations examined account for 7.06% of the variance.

A fourth MLR was calculated to predict participants' expectations on the S_pred scale based on their HEI affiliation. A significant regression equation was found (F (3, 2877) = 21.3, p < 0.001) with an R^2 of 0.0217. Participants' predicted expectations on the S_pred scale is equal to 4.30 + 0.59 (Edinburgh) + 0.41 (Madrid) + 0.52 (Netherlands) scale units (scale range: 1–7), where a Frankfurt affiliation is the baseline and Edinburgh, Madrid, and the Netherlands affiliations are coded as 0 = not affiliated, 1 = affiliated. Participant's expectations on the S_pred scale increased by 0.59 scale units through an Edinburgh affiliation, by 0.41 scale units through a Madrid affiliation, and by 0.52 scale units through a Netherlands affiliation. All HEI affiliations were significant predictors for expectations on the S_pred scale. In other words, students' expectations of an anticipated prediction on LA Service Features only differ with a small to negligible effect size, while the students' HEI affiliations examined account for 2.17% of the variance.

A fifth MLR was calculated to predict the difference of participants' expectations between E_ideal and E_pred scales (Diff_E) based on their HEI affiliation. A significant regression equation was found (F (3, 2877) = 24.8, p < 0.001) with an R^2 of 0.0252. Participants' predicted expectation difference (Diff_E) is equal to −0.70 + 0.01 (Edinburgh) − 0.54 (Madrid) − 0.09 (Netherlands) scale units (scale range: 1–7), where a Frankfurt affiliation is the baseline and Edinburgh, Madrid, and the Netherlands affiliations are coded as 0 = not affiliated, 1 = affiliated. Participant's expectation difference (Diff_E) increased by 0.01 scale units through an Edinburgh affiliation, decreased by 0.54 scale units through a Madrid affiliation, and decreased by 0.09 scale units through a Netherlands affiliation. The only significant predictor for the difference of participants' expectations between E_ideal and E_pred scales (Diff_E) was a Madrid affiliation, while Edinburgh and Netherlands affiliations were found insignificant. In other words, students' confidence in the realization of LA Ethics and Privacy only differs with a small to negligible effect size, while the students' HEI affiliations examined account for 2.52% of the variance. The Edinburgh and Netherlands survey coefficients were not statistically significant, indicating higher similarities for the Frankfurt, Edinburgh and Netherlands students' confidence.

Finally, a last MLR was calculated to predict the difference of participants' expectations between S_ideal and S_pred scales (Diff_S) based on their HEI affiliation. A significant regression equation was found (F (3, 2877) = 112, p < 0.001) with an R^2 of 0.1040. Participants' predicted expectation difference (Diff_S) is equal to −1.15 + 0.40 (Edinburgh) − 0.19 (Madrid) + 0.85 (Netherlands) scale units (scale range: 1–7), where a Frankfurt affiliation is the baseline and Edinburgh, Madrid, and the Netherlands affiliations are coded as

TABLE 5 Results of MLR analysis—differential scales.

Predictor	Estimate	*SE*	*t*	*p*
Model coefficients—confidence in the realization of LA Ethics and Privacy (DIFF_E)				
Intercept[a]	−0.6969	0.0608	−11.470	<0.001
Edinburgh (UK)	0.0144	0.0773	0.186	0.852
Madrid (ESP)	−0.5403	0.0808	−6.688	<0.001
Open Univ. (NL)	−0.0887	0.0702	−1.264	0.206
Model coefficients—confidence in the realization of LA Service Features (DIFF_S)				
Intercept[a]	−1.150	0.0603	−19.07	<0.001
Edinburgh (UK)	0.400	0.0767	5.21	<0.001
Madrid (ESP)	−0.194	0.0802	−2.42	0.016
Open Univ. (NL)	0.850	0.0697	12.20	<0.001

[a]Represents a reference level, defined by the Frankfurt (GER) data set.

0 = not affiliated, 1 = affiliated. Participant's expectation difference (Diff_S) increased by 0.40 scale units through an Edinburgh affiliation, decreased by 0.19 scale units through a Madrid affiliation, and increased by 0.85 scale units through a Netherlands affiliation. All HEI affiliations were significant predictors for the difference of participants' expectations between S_ideal and S_pred scales (Diff_S), while the students' HEI affiliations examined account for 10.4% of the variance. In other words, students' confidence in the realization of LA Service Features differs with a notable small to medium effect size.

5 | DISCUSSION

To answer our research questions, we investigate each in a separate subsection and summarize our main findings.

5.1 | RQ1: What are the expectations of Goethe University Frankfurt students for LA?

Goethe University students show general similarities to other students in their SELAQ response pattern: Responses to items on the ideal scales are, on average, higher than those responses made on the predicted scales. This was an anticipated response given that the ideal expectation seeks to measure students' desired LA service (Whitelock-Wainwright et al., 2019); thus, a ceiling effect is not unexpected. Predicted scales responses did not display such extreme response styles, which can be attributed to the measurement of what students realistically expect. Numerous factors could affect response patterns to the predicted scales, including institutional feasibility, perceptions of data literacy, or general pessimistic attitudes. Given that the scales are only focused on measuring expectations, there remains a gap in understanding those factors affecting the expectations held.

Within the Goethe University sample, a significant difference in ideal Service Feature Expectations (S_ideal) between male and female students could be identified. This difference seems to be worth researching in further studies, together with other factors that may influence students' expectations on LA. However, since seven out of eight comparisons within the sample revealed no significant differences, LA expectations are relatively evenly distributed among Goethe the University students. At the same time, the finding suggests that LA systems at Goethe University only have to be adapted to a limited extent to these user groups from a student perspective. Especially concerning the need for impulses for more integrated LA systems (Romero & Ventura, 2020), these results could be used to establish institution-wide LA systems at Goethe University, which would contribute to the current challenge of standardizing measures, visualizations and interventions on a broader scale (Ifenthaler & Yau, 2020).

5.2 | RQ2: How do these expectations compare to students from other HEIs in Europe?

The comparison of the surveys reveals similarities in several aspects. Especially the scales concerned with LA Ethics and Privacy seem, on the one hand, to be very highly rated and, on the other hand, barely distinguishable from each other. Students' ideal expectations of LA Ethics and Privacy hardly differ across the surveys examined. Students' predicted expectations of LA Ethics and Privacy only differ with a small to negligible effect size in the surveys studied. This suggests that the underlying aspects of ethics and privacy are fundamental principles (Slade & Tait, 2019) in implementing LA from the students' perspective, which apply regardless of the learning environment or personal attitudes. The Frankfurt students align with these principles.

The scales concerned with LA Service Features appear to be rated lower on average and show more individuality in the results of the surveys. However, students' expectations of ideal LA Service Features only differ with a small effect size in the surveys studied, whereas a significant difference can be noticed between the Frankfurt survey and all other surveys. Moreover, students' predicted expectations of LA Service Features only differ with a small to insignificant effect size in the surveys studied, whereas a significant difference can also be noticed between the Frankfurt survey and all other surveys. This indicates a general baseline requirement for LA Service Features that differs only slightly across HEIs. Although the Frankfurt students show relatively low expectations on both scales, this baseline requirement for LA Service Features can also be identified among them. It does not seem to be valued as highly as the fundamental principles of LA Ethics and Privacy, but it is still considered necessary.

The differential scales which relate the ideal expectations to the predicted expectations show similar patterns to the underlying scales. They are commonly interpreted as a lack of confidence in realizing student expectations and thus indicate a need for action by HEI administrations. In this sense, the students' confidence in the realization of LA Ethics and Privacy only differs with a small to insignificant effect size in the surveys studied, whereas the students' confidence in the realization of LA Service Features differs with a small to medium effect size. For the latter, significant differences can be found between the Frankfurt survey and all other surveys. Whilst implementing the LA Ethics and Privacy principles seems to be trusted to a similar extent by students across the surveys, there is not an entirely consistent picture concerning LA Service Features. The Netherlands survey deviates most from the Frankfurt survey, showing considerably more confidence in implementing LA Service Features, especially compared to the Frankfurt and Madrid data sets. This could be attributed to the fact that the Netherlands survey was the only one conducted at a distance learning university, whose success is much more dependent on online services and predominantly attended by students with a different demographic composition. With those online services in place, implementing LA services might be a minor step, as LA-relevant data is already being generated.

All in all, the results add to the picture of LA stakeholders expectations in Europe. The similarities found between students at European HEIs were more remarkable than expected. Although the participants from the Netherlands have different demographic characteristics and experiences with distance learning, their SELAQ results are still comparable to those of the other surveys which indicates that these demographics do not play a major role in the expectations of LA. A similar observation can be made considering that the Frankfurt survey was conducted years after the others. Although the learning environment has changed due to the COVID pandemic, according to our results, this has not affected students' expectations of LA fundamentally. Even in the context of the paid model of higher education in the UK, no profound deviations were found. This suggests that students' expectations of LA are relatively stable across Europe. Since LA is a still evolving and maturing field of practice and research (Viberg et al., 2018), which needs to take students' desires into account (Ochoa & Wise, 2021), these insights could be helpful for future LA projects, guidelines (Scheffel et al., 2022), and implementations (Verbert et al., 2020). Especially in relation to the 'Transferability' challenge of LA (Baker, 2019) and the need to broaden the focus from smaller scales to organizational and cross-organizational LA (Dawson et al., 2018), a general similarity of students' expectations in Europe can be interpreted as an advantage when designing LA that is more standardized or modular.

Challenges such as increased reliability (Scheffel et al., 2017) or better connections to learning science (Jivet et al., 2017) could be addressed on a larger scale, likely contributing to a more general understanding of LA. Finally, this insight supports the idea of exchanging experiences with LA across institutions (Hilliger et al., 2020) instead of reinventing the wheel by building tailored solutions from scratch. At the same time, individual needs of HEIs could still be met as part of fine-tunings or enhancements.

5.3 | Limitations

There are some limitations to this study that need to be considered when interpreting the results. First of all, the amount of SELAQ surveys considered is limited. This is because only a few extensive SELAQ surveys have been conducted so far. In this light, with this publication, we are helping to ensure that future studies can make use of a larger SELAQ dataset. The second limitation lies in the location of the HEIs where the surveys were undertaken. All of the HEIs are located in Europe. On the one hand, this is helpful to ensure the comparability of the surveys, but on the other hand, it limits the generalizability of the results obtained in this study. A further investigation, including results from different continents, could lead to a clearer picture of the international differences in student expectations regarding LA. The third limitation concerns the time lag of the surveys. The Frankfurt survey was collected several years after the others. Meanwhile, the progress of digitalization and the impact of the COVID pandemic may have affected students' expectations. However, comparisons with SELAQ surveys conducted earlier at Goethe University could not confirm this hypothesis so far. The fourth limitation can be identified in the teaching modality. Only one out of four of the HEIs considered primarily offers distance learning. Since a small to medium effect size could be determined, especially in the differential scale regarding LA Service Features, a future study should look at the difference between HEIs with and without distance learning. For this, however, a further SELAQ survey would have to be conducted on at least one more distance learning HEI. The last limitation we want to mention is that the survey was initially developed in English and then translated into Spanish, Dutch and German. Therefore there might be misinterpretations due to the translations. However, we did our best to keep the semantics of the items consistent and understandable for the students from Frankfurt, Madrid, and the Netherlands.

6 | CONCLUSIONS

In this paper, we present a study examining the expectations of Higher Education students from Frankfurt, Edinburgh, Madrid and the Netherlands for ideal and predicted expectations for implementing and using LA. We conducted an additional survey at the Goethe University Frankfurt to expand the database to SELAQ responses. Overall, the students from all four countries showed high expectations on the ideal scales. However, on the predicted scales, their expectations were considerably lower. These overall empirical findings indicate a high demand for LA and a certain lack of confidence in meeting these expectations.

Regarding similarities and differences among students from these four countries, we found that differences in LA Ethics and Privacy are hardly noticeable. In terms of Service Features, there is a relatively small effect. These results indicate that European students tend to share similar expectations of LA. This means that from a student perspective, the requirements of LA systems are relatively similar across HEIs. Therefore, to support the implementation of LA, HEIs should share their experiences and contribute to a more standardized LA instead of building tailored solutions from scratch.

There are two conceivable low-hanging future research activities at the national and international levels. First of all, there is only one SELAQ data sample from a single HEI per country. It is questionable to what extent this data sample is generalisable and represents a country as a whole. Therefore, we plan to extend the SELAQ data sample in Germany on a national level by conducting additional SELAQ studies at additional HEIs. A larger national SELAQ sample is particularly interesting as Germany has recently funded over 60 large-scale LA projects subjects to a new "AI for teaching research strategy" that started in early 2022. The strategy can serve to compare SELAQ results among German HEIs. A particular focus will be placed on comparing research universities and universities of applied sciences, technical and non-technical universities, as well as distance and attendance universities. Suppose those additional national SELAQ surveys were in line with the results of this paper and did not show major differences in students' expectations, the German government, as well as the German LA community, should adapt their current practice and work towards a joined LA infrastructure rather than supporting various local LA solutions, tailored to each HEI.

On the international level, it would be interesting to compare the European SELAQ data sample to data samples from other continents, for example, Latin America (Hilliger et al., 2020). We expect countries with different cultural backgrounds also to have different expectations on the SELAQ scales.

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DATA AVAILABILITY STATEMENT

The data supporting this study's findings are available from the corresponding author upon reasonable request.

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