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Assessing the Readiness of Students in Adopting Learning Analytics in Higher Education

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Abstract

Purpose: Getting students involved in developing learning analytics (LA) services is a major challenge in the academic world. Despite calls for more stakeholder involvement, research into students' views and expectations of learning analytics services is scant. Improving end-user buy-in and resource planning is possible by addressing these concerns and learning about student expectations before rolling out LA.

Methodology: An extensive literature review is included, with a focus on previous research into the value, existing models, and difficulties of implementing LA. To fill this void, we used the SHIELA approach to survey students' beliefs and expectations concerning LA adoption. Factor loading, construct validity, and discriminant validity tests are performed in SmartPLS 4 to ensure the accuracy and credibility of the data. A structural equation model further verified the relationship between students' anticipations and their actual acceptance of LA.

Findings: Our research confirms that the effectiveness of LA adoption is highly influenced by the three highlighted constructs: privacy and ethics and organizational and meaningful expectations. The research also showed that the student considered creating a detailed learning profile for each module to be the best application of LA. They believed LA would give them feedback on their learning and help them make better decisions. They think institutions have a moral and legal responsibility to act, which means they should also include, promote, and empower students. Institutions must take the necessary precautions to reduce risks, even though teaching staff should share the load.

Originality and Value: The research supplies university officials with data for improving their LA adoption tactics while also informing students of new ways in which LA might inform their own educational choices. This paradigm shift and the higher education sector's sustained, productive interest in learning analytics will lead to better results for students, universities, and society. Based on the findings, the study also suggests several avenues and topics for future research.

Keywords: Higher Education, Learning Analytics, Educational Data Analytics, Technology adoption in higher education, Strategic planning in higher education.

INTRODUCTION

Learning analytics uses standard analysis technologies, such as machine learning and statistical techniques, to provide information that improves decision-making in higher education[1]. Its goal is to gather and analyze user data trails using digital technologies to comprehend their changing behaviors and actions[2], [3]. They are being accepted in higher education all around the world, as evidenced by their rapid expansion and the amount of literature produced by ongoing research in this area[1], [4], [5]. Due to their potential for active learning, enhanced teaching and learning strategies, the use of early interventions to help student learning, increased student throughput, and higher student retention, they have become increasingly popular[6]. In higher education institutions (HEIs) of the twenty-first century, the focus on learning is shifting from teacher-centric to student-centric[7]. According to [1], this technology supports academics, teachers, and students in preparing students for the twenty-first century while addressing their difficulties and issues.

LA is, by definition, student-centered [8], yet there have been few attempts to investigate students' perspectives on the use of LA [9]–[12]. Only 6% of the 93 publications detailing LA dashboard installations discussed the services students would anticipate [13]. Although early stakeholder participation has been recommended, particularly for LA [14], [15], there are few examples of this occurring [16]. Given the importance of actively researching and analyzing stakeholder expectations, particularly concerning future service satisfaction and utilization, student participation cannot continue at a low level [17]. Without stakeholder input, the expectations and opinions of institutional administrators will likely dominate the various LA policies now available [18]. As a result, services may indicate a disparity between what firms believe students should receive and what they want [19]. Before deploying LA, these issues must be overcome before deploying LA, and academic expectations must be understood for improved end-user buy-in and resource planning [20]. Another issue is that, despite its extensive usage in rich countries, little is known about how it is used in less developed countries [21], [22]. According to [1] and [23], research in specific locations, such as North Africa and the Middle East, is restricted. Their claims were supported by the literature evaluation undertaken for this investigation.

In the present study, we have attempted to address this deficiency by investigating students' expectations of adopting LA services in the Gulf region, particularly Saudi Arabia. During the development of this study, accessibility and comprehension of the contents from the student's perspective were always taken into account. A conceptual model for examining the learner's expectations towards the adoption of LA has been created due to a thorough review of the relevant studies. The survey data is utilized to test and validate the model using structural equation modeling, which identifies the primary elements impacting learning analytics. The HEIs can then focus their student-direct involvement strategies on certain LA implementation areas that are particularly important.

LITERATURE REVIEW

The rapid development of learning analytics continually defines the key areas of higher education [1], [24]. For several reasons, such as COVID-19 contact limits and a firmer belief in the advantages of online learning, the adoption rate and utilization of this type of learning have greatly increased [25], [26]. Several benefits have resulted from the use of learning analytics and data analytics in higher education, including the ability to recognize at-risk students, track students' progress, foresee each student's particular learning needs, and pinpoint potential factors influencing academic achievement [27], [28]. Learning analytics draw their data from learning management systems (LMS) like Moodle, Canvas, and Blackboard [29], [30]. Giving students timely, precise, and on-task feedback on their academic assignments, performance, and progress is one of LA's potentials [12], [25], [31].

Based on the literature review and expert input, we defined three broad themes that describe LA services [32]: ethical and privacy expectations, organizational expectations, and meaningfulness expectations. It is essential to recognize that these issues constitute groupings that embody diverse LA research streams and discourses.

Theoretical Framework of the Study

Ethical and privacy expectations

The LA literature provides extensive guidance on how to acquire, manage, and analyze student data in an ethical manner [9], [33]–[36]. The authors of this article stress the need for openness and permission-based service provision in LA [35], [36]. According to Prinsloo & Slade [35], involving students in data management decisions (such as which data to utilize and how it will be interpreted) is crucial to the growth of LA services. Students interviewed by Slade & Prinsloo [34] indicated a strong desire for the university to get informed consent or provide an opt-out option before any LA process. Similarly, studies conducted by

[37], [38] found that students have high expectations that their privacy will be respected at all times, that they will be allowed to give their informed consent, and that the institution will be open and honest with them. Although students objected to having their personal information processed, Ifenthaler & Schumacher [39] found that they were fine with using the collected data for academic purposes. Each of these authors emphasizes the necessity of student participation in institutional choices about the rollout of LA services. Because of these two considerations, data security and permission were assumed to be included in ethical and privacy requirements.

H1: Students' ethics and privacy expectations significantly affects LA adoption in HEIs

Organization Expectations

According to a survey by Roberts et al. [37], students thought that receiving LA services would help their ability to learn independently. The author argues that because self-reliance is important for higher education success, LA services should not encourage a metric-centric mindset. These student perspectives agree with[11], [37]'s worries about the duty to act. They agree that improving student support through data analysis is important but emphasize that doing so must never come at the price of the student's responsibility to acquire knowledge [40]. Researchers who worry that intrusive LA services encourage a passive society favor this idea [41], [42]. In other words, students' abilities to be self-directed learners who regularly assess their performance and set goals are not considered by the LA programs meant to help failing students [41]. Recognizing students as partners in their education should be a central tenet of LA services [42], [43]. When determining whether or not to provide LA services that limit students' ability to make decisions based on the data they get, universities should keep this in mind and steer clear of those that do [44], [45].

The literature emphasizes the subject's significance and offers a crucial student perspective on who is primarily accountable for learning in the setting of LA services (the student or institution). It will then complement past discussions made by students and educators [11], [37].

H2: Students' organizational expectations significantly affects LA adoption in HEIs

Meaningful Service Expectations

It is anticipated that gathering and evaluating student data will lead to establishing a service focused on enhancing both student achievement and the educational experience [8], [46]. However, few efforts have been made to determine the elements students seek from LA services (For instance, just 6% of the LA dashboard research included a needs assessment; [13]). As underlined in the work of Schumacher & Ifenthaler

[12], it is crucial to consider student expectations of LA service qualities before any deployment. Making the required efforts to comprehend what is expected of the major stakeholders is crucial if you want to assure future acceptability [17], [47], [48]. The many LA service types reported in the literature differ depending on the educational problem they are intended to address. Identifying underperforming or dangerous students has been a standard service delivery [12], [49]. There is a belief that measures can be implemented to lessen the risk that the student will drop out [50], while Dawson et al. [51] argue that this might only sometimes be the case. Some strategies have shifted their focus away from developing prediction models to pinpoint at-risk pupils in favor of developing instruments to boost student-teacher interaction or provide visual summaries of student achievement [13], [52], [53]. These services are always designed to improve students' education, even though academics rarely find a means to measure what students anticipate from them. It would appear that efforts are being made to enhance both the classroom setting and the student learning experience with the newly built LA service capabilities. However, the perspectives of academics, rather than those of students, tend to shape these changes, which can have unintended consequences. Student viewpoints teach them to demand features improving their capacity as independent learners rather than considering them passive customers.

Both service and intervention requirements share the major theme of meaningfulness. Meaningful expectations have been shown to have a big part in predicting the future success of technology [17]. The impression of the utility of special functions (such as visualization and the level of detail provided) impacts adoption rates for LA services, which also bears this out [54]. When taken together, these considerations certainly highlight the importance of figuring out what services stakeholders want, with a focus on the type of information and its applicability to learning.

As a result, we have put forth the third hypothesis below to evaluate what students anticipate from implementing LA in HEIs:

H3: Students’ meaningful expectations significantly affects LA adoption in HEIs

RESEARCH METHODOLOGY

Research Design

This study aims to better comprehend student expectations for using LA in HEIs. Using a survey approach allowed the research's goal to be accomplished. A survey was decided to be appropriate for this research to check the elements required for adopting LA and assess the suggested model. To further understand the essential elements influencing their adoption and usage of LA for enhancing student learning outcomes, data was gathered from students at three HEIs in Saudi Arabia (Arts, Commerce, and Medicine).

Instrument

The "Student Expectations of Learning Analytics Questionnaire (SELAQ)," which included two scores evaluating ideal and predicted expectations (i.e., what a person hopes to receive versus what a person expects to receive), served as the theoretical basis for the creation of the questionnaire [55]. Appendix A contains the 12 questions that make up the questionnaire gauging students' expectations of LA services. This information is broken down into three categories according to the SHEILA framework created by Y.-S. Tsai et al. [56]: F1 (ethical and privacy expectations; 5 items), F2 (organizational expectations; 3 items), and F3 (meaningful expectations; 4 items).

The questionnaire was translated into Arabic to strengthen the notions' linguistic and cultural validity. Also, a small group participated in a pilot project to adapt ideas to the sociocultural context by replacing general notions with more precise ones to promote greater comprehension in the local setting. The student's idealized and realistic expectations for a LA service were matched to two "seven-point Likert scales (1 = strongly disagree, 7 = strongly agree)" that were used to rate the responses (predicted expectations). The invitations to participate were sent out via email.

Sample

Students at Jazan University received the 12-item SELAQ (Appendix A) questionnaire using an online survey method. The 12 items were chosen following the study by Whitelock-Wainwright et al. [55]. 160 female responses were gathered out of 435 total responses. The age range of the students was 18 to 35 (M = 22.71, SD = 2.525). Among the sample, 26% (114 out of 223) were studying arts and humanities, 51% (222 out of 223) were studying business, and 23% (98 out of 223) were studying medicine and health care. The fact that 70% of the students were in their third or final year of study suggests that they have been in college long enough and are mature enough to provide comments. Table 1 displays the information.

Table 1: Demographic Details

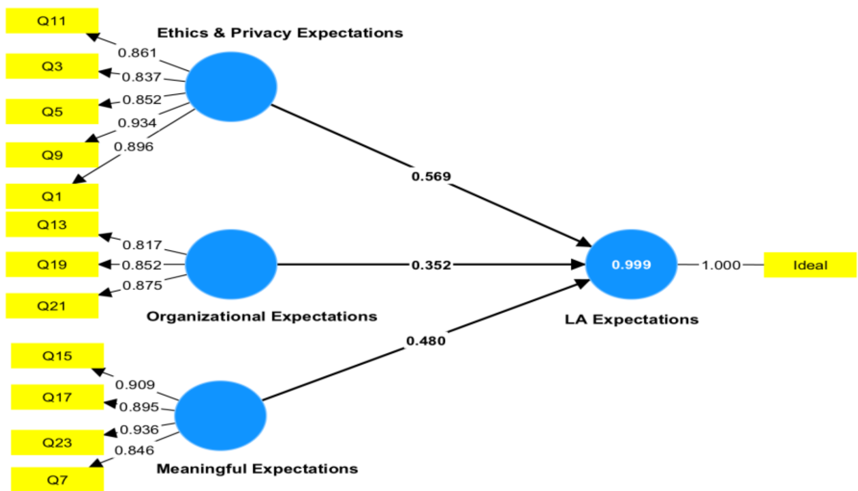
Domain	**Characteristic**	**N**	**% of the Sample**
Gender	*Male*	*275*	63%
	Female	*160*	37%
Age	*below 20 years*	139	*32%*

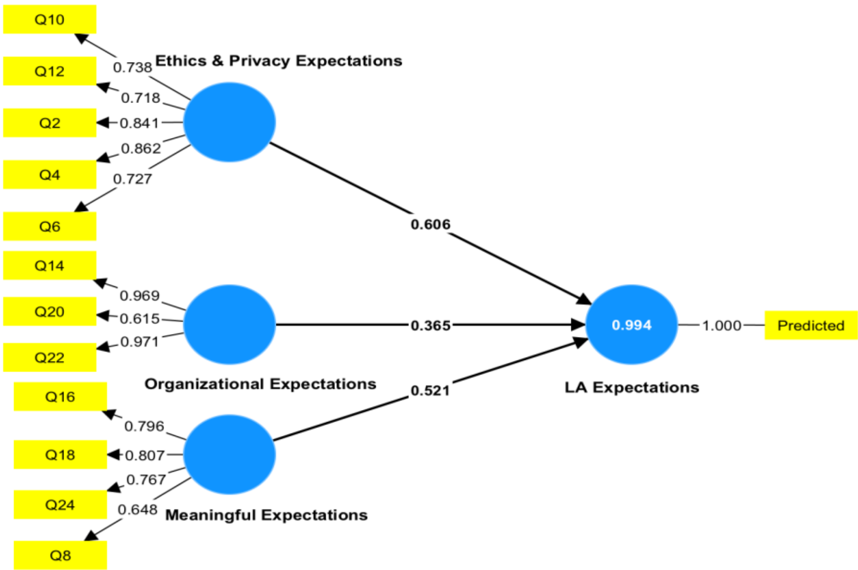
	21-25 years	235	*54%*
	26-30 years	35	*8%*
	above 30 years	26	*6%*
Program of Study	*Arts & Humanities*	*114*	*26%*
	Business	*223*	*51%*
	Medicine & Healthcare	*98*	*23%*
Year of study	*Year I*	*39*	*9%*
	Year II	*91*	*21%*
	Year III	*139*	*32%*
	Year IV	*165*	*38%*

Data Analysis

Using SmartPLS 4, we calculated the student's expectations by comparing the ideal and projected responses. The mean averages of the ideal and expected ratings for each item in each case were used to compare the observations further, and the differences between the two were determined using paired t-tests. The convergent and discriminant validity of the measuring scale was examined in this study. In addition, "structural equation modeling (SEM)" was utilized to confirm the link between the student's meaningful expectations for LA adoption and organizational, ethical, and privacy expectations. The structural equation model for both ideal and predicted responses is depicted in Figure 1:

Figure 1: Structural Equation Model





Construct Reliability & Validity

In order to determine the validity and reliability of the constructs, the measurement model was evaluated. Factor loading for completed items, as well as ideal (I) and predictive (P) expectations, are presented in Table 2, along with reliability and validity results for the entire sample. All model components have factor loading values above 0.50 to start, which satisfies the [57] requirement. Cronbach's alpha is a measure of the internal consistency of a set of items that can be used to evaluate the dependability of a construct. Composite reliability is a type of construct dependability that looks at the consistency of a total score after numerous components have been added together. Cronbach's alpha, rho a, and composite reliability (CR) values exceeded the threshold. Seven hundred is used to indicate reliability [58]. According to Hair et al. [59], rho and Cronbach's alpha composite reliability values were moderate. All CRs and AVEs were much above the critical values of 0.500 and 0.700, respectively, indicating convergent validity. The level of a construct's expected relationships with other constructs is what convergent validity assesses. The average variance extracted (AVE) is a measure of convergent validity; it is the average percentage of construct variance that can be accounted for by the indicator variables. The three proposed constructs meet the necessary conditions (Table 2).

Discriminant Validity

Fornell & Larcker [60] state that the square root of the correlation between the latent variables and AVE was used to assess discriminant validity (see Table 3). This proves that the test has discriminant validity.

Table 2 Reliability & Validity of the Constructs

		Outer loadings		Cronbach's alpha		Composite reliability (rho_a)		Composite reliability (rho_c)		Average variance extracted (AVE)	
		Ideal	Predicted	Ideal	Predicted	Ideal	Expected	Ideal	Expected	Ideal	Expected
Ethics & Privacy (E)	Q1 <- E	0.896	0.841	0.92	0.836	0.926	0.84	0.943	0.885	0.768	0.608
	Q3 <- E	0.837	0.862								
	Q5 <- E	0.852	0.727								
	Q9 <- E	0.934	0.738								
	Q11 <- E	0.861	0.718								
Organizations Expectation(O)	Q13 <- O	0.817	0.969	0.81	0.822	0.814	0.909	0.885	0.898	0.72	0.753
	Q19 <- O	0.852	0.615								
	Q21 <- O	0.875	0.971								
Meaningful Expectations(M)	Q7 <-M	0.846	0.648	0.92	0.755	0.931	0.776	0.943	0.842	0.805	0.573
	Q15 <-M	0.909	0.796								
	Q17 <-M	0.895	0.807								
	Q23 <-M	0.936	0.767								

(Source: Author’s compilation using SmartPLS 4)

Table 3(A) Discriminant Validity: Fornell-Larcker Criterion (Ideal Scenario)

	Ethics & Privacy Expectations	LA Expectations	Meaningful Expectations	Organizational Expectations
Ethics & Privacy Expectations	0.874			
LA Expectations	0.334	1		
Meaningful Expectations	0.017	0.435	0.897	
Organizational Expectations	0.757	0.419	-0.006	0.851

(Source: Author’s compilation using SmartPLS 4)

Table 3(B) Discriminant Validity: Fornell-Larcker Criterion (Predicted Scenario)

	Ethics & Privacy Expectations	LA Expectations	Meaningful Expectations	Organizational Expectations
Ethics & Privacy Expectations	0.779			
LA Expectations	0.761	1		
Meaningful Expectations	-0.054	0.521	0.757	
Organizational Expectations	0.502	0.716	0.09	0.868

(Source: Author’s compilation using SmartPLS 4)

Hypotheses Testing

Smart PLS uses bootstrapping and latent variable modeling to derive p-values or confidence intervals for the tested hypothesis. The p-value or confidence interval can then be used to infer whether or not the data support the alternative hypothesis. The p-value calculates the likelihood that the observed data resulted from pure chance under the assumption that the null hypothesis is correct. Since the p-value is small (less than 0.05), we can reject the null hypothesis and accept the alternative. When the p-value is high (more than 0.05), there is insufficient evidence to rule out the null hypothesis. The results of the hypothesis testing are presented in Table 6.

Table 4: Hypotheses Testing

Hypotheses		**Original sample (O)**		**Standard deviation (STDEV)**		**T statistics (|O/STDEV|)**		**P values**		**Observation**
		I	**P**	**I**	**P**	**I**	**P**	**I**	**P**	
H1	E -> LA Expectations	0.569	0.606	0.029	0.039	19.394	15.511	0.0000	0.0000	Supported
H3	M -> LA Expectations	0.48	0.521	0.046	0.041	10.482	12.781	0.0000	0.0000	Supported
H2	O -> LA Expectations	0.352	0.365	0.02	0.027	17.432	13.367	0.0000	0.0000	Supported

(Note: “I” means ideal and “P” means predicted and Significance Relationship: P value <0.05 & T Statistics >1.96)

1. H1 evaluates whether students’ expectations related to ethics & privacy significantly affects LA adoption. The result revealed that it has a significant impact on hypothesized variable. Hence H1 was supported.

2. Furthermore, H2 evaluates whether students’ expectations related to organizational support significantly affects LA adoption. The result

revealed that it has a significant impact on hypothesized variable. Hence H2 was supported.

3. And H3 evaluates whether students' expectations related to meaningful use of LA services significantly affects LA adoption. The result revealed that it has a significant impact on hypothesized variable. Hence H3 was supported.

Descriptive Statistics

Table 5 provides item-level descriptive statistics on both the ideal and anticipated expectation scales, while Table 6 provides similar statistics broken down by gender and topic of study (Table 7). Table 5 shows that the average responses are higher on the ideal vs. anticipated expectation scale. The mean values for meaningful expectation items (ideal expectation range: 6.39–6.51, projected expectation range: 4.86–5.07) are higher than those for organizational expectation items (ranging from 6.41 to 6.46 for ideal expectations and ranging from 4.93 to 5.03 for predicted expectations), as shown in Table 5. However, students did not seem to have a strong reaction to Item 1 from the ethical and privacy expectation component ("The university will ask for my consent before using any identifiable data about myself, e.g., ethnicity, age, and gender"; M = 6.40, SD = 0.563; Table 5) or projected expectations (M = 5.03, SD = 0.683; Table 5). The average response for both ideal and expected expectations was highest for Item 9's significant expectation (M = 6.519, SD = 0.524; Table 5) ("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").

Table 5 Descriptive Statistics for Ideal & Predicted Expectations

		Ideal Expectations			Predicted Expectations		
Factor Key	**Item**	**M**	**SD**	**Skew**	**M**	**SD**	**Skew**
Q1	1	6.405	0.563	-0.266	5.038	0.683	-0.049
Q2	2	6.405	0.563	-0.266	4.924	0.708	0.111
Q3	3	6.418	0.565	-0.312	5.025	0.675	-0.031
Q4	4	6.392	0.538	-0.054	4.924	0.759	-0.047
Q5	5	6.43	0.52	0.01	4.899	0.756	-0.006
Q6	6	6.43	0.52	0.01	4.949	0.654	0.053

Q7	7	6.418	0.565	-0.312	5	0.656	0
Q8	8	6.418	0.542	-0.15	4.937	0.643	0.059
Q9	9	6.519	0.524	-0.346	5.076	0.759	-0.13
Q10	10	6.468	0.57	-0.501	5.038	0.754	-0.245
Q11	11	6.468	0.57	-0.501	4.861	0.838	0.008
Q12	12	6.456	0.523	-0.09	4.937	0.769	-0.06

The ideal (M = 6.52, SD = 0.544; Table 6) and projected (M = 5.141, SD = 0.783) expectations for men were highest for item 9 from meaningful expectations. On the other hand, the average female response was higher than the ideal and anticipated values for organizational expectation item 12 (M = 6.483, SD = 0.509, and M = 4.862, SD = 0.789, respectively; Table 6). Table 7 shows that the average response score on the ideal scale varies from 6.62 to 6.68 for medicine & healthcare and 4.72 to 5.28 for predicted expectations, depending on the field of study. Table 7 shows that the highest mean averages for ideal (M = 6.556, SD = 0.511) and predicted (M = 5.333, SD = 0.686) scales were recorded for items 2 and 3 in the arts and business education categories, respectively. In contrast, item 10 in medicine and health science education recorded the highest mean averages for ideal (M = 6.680, SD = 0.476) and predicted (M = 5.280, SD = 0.614) scales.

Table 6 Descriptive Statistics for Ideal & Predicted Expectations by gender

		Ideal Expectations			Predicted Expectations		
Gender	**Factor Key**	**M**	**SD**	**Skew**	**M**	**SD**	**Skew**
Male	Q1	6.420	0.575	-0.346	5.040	0.669	-0.045
	Q2	6.420	0.538	-0.078	4.940	0.682	0.075
	Q3	6.460	0.542	-0.235	5.080	0.724	-0.123
	Q4	6.400	0.535	0.000	5.020	0.714	-0.029
	Q5	6.460	0.542	-0.235	4.980	0.742	-0.280
	Q6	6.460	0.542	-0.235	5.000	0.670	0.000
	Q7	6.460	0.579	-0.496	4.980	0.622	0.012
	Q8	6.440	0.577	-0.420	4.980	0.654	0.020
	Q9	6.520	0.544	-0.479	5.140	0.783	-0.255

	Q10	6.500	0.544	-0.396	5.020	0.742	-0.032
	Q11	6480	0.544	-0.315	4.860	0.833	0.052
	Q12	6.440	0.541	-0.156	4.980	0.769	-0.246
Female	Q1	6.379	0.561	-0.136	5.034	0.731	-0.054
	Q2	6.379	0.622	-0.463	4.897	0.772	0.184
	Q3	6.345	0.614	-0.349	4.931	0.593	0.009
	Q4	6.379	0.561	-0.136	4.759	0.830	0.093
	Q5	6.379	0.494	0.525	4.759	0.786	0.469
	Q6	6.379	0.494	0.525	4.862	0.639	0.119
	Q7	6.345	0.553	-0.008	5.034	0.731	-0.054
	Q8	6.379	0.494	0.525	4.862	0.639	0.119
	Q9	6.517	0.509	-0.073	4.966	0.731	0.054
	Q10	6.414	0.628	-0.582	5.069	0.799	-0.580
	Q11	6.448	0.632	-0.706	4.862	0.875	-0.060
	Q12	6.483	0.509	0.073	4.862	0.789	0.257

Table 7 Descriptive Statistics for Ideal & Predicted Expectations by field of study

		Ideal Expectations			Predicted Expectations		
College	**Factor Key**	**M**	**SD**	**Skew**	**M**	**SD**	**Skew**
Arts & Humanities	Q1	6.500	0.618	-0.840	5.222	0.732	-0.383
	Q2	6.556	0.511	-0.244	5.333	0.686	-0.547
	Q3	6.389	0.698	-0.724	5.056	0.802	-0.106
	Q4	6.500	0.514	0.000	4.889	0.758	0.195
	Q5	6.556	0.511	-0.244	5.000	0.686	0.000
	Q6	6.556	0.511	-0.244	5.000	0.686	0.000
	Q7	6.444	0.511	0.244	5.056	0.539	0.073
	Q8	6.556	0.511	-0.244	4.944	0.639	0.041
	Q9	6.556	0.511	-0.244	4.944	0.725	0.086
	Q10	6.500	0.514	0.000	5.111	0.676	-0.132
	Q11	6.333	0.686	-0.547	5.000	0.907	-0.531
	Q12	6.500	0.514	0.000	5.056	0.802	-0.106
Business	Q1	6.417	0.554	-0.185	5.083	0.649	-0.078

	Q2	6.389	0.599	-0.389	4.861	0.639	0.122
	Q3	6.500	0.507	0.000	5.167	0.507	0.309
	Q4	6.389	0.549	-0.079	4.944	0.826	-0.215
	Q5	6.444	0.504	0.233	4.917	0.770	0.146
	Q6	6.444	0.504	0.233	4.917	0.692	0.110
	Q7	6.389	0.599	-0.389	5.028	0.810	-0.052
	Q8	6.444	0.504	0.233	4.917	0.692	0.110
	Q9	6.444	0.558	-0.293	5.028	0.774	-0.049
	Q10	6.306	0.624	-0.315	4.833	0.845	0.033
	Q11	6.389	0.549	-0.079	4.611	0.766	0.410
	Q12	6.333	0.535	0.132	4.750	0.770	0.075
Medicine & Healthcare	Q1	6.320	0.557	0.010	4.840	0.688	0.216
	Q2	6.320	0.557	0.010	4.720	0.737	0.509
	Q3	6.320	0.557	0.010	4.800	0.764	0.366
	Q4	6.320	0.557	0.010	4.920	0.702	0.112
	Q5	6.320	0.557	0.010	4.800	0.816	-0.100
	Q6	6.320	0.557	0.010	4.960	0.611	0.015
	Q7	6.440	0.583	-0.434	4.920	0.493	-0.221
	Q8	6.280	0.614	-0.224	4.960	0.611	0.015
	Q9	6.600	0.500	-0.435	5.240	0.779	-0.463
	Q10	6.680	0.476	-0.822	5.280	0.614	-0.224
	Q11	6.680	0.476	-0.822	5.120	0.833	-0.238
	Q12	6.600	0.500	-0.435	5.120	0.726	-0.189

DISCUSSION

Interpretation of the results

After reviewing the LA literature, three concepts were identified: "ethical and privacy expectations," "organization expectations," and "meaningfulness expectations" during LA implementation in HEIs [55]. Considering these three factors, 12 student expectations for LA services were compiled [56]. These items were developed utilizing the theoretical framework of expectancies, with specific reference to the work of [61], [62], to provide a more nuanced comprehension of the stakeholder's perspective. We constructed and validated a 12-item survey using this method to learn more about students' expectations of LA resources. Our research showed that students are confident in their instructors' ability to use analytics in their classrooms. Students also believed that teachers would be obligated to help students who are failing or underperforming or could benefit from additional instruction based on findings from other research [63]. These opinions are relevant to what Schumacher & Ifenthaler [12] describe as what LA services should offer students. The students discovered that when incorporating LA into their studies, it was crucial to have an open dialogue concerning their data privacy. It means that good communication is necessary to accept LA [64].

Reviewing the descriptive data allowed us to learn more about what students expect from three different conceptions. The statement "the learning analytics service would show me a complete picture of my learning throughout each module" received the highest average rating on the ideal and anticipated scales (Item 9; Appendix A). Item 9 received the highest average response from both male and female students. However, female students' highest anticipated average score was, "The teaching staff will be proficient in using analytics in the feedback and support they provide to me" (Item 10; Appendix A). The literature, especially the work done by, substantially supports this view [12], [41]. According to a different classification of students based on their fields of study, the highest ideal and expected average response for the arts & humanities was "The university will ensure that all my educational data will be maintained securely" (Item 2; Appendix A); for business studies, it was "The university will seek my consent before my educational data is outsourced for analysis by third party firms" (Item 3; Appendix A); and for medical & healthcare, it was "The teaching staff will be supportive" (Item 10; Appendix A). Recent literature, especially the study by Slade & Prinsloo [34], which found that students felt institutions would always maintain privacy and require informed consent, strongly supports these claims.

While some LA service elements (such as the adoption of early warning systems) may be beneficial, the comparisons performed above using the factor's items show that they may not always be what students are expecting (such as "LA services intended to support academic skills like self-regulated learning"). Hence, even though the potential for LA services to identify low-achieving or at-risk students has drawn much attention [49], it is feasible that students look forward to LA service features meant to aid in better understanding or managing their learning processes.

LIMITATIONS, CONCLUSION, AND FUTURE WORK

Although it is recommended that students be included in the design of LA services [14], it is also important to consider the needs of faculty and administration. [54] claims that educators have preferences regarding the assistance they receive from LA, particularly regarding the value of feedback provided. As a result, even though faculty needs are equally important, LA services should continue to reflect student demands. Therefore, future studies should strive to create and evaluate a method for gauging faculty attitudes toward LA support services. When the SELAQ is used in conjunction with LA, more stakeholder viewpoints can be provided to the institution and considered during the implementation process. We are aware that the opinions shown in our poll do not properly reflect those of the entire country. The lack of "skeptics" suggests that students who found our research topic too challenging or uninteresting opted not to participate in the survey. As a result, our results do not represent anyone other than the students who were genuinely curious about LA. However, the results are crucial for tertiary institutions since they reveal students' expectations regarding LA tools. We can speculate on a wide range of potential follow-up studies for our current effort. Since there is no universally applicable method of governing LA, we found that different types of student participation are appropriate even within the same organization, depending on the student's intended career path and personal goals [56]. Here are some suggestions for the future. Second, students' ideal and expected LA service expectations were statistically different. While many respondents appear aware of the options, others may be in the dark. We suggest digging deeper into these issues to determine if they have anything to do with prior experiences with LA application, organizational culture, philosophical convictions, etc. It is worth stressing that we should have considered students' past LA experience when grading their essays. There could be an opportunity to identify whether desired and anticipated expectations are the product of newly gained experience or a need for more awareness of the potential of LA advancements and to design treatments accordingly.

One of the most important factors in a service's ultimate success or failure is whether or not it meets the expectations of its stakeholders [17], [47]. Stakeholder participation is crucial to a smooth LA rollout since it increases the likelihood that LA services will be well received across the board. This research showed that there had been a disconnect between how LA services have been implemented and students' expectations, increasing the chance of future dissatisfaction when services fail to live up to expectations. Therefore, universities can consider students' anticipations when they plan their rollout of LA services. Institutions and LA system designers can utilize this research as a blueprint for creating user-friendly, standardized tools.

The cultural limits of the SELAQ, which was established and validated only with UK higher education students, must also be considered. As a result, researchers must validate this instrument in a variety of scenarios. It is critical for every university interested in implementing LA services to properly interact with its stakeholders because the issue of uneven stakeholder participation in LA implementations is wider than in UK higher education institutions [40]. Further study, including the approval of equipment translated into multiple languages, is required to evaluate the instrument's validity and reliability in cross-cultural circumstances.

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