Migration Letters
Volume: 21, No: S8 (2024), pp. 783-804
ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)
www.migrationletters.com

Bridging The Gap: Aligning Institutional Expectations And Stakeholder Desires In Learning Analytics Implementation

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Abstract

Purpose—*The primary objectives of LA are to improve student performance and provide students with additional resources and support to ensure their success. Nevertheless, this could indicate a divergence between the expectations of institutions regarding stakeholder expectations and the true desires of stakeholders. It is crucial to resolve these concerns and understand academic staff's expectations before implementing LA to increase end-user buy-in and optimize resource planning.* ***Methodology—****A comprehensive literature review focusing on the significance, existing models, and challenges associated with LA implementation constitutes the study's methodology. The identified gap prompted the implementation of a survey utilizing the SHIELA framework to investigate the perspectives, utilization, and challenges encountered by teaching staff about adopting LA. The data undergoes reliability and validity assessments through SmartPLS 4, which measures construct validity, discriminant validity, and factor loading.*

Findings— *The results of our research indicated that the i[1]nstructional personnel believed that utilizing LA most effectively would support early intervention. The academic staff believed that LA could aid students in decision-making processes and provide constructive criticism regarding their progress in learning. They contend that while institutions and students should share the responsibility, it is institutions' moral and legal obligation to take the necessary precautions to mitigate risks, including encouraging and empowering students.*

Originality/Value— *The research provides educational leaders with the necessary resources to develop more effective strategies for teaching and learning success while equipping students with fresh insights to assist them in making informed decisions regarding their education. We posit that the continued and efficacious attention of the higher education sector toward learning analytics, coupled with the adoption of this paradigm, will yield positive results for universities, students, and society at large. Drawing from the present discoveries, the research proposes several research methodologies and subjects for further inquiry.*

Keywords *Learning Analytics, Stakeholder Expectations, SHIELA Framework, Higher Education, Educational Leadership.*

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1. Introduction

Learning analytics provides information that enhances decision-making in higher education through formal analysis technologies, such as machine learning and statistical tools (El Alfy et al., 2019). The primary objective behind the development of this program was to analyze user data traces through digital technology to gain insight into their ongoing learning behaviours and actions (Han et al., 2020; Siemens et al., 2013). Their rapid growth and the plethora of scholarly works generated by ongoing research in this domain attest to their widespread adoption in higher education worldwide (Başaran & Daganni, 2020; El Alfy et al., 2019; Ngqulu, 2018). Active learning, improved teaching and learning strategies, the implementation of early interventions to support student learning, increased student throughput, and enhanced student retention are just a few of the potential benefits that have contributed to their growing popularity . (El Alfy et al., 2019; Fan et al., 2020). In the twenty-first century, higher education institutions (HEIs) are shifting from a teacher-centric to a student-centric approach to learning (Kivunja, 2014). El Alfy et al. (2019) assert that this technology is assisting educators, academics, and students in preparing students to confront the challenges and concerns of the twenty-first century. Despite the longstanding nature of LA developments in higher education, academicians face challenges regarding LA adoption and acceptance (West et al., 2018). Some problems that might stop LA from moving forward are unclear goals (Mor et al., 2015; R. A. Sheikh et al., 2021), differences in how well academics understand data (Corrin L. K., 2016), a lack of data for making decisions (Bennett et al., 2021), and concerns about ethics and privacy (Ifenthaler & Tracey, 2016). Although there has been considerable emphasis on the importance of early stakeholder involvement, especially in the context of LA (Ferguson et al., 2014; Kollom et al., 2021), actual instances of this are uncommon (Y. S. Tsai et al., 2017).

The absence of stakeholder engagement may result in the prevalent influence of institutional managers' expectations and viewpoints over the myriad LA policies presently at hand (Sclater, 2020). While the main justifications for using LA in these circumstances are to improve academic achievement (Y. S. Tsai et al., 2018) and give students more support (Siemens & Gasevic, 2012), these justifications are still subject to the preconceived notions of administrators. They may need to consistently reflect the expectations of other stakeholders (including students and faculty). As a result, there may be a discrepancy between the services organizations guarantee customers and the services consumers truly desire (Ng & Forbes, 2009). It is crucial to resolve these concerns and understand academic expectations before implementing LA to increase end-user support and optimize resource allocation.

Despite the extensive utilization of LA in developed countries, there still needs to be more understanding regarding its application in developing countries, including the beneficiaries, implementers, and resulting attitudes (Hommel et al., 2019; Parrish & Richman, 2020). The findings of this study's literature review supported the claims made by El Alfy et al. (2019) and Mahmoud et al. (2021) regarding the scarcity of research in specific geographical areas, including North Africa and the Middle East. We have endeavoured to address this deficiency in the present study by investigating the anticipations of faculty members regarding the implementation of LA services in Saudi Arabia and the Gulf region as a whole. Accessibility and comprehension of the materials from the teaching staff's perspective were consistently considered throughout the design of this research. A comprehensive examination of the pertinent research leads to the development of a theoretical framework for examining the anticipations of the faculty regarding the implementation of LA. The survey data is used with structural equation modeling to test and validate the model. This process identifies the primary determinants that impact learning analytics. By doing so, HEIs can identify specific LA implementation areas that will receive increased attention from their instructional staff regarding direct engagement strategies.

2. Literature Review

The rapid advancement of learning analytics is consistently reshaping significant subjects within higher education (El Alfy et al., 2019; Gasevic et al., 2019). The adoption rate and utilization of online learning have increased substantially due to several factors, including COVID-19 contact restrictions and a greater belief in its benefits (Gibson & de Freitas, 2016). The utilization of learning analytics and data analytics in higher education has yielded several benefits, such as the capacity to detect students who are at risk of failing to meet academic standards, track the advancement of students, predict the specific learning needs of each individual, and identify potential determinants of academic success (Clark et al., 2020; El Alfy et al., 2019). The data sources for learning analytics include learning management systems (LMS) such as Moodle, Canvas, and Blackboard (R. Sheikh & Goje, 2021; Xin & Singh, 2021).

An advantageous feature of LA is its capacity to provide students with timely, precise, and relevant feedback regarding their academic assignments, progress, and achievements (Banihashem et al., 2022; Schumacher & Ifenthaler, 2018). In the eyes of the students, constructive criticism is any approach or piece of knowledge that may enhance their capacity to regulate their education (Cavalcanti, 2020). In order to foster student autonomy in learning management, instructors must allocate substantial resources toward delivering efficacious feedback (Jin et al., 2022; Pinheiro Cavalcanti et al., 2019). Academic personnel may need help independently assessing students' progress and providing feedback when learning environments become more dispersed, shifting from face-to-face instruction to formal and informal online platforms. Conversely, by providing performance data to educators, LA can assist the teaching staff in fostering students' autonomy in learning (Lodge et al., 2019). Cazan (2013) recommended that educators assist students in developing task-specific methodologies, metacognitive awareness of academia, effective self-monitoring strategies, the capacity to utilize feedback strategically, and active metacognition engagement.

Despite the teaching staff's potential to assist students in developing their metacognitive abilities, enhancing their feedback processes, and ultimately improving their instructional practices, there remains an unbridged divide in adopting LA (Durall & Gros, 2014). There has been a growing recognition of the potential of LA. However, Ferguson et al. (2016) have observed that the implementation of LA by organizations needs to have the level of systematic approach one might expect. A recent evaluation of the literature by Viberg et al. (2018) revealed that only 6% of the 252 papers included satisfied the criterion of "wide adoption and utilization of LA, including deployment at scale." While several factors contribute to this, one of the most significant is the consideration of LA's end users' preferences and needs throughout the service's planning and development process. Lack of student and teacher feedback integration during the development of LA solutions may hinder the technology's broad implementation in classrooms and educational institutions (Alvarez et al., 2020). Shum et al. (2019) posit that incorporating nascent technologies into practical environments entails obstacles of a technical and human nature, encompassing cognitive, social, organizational, and political dimensions. Tsai et al. (2017) also address this matter, arguing that the lack of involvement of relevant stakeholders and the subsequent absence of a shared understanding contribute to the limited utilization of LA services in higher education. Given that the successful implementation of LA requires exceptionally qualified instructors and solutions that consider the learners' requirements (Siemens et al., 2013), this could potentially undermine the efficacy of LA. Dollinger et al. (2019) argue that the significance of a technology to its consumers is more important than its technical capabilities and functions. Developing pedagogical services that align with educators' objectives and fulfil the intended users' requirements is a challenging endeavor.

Educators should be involved in that process, as they can analyze the data and determine how to employ it to improve the instructional design (Alhadad et al., 2018). Prieto et al. (2018) and West et al. (2018) have put forth various approaches to integrating key stakeholders. Additional studies have examined the intentions and results of academic staff regarding LA solutions and employee participation in LA processes. To promote LA adoption in HEIs and bridge the gap between LA solutions and academic personnel requirements, Dollinger & Lodge (2018) proposed co-creating LA with educators. Similarly, Chatti & Muslim (2019) introduced the notion of user-centered LA as a potential resolution that emphasizes the importance of satisfying user requirements and the user-centric aspects of LA. Active user participation throughout LA's planning, design, implementation, and evaluation phases is critical for meeting the needs of numerous users. Assisting in the interstakeholder design of LA enhancements, Alvarez et al. (2020) proposed a card-based co-design instrument. Positive preliminary assessments indicate that this tool effectively facilitates the participation of diverse stakeholders in the design process of technologies intended for learners, instructors, and other non-technical users. West et al. (2018) questioned academic staff members from Australia and Malaysia about their experiences with and needs for LA, emphasizing their participation in LA initiatives. The study results indicated that scholars would rather utilize LA to improve their lessons than ensure student retention. Research conducted by Howell et al. (2018) and Wong & Li (2018) provides an additional noteworthy example of investigating the perspectives of teaching personnel regarding LA. Their investigation unveiled that teaching staff members not only anticipated benefits for student learning but also proposed measures that would streamline the process of instruction and learning. Additionally, to intervene earlier with underachievers, the teaching staff wishes to comprehend how LA services might affect their responsibilities. Based on the results obtained, it is evident that higher education institutions must engage the teaching staff in LA processes right from the outset to effectively integrate LA into their instructional approaches (Demetriosssampsonn· et al., 2022).

The objective of this research is to increase understanding of the expectations that academic personnel have for LA services. By analyzing four distinct specializations, we hope to ascertain the expectations of academic staff members at Gulf Region HEIs regarding LA services. In this study, we investigate the expectations of the teaching staff on two levels: initially, we inquired about their overall expectations, and secondly, we challenged them to distinguish explicitly between their desired ideal and the outcomes they expect to transpire.

For this reason, we have formulated the subsequent four hypotheses in order to evaluate the preparedness of faculty members in higher education institutions (HEIs) to embrace LA:

H1: Teaching staffs' awareness related to the goals of LA significantly affects HEIs readiness for it

H2: Teaching staffs' perception related to their need of LA services significantly affects HEIs readiness for it

H3: Teaching Staffs' view about students' need to LA services significantly affects HEIs readiness for it

H4: Teaching staffs' awareness related to the implementation challenges of LA services significantly affect HEIs readiness

3. Research Methodology

3.1 Research Design

This research aims to gain a deeper understanding of the expectations of faculty members concerning the implementation of LA in HEIs. Achieving the research objective was possible by employing a survey methodology. A survey was considered suitable for this research to validate the essential elements required for implementing LA and assess the proposed framework. Data was gathered from the teaching staff of four Saudi Arabian higher education institutions (Arts, Business, Computer Sciences, and Medicine) to understand better the critical factors that influence their approval and utilization of LA to support student learning outcomes.

3.2 Instrument

The survey utilized the same theoretical framework as the "Student Expectations of Learning Analytics Questionnaire (SELAQ)," which assessed ideal and predicted expectations (i.e., the discrepancy between what an individual hopes to obtain and what they anticipate receiving) through the use of two scores (Whitelock-Wainwright et al., 2019). Appendix A contains the questionnaire containing the sixteen items used to assess the expectations of teaching staff regarding LA services. These elements are categorized into four constructs according to Y.-S. Tsai et al. (2018). The F1-goals of LA (2 items), F2-need for LA services by teaching staff (4 items), F3-evaluation of students' need for LA services by teaching staff (5 items), and F4-implementation issues comprise the Tsai et al. (2018) SHEILA framework. Figure 1 illustrates the development of the model's theoretical framework utilizing SmartPLS 4.

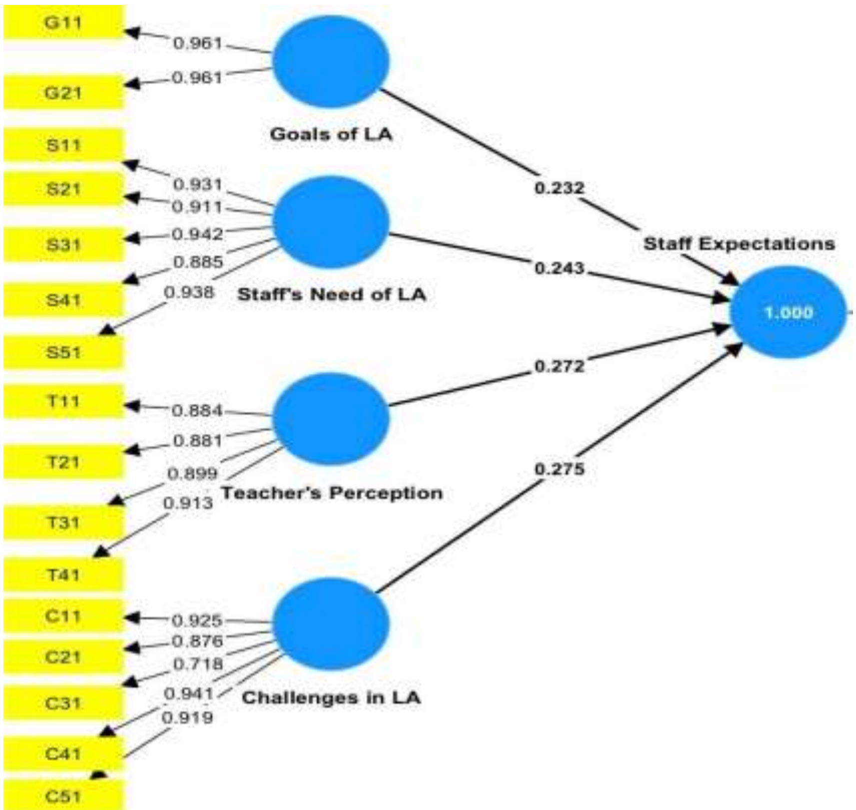

Figure 1: Theoretical Framework for Staff Expectations from LA

(Source: Theoretical model with factor loading using SmartPLS 4)

To enhance the linguistic and cultural validity of the concepts, a limited number of groups participated in a pilot study that aimed to adapt ideas to the cultural context by substituting particular concepts to promote greater comprehension in the local setting. The responses were evaluated utilizing two "seven-point Likert scales" (predicted expectations) based on the instructional staff's idealized and practical expectations for an LA service (1 = strongly disagree, 7 = strongly agree). The participation invitations were disseminated via email. Using SmartPLS 4, the mean averages of the anticipated and ideal ratings for each item in each example were compared to determine the ideal and projected expectations for LA services for the four components. Any discrepancies between the two sets of ratings were then analyzed using paired t-tests.

4. Results

4.1 Construct Reliability & Validity

In order to ascertain the constructs' validity and dependability, an evaluation was conducted of the measurement model. The factors that contributed to the satisfactory items' factor loadings and the reliability and validity outcomes for the entire sample are detailed in Table 1. These factors include the ideal (I) and predicted (P) expectations. As stated by Hair et al. (2010), the factor loading values of all model components exceed the minimum acceptable threshold of 0.50. While factor loadings exceeding 0.7 are preferable (Vinzi et al., 2010), outer loadings below 0.7 are more common in social science research. Statistical dependability measures included Cronbach's alpha, rho_a, and composite reliability (CR); these metrics exceeded the recommended threshold of 0.700 (Wasko & Faraj, 2005). Hair et al. (2017) determined that the rho_a value fell between Cronbach's alpha and composite reliability. The average variance extracted (AVE) and CRs were substantial or extremely close to 0.500 and 0.700, respectively, supporting convergent validity. Fornell & Larcker (1981) suggested a way to check the discriminant validity of a test by looking at the relationship between the hidden variables and the square root of AVE (see Table 2). Consequently, we can also affirm discriminant validity.

4.2 Descriptive Statistics

Assessing the expectations of the teaching staff involved utilizing SmartPLS 4 to determine the discrepancy between the two responses (i.e., the ideal and the predicted). One hundred and two teaching staff respondents (males = 63; females = 39) from four academic disciplines at Jazan University out of a possible 198 responded to the sixteen-item survey (Appendix A). The survey was distributed via email and direct distribution. A total of 102 responses were received, of which 62% were male and 38% were female (Business = 38, Computers = 24, Arts=18, Medicine=12, Others = 10). This corresponds to a response rate of 52%. This was a self-selected sample of academic personnel from the four disciplines who agreed to be contacted for research purposes. In order to ensure the sample's representativeness of the entire teaching staff, additional demographic information was compared to this sample, including gender, teaching experience, and specialization (refer to Table 3).

Table 2(A) Discriminant Validity: Fornell-Larcker Criterion (Ideal Scenario)

Ideal Scenario	Challenges of LA	Goals of LA	Teacher's Need of LA	Teacher's perception

Challenges of LA	0.88			
Goals of LA	0.945 0.961			
Teacher's Need of LA	0.944	0.929	0.894	
Teacher's perception	0.948	0.956	0.928	0.922

(Source: Author’s compilation using SmartPLS 4)

Table 2(B) Discriminant Validity: Fornell-Larcker Criterion (Predicted Scenario)

Expected Scenario	Challenges of LA	Goals of LA	Teacher's Need of LA	Teacher's perception
Challenges of LA	0.86			
Goals of LA	0.877	0.947		
Teacher's Need of LA	0.939	0.862	0.851	
Teacher's perception	0.902	0.846	0.897	0.882

(Source: Author’s compilation using SmartPLS 4)

Table 3 Sociodemographic characteristics of the respondent

Domain	Characteristic	N	% of the Sample
Gender	Male Female	63 39	62% 38%
Teaching experience	0-5 years	32	31%
	6-10 years	27	26%
	11-15 years	24	24%
	> 15 years	19	19%
Specialization	Business	38	37%
	Computer Science	24	24%
	Arts	18	18%
	Medicine	12	12%
	Others	10	10%
Academic Position	“Professor	10	10%
	Associate Professor	19	19%
	Assistant Professor	31	30%
	Lecturer”	42	41%
Administrative Position	HOD	7	7%
	Head of any Committee	59	58%

	others	36	35%

(Source: Author's compilation using SmartPLS 4)

The descriptive statistics (Table 4) comprehensively comprehend the teaching staff's expectations regarding LA services. Consistent with expectations, the responses to the ideal expectations scale exhibited a ceiling effect. This scale represents the ideal service that teaching staff would desire, so responses are likely overly optimistic. Nevertheless, compared to the anticipated responses projected by the instructional staff, the responses provided could have been better. This differentiation between ideal and anticipated expectation responses enhances the measure's validity, as the results are consistent with two levels of belief. Refer to Figure 2.

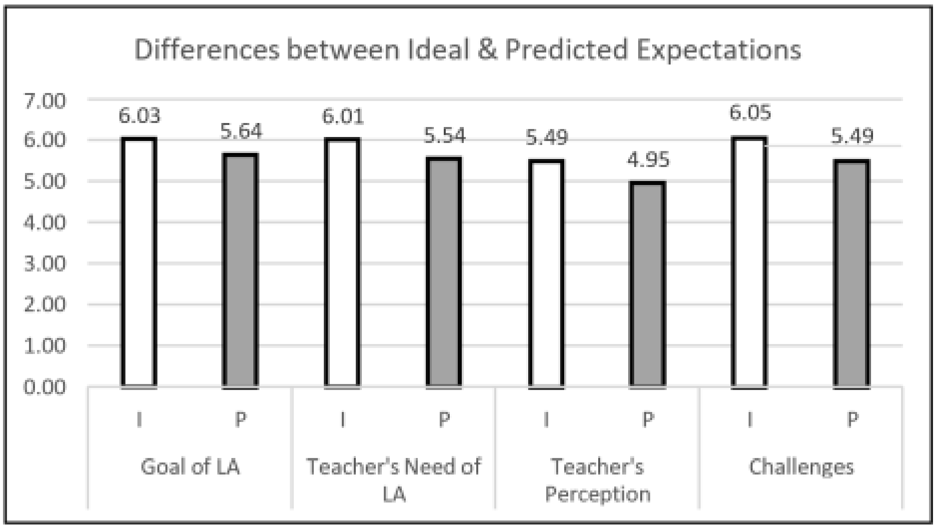

Figure 2 Ideal & predicted expectations across four factors of LA (Source: Author's Compilation)

Comparing the four LA constructs reveals that the most significant is construct F4. The distribution of frequent responses between ideal and predicted expectations informs this conclusion (refer to Figure 2). F2 and F3 are the most significant elements after F1. Out of the ideal (M = 6.24, SD = 1.54; Table 4) and predicted (M = 5.60, SD = 1.57; Table 4) expectations for factor F4, item 4 ("I will be able to obtain data on my students' development in a course that I am teaching/tutoring"; Appendix A) elicited the highest mean response. The average predicted expectation is highest for Item 5, which grants access to data regarding all pupils enrolled in a program (M = 5.68, SD = 1.54; Table 4).

Additionally, the report includes descriptive analyses for every item and breaks down the factor means by gender and other demographic characteristics (see Figure 3 and Figure 4). As shown in Figure 3, the average relevance for both the ideal and predicted expectation across four factors for LA is significantly greater among male respondents than among female respondents. This may be because women in Saudi Arabia are more likely to divulge information. Figure 4 presents the supplementary responses contingent upon experience, specialization, academic rank, and administrative experience.

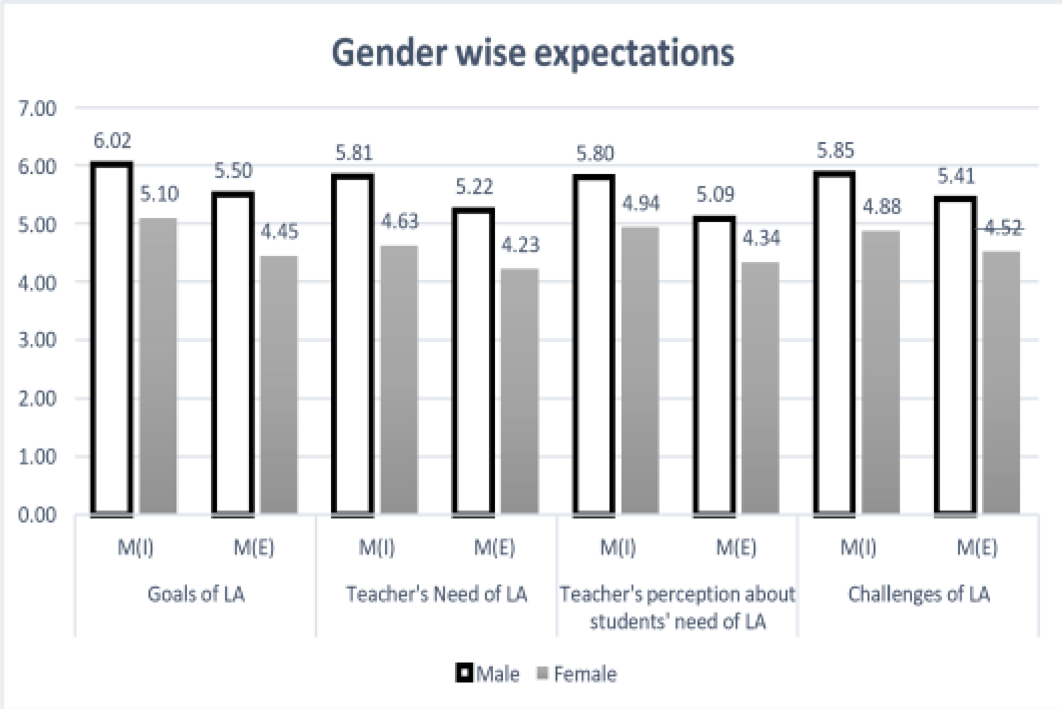

Figure 3 Gender-wise teaching staff expectations for LA (Source: Author's Compilation)

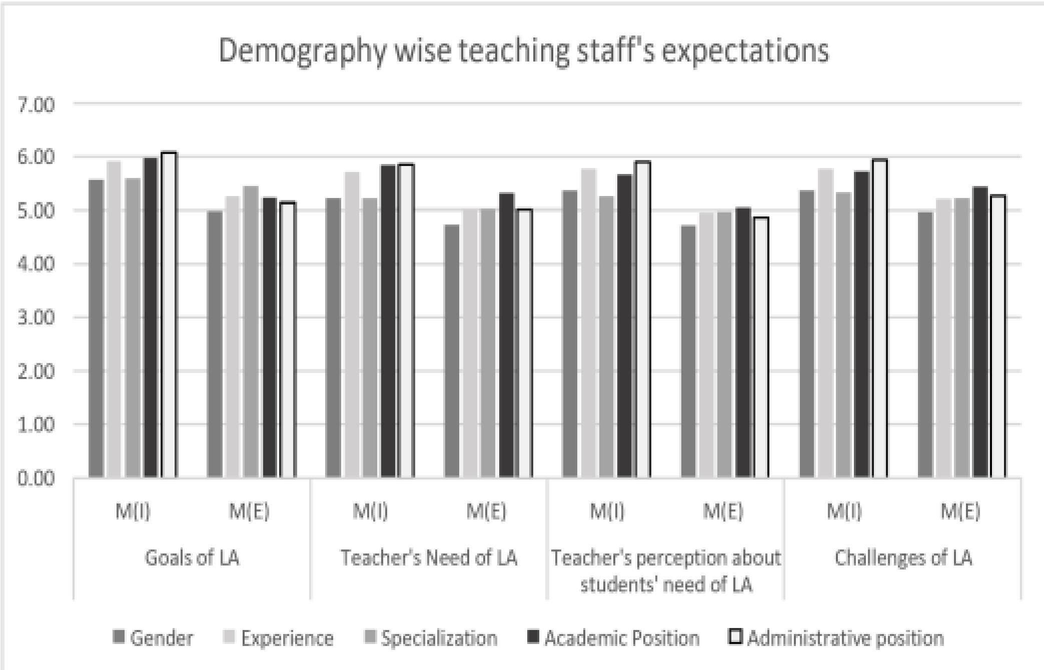

Figure 4 Demography wise teaching staffs' expectation (Ideal Vs Predicted) (Source: Author's
Compilation)

Table 4 Descriptive statistics for teaching staffs' expectation (ideal Vs predicted)

		Ideal Expectation		Predicted Expectation	
Item	**Key**	**M**	**SD**	**M**	**SD**

1	G1	6.21	1.45	5.64	1.46
2	G2	5.85	1.47	5.65	1.50
3	C1	6.15	1.52	5.66	1.54
4	C2	6.24	1.54	5.60	1.57
5	C3	5.98	1.59	5.68	1.54
6	C4	6.01	1.57	5.62	1.58
7	C5	5.89	1.58	5.54	1.61
8	T1	5.97	1.65	5.55	1.68
9	T2	6.11	1.69	5.45	1.73
10	T3	6.06	1.68	5.56	1.72
11	T4	5.89	1.77	5.63	1.78
12	S1	6.20	1.84	5.57	1.87
13	S2	6.17	1.94	5.67	1.76
14	S3	6.09	1.65	5.40	1.87
15	S4	5.89	1.23	5.13	1.56
16	S5	5.92	1.75	5.67	1.93

(Source: Author's Compilation using SmartPLS 4)

4.3 Structural Model Analysis

After verifying the validity and reliability of the construct measurements (refer to Table 1 and Table 2), the subsequent phase involves assessing the outcomes of the structural model. We have examined the structural model for potential collinearity issues at this juncture. To estimate the path coefficient, the structural model employs OLS regressions between each endogenous construct and its corresponding predictor construct. A skewed path coefficient may result from substantial collinearity among the predictor constructs during the estimation procedure. Also generated by the 5000 samples utilized in this investigation are 95% confidence intervals. When the confidence interval deviates from zero, it indicates the presence of a significant relationship. Table 6 provides a summary of the outcomes of the hypothesis testing.

1. H1 evaluates whether teaching staffs' awareness related to the goals of LA significantly affects HEIs readiness. The result revealed that it has a significant impact on hypothesized variable. Hence H1 was supported as shown in Figure 5.
2. Furthermore, H2 evaluates whether Teaching staffs' perception related to their need of LA services significantly affects HEIs readiness for it. The result revealed that it has a significant impact on hypothesized variable. Hence H2 was supported as shown in Figure 5.
3. And H3 evaluates whether Teaching Staffs' view about students' need to LA services significantly affects HEIs readiness for it. The result revealed that it has a significant impact on hypothesized variable. Hence H2 was supported as shown in Figure 5.
4. And H4 evaluates Teaching staffs' awareness related to the implementation challenges of LA services significantly affect HEIs readiness. The result revealed that it has a significant impact on hypothesized variable. Hence H2 was supported as shown in Figure 5.

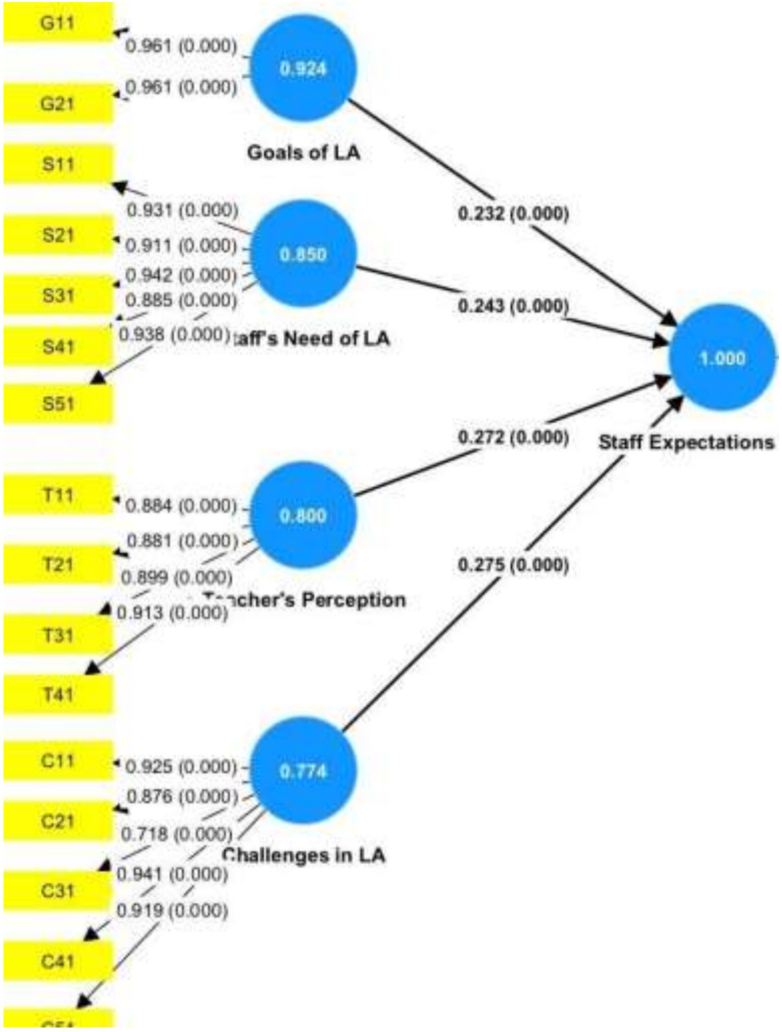

Figure 5 Graphical output of Hypotheses Testing (Source: Theoretical model with factor loading using SmartPLS 4)

A paired-t test analysis of the means of the ideal and predicted observations for each item yielded an additional significant finding that supported the hypotheses (refer to Table 7). The results indicate positive distinctions for all four criteria from the perspective of the teaching staff, which suggests that they are essential for the implementation of LA in HEIs.

5. Discussion & Conclusion

Four constructs were identified after a study of the LA literature (Whitelock-Wainwright et al., 2019), including the goals of LA, the need for LA among teachers, the need for LA among students, and difficulties encountered during LA implementation in HEIs. The expectations of the teaching staff for LA services were based on these four elements, and 16 items were identified(Y.-S. Tsai et al., 2018). These items were developed within the theoretical framework of expectancies, primarily using the work of David et al. (2004) and Dowling & Rickwood (2016) to provide a more complex understanding of the stakeholder's view. Based on the aforementioned framework, a 16-item questionnaire was created and validated in order to gain a general grasp of the ideal and predicted expectations of academic staffs related to LA tools. Our study's results showed that staff members thought the ideal way to use LA was to encourage prompt early intervention if a review of a student's academic records suggested that they might be having any problems or issues. The teaching staff also believed that one of LA's potentials was to assist students in making decisions and to give feedback on their progress in learning, both of which have been noted in other studies (Pinheiro Cavalcanti et al., 2019). The academic staff learned that it was essential to have open discussions about the subject while adding LA into their lesson plans. This suggests that effective communication is essential for the adoption of LA.(Colvin et al., 2016).

Of the hypothesis regarding what the teaching staff expected from LA, we discovered that while they recognized LA's significant potential to help learning and teaching, academic staff members were less certain that all of their ideal expectations would be met. Ideal and predicted expectations for teaching staffs from various backgrounds differed significantly. Another intriguing finding from the survey information in all circumstances was the usually consistently low expectation and willingness for teaching staff to be required to act in response to information indicating students are threat of not succeeding or doing adequately below expectations. Similar to this, a study by Prinsloo & Slade (2017) found that although LA helps various stakeholders learn more about kids, it does not always lead to action. They argue that while institutions and students should share responsibility, institutions also have a moral and legal obligation to act, i.e., to include students and provide them with the knowledge and tools they need to take the necessary safety precautions. This would imply that, although being aware of the value and benefits of LA for both the students and their own practices, the academic staff did not view it as a substantial part of their instructional strategies.

We are aware that our survey does not fairly represent the opinions of the entire country. Additionally, the low number of "skeptics" indicates that teachers who found the topic of our study to be challenging or irrelevant did not respond to the poll. Our findings therefore most likely just represent the viewpoints of the teaching staff members who were curious about LA. But these results are significant for HEIs since they show what the academic staff expects from LA tools. We may envision a number of future directions for our study's research. We discovered that academic personnel ought to be involved in diverse ways even within the same organization depending on their experiences and expectations, which supports our study's finding that LA cannot be controlled with a one-size-fits-all strategy (Y.-S. Tsai et al., 2018). For the future, we recommend the following ideas. First, we found statistically significant disparities in the teaching staff's ideal and predicted expectations for the LA services. While most employees seem to be aware of the potential, some are unsure of what can actually be accomplished. We advise further research into these reservations to determine whether they are related to past experiences with LA applications, instructor expertise, philosophical viewpoints, etc. It is crucial to highlight that we did not specifically take academic staff members' prior LA experience into account, but we will do so in the future. This may offer a chance to assess whether desired and anticipated expectations are due to recently gained experience or a knowledge deficit of the potential of LA innovations, and to tailor the interventions accordingly.

Without a doubt, the involvement of stakeholders is a crucial requirement for the successful adoption of LA since it ensures that LA services are widely accepted inside the institution. This study outlined the expectations of the teaching staff in order to better understand their requirements. As a result, it can serve as a road map for higher educational institutions and LA system developers to provide standardized tools that are simple for users to adopt.

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Table 1 Reliability & Validity of the Constructs

Outer loadings				Cronbach's alpha		Composite reliability (rho_a)		Average variance extracted (AVE)	
		I	P	I	P	I	P	I	P
Challenges of LA	C1<- Challenges	0.938	0.852	0.896	0.911	0.911	0.915	0.767	0.74
	C2<- Challenges	0.865	0.861						
	C3<- Challenges	0.743	0.769						
	C4<- Challenges	0.942	0.883						
	C5<- Challenges		0.928						
Goals of LA	G11 <- Goals	0.961	0.943	0.918	0.884	0.918	0.887	0.924	0.896
	G21 <- Goals	0.961	0.95						
Teacher's Perception about students' Need	S11 <- Perception	0.931	0.892 0.895	0.917	0.873	0.919	0.876	0.8	0.725
	S21 <- Perception	0.911	0.892						
	S31 <- Perception	0.942							
	S41 <- Perception	0.885	0.835						
	S51 <- Perception	0.938	0.895						
Teacher's Need of LA	T11 <- Need of LA	0.884	0.845 0.877	0.956	0.929	0.957	0.929	0.85	0.779
	T21 <- Need of LA	0.881							
	T31 <- Need of LA	0.899	0.874						

	T41 <- Need of LA	0.913	0.807

(Source: Author's compilation using SmartPLS 4)

Table 5 Differences between ideal and predicted expectations based on demographics (as appendix)

	Goals of LA		Teacher's Need of LA		Teacher's perception about students' need of LA		Challenges of LA	
	M(I)	**M(E)**	**M(I)**	**M(E)**	**M(I)**	**M(E)**	**M(I)**	**M(E)**
Gender	5.56	4.98	5.22	4.72	5.37	4.71	5.37	4.97
Male	6.02	5.50	5.81	5.22	5.80	5.09	5.85	5.41
Female	5.10	4.45	4.63	4.23	4.94	4.34	4.88	4.52
Experience	5.91	5.25	5.70	5.01	5.76	4.96	5.76	5.20
0-5 years	6.63	5.38	6.81	5.31	6.70	5.30	6.60	5.30
6-10 years	5.91	4.68	5.66	4.41	5.71	4.33	5.75	4.53
11-15 years	5.60	5.60	5.28	5.23	5.54	5.26	5.66	5.68
above 15 years	5.50	5.33	5.06	5.10	5.08	4.95	5.05	5.30
Specialization	5.58	5.44	5.22	5.03	5.25	4.97	5.33	5.22
Arts	5.10	5.60	4.70	5.45	4.44	5.08	4.76	5.56
Business	5.93	4.74	5.80	4.67	5.88	4.60	5.86	4.87
Computer Science	5.64	6.07	5.04	5.50	5.34	5.60	5.37	5.77
Medicine	5.67	5.33	5.33	4.50	5.33	4.60	5.33	4.67
Academic Position	5.97	5.23	5.83	5.31	5.67	5.05	5.72	5.43
"Professor	6.00	5.00	5.50	5.25	5.20	5.30	5.60	5.70
Associate Professor	6.50	5.50	7.00	6.25	6.40	5.20	6.20	5.80
Assistant Professor	5.69	5.08	5.52	4.69	5.58	4.80	5.58	4.91

Lecturer"	5.70	5.35	5.31	5.05	5.48	4.91	5.49	5.30
Administrative position	6.07	5.14	5.85	5.02	5.90	4.87	5.94	5.27
HOD	6.83	5.00	6.75	5.25	6.73	4.87	6.80	5.60
Head of other committees	5.77	5.08	5.50	4.83	5.58	4.77	5.66	4.95
Other	5.62	5.33	5.30	4.99	5.39	4.96	5.37	5.25

(Source: Author's Compilation)

Table 6 Hypotheses Testing

Hypotheses		**Original sample (O)**		**Standard deviation (STDEV)**		**T statistics (|O/STDEV|)**		**P values**	
		Expecte		**Expecte**		**Expecte**		**Expecte**	
H4	Challenges of LA -> Staff Expectations	0.275	0.271	0.02	0.023	13.892	11.812	0.0000	0.0000
H1	Goals of LA -> Staff Expectations	0.232	0.24	0.026	0.017	9.042	14.268	0.0000	0.0000
H2	Teacher's Need of LA -> Staff Expectations	0.272	0.279	0.026	0.02	10.296	13.697	0.0000	0.0000
H3	Teacher's perception -> Staff Expectations	0.243	0.254	0.025	0.022	9.662	11.514	0.0000	0.0000

(Source: Author's Compilation using SmartPLS 4)

Table 7 Paired t-test for items describing teaching staff's expectations (Ideal Vs Predicted)

				Paired Differences				
		Mean	**STD**	**Md**	**STD**	**t**	**df**	**Sig. (2-tailed)**
Goal of LA	Ideal	6.03	1.46	.394	1.235	2.729	36	.010
	Predicted	5.64	1.48					
Teacher's Need of LA	Ideal	6.01	1.70	.462	1.422	1.781	36	.083
	Predicted	5.54	1.73					
Teacher's Perception	Ideal Predicted	5.49	1.436					
	ideal predicted	4.95	1.323	.578	1.456	2.231	36	.032
Challenges		6.05	1.68					
		5.49	1.80	.441	1.405	2.948	36	.006

(Source: Author's Compilation using SmartPLS 4)

Appendix A: Teaching Staffs' expectation questionnaire

Responses to each question are scored on two seven-point Likert scales (1 = Strongly Disagree, 7 = Strongly Agree), which represent the ideal expectations of the teaching staff and the predicted expectations of the teaching staff for the service (predicted expectations). The following topics were used to organize the items for our analysis: the goals of learning analytics (15, 16), teaching staffs' needs for LA services (2, 3, 13, 14), teaching staffs' perceptions of students' needs for LA services (6, 7, 8, 10, 12), and challenges in implementing LA services at HEIs (1, 4, 5, 9, 11).

1) The university shall provide me with instructions on gaining access to learning analytics pertaining to my students.
2) The University shall offer professional development opportunities to its personnel to use learning analytics for instructional purposes.
3) The university shall foster candid dialogues to facilitate the exchange of insights regarding learning analytics services.
4) Data pertaining to the progress of my pupils in a course that I am instructing or supervising will be accessible to me.
5) Within a programme, I will have access to information regarding any student.
6) According to the data they receive, the learning analytics service will empower students to determine their own courses of action.
7) Upon identified challenges or concerns indicated by an examination of a student's academic records (e.g., underachievement or imminent failure), the university shall promptly furnish assistance through guidance from personal tutors.
8) Based on an analysis of their educational data, the university shall provide students with periodic updates regarding their progress in learning.
9) The learning analytics service shall gather and deliver precise data without errors, including erroneous evaluations.
10) The learning analytics service shall demonstrate the correlation between a student's learning progress and the learning goals or course objectives.
11) The learning analytics service will deliver the feedback in a comprehensible and straightforward format.
12) The learning analytics service shall furnish students with a comprehensive profile detailing their academic progress in each course, including attendance, learning outcomes, and the number of times they accessed online materials.
13) The faculty will possess the necessary skills and knowledge to effectively integrate analytics into the support and feedback offered to pupils.
14) Action (i.e., providing support to students) will be the responsibility of the teaching staff in the event that analytics indicate

a student is at risk of failing, performing inadequately, or has room for improvement in their academic progress.
15) The learning analytics service's feedback will be utilised to enhance students' academic and professional competencies (e.g., referencing and essay writing) in preparation for their future employment.
16) I will gain a more comprehensive understanding of my students' learning progress by utilising learning analytics.