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Evaluating Learning Analytics Usability Factors Towards Learner Performance Assessment in Virtual Environment in Kenyan Universities

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Abstract- The purpose of the study was to evaluate the learning analytics usability factors towards e-learning learner performance assessment in Kenyan Universities. The study used quantitative methodology toward achieving the purpose of the study. Quantitative approach was attained through using five- point Likert scale distributed through random sampling to eight universities in Kenya. A focus on those students using e-learning whether blended or virtual learning. The findings revealed two factors: Perceived Usefulness and Perceived Ease of Use.

Keywords – Learning Analytics, Learning Analytics Tools, Learning Analytics Usability, Virtual Learning environments, Lerner Performance Assessment, Perceived Usefulness, Perceived Ease of Use.

I. INTRODUCTION

Learning Analytics (LA) involves the structured collection, analysis, and reporting of data related to learners and their learning environments. Its primary aim is to extract actionable insights into student behavior, engagement, and learning challenges [1][2]. Distinct from the broader concept of LA, Learning Analytics Tools (LATs) refer to specialized digital platforms designed to facilitate these analytical processes within educational systems. These tools support functions such as tracking grades, monitoring attendance, and evaluating student participation, essential components in e-learning [3][4].

LATs often utilize visual dashboards and predictive algorithms to present student data in accessible formats. These features enable instructors to make informed decisions and implement timely pedagogical interventions. For example, learning analytics dashboards (LADs) provide instructors and learners with real-time information on student engagement, allowing targeted academic support based on individual learner patterns [2][5].

Despite the growth of e-learning, assessing student progress in fully online settings remains a significant challenge. This challenge hindered widespread adoption of e-learning, leading to the development of LATs. [6][7]. LAT therefore, serve a critical function by offering digital solutions for monitoring and enhancing student outcomes helping instructors provide timely, personalized academic support [2][5]. This makes LATs such as LADs a cornerstone in modern educational practice.

Problem Statement

The shift to online learning has accelerated the adoption of Learning Management Systems (LMS) in universities, bringing with it the opportunity to leverage Learning Analytics (LA) for monitoring student engagement and academic performance. Despite the increased awareness of LA and its benefits, many universities face challenges in applying these tools effectively, particularly due to limited understanding of usability principles that support meaningful student interaction and performance enhancement [7].

Challenges persist in usability of the LA tools such as system complexity and difficulties in interpreting feedback, preventing students and educators from leveraging LA tools to enhance learner performance and outcomes. Moreover, most LA tools are designed primarily for lecturers, while few are specifically tailored for learners [7].

Ultimately, LA usability remains limited due to complex implementation challenges and insufficient guidance on building organizational capabilities for leveraging LA [8]. Notably, there is a scarcity of comprehensive models that integrate usability factors with performance metrics specifically for e-learning learners in universities.

This study therefore aimed to address these research gaps by investigating the LA usability factors linked with student performance in virtual environments in Kenyan universities.
Although several studies have examined the effect of the digital shift during the Covid-19 pandemic and the effectiveness of e-learning systems [2] [5] [9], there is a noticeable gap in research focused specifically on how such systems have functioned within the context of Kenyan universities [10]. Further research

is therefore needed to assess the effectiveness of e-learning analytic initiatives in Kenya, particularly regarding the analytics usability factors.

Objective of the Study

The study's objectives were:

- To determine the LA usability factors towards learner performance assessment
- To assess the level of LA usability factors in virtual learning environment in Kenyan Universities.

Research Questions

- The study was guided by the following research questions:
- What usability factors influence the effectiveness of LA in assessing learner performance?
- What is the level of the LA usability factors in virtual learning environment in Kenyan Universities?

II. LITERATURE REVIEW

Usability is a key concern in the implementation of LA in educational institutions. It is defined as the extent to which users can learn, use, and derive satisfaction from a system. [11] Below are the identified factors for LA usability from previous studies:

- **Perceived Usefulness (PU):**

Perceived usefulness (PU) is a pivotal construct in evaluating the usability of Learning Analytics (LA) systems, particularly in virtual learning environments within Kenyan universities. PU is defined as the degree to which users believe a system enhances academic performance. It significantly influences learner engagement and sustained system use [7]. Grounded in the Technology Acceptance Model (TAM), PU is positioned as a central determinant of user adoption, although TAM's limitations in addressing broader system-level attributes have led to its integration with the DeLone and McLean Information Systems Success Model (D&M IS Success Model), which incorporates system functionality and user satisfaction as key predictors of continued use [12][13]. Empirical studies affirm that attributes such as clarity, interactivity, and intuitive design enhance PU, especially when learners perceive direct academic benefits like personalized feedback and actionable insights [5][14][2]. Instruments such as the USE Questionnaire have validated PU as a core dimension of usability, reinforcing its role in both initial adoption and long-term learning success [15]. This aligns directly with the study's objective to empirically evaluate LA usability factors influencing learner engagement and performance in virtual environments.

Perceived Ease of Use (PEoU)

Perceived ease of use (PeoU) is a critical construct in the assessing the effectiveness of e-learning systems, as it is often linked to users' initial acceptance and continued engagement. It is generally defined as the extent to which users believe that using a particular system will require little effort. The systems are designed with simple interfaces, clear navigation, and low complexity hence reducing users' cognitive load. [7] This reduction in cognitive load contributes positively to the overall usability of the system, as users can focus more on learning tasks rather than on figuring out how to operate them. [14].

PEoU is strongly associated with "effort expectancy," a concept emphasized in models like UTAUT, which links the ease of system interaction to users' willingness to engage [16]. This implies that systems perceived as easy to use are more likely to be accepted and integrated into regular academic practices [2]. This also affects how learners interact with it and whether they continue using it over time. Additionally, systems that prioritize ease of use not only improve task efficiency but also boost users' satisfaction and belief in the system's value [5].

User Satisfaction

User satisfaction is consistently identified in the literature as a fundamental outcome of system usability, particularly within e-learning environments. It reflects the user's affective response to the degree to which a system meets their expectations and supports their learning objectives [17]. This suggests that a positive learning experience, driven by clear instructional design, helpful features, and reliable system performance, translates into higher levels of perceived usability and increased system acceptance [7] [16].

The D&M IS Success Model uses system functionality, as determinants of satisfaction and continued use [12].
Satisfaction is strengthened by features such as visual appeal, simple navigation, and timely feedback. These elements minimize frustration and allow users to feel more in control of their learning [5] [14]; hence improving their overall user experience and contribute to satisfaction [18]. The emotional response triggered by user-friendly design also fosters trust and consistent engagement. Tools like the System Usability Scale (SUS) and the Computer System Usability Questionnaire (CUSQ) offer ways to measure this experience objectively. When users find a system both practical and enjoyable, they are more likely to recommend it, reinforcing its value within learning environments [2].

Learnability

Learnability is a key dimension of e-learning system usability, referring to how quickly and easily users can become proficient in using a platform. It directly influences user adoption, satisfaction, and long-term engagement, particularly in settings where users vary widely in their digital literacy. Learners view the system more favorably when they can efficiently access course materials, follow well-structured instructions, and complete learning tasks with ease [7]. These initial interactions shape the learner's perception of usability and establish a foundation for continued use.

Although often considered as subset of perceived ease of use, learnability has a distinct value in usability models. The students' ability to quickly understand and navigate learning management systems (LMS) significantly enhances their perception of usability [19]; [2]. While learnability has a stronger influence on perceived ease of use than on perceived usefulness or behavioural intention, its impact is nonetheless essential for fostering a user-friendly environment, especially for novice users [19].

Learnability is therefore defined as the speed and ease with which users master a system, noting that high learnability minimizes the need for extensive training and support [18]. Systems with high learnability reduce users' dependence on external guidance and technical help, thereby improving efficiency and reducing barriers to participation. This is particularly relevant for institutions aiming to scale e-learning quickly without overwhelming support infrastructure [14].

While learnability is frequently integrated into broader constructs like ease of use, it plays a distinct and strategic role in encouraging rapid system uptake [13]. Many studies concur that learnability is a foundational element in the design and evaluation of e-learning systems [13], [20]. Its influence extends beyond simple user adaptation to affect engagement, satisfaction, and institutional scalability.

III. METHODOLOGY

The study was guided by a post-positivist philosophical worldview, which supports the collection of objective, measurable data while recognizing the role of context in shaping human experiences [21].

Quantitative research design was used to collect measurable data from university students in Kenya. Quantitative method was chosen due to the scalability, objectivity, and potential to generalize findings to broader populations. Structured instruments like surveys helped reduce bias and enabled efficient data collection and analysis across the diverse learning contexts [23]
The specific method applied was a survey using questionnaires administered to students via research assistants across selected universities. This strategy allowed the study to gather detailed feedback on students' perceptions of LA tools in e-learning platforms such as Moodle and Blackboard [24]. The target population included all learners using LMS tools within Kenya's 73 chartered universities (CUE, 2024). Sampling was carried out through simple random selection, promoting fairness and representation while reducing bias in the data [25]. The final sample size was determined using Singh's (2006) formula, leading to selection of only 8 universities. Using Taro Yamane formula, the final sample size selected was 399.

Physical questionnaires distributed through aid of research assistants were used to collect data from students on their perceptions of Learning Analytics (LA) usability. The questionnaire included checklist questions and five-point Likert scale items. Questionnaire was chosen as it is effective for data collection from large populations and plays a critical role in gathering insights into individual perspectives [24].

The questionnaire used in the study included mix of questions: ones the researchers created after reviewing existing literature, and others borrowed from well-known tools. It used parts of the System Usability Scale (SUS), which is a reliable tool for quickly measuring how user-friendly a system is [26]. It also included items from the USE questionnaire by Lund (2001), which focuses on four key areas of user experience: how useful the system is, how easy it is to use and learn, and how satisfied users feel [27]. The USE questionnaire has 30 questions rated on a 7-point scale, making it thorough and suitable for understanding user feedback in detail [28]. This blend of tools helped the study capture both overall usability and specific aspects of how learners interact with e-learning systems.

A combination of questions was opted as opposed to complete adoption as it allowed to leverage the strengths of standardized questionnaires which were already validated and tested while at the same time addressing the unique aspects of the study [29].

A 44-item questionnaire was thus used which included all the four constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEoU), Learnability (L) and User Satisfaction (US). The constructs were broken down as follows:

Table 1: Construct Breakdown

Construct	Abbreviations	Number of Items
Perceived Usefulness	PU	17
Perceived Ease of Use	PEoU	10
Learnability	L	8
User Satisfaction	US	9
Total		44

The questionnaire was based on a five-point Likert scale, ranging from Strongly Disagree (1) to Strongly Agree (5), with higher scores indicating greater level of agreement.
To ensure the questionnaire was valid, validity of the questionnaire was examined through content, construct, and face validity, with statistical methods like Confirmatory Factor Analysis used to check whether related items grouped correctly. Experts in ICT also reviewed the questionnaire for clarity, while a pilot study tested its relevance and helped revise unclear parts. External validity was supported by using a representative sample and excluding pilot respondents, making it possible to generalize findings.

Reliability was measured through internal consistency test using Cronbach's Alpha. This ensured that the data collection tools generate accurate, relevant and meaningful data [30].

Table 2: Internal Consistency Reliability Measure
Number of Items Cronbach

	Number of Items	Cronbach Alpha
Overall LA Usability (LAU)	44	0.983
LA Usability Factors		
Perceived Usefulness	17	0.916
Ease of Use	10	0.934
Learnability	8	0.936
Satisfaction	9	0.937

A Cronbach's alpha value of 0.90 and above is considered as excellent reliability [31]. Results from Table 1 above shows that all the variables had a Cronbach's Alpha value of more than 0.7 hence signifying the reliability of the constructs.

In addition to reliability, validity test was run using Kaiser-Meyer-Olkin (KMO) whose values range from 0 to 1. A KMO value exceeding 0.5 indicates that the constructs used was valid. The Validity results are presented in Table 2 below:

Table 3: Validity Test

Variable	KMO	Approx. Chi-Square	Df	Significance
Usability	.980	15102.173	946	.000

Results from Table 3 above show that the KMO index for all the variables was more than 0.5 with p values of Bartlett's test less than 0.05 which implies that the tool was valid.
A multi- method approach was used in identifying and assessing the LA usability factors.

The first objective of the study determining LA usability factors towards learner performance assessment was analyzed through first conducting factor analysis on the constructs to determine the validity of the constructs and extract the reliable indicators. Exploratory studies using Construct Extraction through factor analysis- Kaisen criteria and scree plot were used to help identify patterns and trends, offering valuable context for refining the research focus. Additionally Inferential analysis such as Kendall and Chi-square tests were also applied to address this objective.
The second objective, to assess the level of learning analytics usability utilized descriptives analysis such as mean and standard deviations to assess the level of learning analytics usability factors.

IV. DATA ANALYSIS

Participant Profile
The profile of the respondents was analyed through use of descriptive analysis using frequency counts and percentages. to provide profile of the respondents

Table 4: Demographics of the Respondents

	Frequency	Percentage (%)
GENDER:		
Male	216	54.1
Female	183	45.9
AGE		
Below 18	1	0.3
18-24	341	85.5
25-34	43	10.8
35-44	13	3.3
45 and above	1	0.3
LEVEL OF STUDY		
Undergraduate	387	97
Postgraduate	12	3.0
MODE OF STUDY		
Blended Learning	385	96.5
Online	14	3.5

Table 4 above shows the demographics summary of the respondents. More than half of the respondents (54.1%) were male, whereas female were only 45.9%. majority of the respondents were within the 18 to 24 age brackets. This is consistent with the expectation in institution of higher learnings where most learners are below 25 years of age. There were very few students who were below 18 years or above 45 years. It is interesting to note that majority of them were falling in the undergraduate category at above 97% and only 3% were post-graduate. This also explains the higher number of respondents in the age group between 18 to 24 years as this is mostly the age for undergraduate studies. Majority of the students (96.5%) were engaged in blended learning rather than fully online learning. This aligns with prevailing trends in higher education, where most institutions integrate both face-to-face and digital learning methods as opposed to fully virtual programs. In Kenya, only a limited number of universities have now introduced fully virtual programs.

Trend in usage of E-learning Platforms

The trend for usage of e-learning platform was analysed through descriptive analysis run on the different platforms used, the frequency of the usage and duration of the respondents in using these platforms.

Table 5: Usage of e-learning platforms

Platform	Frequency	Percent
Moodle	140	35.09
Google Classroom	115	28.82
Sakai	93	23.31
Canvas	28	7.02
Blackboard	13	3.26
MOOCs	8	2.01
Coursera	2	0.50
Total	399	100

Table 5 above, displays the usage of different e-learning LA platforms among respondents. The analysis revealed Moodle (35.09%), Google Classroom (28.82%), and Sakai (23.31%) were the most popular e-learning platforms, making up over 80% of total usage. Canvas was used by a smaller group (7.02%), while platforms like Blackboard, MOOCs, and Coursera were rarely used, each below 5%.

Table 6: Duration of using E-learning Platform

	Frequency	Percent
Less than 6 months	129	32.3
6 Months to 1 Year	80	20.1
1 to 2 Years	79	19.8
More than 2 years	111	27.8
Total	399	100

Table 6 above presents the duration of e-learning platform usage among respondents. About one-third (32.3%) started using them less than six months ago. 20% have engaged with it for the period between six months to a year and 19.8% have used it for one to two years period. The remaining 27.8% have been utilizing the platform for more than two years. These results indicate a diverse range of user experience levels, encompassing new users and those with more experience.

Table 7: Frequency Usage of e-learning Platform

	Frequency	Percent
Daily	177	44.4
Weekly	143	35.8
Monthly	32	8
Rarely	47	11.8
Total	399	100

Table 7 above presents data on respondents' frequency of engagement with the e-learning platform. Nearly half (44.4%) use it daily, demonstrating regular engagement. Another 35.8% access the platform weekly, indicating consistent but less frequent usage. Monthly users make up the smallest proportion (8%); while 11.8% use it only occasionally. These findings indicate varying levels of engagement, with the majority of users interacting with the platform frequently.

Normality Test

Normality test was conducted so as to determine which analytical method to use: parametric versus non-parametric.

Table 8: Test for Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	df	Sig.
LAU	.083	399	.000	.975	399	.000
a. Lilliefors Significance Correction						

The results from table 8 above for both Kolmogorov-Smirnov and Shapiro-Wilk tests indicated a significant p-value of 0.000 which is less than 0.05. This means that the data is not normally distributed hence the study used non-parametric data analysis.

- **Objective 1:** Determine Learning Analytics Usability (LAU) Factors

The research question "What usability factors influence the effectiveness of LA in assessing learner performance?" was addressed using construct extraction so as to be able to extract the indicators and identify the LAU factors.

Construct Extraction

The 44 indicators of e-learning analytics usability constructs were subjected to factor analysis so as to help identify patterns and relationships. The succeeding sub sections present the results of factor analysis.

Construct Extraction was carried out to help cluster the questions into mutually exclusive groups making patterns and relationships easily detected, analyzed and interpreted based on common variances, [32]. Only variables that contributed significantly to the variations were retained for further analysis. All the four-sub variables in this research were subjected to factor analysis.

The respondents were tasked with rating their level of agreement of forty-four (44) different indicators with respect to Learning Analytics Usability (LAU) on a scale ranging from (1) to (5) where (1) was strongly disagree and (5) being strongly agree. Their responses were analyzed using exploratory factor analysis to identify key constructs and their corresponding indicators.

The number of components extracted were determined using two different methods: Kaisen criterion and Scree plot analysis. Kaiser's criterion was applied first by reviewing the total variance explained table, where components with an eigenvalue greater than one (1) were selected.

Kaisen criteria was the first method by checking on the Total variance explained table where the eigen value was greater than one (1). Principal component analysis was used to subject the elements of e-learning analytics usability to further factor analysis using variance test. Table 9 below presents an extract of the total variance explained under E-learning analytics usability.

Table 9: Total Variance Explained

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	25.337	57.583	57.583
2	1.777	4.038	61.621
3	.893	2.030	63.651
4	.854	1.941	65.592
5	.776	1.763	67.355
6	.699	1.589	68.944
7	.660	1.500	70.444
8	.637	1.447	71.891
9	.617	1.402	73.293

The table 9 above shows that two factors account for the majority of variation in E-learning analytics usability of up to 61.675%. The first factor accounts for 57.658% while the second factor accounts for 4.017%. Both factors had Eigen values of more than 1.

The second method used was the scree plot where the change in direction (kink) in the line graph was identified and the components above the elbow were retained. Figure 4.1 below shows the LA Usability scree plot graphically indicating the analyzed data.

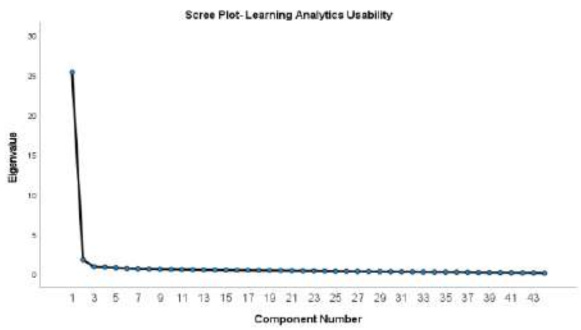

Figure 1: LA Usability scree plot

According to Figure 1 above on the scree plot for LA Usability, the kink appeared after the second component.

Thus this indicates that the first two components were retained indicating that learning analytics had two factors.

Factor Extraction

Before conducting factor analysis, it is essential to assess whether the data is suitable for this method. This is done by evaluating sample adequacy using the Kaiser-Meyer-Olkin (KMO) test. The KMO index ranges from 0 to 1, with values above 0.5 indicating that the data is appropriate for factor analysis [32]. Additionally, Bartlett's Test of Sphericity is used to confirm the suitability of the data. A p-value of less than 0.05 suggests that factor analysis can proceed. Table 10 presents the KMO and Bartlett's Test results for e-learning learning analytics usability.

Table 10: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.98
Bartlett's Test of Sphericity	Approx. Chi-Square	15102.173
	Df	946
	Sig.	.000

Table 10 above shows that the value of KMO index was 0.98 which is more than the minimum proposed value of 0.5 with Bartlett's test of Sphericity having a P value of 0.000 which is less than 0.05. Therefore, this implies there is sample adequacy and the data is ideal for factor analysis.

The rotated component matrix was generated to show how the constructs were loaded onto the factors. Only components that had a loading value of more than 0.4 and were non- negative were retained. Table 11 presents the rotated component matrix for the indicators.

Table 11: Rotated Component Matrix
Component

	Component	
	1	2
PU1		.724
PU2		.754
PU3		.703
PU4		.706
PU5		.649
PU6		.722
PU7		.744
PU8		.752
PU9		.557
PU10		.561
PU11		.643
PU12		.607
PU13	.580	
PU14	.582	
PU15	.605	
PU16	.584	
PU17	.666	
PEoU1	.674	
PEoU2	.650	
PEoU3	.692	
PEoU4	.732	
PEoU5	.694	
PEoU6	.681	
PEoU7	.672	
PEoU8	.631	
PEoU9	.648	
PEoU10	.753	
L1	.726	
L2	.686	
L3	.707	
L4	.710	
L5	.726	
L6	.749	
L7	.708	
L8	.723	
US1	.702	
US2	.654	
US3	.693	
US4	.698	
US5	.607	
US6	.687	
US7	.692	
US8	.629	
US9	.628	
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.		

Twelve constructs were loaded on to factor one and the remaining 32 indicators are loaded on factor 2. Factor one was therefore named: Perceived Usefulness and Factor 2 Ease of Use.

Table 12: Inferential Analysis

LAU Factor		Value	Significance
PU	Pearson Chi-Square	601.938[a]	<.001
	Kendall's b	.706	.000
PEoU	Pearson Chi-Square	828.801[a]	<.001
	Kendall's b	.643	.000

Inferential analysis was conducted to examine the relationship between the LAU Perceived Usability indicators and the overall construct of perceived usability. Kendall's correlation test was applied, with the null hypothesis (H_0) stating that no statistically significant relationship exists between the indicators and the construct. As presented in Table 12, the results yielded a Kendall's coefficient of concordance of 0.706, indicating a moderate level of agreement among respondents. The Chi-Square value was 601.938, with a p-value less than 0.001, which is statistically significant at the 0.05 threshold. Based on these findings, the null hypothesis was rejected. This confirms that the responses exhibit a consistent and meaningful pattern, suggesting a significant relationship between the LAUPU indicators and the overall construct.

Additionally, inferential analysis was also performed to establish the relationship between the various LAU Perceived Ease of Usefulness indicators using Kendall's correlation test. The null hypothesis (H0) for this test was: There is no statistically significant relationship between the LAU Perceived Ease of Use Indicators and LAU Perceived Ease of Use construct. From the test, the findings of the inferential analysis as shown in Table 12 indicate a strong concordance relationship with Kendall's coefficient of concordance being 0.643. This indicates strong agreement among respondents on the perceived ease of use of learning analytics. A coefficient close to 1 (one) suggests that most respondents have similar views, reinforcing the idea that learning analytics is widely regarded as user-friendly and accessible. The Chi-Square value was 828.801 with a significant p-value (<0.001) of less than 0.05, thereby failing to accept the null hypothesis (H0). This implies there is statistically significant relationship between PEoU indicators and PEoU construct. This means that the responses show a meaningful pattern rather than random

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variation. These findings resonate with [33], who emphasized the importance of user experience consistency in learning analytics adoption.

- **Objective 2:** Assess the level of LA Usability Factors in virtual learning environment in Kenyan Universities.

Table 13: LA Usability Factors

LAU Factor	Number of Indicators	Mean	Std. Deviation
PU	12	3.1389	.97090
PEoU	32	3.1529	.94994

The research question: "What is the level of the LA usability factors in virtual learning environment in Kenyan Universities?" was addressed using descriptive statistics on the respective indicators for the two identified usability factors.

Table 13 LA usability measurement depicts the perceived level of LA usability amongst the respondents

The summary of the Learning Analytics Usability (LAU) Factors shows that users generally have a positive experience with learning analytics tools, with mean scores all above 3, indicating moderate to high agreement.

1. Perceived Ease of Use (PEoU), had the highest mean (3.1529), indicating that users moderately agreed on the ease of use of the LA tools. This also combines the user perception on ease of learning and their satisfaction toward the e-learning tools.
2. Perceived Usefulness (PU) was rated at 3.1389, meaning users felt that the tools served their purpose effectively.
3. The standard deviation values ranging from 0.94994 to 0.97090, mean that there is some variation in user experiences, while many found the tools easy and satisfying, others may have encountered challenges.

Summary of Findings

Table 14: Summary of Findings

Objective	Analysis Methods	Findings	Interpretations of findings
Objective 1: To establish LAU factors	KMO & Bartlett test	KMO > 0.5 and Bartlett's p< 0.05	Valid, significant – data ideal for factor analysis
	Construct Extraction through Factor Analysis	Converged into two factors using Kaisen criteria - eigen value >1 1. Perceived Usefulness (PU) 2. Perceived Ease of Use (PEoU)	Resulted in identification of two LAU factors – PU & PEoU
	Scree plot	2 factors	
	Factor extraction through Rotated component matrix	PU - 12 indicators PEoU - 32 indicators	
	Inferential analysis – Pearson Chi-square & Kendal's coefficient	PU - Kendall's co-efficient (.706; p-0.000); Chi-square- (601.938; p<0.001) PEoU - Kendall's co-efficient (.643; p-0.000); Chi-square- (828.801; p<0.001)	Statistically significant relationship between the constructs and the indicators
Objective 2: Assess the level of LAU factors	Descriptive statistics	PU –-overall construct mean 3.1 PEoU –overall construct mean 3.2	Moderate agreement

V. CONCLUSION

The findings of the study revealed two factors: Perceived Usefulness and Perceived Ease of Use as usability factors for e-learning analytics among university students in Kenya.

Future study can be done to test these LA usability factors against causal relationship with learner performance metrics so as to determine whether learning analytics usability has significant influence on learner performance in virtual learning environment.

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