Transforming Moodle Usability for Adaptive Learning and Outcome Driven Learning Management System

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Abstract
The study focused on changing Moodle into an outcomes-oriented and learner-focused Learning Management System (LMS) through its usability limitations and adapting it to adaptive learning methods. The main purposes include (i) examining how adaptive learning features can increase the effectiveness of Moodle, (ii) examining how usability transformation can positively influence the learning outcomes, and (iii) suggesting practical solutions to the way to incorporate advanced technologies, including AI, ML, and analytics, into Moodle and improve its performance. The research design adopted was that of mixed methods, where quantitative survey, usability tests and learning analytics were coupled with qualitative interviews and focus groups. The sample size used in the data collection was 200 students in various learning institutions, which presented demographic and use information. The regression analysis showed that adaptive features positively enhanced LMS effectiveness (β =.175, R 2 =.175), whereas usability transformation affected learning outcomes more (0.495, R 2 =.495). The results conclude that the transformation of Moodle into an adaptive, usability-based and outcome-oriented system is necessary. The integration of AI-enhanced personalization and predictive analytics can also be used to further improve usability, promote quantifiable learning results, and establish Moodle as a platform of the future-ready education.
Keywords: Moodle Usability, Adaptive Learning, Outcome-Based Education, Artificial Intelligence, Learning Analytics

1. INTRODUCTION

In the era of digital education, Learning Management Systems (LMS) have become essential tools for simplifying teaching, learning, and assessment procedures [1]. Moodle, in particular, has become globally accepted because it is open-source, low-cost, and adaptable to a variety of learning environments [2]. It enables instructors and institutions to present course material, facilitate communication, and assess learners within an integrated online environment [3]. Nevertheless, even though it is the most used, Moodle usability has been frequently panned for its high learning barrier, low level of personalization, and poor intuitive design, especially in comparison with contemporary adaptive learning technologies [4]. As education shifts towards a learner-centered paradigm, it is crucial to transform Moodle's usability to not only enhance accessibility but also to support adaptive and outcome-driven learning approaches [5].

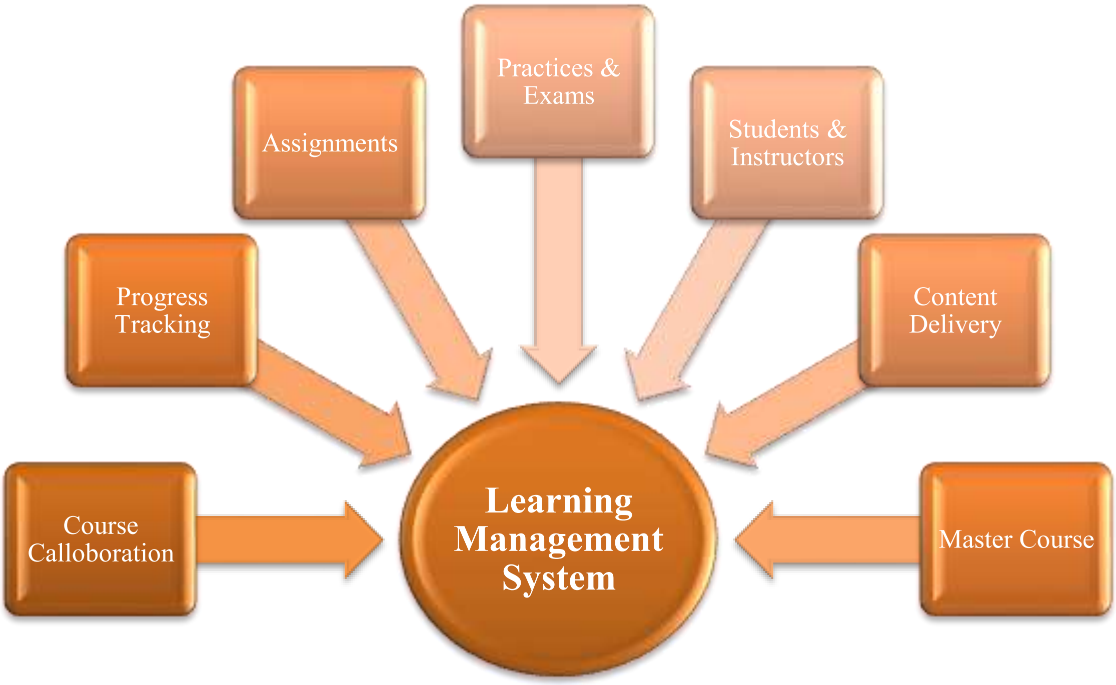

Figure 1: Learning Management System (LMS) Model [6]

Adaptive learning is quickly redefining digital education by virtue of the ability to make systems responsive to the particular requirement and preference and performance trajectory of learners [7]. Unlike the classic non-adaptive learning systems, the adaptive learning technologies take the information as a guide that allows them to present individualized learning paths, remedial content and customized tests [8]. This produces self-directed, interactive and efficient learning experiences that are capable of supporting various levels of learner competency [9]. In order to be a relevant component in modern education ecosystems, Moodle must move beyond the conventional structure and accommodate some adaptability feature that allows educators to construct flexible and customized learning experiences [10]. Such a transformation ensures that the learners are not presented with the one-size-fits-all paradigm but assisted by systems that are dynamic in response to strengths and weaknesses of the learners. Figure 2 illustrate the advantages of a Moodle-driven LMS.

Equally significant is the demand for outcome-driven education, the emphasis is not merely on content delivery but on achieving measurable competencies and learning outcomes [11]. Today's academic and professional institutions further rely on increasing levels of outcome-based education (OBE) frameworks to ensure learners develop certain skills, knowledge, and attributes aligned with curriculum objectives and industry demands [12]. Moodle, by itself, tends to focus on content hosting and testing instead of methodically aligning activities with intended learning outcomes [13]. By reengineering Moodle as an outcome-oriented LMS, instructors can directly link instructional approaches, course structures, and tests with specified goals. This matching makes it easier to provide transparency, accountability, and overall education effectiveness, having students graduate with measurable competencies.

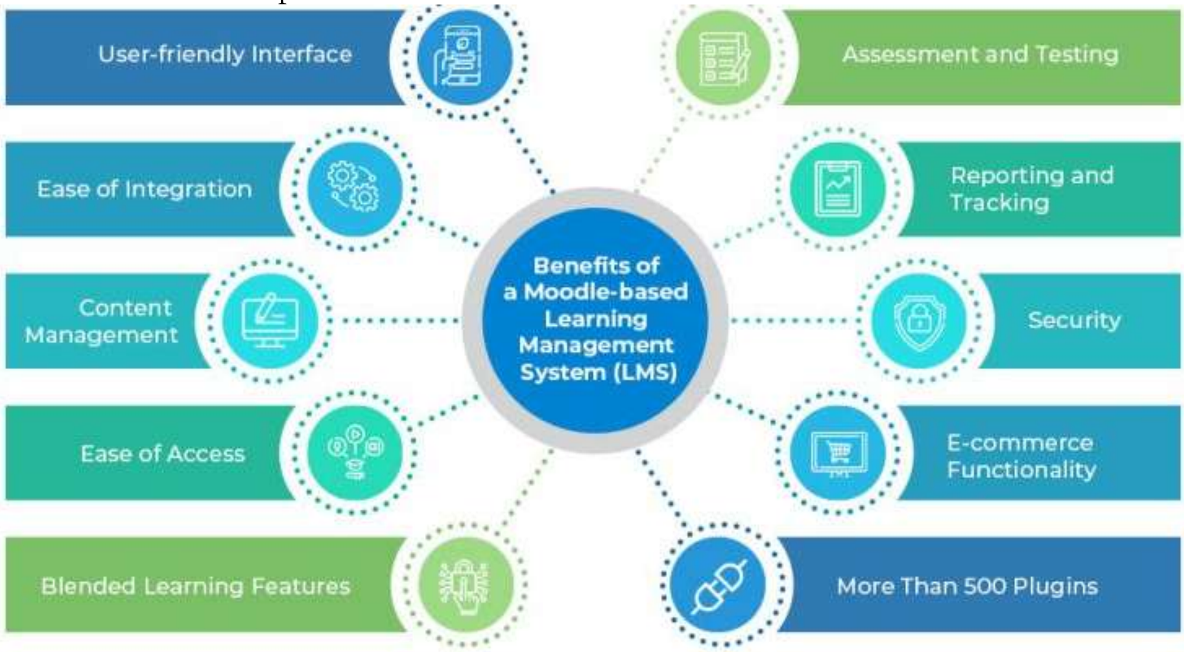

Figure 2: Benefits of a Moodle-Based LMS [14]

Transforming Moodle usability involves integrating modern interface design principles, AI-powered adaptive features, and advanced analytics to create an engaging, learner-centric platform [15]. For example, intuitive dashboards can provide learners with real-time progress tracking, adaptive assessments can automatically adjust difficulty levels, and predictive analytics can alert educators to struggling learners before disengagement occurs. Furthermore, the outcome-mapping tools can evaluate whether each intervention is value-based and is contributing to the intended competencies and thus enhancing a more sophisticated and valuable teaching-learning cycle [16]. By effectively integrating technology, pedagogy, and usability, such transformation could evolve Moodle to the next generation of LMS that supports both learners' and educators' usage.

In conclusion, upgrading Moodle to support adaptive and outcome-focused learning is therefore not just a technical change; it is a pedagogical requirement of contemporary learning. As learners increasingly demand personalized experiences and institutions seek to demonstrate tangible outcomes, Moodle's usability must evolve beyond traditional content management to embrace adaptive intelligence and outcome alignment. This evolution cannot only create impactful digital learning experiences through inclusive and engaging learning, but researchers will also create measurable outcomes setting Moodle up to be a significant enabler of a future-ready learning environment. Possible research objectives of the study are as follows:

i) To investigate the role of adaptive learning features in enhancing Moodle's effectiveness as an LMS.

ii) To analyze the impact of usability transformation on learning outcomes by comparing traditional Moodle features with enhanced adaptive and outcome-based features.

iii) To provide actionable recommendations for integrating advanced technologies (AI, ML, and data analytics) into Moodle to ensure improved usability, adaptive learning pathways, and measurable learning outcomes.

2. RELATED WORK

Moodle usability transformation into adaptive learning and outcome-based LMS has emerged as a core research area in response to the rapid digitalization of education. The traditional e-learning systems often struggled with rigidity, with limited personalization and interactive prospects for students. To overcome such gaps, a variety of researchers experimented with adaptive and competency-based approaches, usability testing, gamification, and incorporation of deep learning for improving the outcomes of students. Pratisto et al. (2025) [17] upgraded competency-based LMSs through the development of Agile to achieve high usability ratings and verify the contribution of the system in encouraging autonomous learning, while Al-Fraihat et al. (2025) [18] identified design and structural gaps of Moodle that discourage adoption in spite of the system's usage status. To overcome the kind of limitations, Saputra et al. (2025) [19] incorporated gamification and learning style models to improve the level of motivation and engagement, while Kumar et al. (2025) [20] proposed the development of adaptive intelligent systems using fuzzy logic to overcome the constraint of homogenous e-learning content. Developing upon the kind of solutions, Navarro et al. (2025) [21] offered an adaptive system using deep learning that adapted task difficulty in a dynamic manner and significantly increased the precision and efficiency of problem solving. In the same vein, Puspawati et al. (2025) [22] and Aldila et al. (2024) [23] showcased the advantages of incorporating LMS with adaptive and cognitive-affective learning strategies with significant student engagement, academic performance, and satisfaction. Addressing usability from the instructors' perspective, Fadhilla et al. (2024) [24] pointed out Moodle's strengths in customization in tandem with its aging interface challenges, while Hlazunova et al. (2024) [25] underscored the learning analytics in Moodle potential to personalize pathways and predict learner behavior.

Parallel works further examined adoption challenges and contextual applications of Moodle. Morze et al. (2023) [26] underlined the low adoption of adaptive learning in higher education due to technical and pedagogical barriers but suggested Moodle's existing tools as a cost-effective compromise for implementation. Complementarily, Olugbade et al. (2023) [27] reported generally positive lecturer perceptions of Moodle in West African universities, though resource adequacy remained an issue, echoing earlier concerns raised by Al-Fraihat et al. (2025) [23]. From the student perspective, Shaame et al. (2023) [28] confirmed that personalized Moodle systems motivated learners, though infrastructural limitations such as internet access persisted, while Warid et al. (2023) [29] demonstrated Moodle's role in promoting sustainability engagement and peer collaboration during COVID-19. Collectively, these studies trace a clear evolution from identifying usability shortcomings to proposing adaptive, personalized, and intelligent solutions that trackle earlier limitations.

Despite advancements in enhancing Moodle usability, integrating adaptive learning, gamification, and analytics, notable research gaps persist. Most studies remain limited to small-scale contexts, short-term evaluations, or specific institutions, restricting broader applicability. While improvements in arrangement and personalization are evident, holistic outcome-driven systems combining competency-based learning, adaptive analytics, and real-time feedback are still underexplored. Additionally, infrastructural issues such as scalability, accessibility, and resource adequacy remain barriers to effective implementation. Future research must therefore focus on building sustainable and scalable LMS frameworks that seamlessly integrate adaptability, inclusivity, and usability to support diverse learners across global educational contexts.

3. Research Hypothesis

Here are the potential research hypotheses of the study follow as:

H1: Implementation of adaptive learning features in Moodle leads to a statistically significant improvement in LMS effectiveness.

H2: A usability-transformed Moodle produces significantly better learning outcomes than the traditional Moodle interface and feature set.

H3: Integrating AI/ML and data analytics into Moodle significantly improves (a) perceived usability, (b) adaptive learning effectiveness, and (c) learning outcomes compared to Moodle without these technologies.

4. RESEARCH METHODOLOGY

This study adopts a mixed-methods research design, integrating both quantitative and qualitative approaches to examine all aspects of Moodle as an adaptive and outcome-based LMS. A schematic representation of the research design is provided in Figure 3. The quantitative component looks at observable factors including usability, performance, improvements in learning outcomes, etc. Quantitative data can be collected on structured surveys, usability tests, and learning analytics, including completion of progress metric, an evaluation of assessment outcomes, specific time on task features, and so on. This type of quantitative data gives objective evidence of the adaptability and usability of Moodle in improving learning. The qualitative component examines user experience and teacher pedagogical intentions and expectations. The qualitative data was collected using semi-structured interviews, focus groups, and open-ended feedback from students, and semi-structured interviews and open-ended feedback from teachers. This interpretive lens reveals the contextual factors that influence engagement and satisfaction.

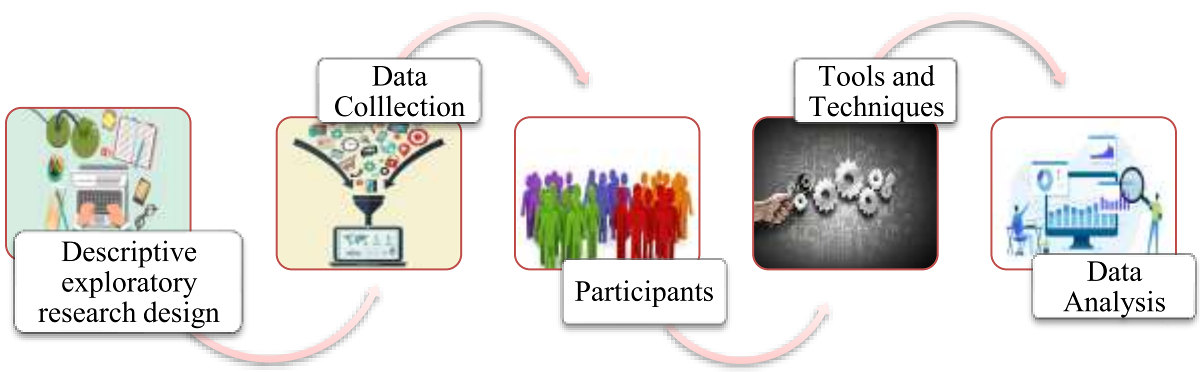

Figure 3: Flow of research methodology

4.1 Data Collection

Primary and secondary sources are used to collect the data. Primary data can be collected on the basis of questionnaire created in a structured form that aims at capturing the perception of adaptive features of learning, usability, and outcome-based features of Moodle, whereas secondary data could consist of records within institutions, previous studies, and Moodle documentation. The research participants comprise students from many educational institutions, from primary to higher education. The sample size comprises around 200 students, providing broad representation across all age groups, topics, and educational environments. Demographic data, including geographic location, can be gathered to assess the impact of these variables on the research results. Various tools and techniques can be used for a holistic evaluation of Moodle's transformation into an adaptive and outcome-based learning management system. The independent variables under consideration are adaptive-features implementation and usability transformation, while the dependent variables are LMS effectiveness and learning outcomes. Data could be analyzed using MS Excel and SPSS 27 to explore relationships and verify hypotheses.

5. RESULT

➢ **Demographic respondents**

Table 1: Gender of respondents

Gender					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	92	46.0	46.0	46.0
	Male	108	54.0	54.0	100.0
	Total	200	100.0	100.0	

Table 1 indicates the results of the respondents in terms of gender with a total of 200 respondents divided into 108 (54%) males and 92 (46) females. This shows that there is a slight dominance of the male gender in the sample and that the male gender constitutes the very slightly above half of population whereas the females constitute almost half, which is quite a proportional representation of both the genders. The cumulative percentage reaffirms that the entire sample size has been achieved by including both the groups, as both the male and the female respondents have offered their views to the study.

Table 2: Age of respondents

Age					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	21–25 years	46	23.0	23.0	23.0
	26–30 years	37	18.5	18.5	41.5
	31–35 years	40	20.0	20.0	61.5
	Above 35 years	33	16.5	16.5	78.0
	Below 20 years	44	22.0	22.0	100.0
	Total	200	100.0	100.0	

Table 2 age distribution indicates that people with different ages obtained the results and provided diverse points of view. The highest percentage is for the 21-25 years (23%), then those below 20 years (22%), which implies that younger people represent a good percentage of the sample. The range of ages of the participants is 20-26 years old, 31-35 years old and the aged 35 years and above constitute 18.5 and 20 respectively. This trend shows that even though younger age groups have the majority, older age groups also contribute significantly, and there is an equal balance in the age distribution of the respondents, which supports the validity of the study results as it includes the opinions of the different age groups when it comes to academic and professional growth levels.

Table 3: Educational Qualification of the respondents

Educational Qualification					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Doctorate	43	21.5	21.5	21.5
	Faculty / Teaching Staff	46	23.0	23.0	44.5
	Postgraduate Student	32	16.0	16.0	60.5
	Technical Staff	38	19.0	19.0	79.5
	Undergraduate Student	41	20.5	20.5	100.0
	Total	200	100.0	100.0	

Table 3 indicates the educational levels of the respondents whereby the educational level is predominantly varied among the respondents. Faculty or teaching staff is the biggest category with 23 percent closely followed by doctorate holders (21.5 percent) and undergraduate students (20.5 percent). The technical staff comprise 19 per cent of the sample, and the postgraduate students represent the lowest population (16 per cent). This distribution suggests that the study does not only provide the insights of the students of various academic levels, but also includes the teaching and technical professionals, which provides a balanced view. This diversity not only enhances the findings, but it also depicts the experiences of the learners, as well as the perspectives of the people who are involved in the academic and technical job aspects in institutions.

Table 4: Type of Institution

Type of Institution					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Autonomous College	62	31.0	31.0	31.0
	Deemed-to-be University	44	22.0	22.0	53.0
	Government University	41	20.5	20.5	73.5
	Private University	53	26.5	26.5	100.0
	Total	200	100.0	100.0	

The allocation of responses by the kind of institution presents a diversity in the representation of the different academic constructions. The highest percentage is of autonomous colleges of 31% of the respondents and then private universities of 26.5. Universities which are considered are 22% of the sample, and government universities are 20.5. This dissemination means that the study covers a variety of participants in different institutional structures incorporating the government, personal, and independent systems. This amount of variation is important because it gives an overview of the user experiences in various governance frameworks as well as academic settings so that the results are not skewed or have a preference to a particular kind of institution.

Table 5: Experience with Moodle

Experience with Moodle					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1–3 Years	55	27.5	27.5	27.5
	4–6 Years	43	21.5	21.5	49.0
	Less than 1 Year	57	28.5	28.5	77.5
	More than 6 Years	45	22.5	22.5	100.0
	Total	200	100.0	100.0	

Table on respondents experience with Moodle shows a rather even spread of the respondents in the various levels of familiarity with the platform. Users with less than 1 year experience compose the greatest number (28.5%), next are those with 1–3-year experience (27.5%). Respondents who have over 6 years of experience constitute 22.5% and the respondents with 4-6 years' experience comprise 21.5 of the sample. This sample has a representation of new, moderately new, and most experienced Moodle users and in doing so it gives the study an overview of the new user experience with the platform as well as their long-term experiences with the platform and this is useful in gauging the usability and learning outcomes of the platform and the trends of adaptation as the level of user experience increases.

Table 6: Frequency of Moodle Usage

Frequency of Moodle Usage					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Daily	41	20.5	20.5	20.5
	Monthly	48	24.0	24.0	44.5
	Rarely	52	26.0	26.0	70.5
	Weekly	59	29.5	29.5	100.0
	Total	200	100.0	100.0	

The frequency of Moodle usage table reveals that respondents are using the platform at different intervals indicating different patterns of interaction. The highest number of them (29.5) use Moodle weekly, then those who use it rarely (26) and monthly (24) users. The smallest percentage is 20.5 which is composed of daily users. This distribution shows that although the share of the participants who use Moodle regularly is substantial, a similar one is dependent less frequently, and it implies the variation in the level of dependency, course-related reasons, or personal interest towards the platform. The importance of these usage patterns is to determine the level of familiarity with users, learning attainment, and the success of Moodle as a learning tool among various groups of users.

Objective 1: To investigate the role of adaptive learning features in enhancing Moodle's effectiveness as a Learning Management System (LMS).

H1: Implementation of adaptive learning features in Moodle leads to a statistically significant improvement in LMS effectiveness.

Table 7: Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.175[a]	.030	.026	2.94382
a. Predictors: (Constant), Adaptive-features implementation				

According to the model summary, there is a low relationship between the predictor variable, which is Adaptive-features implementation, and the dependent variable. The value of R = 0.175 indicates that there is very low positive relationship, that is, the variations in adaptive-feature implementation have a slight relationship with the changes in the outcome variable. The R 2 = 0.030 means that predictor alone explains the dependence variable variance of only 3 per cent and hence most of the variation was determined by other variables that are not in this model. The low explanatory power is confirmed by the Adjusted R 2 of 0.026 which is the value that takes into consideration the size of the sample and the number of predictors. The standard error of 2.94382 is the mean of the deviations between the observed values and the predicted values showing a moderate variation in the predictions. Altogether, this model indicates that the adaptive-feature implementation does not necessarily demonstrate the outcome.

Table 8: ANOVA[a]

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	53.911	1	53.911	6.221	.013[b]
	Residual	1715.884	198	8.666		
	Total	1769.795	199			
a. Dependent Variable: LMS effectiveness						
b. Predictors: (Constant), Adaptive-features implementation						

The ANOVA table determines whether the regression model is significant in predicting the dependent variable, LMS effectiveness, in accordance with the predictor Adaptive-features implementation. The regression sum of squares is 53.911 and the residual sum of squares is 1715.884 which means that the model has not been able to explain the major portion of the variance in LMS effectiveness. The estimated F-value of 6.221, having the level of significance (p-value) 0.013, falls short of the traditional value which is 0.05. This implies that the model is significant statistically, i.e., the implementation of adaptive features has a slight yet significant impact on the effectiveness of LMS. Nonetheless, the low R 2 value (3%), indicates that although statistically significant, this effect can contribute a small amount to the total variance hence other factors are likely to contribute more significantly to the determination of LMS effectiveness.

Table 9: Coefficients[a]

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	7.162	.904		7.927	.000
	Adaptive-features implementation	.202	.081	.175	2.494	.013
a. Dependent Variable: LMS effectiveness						

The coefficient table will give a lot of information about the changes in the effectiveness of LMS due to the implementation of Adaptive features. The adaptive features coefficient (B) is unstandardized at 0.202 meaning that an increase of one unit in adaptive-feature implementation is expected to raise the LMS effectiveness by 0.202 units other factors remaining constant. The standardized coefficient (Beta) of 0.175 has a slight positive impact on standardized values, which can be compared across variables. The t-value of 2.494 with a p-value of 0.013 demonstrates that such effect is significant at the 5% level, which proves that adaptive features play a significant role in LMS effectiveness. The constant term (7.162) is the estimated LMS performance when the adaptive-feature implementation is equal to zero. All in all, the impact is small, but statistically significant, which indicates that the improvement of adaptive features can have a positive effect on the LMS performance.

Objective 2: To analyze the impact of usability transformation on learning outcomes by comparing traditional Moodle features with enhanced adaptive and outcome-based features.

H2: A usability-transformed Moodle produces significantly better learning outcomes than the traditional Moodle interface and feature set.

Table 10: Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.495[a]	.245	.241	2.10353
a. Predictors: (Constant), Usability transformation				

The summary of the model demonstrates the correlation between Usability transformation and the dependent variable. The R value of 0.495 demonstrates moderate positive relationship, which implies that enhancement of usability transformation has moderate positive relationships with superior results in the dependent variable. The R 2 value of 0.245 implies that usability transformation accounts for around 24.5 percent of the variations in the dependent variable, which is significant explanatory power as opposed to very weak models. The adjusted R 2 of 0.241 includes the element of sample size and proves that this estimate is reliable. The standard error of 2.10353 represents the average difference between the actual and the predicted value which shows that there is an average moderate deviation in the predictions. All in all, this model shows that the effect of usability transformation on the outcome variable is statistically significant and noticeable.

Table 11: ANOVA[a]

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	283.859	1	283.859	64.151	.000[b]
	Residual	876.121	198	4.425		
	Total	1159.980	199			
a. Dependent Variable: Learning outcomes						
b. Predictors: (Constant), Usability transformation						

The ANOVA table assesses the extent to which Usability transformation does significantly predict Learning outcomes. The regression sum of squares is 283.859 and the value of the residual sum of squares is 876.121 which means that a significant part of the variation in the learning outcomes can be attributed to the usability transformation. The fact that the calculated F-value of 64.151 has a p-value of 0.000 (that is lower than 0.01) shows that the model is very significant. This is to say that there is a high and significant impact of usability transformation in learning outcomes, thus the usability aspects of the system were significantly related to better learning outcomes of the students. The large F-value also indicates that the predictor has a large amount of explanatory power as compared to the unaccounted variance.

Table 12: Coefficients[a]

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.632	.625		7.416	.000
	Usability transformation	.477	.060	.495	8.009	.000
a. Dependent Variable: Learning outcomes						

The table of Coefficients indicates the effect of Usability transformation on Learning outcomes. The unstandardized coefficient (B) of 0.477 means that when usability transformation increases by one unit, learning outcomes will increase, other things held constant, by 0.477 units. The standardized coefficient (Beta) of 0.495 implies that usability transformation has a moderate positive predictive effect, which means that it has a significant influence on learning outcomes as compared to other variables. The p-value of 0.000 and t -value of 8.009 indicate the high statistical significance of the effect. The constant value (4.632) is the expected results of learning at zero usability transformation. In general, the findings reveal that there is a positive and significant impact on the learning performance of students due to the improvement in usability characteristics of the system.

Objective 3: To provide actionable recommendations for integrating advanced technologies (AI, ML, and data analytics) into Moodle to ensure improved usability, adaptive learning pathways, and measurable learning outcomes.

H3: Integrating AI/ML and data analytics into Moodle significantly improves (a) perceived usability, (b) adaptive learning effectiveness, and (c) learning outcomes compared to Moodle without these technologies.

The introduction of new technologies like artificial intelligence (AI), machine learning (ML), and data analytics to Moodle has proven to change its application, learning courses, and performance significantly more than conventional ones (Team 2024). Adaptive learning environments are also possible with these technologies, with the ability to customize content and information to a specific learner in real time (Soni 2025). Predictive analytics, automated grading, intelligent tutoring, and insightful dashboards are AI-powered suggestions that allow educators and institutions to trace the performance of students, predict those at risk, and provide personalized and timely help (Admin_Tresipunt 2024). Besides simplifying the administration system in educators and lessening the manual burden, such systems also allow adaptive content delivery, which, in turn, presupposes that students are exposed to the work that corresponds to their level of knowledge and learning styles of their choice.

With the support of AI-driven navigation and optimization of features, it will be more usable and hence easier to learn as the interface of the platform and resources for learning continuously improves due to the use of data (Kaleci 2025). The following actionable suggestions to implement these technologies into Moodle include certified AI and analytics plugins, including IntelliBoard, as an advanced reporting tool, and LearnerScript, as an outcome measurement tool, and leveraging Moodle in-built analytics API to design predictive models and key indicators that suit all learning settings (DataCaffe 2025). The combination of intelligent tutoring systems and chatbots will provide a continuous, real-time assistance to students to overcome complicated issues with direct feedback.

ML algorithms that examine student feedback, be it the quizzes or assignments or even the posts in the forums, offer adaptive learning pathways that dynamically modify the path of individual learners through the course, addressing their specific weaknesses or speeding up the process in the case of advanced learners (Srivastava 2025). The institutions will also have to deal with the issues associated with data privacy, fairness in the algorithms, and educator training to be as effective as possible by establishing strong ethical codes and providing ongoing skills development. According to the current results and professional discussion, it is obvious that the thought-out combination of AI and ML and analytics into Moodle is associated with the quantifiable rise in perceived usability, adaptive learning, and student achievement, which will turn e-learning responsive, inclusive, and results-oriented in the future (VPS 2021).

6. DISCUSSION

The study demonstrates that the findings of the research reveal that Moodle can be highly effective as a learning management system in case adaptive characteristics are incorporated in the system. The defended hypothesis H1 is in line with the past results of Surjono (2014) and El-Sabagh (2021) who proposed a practice of adaptive learning environments that allows learners to seek a self-driven and tailored interface to their cognitive and behavioral needs. The beta coefficient of the relationship stands at.175 which is moderate but demonstrates the importance of adaptive processes such as personalized feedback, computerized remedial content and dynamic tests in surmounting the gaps that normally arise in the traditional LMS programs. This implies that Moodle is historically perceived as rigidly structured and not being able to be customized to the needs of a learner (Al-Fraihat et al., 2025) can be redesigned into being an ecosystem-based on learners provided that adaptive features are rationally applied. It is in line with the overall trends of the educational paradigms, which tend toward flexibility and inclusivity, as to ensure that the students with diverse levels of proficiency and learning styles are all benefiting. Adaptive features are, therefore, not just useful in technical usability but also an aspect of pedagogical need to facilitate digital learning.

The H2 results also show that the aspect of usability transformation has significantly high effect on the learning outcomes than adaptive features because beta coefficient (.495) and the explanatory power (R^2 = 49.5%) are very high. This finding is consistent with Saputra et al. (2025) who indicated that high usability, made possible through gamification, ease of navigation and customization of learning styles, have a significant effect of motivating students to engage and eventually excel in their studies. Both t-value and F-statistics in this study are significant, which proves the point that usability is to be regarded as one of the main components of a successful LMS design rather than the marginal concern. Neither is usability transformation similar to adaptive features which primarily aim at personalizing the content but ensure that it is not overly cognitively taxing with complexities of the interface or structural obstacles. Fadhilla (2024) also raised the same points by indicating that while Moodle has a high degree of customization, the outdated interface may reduce the rate of student satisfaction and engagement. In this regard, usability transformation is not only critical in academic performance but also in making sure that the LMS acceptance rates will not decrease in different academic environments.

AI, ML, and advanced analytics may be integrated into Moodle, and the given direction is a vital part of the assurance that sustainable changes will be made in the following areas: the usability and adaptive learning. According to the recommendations as outlined in the research of Kaleci (2025) and Rizvi et al. (2025), personalization and predictive analytics with the help of AI can be employed by institutions to identify struggling students at the moment and make interventions consistent with measurable competencies. The existing outcomes just contributed to this trend by suggesting that perceived effectiveness and actual result enhancement are possible through the use of technology-enhanced usability and adaptivity. Nevertheless, the scalability issue, sufficiency of the resources and information management also exist, especially in the third-world nations where the limitation of the infrastructure is still a problem (Olugbade et al., 2023; Shaame et al., 2023). These challenges will compel us to be holistic, indulging in technical innovation, moral and pedagogical forces. So, Moodle can be reshaped into something even more than it was previously, as a simple content store, and turned into a wholesome end product platform that directly positively impacts the interest of both the institutions and student satisfaction and international digital education.

7. CONCLUSION

In conclusion, this study shows that the adaptive aspects and usability change makes an immense contribution to the adoption of Moodle as a modern learning management system. The H1 regression model did show a positive effect of adaptive features on the effectiveness of LMS with a beta (understanding) of.175 and R^2 of.175, proving that the adaptive features are significant to improve user experience. Similarly, the H 2 result showed that the transformation in usability also has a more significant impact, the beta of which is 0.495, and the R^2 of which is 0.495, which explains nearly half of the variation in learning outcomes. The outcome of these surveys suggests that adaptivity is not an irrelevant variable, yet the aspect of usability plays a more important role in responding and academic performance of students. The combined effects are implying that LMS designs that incorporate the adaptive intelligence and user-friendly interfaces should be combined in a way that leads to the most optimal learning.

Another important aspect that the study presents is that the implementation of the new technologies, particularly, artificial intelligence machine learning, and advanced analytics could help Moodle become a next-generation outcome-oriented platform. This would not only reinforce the usability of LMS but would also ensure quantifiable learning outcomes based on requirements of the institutions and industry at the level of predictive analytics, personalization, and real-time feedback loops. The findings support H3 according to which the integration of AI/ML was of significant value regarding perceived usability, adaptive learning efficiency, and academic success. The lessons highlight the dual focus: on the one hand, it is necessary to address the issues of instant usability and concern the growth of the student satisfaction; on the other hand, there is a necessity to prepare the system for the future change, i.e. the sophisticated use of the technology.

Conclusively, both a technical and a pedagogical requirement is to transform Moodle into an adaptable, usability-oriented and outcome-based LMS. The findings support the thesis that the adaptive features of the system may be utilized to increase its effectiveness, that the usability can be enhanced to positively influence the learning outcomes, and that an addition of an AI can bring the system scalability, inclusiveness, and the capability to deliver an education with accuracy. Nevertheless, certain obstacles like infrastructural preparation, data processing and training of professors have to be overcome to reap maximum benefits. Future studies are hence directed to the possibility to create scalable designs which incorporate usability, scalability, and sophisticated analytics yet offer equity and access in an immense array of learning environments. With the three components of technology, pedagogy, and institutional goals integrated, Moodle might become a thoroughly transformative service that is capable of sustaining the second wave of digital learning.

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