Intelligent Learning Pathways: A Customizable LMS Framework for Modern Education

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Manuscript received April 3, 2025; revised June 12, 2025; accepted August 8, 2025; published February 9, 2026

***Abstract*—The advancement of technology in education has opened new avenues for customized learning experiences, enhancing student engagement and learning outcomes. This research presents an "Intelligent Learning Pathways" model, a customizable Learning Management System (LMS) framework designed to meet the diverse needs of modern educational institutions. The problem addressed is the limitation of conventional LMS platforms, which often lack adaptive, student-centered pathways and real-time data insights to support individual learning journeys. The objective of the research is to develop a flexible, data-driven LMS framework that integrates Artificial Intelligence (AI) and machine learning algorithms to create tailored learning pathways, optimizing content delivery based on students' performance, preferences, and learning styles. The methodology combines user-centric design principles with predictive analytics, enabling the system to adjust content dynamically. Testing involved deployment in a university setting with over 500 students, measuring engagement rates, learning progress, and satisfaction. Results indicate a significant increase in student engagement and learning outcomes, with 85% of participants reporting a more customized learning experience. The research concludes that incorporating intelligent algorithms in LMS can transform educational delivery, making it adaptive and customized, thereby meeting the unique needs of diverse students.**

***Keywords*—Learning Management System (LMS), customized learning, adaptive, Artificial Intelligence (AI)-driven, student engagement**

I. Introduction

E-learning, or Technology-Supported Learning (TSL), integrates computer-based tools such as videos, forums, and other digital media to enhance education. TSL optimizes teaching by providing accessible resources online, creating a flexible framework for distance learning. The core aim of e-learning is to empower students with readily accessible knowledge, fostering self-paced and effective learning experiences. Learning Management Systems (LMS), central to TSL, are increasingly popular due to their ability to deliver content across diverse formats, any time and place. LMS adoption reflects the technological evolution in education, though it presents challenges in adapting to varied student needs and advancing teaching methodologies [1].

Given the speed at which information technology is developing, many educators are reconsidering the antiquated, static classroom teaching methods and the significance of student learning styles in course design and delivery [2]. Many of the current LMSs fail to account for the learning styles of their students, which will have an impact on their academic development. Simultaneously, there are no set standards for creating instructional resources that are appropriate for a student's preferred method of learning that can be integrated into an LMS. Therefore, in order to propose a framework for this, proper teaching taxonomy needs to be identified.

In recent years, there has been a rise in interest in and use of Artificial Intelligence (AI) to improve personalization to support students teaching and learning activities. These adaptive LMS [1, 3] explored AI integration for enhancing the learning experience on LMS platforms to gauge student engagement and performance.

Teaching taxonomy is the categorization of thought processes using a multiple-layer approach that corresponds to the six cognitive levels of complexity. Grouping students according to their preferred learning styles and matching them with the most suitable learning resources is the aim of teaching taxonomy. Personalization is the process of matching the right learning resources to the student's preferred method of learning [1, 4]. One of the current issues with the customized LMS model is that it does not incorporate teaching taxonomy or learning styles, as it only offers a limited number of features compared to a normal LMS [5–7]. Customized learning management system models that incorporate teaching taxonomy into their personalization would be an extra benefit. However, teaching taxonomy that is appropriate for many student types is not included.

Since the processes involved are time-consuming and demand a great deal of attention from everyone involved, many customized LMS models did not offer personalization or the incorporation of teaching taxonomy. For instance, an instructor must use the Felder-Silvermann Learning Styles Model (FSLSM) to create eight distinct sets of learning materials if they are required to offer personalization in the customized learning management system. This is due to the fact that FSLSM is separated into four primary dimensions: Verbal-Visual, Sensing-Intuitive, Sequential-Global, and Active-Reflective. Therefore, it must be in line with the

doi: 10.18178/ijiet.2026.16.2.2516

relevant learning resources to guarantee that personalization is completed. In other words, the instructor must provide eight distinct sets of learning resources for a single subject. Additionally, the instructor must make sure that the features and preparation techniques of its learning materials are compatible with the current LMS model. The problem to be addressed by this research is to incorporate automatic detection of learning style into personalized LMS models which are able to deliver different teaching and learning materials based on the LMS. The objective of the research is to develop a flexible, data-driven LMS framework that integrates AI and machine learning algorithms to create tailored learning pathways, optimizing content delivery based on students' performance, preferences, and learning styles. Many education institutions utilize conventional LMS in order to manage assessments, track student progress, and facilitate the delivery of content. But the majority of conventional LMS platforms take a one-size-fits-all approach and are unable to dynamically adjust to the needs of different students. Manual personalization is possible with certain LMS, for example, when instructors assign different materials to different students, but these methods are frequently static, time-consuming, and not scalable. Several key limitations in current LMS highlight the research gap which is the limited personalization based on learning styles and lack of automated learning style detection. While many LMS systems offer various types of content, it generally does not use learning style concepts to facilitate automated content presentation adaptation. Such incompatibility may result in diminished levels of motivation and less than ideal learning achievement among varying students. Existing LMS also typically employ self-report questionnaires or manual profiling to classify learning style. These methods are not only prone to errors and subjective, but they are also static as it fails to adapt based on the student's evolving behavior or performance.

The purpose of this research is to investigate how to include appropriate teaching taxonomy and individual learning styles into the LMS framework that educational institutions can employ. The aforementioned problems will be resolved by the fully developed LMS which is based on the proposed framework, which will enhance students' academic achievement.

The main objective of this research is to enhance the existing benefits of LMS to become a personalized LMS by extending the LMS functionality with the incorporation of learning styles. Therefore, four research questions will be conducted in order to achieve the goal as follows:

1) What are the existing LMS models?
2) How is the Personalized LMS model developed?
3) What is the suitable teaching taxonomy to be integrated into Personalized LMS model?
4) How to evaluate the effectiveness of Personalized LMS model?

II. Literature Review

To find out the significance and advantages of LMS in raising students' academic performance, the introduction and history of e-learning and LMS in Malaysian higher education institutions will be covered. The types of learning management systems, learning style concepts, and the evolution of the LMS conceptual model are also covered and reviewed in this section.

A wide variety of technology learning applications are included in e-learning. Information and Communication Technology (ICT) is being used to improve the learning process, facilitate communication in the classroom, assess academic performance, manage teaching and learning resources, and create teaching and learning materials [8]. Malaysian universities that offer and facilitate distant learning programs frequently use e-learning. To provide their teaching and learning materials to students worldwide, these universities have employed a variety of LMSs, whether they be open source or commercial [9, 10]. Software that automates the management of learning activities is called an LMS. In the application of e-learning, LMSs play a crucial role.

As shown in Fig. 1 below, a general LMS model that powers the personalization process can be divided into four complementing models [11]. The runtime layer specifies how the adaptation should be carried out, the media space and user model specify what parameters can be integrated, and the domain model specifies what aspects should be integrated [12].

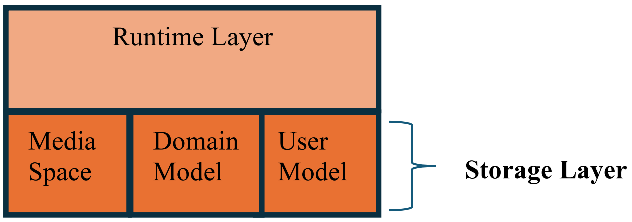

Fig. 1. A generic LMS model.

A few customized LMS models that are currently in use are examined. The first is the Web-based Educational system with Learning Style Adaptation (WELSA). The primary pedagogical objective of WELSA is to offer an educational experience that best fits each student's preferred method of processing and organizing knowledge, as well as social and motivational factors. WELSA is generally made up of three primary parts: the course player, data analysis tool, and writing tools [13]. The authoring tools are primarily used by instructors to create their lesson plans, the data analysis tool interprets student behavior and keeps track of students' activities within the learning management system, and the course player is primarily used by students to monitor interactions between students as well as offering customized subjects to them.

Learning styles are adapted into adaptive e-learning hypermedia using the Learning Style-based Adaptive E-learning Hypermedia System (LS-AEHS) concept. The Honey and Mumford-French version of the Learning Style Questionnaire (LSQ) is used to identify students in order to integrate learning styles [14]. Before their learning styles are determined, the students must personally complete the questionnaire. As a result, the WELSA and LS-AEHS are comparable in that they both use manual methods rather than integrating them into the model to identify students' learning styles [15].

ULUL-ILM is a web based adaptive educational system. ULUL-ILM comprises of three main models which are the user model, a domain model and adaptation model [16].

Similar to Triangular Learner Model (TLM) and Hybrid Dynamic User Model, all these models are essentially manually integrating the learning styles into their respective individual LMS model rather than to automate this process. All the reviews on WELSA, LS-AEHS, ULUL-ILM, TLM and Hybrid Dynamic User Model conclude that there is no automation process being added into the customized LMS model despite there are actually components of integration in their respective model. Hence, the research seeks to integrate automatic identification by integrating the auto recognition of learning type into the tailored LMS model.

Multi-Traits Dynamic User Model established by Hassan and Noureldien [17] are by the combinations of all important components from WELSA, LS-AEHS, ULUL-ILM, TLM and Hybrid Dynamic User Model. This model is built in a way where all the components which are significant and effective are being selective chosen to form the new model which integrates all the advantages and efficiency from each respective model. This means that the Multi-Traits Dynamic User Model likewise does not include the auto identification of learning styles into its model. Table 1 is the summary of the reviewed LMS models.

A small number of LMS studies have been chosen and implemented at private Higher Education Institutions (HEI). In order to suggest an appropriate teaching taxonomy based on students' learning styles, the goal of the review of the current LMS that HEI has adopted is to further identify the common features and functionality of the LMS. The first system is called WBLE, which utilizes Moodle, an open-source LMS. This system is used to help instructors and students in the process of teaching and learning. Communication has been getting better as a result of using WBLE, particularly between teachers and students. Additionally, WBLE serves as a primary resource from which students can access content at any time and from any location. Additionally, it includes all of the resources that students have added for a given subject throughout a given semester. The maximum upload file size, the total number of teaching and learning weeks, the expiration date for learners to access, notifications, and other features can all be changed according to user preferences and requirements. To evaluate the students, instructors can also create quizzes or midterm exams in the WBLE. This has made it easier for the teacher to monitor students' performance. Since all learner activity in the WBLE system is also recorded, the right section of the system may also serve as an additional observation tool for the instructor. The WBLE system can be used to broadcast all recent notices, events, and activities.

The second system is called Multimedia Learning System (MMLS). Unlike WBLE, the MMLS is created internally from the ground up and is not derived from the Moodle system. Overall, WBLE and MMLS features are fairly comparable to each other. Like WBLE, the student's profile is displayed on the MMLS home page. Every subject that students have registered for is shown and listed in the middle of the home page. Simply clicking on the corresponding expansion symbol will provide additional information on the subjects. The user manual's accessibility is one of the primary distinctions between MMLS and WBLE. No user manual of any kind is offered by WBLE, which could be helpful for novice users. In contrast to WBLE, where students must access faculty announcements on the faculty website, MMLS also shows the most recent announcements from the faculty as well as for the subjects taken. Additionally, MMLS provides learners with online quizzes and midterm exams. However, students can examine and download the assignment guidelines as well. MMLS offers services like live video, discussion forums, and chat to help with communication. MMLS and WBLE are comparable in this regard. Additionally, MMLS offers storage space for students to store necessary files [18].

The third system is myLMS. The myLMS may be accessed via Facebook, which greatly facilitates access for students. Subject materials, internal site links, and university and faculty information are all included on the myLMS home page. In essence, myLMS is a single-page website with links to every other page accessible from the same page. These links include the theme music, e-forms, learner surveys and evaluations, radio services, and links to the most recent faculty and university circulation news. Like MMLS and WBLE, it is likewise separated into three primary portions.

The common features and functionalities based on the review of the LMSs are summarized as below:

1) Games, simulations, experimental lab;
2) Problem-based learning;
3) Role play;
4) Presentation;
5) Discussion;
6) Brainstorming;
7) Case study;
8) Question-answer method;
9) Group assignment.

Learning styles are related to theories where the objective is to interpret the distinctions in a student learning style [19, 20]. In other words, learning styles represent the concept that every student learns in a distinctive fashion. According to the learning styles theories, different students may be grouped into distinct learning style. Many research has been done to prove the efficiency of an LMS by combining multimedia with learning styles [3, 21]. Therefore, it is vital to identify specific LMS functions and features which is ideal for diverse students with varied learning style. This can be done by proposing a matching instrument or approaches available in the customized LMS with the students' learning style.

The learning style model from Kolb is introduced by David Kolb in 1984. Kolb Experiential Learning Theory is separated into four stages of learning and four learning types. The four-stage cycle of learning involves the concrete experience which is the basis for observation and reflection which in turn leads to a "theory" from which implications for action can be identified the theory serves as a guide to produce new experiences [22].

Honey and Mumford's learning style was designed by Peter Honey and Alan Mumford based on the work of Kolb [23]. It is also classified into four types of learning styles as in Kolb theory which are the Activist, Theorist, Pragmatist and Reflector. Activists are students with an open-minded approach to learning and desire to involve experiencing things for themselves. Theorist students prefer to turn information into a systematic and logical theory. Pragmatist students prefer to perform experimentation to see whether it works while reflector students prefer to step back and assess from a variety of various viewpoints first. To recapitulate, Honey and Mumford's learning style comprised of tangible experience, introspective observation, abstract conceptualization and active experimentation.

Another famous learning style evaluation is from Myers Briggs. It is based on Bloom's Taxonomy and determined by a 126-item testing instrument [24]. Altogether there are a mixture of 16 learning styles described in this model which is based on extravert against introvert, sensing versus intuition, reasoning versus feeling, and judgment versus perceptive [25]. Myer-Briggs types do have similar practical consequences for teaching to the Honey-Mumford system.

Table 1. Summary of existing LMS model

LMS Models	Authors	User Characteristics Used by the Model	Dynamic Characteristics
Multi-Traits Dynamic User Model	Hassan and Noureldien [17]	• Knowledge • Learning style	• Behaviour Learning style
Hybrid Dynamic User Model	Maslov *et al*. [16]	• Knowledge • Behaviour • Learning style • Goals • Experience	• Knowledge • Behaviour • Learning style • Goals
Triangular Learner Model (TLM)	Nguyen [26]	• Knowledge • Learning style	• Knowledge • Learning style
ULUL-ILM	Wang *et al*. [27]	• Learning style • User profile	• Learning style
LS-AEHS	Mauricio *et al*. [28]	• Learning style	• Learning style
WELSA	Khan *et al*. [13]	• Learning style • Preference	• Learning style

Felder and Silverman Learning Styles Model (FSLSM) combine the students learning style into four dimensions which are the Active/Reflective, Visual/Verbal, Sensing/Intuitive and Sequential/Global. Active students tend to remember and understand material best by doing something active with it such as conversation. Reflective students learn by thinking about information [29]. They will grasp better when they are permitted to have adequate time to reflect on the knowledge and instruction they have been provided. The learning style model by Felder-Silverman is widely utilized in similar research as it is more suitable to be used in education rather than for industrial reasons which is used to identify working preferences of workers based on their learning styles [30]. Table 2 summarizes the existing learning style models.

Table 2. Summary of existing Learning Style model

Learning style model	Dimensions within the model
Kolb model	• Converger/Diverger • Assimilator/Accommodator
Honey-Mumford model	• Activist/Reflector • Theorist/Pragmatist
Myers-Briggs model	• Myers-Briggs model
Felder-Silverman model	• Active/Reflective • Visual/Verbal • Sensing/Intuitive • Sequential/Global

Based on the systematic literature review of the above, a customized teaching taxonomy is proposed based on the students' learning styles as shown in Table 3.

Table 3. Comparison of learning style models

Preferred Learning Style		Corresponding Teaching Style	
Active Reflective	Processing	Active Passive	Students' participation
Visual Verbal	Input	Visual Audio	Presentation
Sensitive Intuitive	Perception	Concrete Abstract	Content
Sequential Global	Understanding	Sequential Global	Perspective

III. Research Methods

Research designs are defined as processes and strategies which facilitate research to make decisions from general assumptions to the specific methods used for collecting data and as well as data analysis. This research aims to integrate learning styles and teaching taxonomy into an LMS model and its impact on the learning process in an LMS environment. The research is divided into five activities: pilot study, LMS model development and the validation and evaluation process as shown in Fig. 2. The research is divided into five activities: pilot study, LMS model development, Personalized Web-Based Learning Environment (P-WBLE) development, and validation and evaluation. The goal is to ensure the integration of these elements into the LMS model.

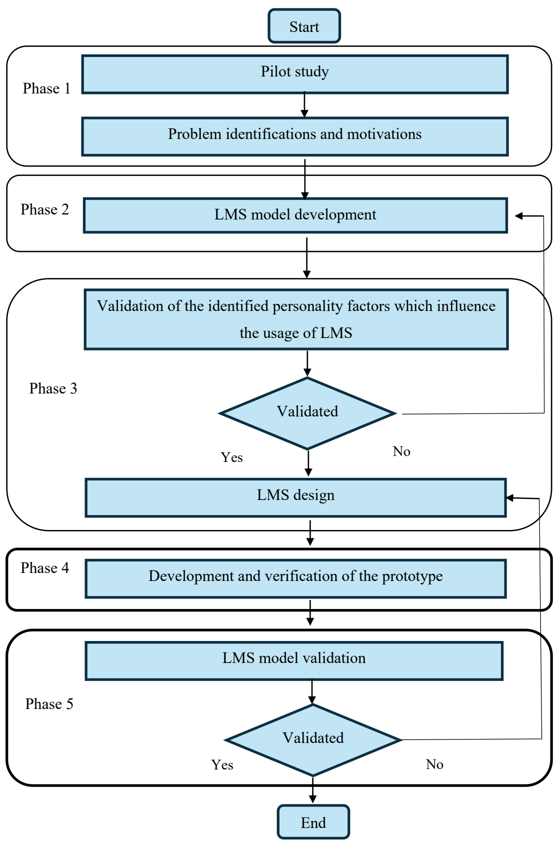

Fig. 2. Research method flow.

The pilot study focuses on the impact of learning style and LMS on teaching and learning in Malaysian Higher Education Institutions (HEIs). The study aims to test research propositions, identify ideas, and establish the research basis. The pilot study was conducted at Universiti Tunku Abdul Rahman (UTAR) in Perak, Malaysia, using Moodle, a Web-based Learning Environment (WBLE) system. This system facilitates communication between instructors and students, facilitates information exchange, and serves as a storage medium for teaching materials. It also includes administrative tools to support instructors and learning operations.

The researcher analyzed questionnaires to identify various students' preferences for using an LMS. They proposed an automatic detection method using a literature-based approach to identify and examine their characteristics and preferences. The FSLSM model, commonly used in customized LMS, was used to establish a proper teaching taxonomy, ensuring the LMS's adaptability and provision of customized learning materials.

The LMS model aims to address the issue of treating all students equally, regardless of their learning style or preferences, as identified in phase 1. The model's formalization involves background identification, theoretical solution integration, and model verification.

A. Phase 1

The validation of variables is crucial in the development of an LMS model to ensure its applicability and significance. A questionnaire with a 5 Likert scale format was used to validate variables, including demographic information. A pilot test was conducted to ensure the validity of the experiments and ensure participants understood the questions. The questionnaire, adopted from previous studies, was reassessed using the Statistical Package for the Social Sciences (SPSS) version 23. The test involved 240 UTAR students in a Computer Systems and Applications course. This course is a course which is taken by students which are not in the computing related undergraduate programme. A briefing was given to ensure understanding of the questionnaires. After the pilot testing, all instruments were examined for patterns and reliability scores were calculated using SPSS version 23 software. The reliability score was summarized in Table 4 below. Statistical analysis through SPSS were used in order to analyze and identify the significance and importance of the variables. These analyses include descriptive analysis and relationship analyses. Descriptive analyses are used as a measure of central tendency and measures of variability. A measure of central tendency includes mean, mode and median whereas measures of variability include standard deviation, skewness and kurtosis. Descriptive analyses are important to help determine the normality of the distribution.

Table 4. Questionnaire from pilot test reliability score

No	Variable	Reliability Score
1	Customized LMS Quality	0.861
2	Course Quality	0.884
3	Service Quality	0.806
4	User Experience	0.839
5	LMS Usage	0.854
6	Perceived Net Benefits (PNB)	0.890

Formula for reliability score: Cronbach's Alpha (α):

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma_t^2}\right) \quad (1)$$

where:

- α = Cronbach's Alpha (reliability coefficient);
- k = number of items (questions, indicators);
- σ_i^2 = variance of each individual item;
- σ_t^2 = total variance of the sum of all items.

The selection of Cronbach's Alpha is due to the degree to which a group of test or questionnaire items have a positive correlation with one another and evaluate the same underlying construct (e.g., learning style, engagement level) is known as internal consistency. It is commonly used in social science and education research, which increases the comparability and legitimacy of your findings. Aside to this, it also works best with instruments that use rating scales, such as Strongly Agree to Strongly Disagree and it is easy to understand and straightforward: α has a value between 0 and 1.

The reliability score for the pilot test questionnaire is 0.942, indicating its reliability and consistency. The questionnaire was distributed to 240 students in UTAR, who are currently using traditional LMS relevant to the study. To ensure a better understanding of the questionnaire, a session was scheduled for non-IT students. The details of the pilot test were announced during a lecture class, and all 240 students agreed to participate. Statistical analysis was conducted using SPSS to identify the significance and importance of the variables. Descriptive analyses were used to measure central tendency and variability, with measures such as mean, mode, and median, and standard deviation, skewness, and kurtosis.

1) Name of course completed: (Provide drop down list);
2) Date you completed this course: (FILL IN);
3) State in which you reside: (Provide drop down list);
4) Did you complete the course in one sitting or did you start the course, stop, and return to it?
5) About how long did it take you to complete the course?
6) In your opinion, was the time it took to complete this course.
7) Did the course "time out" (did you get signed out of your W-BLE account involuntarily) while you were taking it?
8) In order to view the course, did you have to do either of the following:
   - Install/update Adobe Flash Player;
   - Install/update your Internet browser;
   - Both.

1) Did the pages download in a timely manner?
2) Did the links open easily?
3) Was it easy to understand how to start the course?
4) Did you need and/or use any "help" materials?
5) Was the structure of the eLearning course simple/easy to follow?
6) How intuitive is it to navigate?
7) Did you advance the course using:
8) Did you use the chat feature?
9) If you didn't use the chat feature, why?
10) When you restarted the course, did it start where you had left off?

11) Was it difficult to read the font type and size?
12) Was the text broken into small, readable sections?
13) Were the instructions clear for quiz questions and exercises?
14) How do you plan to use the information that you learned from this course? (FILL-IN)
15) Are you interested in taking other courses in the future?
16) Availability and accessibility of ICT infrastructure inside campus.
17) IT staffs are able to support me in the WBLE.

B. *Phase 2*

The specifications and functions of the LMS development are selected from the validated variables. The specifications and functions of the LMS used in this phase will also serves as inputs for the LMS design phase. Fig. 3 illustrates the integration of auto integration learning style and teaching taxonomy into the LMS model.

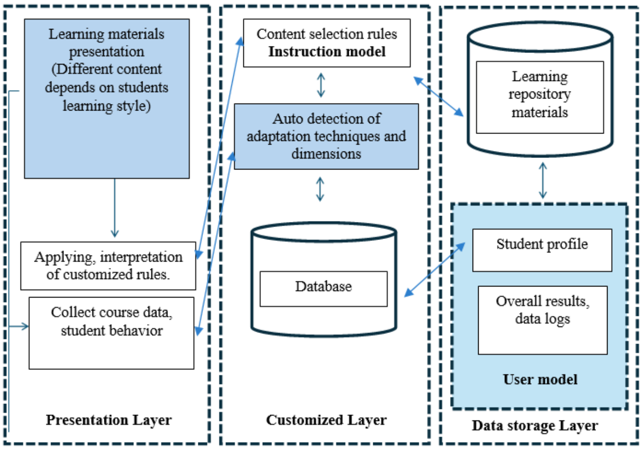

Fig. 3. Proposed customizable LMS framework.

C. *Phase 3*

As for relationship analyses, it is used to generalize the population based on the samples. It focuses on drawing conclusions about the population based on sample analysis and observation. On the other hand, relationships analyses are also conducted in order identify the existence of the relationship between variables.

A number of industry accepted benchmarking methods have been developed to measure the user experience such as System Usability Scale (SUS) and Post-Study System Usability Questionnaire (PSSUQ). SUS is created in 1986 and is mainly used to measure the usability of webpages, applications, software or hardware. SUS only consists of 10 questions and respondents are required to rate using a 5-point Likert scale. On the other hand, PSSUQ is developed by IBM design center in 1992 which is very similar to SUS. But PSSUQ consists of a total of 16 questions as opposed to SUS which is 10. PSSUQ has an answering scale range from 1 to 7 which is more complex compared to SUS. The reason behind the range is to permit respondents to provide more accurate and distinctive responses to each question. PSSUQ is chosen to measure the user experience due to the number of questions that are more applicable and better suited to the research which is for industry based as well as PPSUQ is more suitable to measure information quality as SUS is used to measure learnability. Fig. 4 shows the relationship analysis for the LMS model.

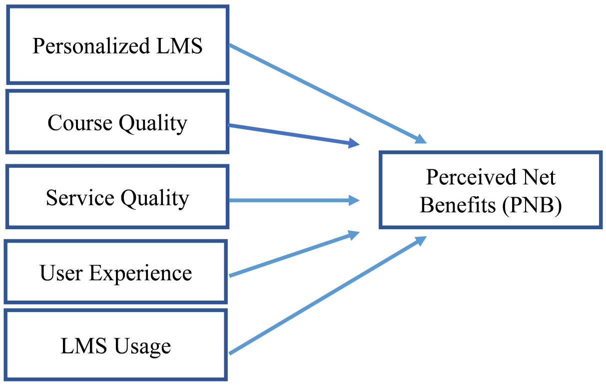

Fig. 4. Variable relationship analysis for LMS model.

D. *Phase 4*

In phase 4, the LMS system is designed to meet the specifications and functions. This design is divided into seven components: requirements specification, functionality design, architectural design, internal design, interface design, and system design. The main requirement is for the LMS to be user-friendly, allowing students to easily find course subjects, locate learning materials, track progress, and communicate with others. A good LMS should allow students to learn from anywhere, provide support, and facilitate communication with similar course subjects.

The P-WBLE system is developed using UML models, tools, technology, system programming, and compilation. The system is designed to cater to the needs of students who use multiple internet browsers to access the LMS. A fully functional system is developed, following requirements and specifications through UML and storyboard.

E. *Phase 5*

The implementation phase transitions from development to implementation, involving activities such as installation, deployment, and rollout. The P-WBLE is installed in a lab environment to ensure its functionality. The system is continuously monitored and adjusted as needed. The system validation process compares each element to the proposed LMS model, ensuring all features and functions are implemented and working properly. A functionality test is conducted, randomly selecting 50 students from a course namely, Computer System and Application (CSA). They are given a checklist to fill out, and minor adjustments are made based on suggestions or comments.

The installation takes place in a lab at UTAR, with the P-WBLE system server installed separately from the existing LMS. The system is tested in an actual environment to ensure proper connection to the server. After completing these steps, the P-WBLE system is ready for use and testing purposes.

Two evaluations were conducted to assess the effectiveness and efficiency of the P-WBLE system. The first was a usability test to understand students' interactions with the system and improve it. The test was conducted in a lab at UTAR, with a lab officer as a moderator. After 30 min, students were given 30 min to explore the system's features and functions. The PSSUQ was chosen as a scenario-based usability evaluation instrument for this research.

The effectiveness test assesses the impact of P-WBLE on students by comparing their performance using traditional LMS (controlled group) and P-WBLE (experimental group).

The experimental design consists of two groups of 150 students, each with two subtopics: "Introduction to Computer" and "Computer Hardware" from the course "Computer Systems and Applications (CSA)". The study aims to compare the performance of students using traditional LMS and P-WBLE, with all participants informed about the experiment at the beginning of the class lecture. The effectiveness test aims to evaluate the effectiveness of P-WBLE in learning.

IV. Result and Discussion

This section presents the results of the proposed LMS model, which focuses on usability and effectiveness tests, through six experiments conducted in a sequence to validate its significance.

A. Experiment 1: Learning Styles on Traditional LMS and Customized LMS

The traditional LMS for teaching CSA was used. This LMS includes the CSA learning content and tutorial content. In the end of every chapter of the learning content, quiz is presented to the students to help them to further enhance their understanding on that particular chapter. However, the students are not forced to undertake the quiz at this stage. The students will only need to take the quiz, which consists of 20 questions which will be administered to measure the students overall learning performance with the traditional LMS.

The traditional Learning Management System (LMS) WBLE from UTAR was used for teaching Computer Systems and Application (CSA), including learning content and tutorial content. A quiz was presented at the end of each chapter to enhance understanding. The students were not forced to take the quiz but only had to answer 20 questions to measure their overall learning performance. Learning styles were set as an independent variable, and dependent variables included time taken to complete learning materials, correct answers, navigation movements, and repetitions. Fig. 5 shows the amount of time the students required to complete the reading. All volunteered students were briefed and conducted FSLSM tests in a laboratory using the LMS for the CSA subject. After 30 min, they had to answer 20 quiz questions about the chapter they had just learned. Table 5 shows the amount of time taken by student to complete the reading of the notes.

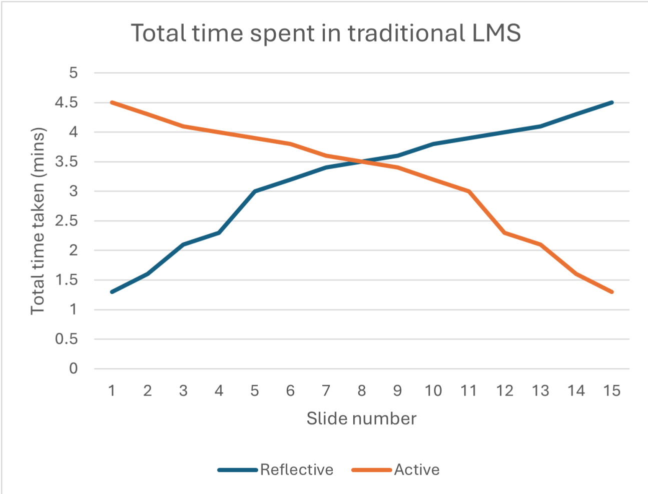

Fig. 5. Amount of time recorded in the traditional LMS environment.

Table 5. Total time taken (unit: min)

Personality type	Page 1–5 (mean/s.d)	Page 5–10 (mean/s.d)	Page 10–15 (mean/s.d)	Total (mean/s.d)
Active (n = 101)	11.48(0.90)	10.59(0.84)	8.38(0.88)	30.45(1.49)
Reflective (n = 49)	4.56(0.84)	12.91(1.24)	12.73(1.12)	30.21(1.84)

Experiment on traditional LMS found no significant impact on students' learning performance as they are not designed to support personalization. The experiment on customized LMS aimed to identify the importance of auto-detection of students' learning style on performance and the use of a customized LMS. The results as shown in Table 6 showed that customized LMS provided more benefits than traditional LMS, consistent with previous studies. A T-test confirmed significant differences in variables such as total time taken, correct answers, navigation, and repetition between these two experiments.

Table 6. Comparison performance between traditional and customized LMS

Description	Means	
	Traditional LMS	Customized LMS
Total correct answers	54.29	82.29
Total numbers of navigations	21.71	10.90
Total numbers of repetitions	10.38	5.47

The study reveals that customized LMS offers more benefits than traditional LMS, as supported by previous studies. A T-test confirmed significant differences in variables like total time taken, correct answers, navigation, and repetition between experiments, as shown in Table 7.

The study compares the performance of active students using a customized Learning Management System (LMS) with those using a traditional LMS. Fig. 6 shows the amount of time the students required to complete the reading. The results show that the customized LMS improves students' understanding of the CSA subject, with higher correct answers and better navigation efficiency. Reflective students also show better results with customized LMS, with a mean score of 78.33 compared to 53.98 for traditional students. Additionally, the number of navigations reduced between the two LMS usages. T-tests confirm that traditional LMS does not have significant effects on active and reflective students, while customized LMS shows significant effects. The results suggest that customized LMS can be a more effective learning tool for students.

Table 6 shows that active and reflective students are spending more time on learning compared to Experiment 1, with their progress being steadier. Using a customized Learning Management System (LMS) compared to a traditional one, both students' learning time is faster, indicating that learning style significantly impacts the learning process. Table 7 provides details of the time taken, total correct answers, total number of navigations and repetitions for both learning styles.

Table 7. Learning styles effects on the traditional and customized LMS

Type of LMS	**Time taken (unit: min)**	**Total correct answers (%)**	**Total no. of navigations**	**Total no. of repetitions**
Traditional	30.45 (1.49)	54.44 (2.52)	22.07 (1.96)	10.28 (1.10)
Customized	28.94 (1.87)	84.21 (2.48)	9.20 (1.88)	4.43 (1.10)
Significance	$p < 0.05$	$p < 0.05$	$p < 0.05$	$p < 0.05$
Traditional	30.21 (1.84)	53.98 (2.62)	20.96 (1.95)	10.60 (1.10)
Customized	25.32 (1.25)	78.33 (2.07)	14.41 (2.05)	7.61 (1.55)
Significance	$p < 0.05$	$p < 0.05$	$p < 0.05$	$p < 0.05$

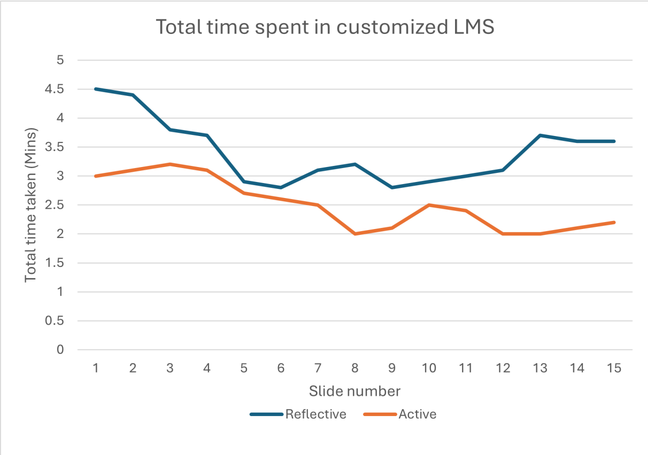

Fig. 6. Amount of time recorded in the customized LMS environment.

B. *Experiment 2: Learning Styles and Teaching Taxonomy*

In the development of a customized Learning Management System, it is crucial to consider the learning style of each student. However, matching this learning style with an appropriate teaching taxonomy can enhance the learning experience. This experiment discussed how learning style should be associated with learning materials in a customized LMS model using the Bloom Taxonomy. It is essential to recognize the difference between active and reflective learning styles when reacting to the same learning material design. This experiment discussed the impact of different learning types on their reactions to a particular learning material design, which could enhance the future design of the customized LMS model. Matching the suitability between learning style and learning material is essential for enhancing the learning experience.

The experiment found that students under the reflective, verbal, sensing, and sequential categories performed below par when learning a CSA subject. Conversely, active, visual, intuitive, and global students performed well with the customized LMS due to their preference for sequential learning. Therefore, instructors need to consider the combination effect between learning style and suitable learning materials when designing the LMS model to cater for multiple students with different learning styles. Previous studies suggest that students with different learning styles may have specific preferences on different learning materials. Active students tend to benefit from general ideas before moving forward for more details, while reflective students prefer conceptual information. Therefore, there may be different preferences towards different learning materials. Experiments were conducted to verify the elements of the learning materials based on the learning style. Some research indicates that students' learning style does not have any association with the learning materials, but those who are match with the wrong learning style and materials perform better. This mismatch encourages students to build their own learning strategies, enhancing the multidisciplinary combination of skills that active students typically possess. In conclusion, understanding the relationship between student's learning style and appropriate learning material is essential for designing a proper and effective customized LMS.

Participants are informed about experiment objectives and procedures and randomly assigned to either CSA 1 or CSA 2. Both versions have a "Next" and "Back" button for navigation. After completing learning materials, they must answer 30 questions on the CSA subject, divided into 20 multiple choice questions and 10 short open-ended questions. Performance results from CSA1 are shown in Table 8.

Table 8. Performance results for CSA 1

Learning Style	**Task Performance (Means / S.D)**	
	Duration of study (unit: min)	No. of correct answers (unit: %)
Active (Controlled group)	30.45 (1.49)	54.44 (2.52)
Active (Experimental group – CSA1)	6.01 (0.97)	77.80 (4.44)
Significance	$p < 0.05$	$p < 0.05$
Reflective (Controlled group)	30.21 (1.84)	53.98 (2.62)
Reflective (Experimental group – CSA1)	11.49 (1.32)	69.31 (5.72)
Significance	$p < 0.05$	$p < 0.05$

Table 8 shows that active students finish learning materials faster than reflective students, with a mean time of 6.01 min compared to 11.49 min for reflective students. However, reflective students spend more time on answering questions, potentially due to a lack of comprehension. Active students, on the other hand, complete the materials in shorter time, resulting in higher percentages of correct answers. ANOVA analysis confirms these differences. Active students are faster in the duration of study and the total number of correct answers. The results suggest that matching learning style with appropriate materials, as in the context of CSA 1, can benefit active students. Active students also perform better in open-ended questions, as they have a better conceptual understanding of the content. The study supports the importance of matching learning materials with learning styles, as seen in previous studies.

The study compares performance variables in two different learning styles CSA 1 and CSA 2, revealing that reflective students perform better than active students. The results show significant differences in all three variables, indicating that reflective students perform better when exposed to appropriate learning materials based on their learning style. The study also reveals that reflective students perform better in multi-choice questions and open-ended questions, indicating their ability to grasp knowledge and score higher answers. The number of repetitions recorded in the experiment can provide insight into how students organize their learning experiences. The group of students that match well with their learning styles may lead to fewer navigations, indicating a proper match between learning style and learning material as shown in Table 9.

Table 9. Performance results for CSA 2

Learning Style	Task Performance (Means / S.D)	
	Duration of study (unit: min)	No. of correct answers (unit: %)
Active (Controlled group)	30.45 (1.49)	54.44 (2.52)
Active (Experimental group – CSA2)	11.50 (1.57)	69.38 (4.77)
Significance	$p < 0.05$	$p < .05$
Reflective (Controlled group)	30.21 (1.84)	53.98 (2.62)
Reflective (Experimental group – CSA2)	5.99 (1.06)	78.35 (4.49)
Significance	$p < 0.05$	$p < .05$

V. Limitations

The major limitations of this research are to collect all data which can be used to represent all HEI in Malaysia. Due to this reason, this research is conducted in a sampling manner which is reflected in experiment where only students from one undergraduate programme are being selected. Generalizing students might pose problem in terms of the granularity of the research. This is because for those students which fall under the category of “balance”, then it would be difficult to categorize these students. It would also be difficult to prove any form of benefits from any type of adaptation proposed in this research. One of the primary barriers to the implementation of personalized learning through AI-powered Learning Management Systems (LMS) is resistance to change by powerful stakeholders, the most prominent being teachers, students, and institutional administrators. Much of this resistance stems from a combination of psychological, cultural, and institutional origins.

Instructors may be skeptical regarding the usefulness of AI-based tools to model human behavior and learning subtleties and are afraid of losing their professional control through automation or even making certain teaching posts obsolete. Instructors are also intimidated by the perceived technological sophistication of integrating new technologies with their existing pedagogy, especially where they feel there is not enough training or confidence in using digital tools. Students themselves are also likely to resist shifting away from traditional, instructor-driven models to more independent, technology-supported learning systems. Such resistance may be a result of unfamiliarity, inadequate digital literacy, or apprehension about being constantly monitored and graded by machine-based surveillance and measurement. Administratively, resistance may be caused by institutional inertia or apprehension of the cost in terms of finance, infrastructure, and human resources for adopting AI-powered LMS platforms. HEI may be reluctant to spend money on technology that demands enormous upfront investment and long-term maintenance in exchange for indefinite short-term benefits.

VI. Conclusion

This research explores the potential of personalizing existing Learning Management Systems to cater to different learning styles. A pilot test was conducted to identify the potential of integrating learning styles with appropriate materials. The findings from the pilot test satisfy the research objectives and questions, and the achievement of all three objectives is discussed. Future research related to customized LMS is also proposed.

The benefits identified through the use of customized LMS will enable students to have a better learning experience, improving their academic performance. The contributions of this research are significant to Information and Communication Technology (ICT) especially in the education sector. The theoretical contribution of the research relates to the experimental approach and data analysis, which states that for certain a group of students with its specific learning style are required to be presented with appropriate learning materials in order to improve the students’ learning experience. The practical contributions are the personalized LMS model developed. There are many personalized LMS models for either educational use or industry uses as a form of knowledge dissemination. Even though there are many personalized LMS models being introduced but there are mostly developed without taking students’ learning style and the appropriateness of learning material as considerations. The integration of automatic detection and presenting suitable learning materials based on students learning style are the main differences compared to a generic personalized LMS model. In short, the proposed to automatic detection and presentation of suitable learning materials based on students learning style are to solve the problems identified in the current usage of LMS in education especially for HEI.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

E. H. Lim is the lead researcher and involved in data analysis, whereas K. H. Cheang assisted in data gathering, and T. Y. Chai as well as Manoranjitham assisted in experimental related matters. T. F. Yong contributed to the manuscript writing, while H. M. Kok assisted in the literature review and overall editing of the paper. All authors had approved the final version.

Acknowledgment

The authors would like to express their sincere gratitude to

UTAR for providing the necessary resources and facilities to conduct this research. Special thanks to all the students who are involved. We are also deeply thankful to all the experts for their constructive feedback, which significantly improved the quality of this manuscript.

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