Adaptive M-Learning Content on the Moodle Platform Using M-Learner Modeling Approach, Ontologies, and Machine Learning Techniques

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Adaptive M-Learning Content on the Moodle Platform Using M-Learner Modelling Approach, Ontologies, and Machine Learning Techniques

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Abstract

Background/purpose. Mobile learning (M-learning) has become a crucial component of higher education due to the increasing demand for flexible and adaptive learning environments. However, ensuring personalized and effective M-learning experiences remains a challenge. This study aims to enhance M-learning effectiveness by introducing an AI-driven Moodle plugin that personalizes learning experiences using a learner-modelling approach.

Materials/methods. The proposed model leverages data from Ibn Tofail University's Moodle platform and integrates DBSCAN and K-means clustering techniques to classify learners based on behavioural, contextual, and emotional factors. The generated clusters enable the delivery of personalized content structured within a Moodle course ontology, optimizing engagement and learning outcomes.

Results. Experimental results on the "Algorithmics and Programming in Python" course show that DBSCAN achieves better clustering accuracy than K-means, as evidenced by cohesion, separation, and silhouette scores. Additionally, an analysis of mobile device characteristics highlights the importance of screen size and RAM capacity in optimizing M-learning experiences.

Conclusion. This study demonstrates the significance of learner modelling and technological adaptation in fostering effective mobile learning environments. By integrating clustering algorithms and ontologies, the proposed approach contributes to the development of intelligent, personalized M-learning applications that enhance accessibility and educational performance.

1. Introduction

Mobile learning is gaining popularity in higher education institutions. The popularity of this educational technology continues to increase due to the restrictions imposed by the COVID-19 pandemic in 2020 (Qazi et al., 2024). However, to provide M-learners with appropriate learning content in such a mobile environment, this study aims to improve distance learning by introducing a new AI-based Moodle plugin designed to support M-learning. By integrating this plugin into the platform, we aim to enhance the engagement and performance of m-learners through adapted pedagogical content. This content is adapted to the learner model and structured according to a Moodle course ontology structure.

Toward this goal, we propose using machine learning algorithms to build a personalized learning environment for M-learners. By leveraging clustering techniques such as DBSCAN and K-means, the system classifies learners according to various factors, including their behaviour, learning style, and emotional state. The clustering of M-learners enables the platform to deliver adaptive content specific to the evolving needs of each learner group (Hwang et al., 2021). Furthermore, the integration of an ontology-based structure improves the accuracy and relevance of recommendations, enabling a more adaptive and dynamic learning experience. The main contributions of this research are as follows:

- Constructing the M-learning dataset: This dataset serves as a repository of learning data extracted from Moodle logs and smartphone attributes. It is structured according to six types of features: profile variables, behavioural variables, context variables, learning style variables, emotional variables, and final performance variables. It is the primary input for our machine learning model and ontology structure.
- Developing machine learning models with DBSCAN and K-means algorithms to group M-learners based on data from a learner modeling approach.
- Deployment of the machine learning models on the E-learning platform: In this phase, we integrated the proposed model into the Moodle platform to enhance adaptive M-learning through ontology-based content recommendations.

Our study contributes to filling a gap in literature by combining machine learning and ontologies to improve the personalization of mobile learning in Moodle. Compared to previous studies, which consider these aspects separately, our approach integrates learner modelling, device context and adaptive content delivery. It is designed to meet significant challenges, such as learner complexity and device variability, by proposing pragmatic and scalable solutions. The results provide both theoretical insights and practical advice for future research and educational technology design.

This paper is structured in several parts to guide the researcher through our approach to developing an adaptive e-learning system on the Moodle platform. The literature review presents the relevant concepts and background information that form the basis of the study. The following part, titled Key Concepts, includes an overview of the Moodle Learning Management System (LMS), its content architecture and the Moodle Mobile application. Moreover, it provides a detailed explanation of important components such as the DBSCAN and K-means clustering algorithms and the role of ontologies in enhancing the adaptive learning system. The section explores how these key concepts are integrated to personalize content for M-learners according to their interactions and performance. This theoretical foundation sets the stage for methodology, where the research design, data collection procedures, learner modeling strategy, and system architecture are presented in detail. The article then moves on to the presentation of the results and a discussion of the findings, focusing particularly on the performance of the clustering algorithms and the analysis of learner performance on the platform before and after adaptation based on the learner model. The article concludes with a discussion of prospects.

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2. Literature review

Mobile learning (M-learning) is developed on the basis of research into intelligent tutoring systems (ITS), E-learning, adaptive learning and Computer-Assisted Learning (CAL) (Jugo et al., 2016). A notable part of the literature has been devoted to predicting learner outcomes based on their behaviour in online courses. Various machine learning and deep learning methods, including classification algorithms and trained neural networks, have been employed in this context. In this section, we present some research that is relevant to our work in the field of M-learning and the utilization of machine learning and deep learning techniques to enhance M-learner's performance.

The study (Adnan et al., 2019) showed the importance of personalizing programming exercises for learners, especially in the challenging field of computer programming. The proposed cloud-supported machine learning system (CSMLS) leverages contextual data from learners' mobile devices to provide personalized learning paths. By suggesting real-world programming challenges based on learners' performance, CSMLS aims to improve mobile learning performance and engagement in computer programming education (Farahah Abdul Halim & Nincarean Eh Phon, 2020). For the prediction of student performance, Rajalakshmi T (Rajalakshmi T, Kaleeswari S, Dr Jai Ruby, Mrs E. Julie Ruth, 2022) used the decision tree, Bayesian classification, and closest neighbour, among other methods. While these techniques primarily focus on traditional educational data, it is important to consider their applicability in the context of mobile learning. Mobile devices have become integral to modern education, and understanding how data mining methods can enhance learner performance in a mobile learning environment is of increasing importance (Sung et al., 2016).

A decisive factor in the effectiveness of the M-learning system is the learner's performance with the features that influence the system (Sophonhiranrak, 2021). It is, therefore, vital to identify and understand the variables that influence optimal student performance. In this study (Sultan et al., 2022), a Fast Learning Network (FLN) model is used to investigate these factors and their relationship to student satisfaction thoroughly. The model comprises six key independent variables, including teacher attitude, e-learning flexibility, virtual engagement, Wi-Fi network quality, diversity of assessment methods and quality of technological resources provided. Its aim is to predict learner satisfaction and, ultimately, improve the quality of mobile learning experiences.

In different learning scenarios, mobile devices can be a source of data concerning learner behaviour in an E-learning platform (Yilmaz, 2016). Using this data, we can identify the attributes that influence learner performance when using smartphones. A study conducted by Adnan and M. (Adnan, Habib, Ashraf, Mussadiq, et al., 2020; Adnan, Habib, Ashraf, Shah, et al., 2020) delineated the learning features of mobile learning, which are categorized into different groups, encompassing aspects such as learning content, learning context, social interaction, target learning objectives, the number of revisions for target objectives, the number of clicks, login frequency, and learner performance.

The literature shows that all user features are equally important in determining their behaviour (Kahraman et al., 2013). Stated differently, learner modelling assigns the same weight to each attribute in the user modelling process. The misclassification of learners in a user-modeling approach is due to neglecting the connection between features and their weights, by which we define the most useful features for our machine learning models (Ghasemieh et al., 2023). Machine learning algorithms, such as artificial neural networks (ANNs) with hidden layers, could determine the importance of features and their corresponding weights when classifying users into different groups (Chen et al., 2020). The process of assigning weights to each feature is known as the weight-tuning approach (Adnan, Habib, Ashraf, Mussadiq, et al., 2020). This approach improves the accuracy of user/learner modelling in prediction and classification scores.

Analyzing current methods and results in mobile learning and machine-learning-based learner modelling provides the theoretical framework for our research. We developed supplementary concepts to support the implementation of an adaptive mobile learning system that adapts M-learning content based on the M-learner's actions, achievements and other relevant contextual information.

3. Key concepts

3.1. Moodle LMS

3.1.1. Content Architecture

Moodle, an acronym for "Modular Object-Oriented Dynamic Learning Environment", is an open-source learning management system (LMS) used by over 50,000 institutions worldwide to deliver course content, assignments, and exams and to complement face-to-face learning (Al-Kindi & Al-Khanjari, 2021; Uzun et al., 2024). In this study, learners' traces on the Ibn Tofail University Moodle platform constitute the main data source. Using learning traces on the Moodle platform requires an understanding of data structure and storage. Moodle uses both relational (MySQL) and non-relational (MongoDB) database management systems. Moodle uses database tables to log learner interactions with Moodle resources and activities. Data retrieved from Moodle includes course content, interactions, and learner contextual information.

As Moodle course content data is stored in a relational database such as MySQL, the course organization in Moodle is based on a top-down tree structure. A Moodle course comprises sections, each containing resources, activities, and blocks (Grigoryeva et al., 2021). The logical hierarchy of a section is illustrated in Figure 1.

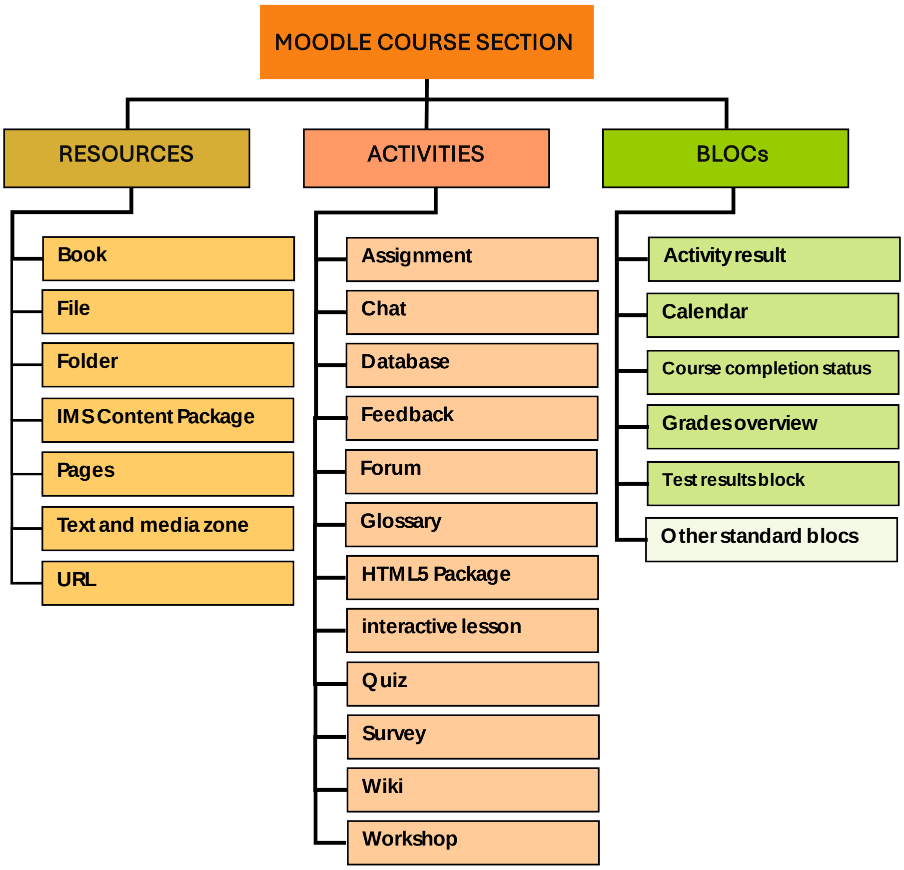

Figure 1. Moodle section components

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Sections, the main elements of the Moodle course, can be organized by themes or periods, such as "Introduction" or "Week 1", and may contain sub-sections for more detailed topics, such as "Reading 1" or "Activity 1". Activities inside these sections or subsections, including quizzes, assignments, and discussions, etc. serve as basic interactive elements where learners interact with the course material. In parallel, resources are used to place learning resources such as web pages, videos, and PDF files, while blocks offer functionality and information with elements such as calendars and overviews of course progress.

3.1.2. Moodle Mobile

Moodle Mobile is the official Moodle platform application, available on the Windows App Store, Google Play, and Apple App Store. This application allows users to connect to the platform from various devices, such as smartphones, tablets, and iPads (Malinchi et al., 2017). Moodle Mobile, as shown in Figure 2, offers the same functionality as the web application, providing easy access to courses, resources, quizzes, etc.

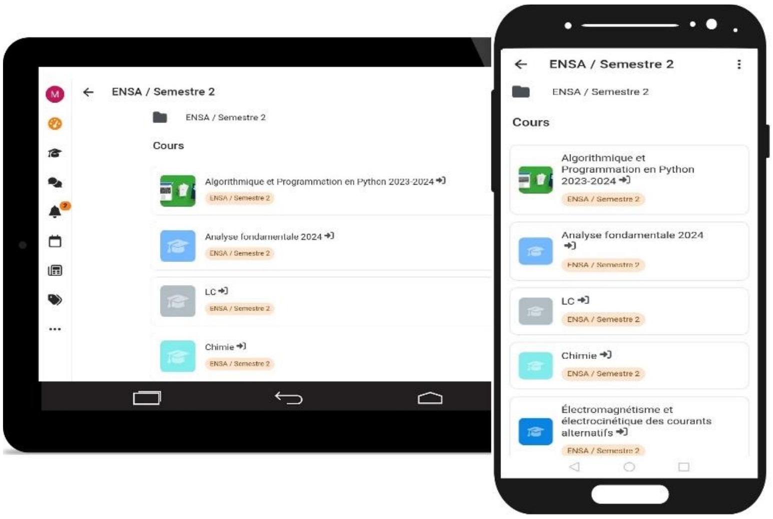

Figure 2. Moodle Mobile Interface

Learners enter the URL of the Moodle platform they wish to access, then log in using their username and password or another authentication method, such as OAuth, to use the Moodle Mobile application. After logging in, they see a catalog of courses from which they can enroll, or access courses in which they are already enrolled. Moodle log analysis shows that the use of Moodle Mobile improves accessibility and engagement with the LMS on mobile devices. Students mainly use the course view functions to access content, while teachers use them to monitor student attendance (Wibawa et al., 2020).

3.2. DBSCAN and K-Means Algorithms

3.2.1. DBSCAN

As a clustering algorithm, DBSCAN (Density-Based Spatial Clustering of Applications with Noise) allows clustering without requiring a predefined number of clusters. It simply identifies dense regions of data points and groups them in the same cluster. DBSCAN initially selects a point that is not selected and checks whether it has a minimum number of neighbors within a specified radius (Zaki Abdulhameed et al., 2024). The point is added to a new cluster if it meets this minimum distance; if not, it is considered noise or a boundary point. Next, the algorithm extends the cluster by checking the neighbours of each newly added point, adding those with a sufficient number of neighbours. This process continues until all dense regions have been clustered and all noise or boundary points have

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been identified. DBSCAN is particularly appropriate for clustering both noisy data and outliers (Chakraborty et al., 2014).

Comparing DBSCAN to other machine learning algorithms used to predict learner performance, each algorithm has its strengths and limitations. Decision trees may be simple to interpret, but they can cause problems with large data sets (Çetinkaya & Horasan, 2021). Support vector machines (SVMs) effectively deal with high-dimensional data and noise (Gaye et al., 2021). By contrast, DBSCAN performs best at identifying clusters in data of varying density and noise, which is particularly useful in E-Learning environments (Trivedi & Patel, 2020). Its capacity to handle clusters of various sizes enables it to detect patterns and group learners according to their performance. Nevertheless, it is important to consider that DBSCAN's performance can be sensitive to the choice of parameters, which can impact its effectiveness with very large datasets.

Our research highlights the use of the DBSCAN algorithm to develop machine learning models to group M-learners based on their interactions and provide them with personalized content to improve their performance. Considering issues such as high dimensionality and variable data density, we aim to improve the capacity of the DBSCAN algorithm to cluster M-learners efficiently and then propose personalized content for each M-learner. By carefully extracting and preprocessing data from the Moodle platform, we enhance the efficiency of DBSCAN, ensuring more accurate and relevant clustering results.

3.2.2. K-means

Clustering is an unsupervised learning method for finding patterns in data, particularly by grouping elements that are similar to each other. Machine learning algorithms using this learning method do not attempt to learn a correlation relationship between a set of observational features X and a value to be predicted Y, as is the case with supervised learning (Daoudi et al., 2022). One of the best-known clustering algorithms is the k-means algorithm (Rodriguez et al., 2019). This is an analytical technique that identifies groups of objects based on their proximity to the center of k groups (map). The center is determined as the arithmetic mean of each group's n-dimensional attribute vector (reduce). The main constraint of this technique is the identification of an optimal number of groups.

The main idea is to choose a set of fixed centers and search iteratively for the optimal cluster. Each object is assigned to the nearest center. After all data has been assigned, the average for each group is calculated; it constitutes the new representatives of the groups. When a stable status has been reached (no data changes group), the algorithm is stopped.

3.3. Ontology

Ontologies represent an important component of the Semantic Web (Khadir et al., 2021). According to Thomas R. Gruber, an ontology is defined as “a specification mechanism” (Gruber, 1995). Originating as a philosophical term meaning a systematic account of existence, it acquires a specific meaning in the fields of computer science and information science. In these contexts, ontology is seen as a set of primitive representations used to model a domain of knowledge. It formalizes the representation of knowledge, standardizes vocabulary, describes the reasoning applied to this knowledge and facilitates the sharing and further use of knowledge between different systems (Gruber, n.d.).

As a knowledge representation language, ontologies include different elements (Khadir et al., 2021):

- Classes, which symbolize the concepts used to describe objects and relationships in a particular domain.

- Instances (or individuals), which represent the objects populating the ontology, with attributes defining the properties of objects or classes.
- Relations, which express associations between the domain's concepts.
- Formal axioms, often used to represent knowledge that other components cannot formally define, model statements that are always true.

In our research, we develop an ontological structure for a Moodle course to understand and illustrate the underlying structures of Moodle courses, as well as the interactions between the different classes of this ontological structure. Using an ontological structure provides a clear and organized representation of the various components of a Moodle course, such as pedagogical resources, learning activities, and assessments. By providing an overview of the relationships and dependencies between course components, this modelling facilitates the analysis and optimization of learning paths. Furthermore, our ontology can be used to improve the personalization and adaptability of content to specific M-learner profiles and requirements, making the M-learning environment more reactive.

The ontological structure will be used to propose customized content to an M-learner model. This M-learner model is created from a set of learners with similar characteristics generated by unsupervised machine learning algorithms (DBSCAN and K-means). The continuous generation and updating of an M-learner model enable us to customize pedagogical content to meet the specific needs of each group, optimizing learning efficiency and relevance.

3.4. Merging key concepts

This study integrates some key concepts to develop an adaptive M-learning system on the Moodle platform. Moodle LMS provides the fundamental platform for organizing and delivering M-content, where Moodle Mobile extends this functionality to various devices, improving accessibility. Machine learning algorithms, in particular DBSCAN and K-means, analyze learner interactions and performance data to predict M-learner performance and identify at-risk M-learner. K-Means clustering groups M-learners based on similar characteristics, creating detailed M-learner models that can be used to deliver personalized M-content tailored to the needs of each group.

An ontological structure completes this approach, providing a clear representation of the components of a Moodle course, such as resources, activities and assessments. It highlights the relationships and dependencies between these components, facilitating the analysis and optimization of M-learning paths. By merging ontologies with learner-generated machine learning models, we can offer personalized content that adapts to changing M-learner needs and preferences, improving the efficiency and relevance of the M-learning experience. Figure 4 illustrates the use and combination of these concepts.

4. Methodology

4.1. Dataset building

In this study, we explore a dataset based on traces extracted from Ibn Tofail University's Moodle platform. The dataset includes various features (see Table 1) categorized into profile, behavioural, contextual, learning styles, emotional, and performance aspects.

Profile features include essential identifiers and personal preferences that customize the learning platform to individual needs. These features range from `User_id`, a unique identifier for each user, to `Technology_Skills_Competency`, which assesses a user's technology skills at different levels, from beginner to expert. `Qualification` details the learner's academic or professional qualifications, which is essential to align the course content with the learner's educational level. In addition, `Language_Preference` facilitates language-dependent customization of the Moodle interface, improving accessibility and user engagement.

Behavioural features provide information on learner activities within the platform, including measurements such as `Nbr_action`, which counts the total number of user interactions, and `days_with_actions`, which highlights engagement over time. These behaviours, combined with `Duration_First_last_connection`, which tracks the interval between the user's first and last connections, offer valuable data on learner engagement and interaction models in courses. Contextual features relate to the learners' technical environment, noting their device types and specifications such as `Device_name`, `Device_model`, and `Screen_Size`. This information is important for optimizing the delivery of m-learning content on different types of devices.

Performance features provide results of a learner and include `Final_Grade` and `Avg_score_finished_quiz`, which provide a quantitative assessment of the learner's achievement and comprehension. However, learning style and emotional characteristics explore the psychological and cognitive dimensions of learning: `Social_Style` and `Sensory_Preferences` help to personalize learning paths according to social and sensory preferences, while `Sentiment_Analysis` and `Stress_Level` assess emotional engagement and stress, enabling interventions that support emotional well-being and effective learning.

This dataset offers precious information on the interactions, behaviors, and performance of learners in the Moodle platform providing a solid basis for the implementation of machine learning techniques to improve M-learners performance on the Moodle platform.

Table 1. Dataset Features

Features' categories	Features	Description
Profile features	User_id	A unique identifier is assigned to each user.
	Technology_Skills_Competency	Assess the learner's comfort and capability with technology using these values: Beginner, Intermediate, Advanced, Expert.
	Qualification	Indicates the learner's level of education or certification. Possible values are bachelor's degree, engineering degree, doctorate, university technology diploma, technician, professional certifications, and no formal qualification.
	Language_Preference	The learner can choose their preferred language for the platform interface, such as English, Arabic, French, etc.
Behavioural features	Nbr_action	The count of actions performed by the user.
	days_with_actions	The number of days on which the user performed actions.
	Duration_First_last_connection	The time duration in days between the user's first and last connection.
	Nbr_resource_viewed	The count of viewed resources.

	Problem_posted_count	The count of forum discussions created by the user.
	nbr_assign_submission	The count of assignment submissions.
Context features	Device_name	Name of the user's device, defaulting to "Desktop" if not available.
	Device_model	Model of the user's device, defaulting to "Desktop" if not available.
	RAM_Capacity	Device's Random-Access memory (RAM) capacity.
	Screen_Size	The screen size of the user's device ranges from 4.0 to 6.8 inches or '21 to 27' if not specified.
	Location	The location of a mobile device connection, whether in or out of class, is defined based on the IP address.
Performance features	Unfinished_Quiz	The count of unfinished quizzes.
	Final_Grade	Final grade for the course.
	Avg_score_finished_quiz	Average score for completed quiz.
Learning styles features	Social_Style	Options include Solitary (learns best alone), Group (prefers collaborative environments), and No Preference (comfortable in any setting).
	Sensory_Preferences	Categories include Visual (prefers visual aids), Aural (learning best through listening), and Physical (kinesthetic learner, enjoys hands-on activities).
Emotional features	Sentiment_Analysis	Analyzes textual communications to classify emotions as either *Positive or Negative*.
	Stress_Level	It can be measured using a self-report survey tool where students categorize their stress as Low, Moderate, or High.

4.2. Learner modelling approach

It is important to make a clear distinction between the model and the learner profile. A learner's profile is a collection of information about a learner, generally collected by registration or survey at the start of their learning process (DAOUDI et al., 2020). The learner model, by contrast, represents the system's perception of the learner. This extends the profile's static details to the system's dynamic information collected and processed. It considers the learner's context, learning style, personal information and skills, performance within the system, level of involvement and emotional state (Figure 3). The learner model is continually updated based on the learner's interactions with the system (Sheeba & Krishnan, 2019).

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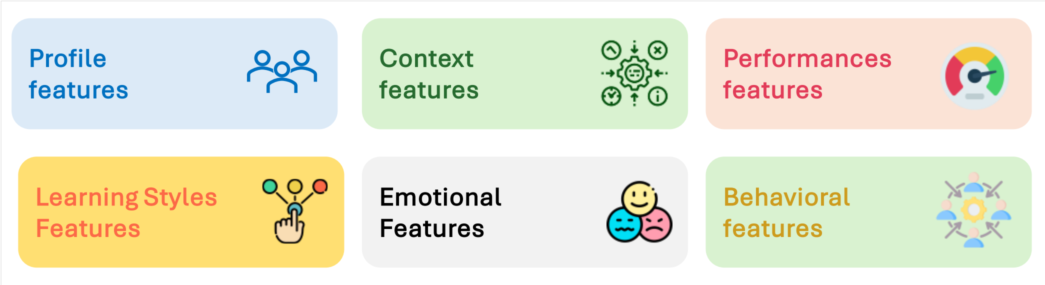

Figure 3. Learner Model Features

4.3. M-Learning system architecture

In this study, we propose a methodology for developing an adaptive m-learning system, using mainly data from the Moodle platform. The initial phase involves collecting learner traces, including Moodle log files and database records, responses to customized questionnaires, and the investigation of the characteristics of mobile devices used by learners. This initial data collection is essential for assessing learner engagement and mobile device preferences (Figure 4)..

After the data collection step, we begin data pre-processing. This step is comprehensive and includes data cleaning, encoding, feature selection, and normalization, all preceded by a rigorous data anonymization process using "Data Masking" as a main technique. This technique is used to mask the personal identifiers of learners and teachers, replacing them with numerical codes to prevent the unique identification of individuals, respecting data confidentiality and ethical standards.

Next, the use of PCA in clustering reduces the dimensionality of the data, improving the efficiency and accuracy of clustering algorithms by focusing on the most significant features. The use of unsupervised learning algorithms provides homogeneous clusters, which form the basis for the generation or refinement of the learner model. These learner models, integrated with an ontological structure for Moodle courses, provide adaptive and personalized m-learning content based on the learner's profile, context, skills, style, emotion, and preferences. This personalized approach should improve the m-learning experience considerably.

Finally, learner feedback feeds into continuous learner model updates, ensuring that m-learning content remains aligned with evolving learner requirements and feedback. This iterative process illustrates the dynamic adaptation at the core of the proposed system and encapsulates the principles of a personalized, responsive m-learning environment. Using this methodology, we aim to advance the field of personalized learning with a focus on accessibility, engagement, and effectiveness.

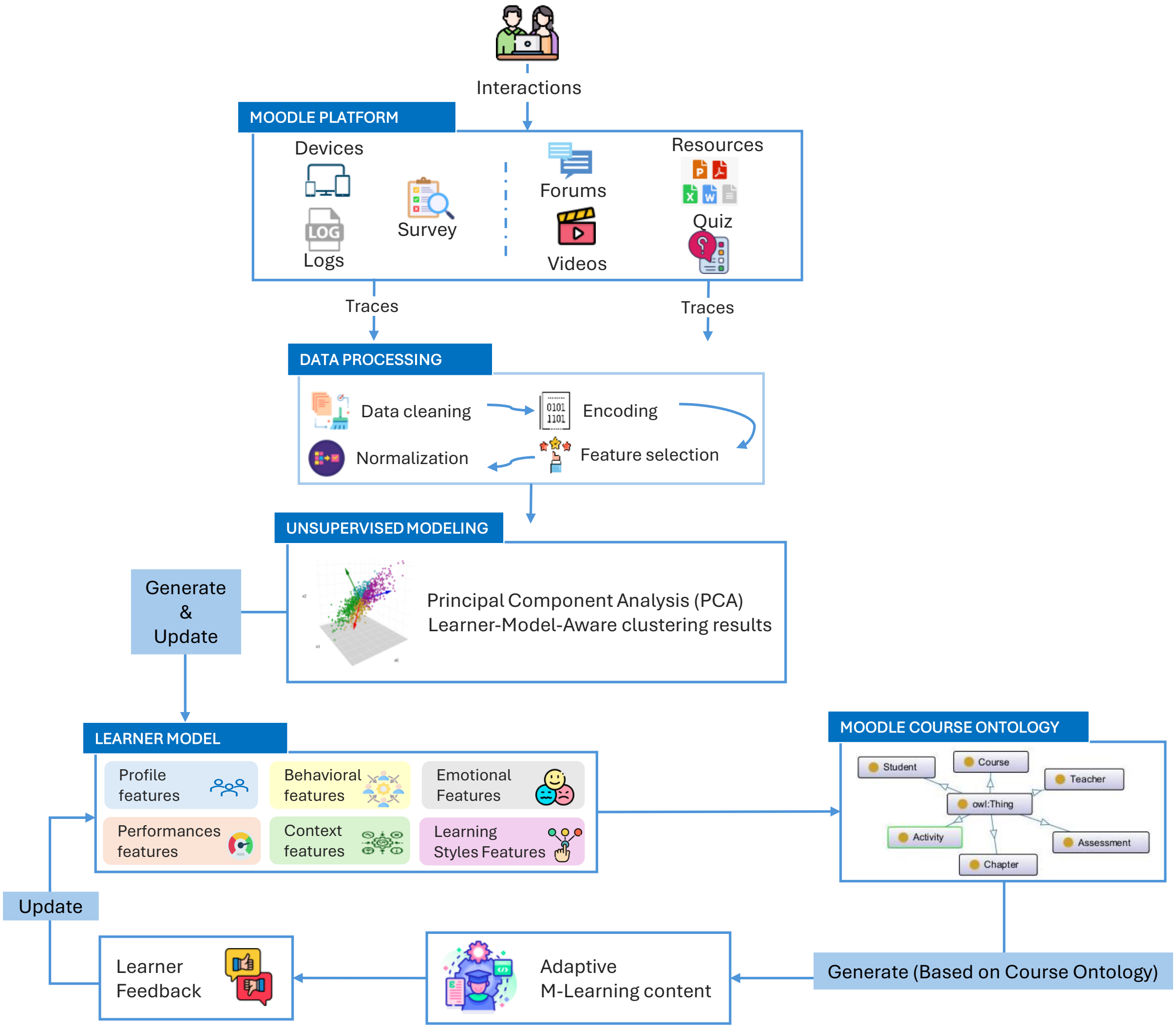

Figure 4. Proposed M-learning System Architecture

4.4. Data preprocessing

Data preprocessing is an essential phase in preparing datasets for machine learning models. Raw data usually contain outliers, missing values, or inadequate format, which can make them unsuitable for direct use. In the present research, the collected data on the Moodle platform passed through a rigorous preprocessing phase to ensure its quality and suitability for the development of efficient machine learning models.

4.4.1. Data Imputation and Normalization

To address missing values in the dataset, we employed median imputation, replacing missing data points with the median value of the feature concerned. This method minimizes the impact of extreme values and ensures that the dataset remains representative and reliable for post-data analysis. After imputation, we checked for missing values to confirm that the dataset was complete.

Then, we standardized the numerical features using Scikit-learn's StandardScaler, which centers the data around the mean and scales it to a standard deviation of 1. This normalization step ensures that no single feature disproportionately influences the machine learning models. StandardScaler was selected due to its suitability for features with a normal distribution, aligning with the assumptions of several machine learning algorithms. The scaling was applied post-outlier removal to ensure that the data was clean and evenly scaled.

4.4.2. Detecting and Eliminating Outliers

Outliers were identified and removed using the Isolation Forest algorithm, configured with a contamination rate of 5%. This technique isolates anomalies by constructing decision trees, effectively identifying and removing outliers from the dataset. The outliers were filtered out, enhancing the quality of the data for modelling. A boxplot visualization of remaining outliers was produced to illustrate the effectiveness of the outlier detection and removal process (Figure 5).

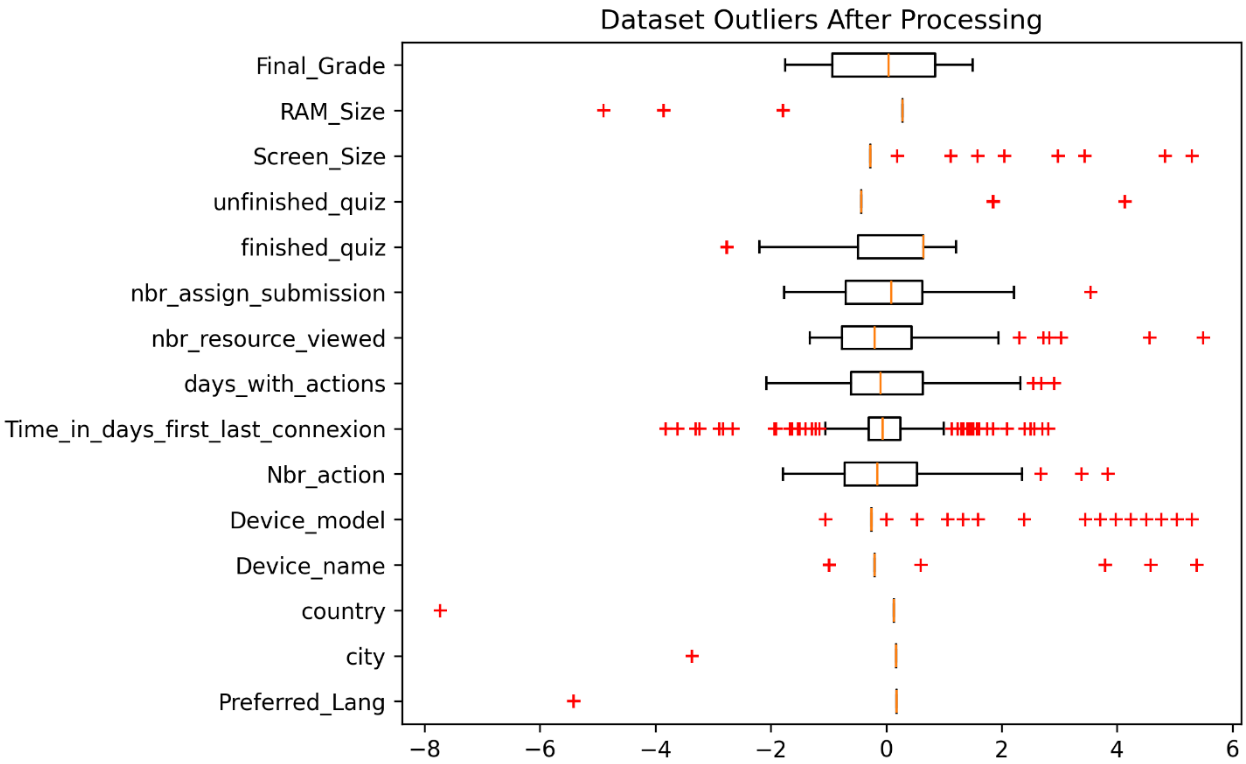

Figure 5. Dataset Outliers After Processing

4.4.3. Dimensionality Reduction and Correlation Matrix

Dimensionality reduction was performed using Principal Component Analysis (PCA) to project the data into two principal components, facilitating visualization and analysis. Additionally, a correlation matrix was computed to assess the relationships between different features. This matrix revealed both positive and negative correlations among learner characteristics on the Moodle platform, providing valuable insights into learner interactions and performance dynamics.

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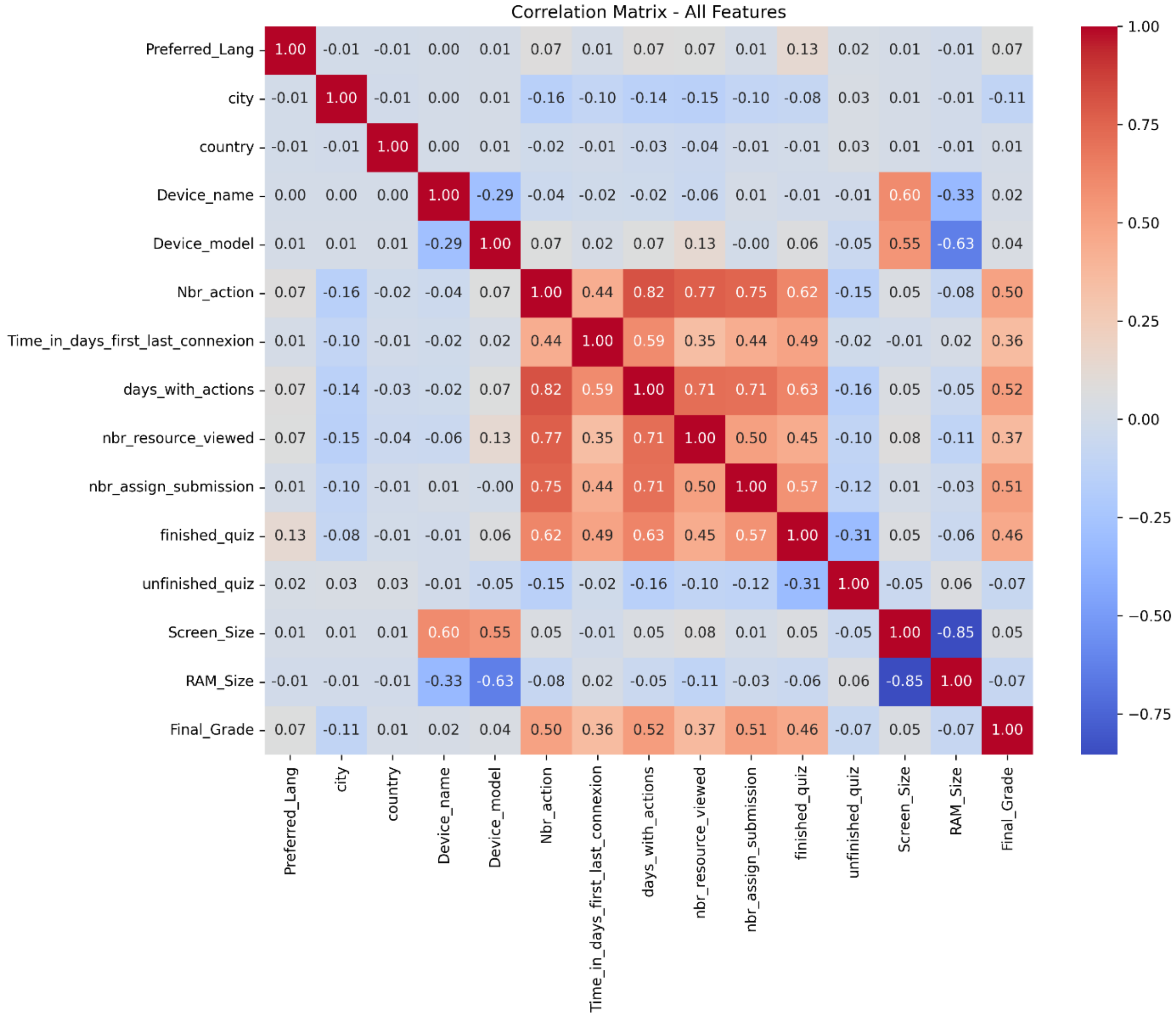

Figure 6. Correlations between features across datasets

As shown in Figure 6, correlation analysis indicates that device characteristics and engagement metrics exhibit variable relationships with learner performance. 'Screen_Size' shows a moderate correlation with engagement measures but only a low correlation with 'Final_Grade', suggesting a limited impact on learner performance. Conversely, RAM_Size' has a slight correlation with performance indicators, indicating it is less influential.

Engagement metrics such as 'Nbr_action', 'days_with_actions', and 'nbr_resource_viewed' demonstrate strong positive correlations with each other and with 'Final_Grade'. This suggests that higher levels of engagement and interaction with course resources are associated with better academic results. Additionally, nbr_assign_submission' and 'finished_quiz' have moderate correlations with 'Final_Grade', reinforcing the role of assignment completion and quiz participation in influencing performance. Overall, the analysis highlights that while device characteristics have some influence, engagement parameters play a more significant role in determining academic performance.

4.5. Ontology Modeling Approach

The ontology presented in figure 7 is designed to model adaptive m-learning systems, leveraging Semantic Web technologies to enhance personalized educational content. At its core, the ontology delineates various classes and properties to represent distinct aspects of the m-learning environment. Key classes include 'M_Learner_Model', which serves as a superclass for various learner attributes such as 'Behavioral', 'Emotional', 'Context', 'Profile', and 'Performance'. These

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subclasses capture detailed learner profiles and interactions, allowing for a nuanced understanding of individual learning behaviours and preferences. For instance, the 'Behavioral' class encompasses user activity and engagement properties, such as 'hasDaysWithActions' and 'hasNbrAction', which are crucial for analyzing learner behaviour over time. Similarly, the 'Context' class includes properties like 'hasDeviceModel' and 'hasScreenSize' to represent the technological environment in which learning occurs.

Figure 7. Ontology overview

On the data side, the ontology utilizes 'DatatypeProperty' to define characteristics like 'hasFinalGrade', 'hasLanguagePreference', and 'hasQualification', which pertain to the learner's performance and profile. Object properties such as 'isBasedOn' and 'isPartOfSectionOrSubSection' establish relationships between various components of the learning system, linking assessments to learner models and personalized content to sections or subsections of educational materials. This structured approach facilitates the creation of a highly adaptable learning environment, where educational content can be tailored based on a comprehensive understanding of the learner's profile, behavior, and context. By integrating these elements, the ontology aims to support the development of sophisticated m-learning systems that offer personalized and context-aware learning experiences.

5. Results

The objective of this study is to develop an adaptive M-Learning model based on the DBSCAN and K-means clustering approaches, combined with ontologies, to personalize course content on the Moodle platform. This research is being conducted at the Ibn Tofail University in Kénitra, Morocco, using a Moodle platform that is hosting all the MOOC and SPOC courses from the university's different faculties and schools. The results, both from the experiments conducted and performance analyses, provide important information that will be discussed in the following sections.

We selected the course 'Algorithmics and Programming in Python,' offered in the second semester (February to May) of 2024 for students at the National School of Applied Sciences, Ibn Tofail University. This course provided a valuable dataset due to its timing and the level of learner engagement, capturing a wide range of interactions on the Moodle platform. The choice of this specific course is instrumental in analyzing learner behaviour and improving our clustering model. In

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accordance with ethical and confidentiality standards, we obtained the Moodle platform administrator's approval and anonymized learners' personal information. We collected data on M learners' interactions with the platform, ensuring that all extracted characteristics are subject to a thorough pre-processing process. The first step in this process was the anonymization of M-learner data, which was in line with ethical guidelines, confidentiality requirements, and Moroccan legislation. We used "data masking" as the main technique, replacing learners' names with numerical codes that prevent the unique identification of individuals.

5.1. Characteristics of Mobile Devices

By analyzing the characteristics of Mobile/Desktop devices used on the Moodle platform, we can reveal several significant trends that can inform the design and adaptation of e-learning content. Our dataset reflects the predominant use of desktop computers, which make up most devices accessed. This high prevalence of desktops suggests that learners primarily engage with educational content in a more traditional computing environment, probably due to their larger screens and more powerful hardware capabilities (see Table 2).

Table 2. Specifications of devices used by learners

Device_name	Screen_Sizes	RAM_Sizes	Quantity
Desktop	21 to 27	8	128
ITEL	6.6	2	1
LENOVO	10.1	4	1
UMIDIGI	6.52	4	1
OPPO	6.53	4	1
Xiaomi	6.53, 6.67	4, 8	5
samsung	6.2, 6.4, 6.5, 6.7	2, 4, 6, 8	4
realme	6.5	4	1
HUAWEI	6.21	3	1
Apple	5.4, 5.5, 6.1, 6.7	3, 4, 6	9
HONOR	6.57	8	1

For mobile devices, there is a clear preference for larger screens, with a concentration between 6.1 and 6.7 inches. This trend is particularly important for adaptive M-learning systems, as larger screens facilitate a more immersive and interactive learning experience, potentially improving user engagement and M-content accessibility. The data reveals that mobile devices with screen sizes between 6.1 and 6.7 inches are the most frequently used, indicating that adaptive content should be designed to take advantage of these screen dimensions to optimize readability and interaction.

Regarding RAM, most mobile devices used by learners are equipped with 4 to 6 GB. This suggests that most users have devices capable of handling typical educational applications and adaptive content without significant performance problems. However, it's worth noting that only a small subset of users - particularly two people - are using smartphones with just 2 GB of RAM. This limited memory can impact the ability to interact effectively with more complex or resource-intensive content. Consequently, adaptive m-learning strategies should make provisions for users with lower RAM, for example by simplifying or minimizing content to ensure smooth performance across all devices.

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In summary, the data highlights the necessity for adaptive learning systems on Moodle to accommodate a wide range of device specifications, with a particular focus on optimizing M-content for varying screen sizes and memory capacities. By addressing these device characteristics, educational platforms can enhance the effectiveness of their M-learning content, ensuring a more equitable and accessible learning experience for all users.

5.2. Clustering Algorithm Performance

The performance of the DBSCAN and K-Means clustering algorithms was assessed using learners' traces and grades to evaluate accuracy in identifying distinct learner models. The analysis involved comparing key metrics such as intra-group cohesion, inter-group separation, Silhouette score, and Davies-Bouldin index, which are important for evaluating the quality of the groups constructed by the algorithms. The results, summarized in Table 3, give an overview of both algorithms' performance and illustrate the relative differences between the DBSCAN and K-Means algorithms in our context.

Table 3. Comparative Analysis of K-Means and DBSCAN Clustering Metrics

Metric	K-Means	DBSCAN
Intra-cluster Cohesion	21.178037849053528	5.679904245101294
Inter-cluster Separation	2.4330743412254345	3.350782874043187
Silhouette Score	0.7945424118210258	0.8998884002974906
Davies-Bouldin Index	0.31917218611687753	0.13958414450564263

The clustering results clearly show that DBSCAN is more accurate than K-Means in clustering our dataset. As illustrated in Table 3, DBSCAN achieved an intra-cluster cohesion of 5.68, considerably lower than the 21.18 achieved by K-Means. This low value indicates that the points within each DBSCAN cluster are much closer to each other. Furthermore, DBSCAN's inter-cluster separation is 3.35, higher than that of K-Means (2.43), suggesting that the clusters identified by DBSCAN are more distinct and better separated from each other.

Based on evaluation metrics, the Silhouette score for DBSCAN is 0.90, compared with 0.79 for K-Means. This higher score for DBSCAN indicates that the algorithm produces more cohesive and better-defined clusters. Moreover, the Davies-Bouldin index for DBSCAN is 0.14, compared with 0.32 for K-Means. A lower Davies-Bouldin index indicates better clustering performance, as it reflects more compact clusters with better separation between them. Overall, these metrics clearly indicate that DBSCAN performs more efficiently than K-Means in our clustering context.

As indicated above, DBSCAN clearly achieved better results than K-Means for our learner dataset from the "Algorithmics and Programming in Python" course designed for first-year students at the National School of Applied Sciences, Ibn Tofail University. DBSCAN enabled the creation of more compact and distinct clusters. The next step involved examining the characteristics common to each cluster to identify patterns and propose mobile content adapted to M-learners and adaptive content for desktop learners.

5.3. In-Depth Analysis of DBSCAN Clusters

Our correlation analysis between key variables and DBSCAN clusters shows that 'Screen_Size' has the strongest positive correlation with clusters, at 0.124 (see Table 4). This suggests that learners using devices with larger screens tend to cluster together in specific groups. Although this is the most notable correlation, its relatively low value indicates that device characteristics, such as screen size,

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play a minor role in the formation of clusters. Similarly, 'Final_Grade' displays a very weak positive correlation (0.0386), implying that academic performance has a minimal effect on how learners are grouped.

Furthermore, 'Nbr_action' and 'RAM_Size' both exhibit slight negative correlations with clustering, at -0.0339 and -0.0337, respectively. This suggests that learners with fewer interactions or devices with lower RAM capacities are more likely to be grouped in certain clusters. 'Unfinished_quiz' also shows a weak negative correlation (-0.0507), indicating a slight tendency for learners who leave quizzes incomplete to be grouped together. These results imply that other behavioural or contextual factors may exert a greater influence on cluster formation.

Table 4. Significant correlations with clusters

Variable	Correlation with Clusters
Screen_Size	0.124587
Final_Grade	0.038616
Nbr_action	-0.033994
RAM_Size	-0.033731

The correlation between engagement and performance in Cluster 1 is -0.27, indicating a low negative relationship between the number of actions performed on the platform and academic performance (Table 5). M-learners in this cluster have an average of 1227 actions and an average final grade of 6.83. The standard deviation of final grades is 5.56, suggesting a relatively wide range of academic performance within this cluster. The screen size of the devices used by M-learners in this group averages 6.56 inches, and the RAM size is 4.67 GB.

In Cluster 2, the engagement-performance correlation is 0.75, indicating a strong positive relationship between the number of actions and academic performance. The average number of actions is 956.43, and the average final grade is 15.64, with a standard deviation of 2.53, indicating greater consistency in performance. M-learners in this group use devices with an average screen size of 6.1 inches and 5.86 GB of RAM.

Table 5. Cluster Characterization

Learner Cluster	Avg RAM Size	Avg Nbr_action	Avg Final_Grade	Engagement-Performance Correlation
Cluster 1	4.67	1227.00	6.83	-0.27
Cluster 2	5.86	956.43	15.64	0.75
Cluster 3	5.25	681.88	10.63	-0.31
Cluster 4	4.43	889.43	14.29	-0.51

M-learners in Cluster 3 use devices with a larger average screen size of 6.7 inches and 5.25 GB of RAM. Their engagement level is moderate, with 681.88 actions on average, and they achieve an average final grade of 10.63. The standard deviation of final grades is 3.45, indicating some variation in performance but still more consistent than the performance seen in Cluster 1. M-learners in Cluster 4 use devices with a smaller screen size of 5.8 inches and 4.43 GB of RAM. Engagement is respectable,

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with an average of 889.43 actions, yet the average final grade remains better at 14.29, with a standard deviation of 2.87, reflecting relatively consistent academic outcomes.

5.4. Content Personalization via Ontologies

The integration of ontologies has enabled the definition of specific concepts and relationships between the elements of a Moodle course and the learner model, allowing for more precise customization of educational content. By leveraging learner clusters, ontologies were employed to recommend educational resources tailored to each learner model. Ontology-based recommendations significantly enhanced M-learner engagement, as demonstrated by increased time spent on the platform and higher levels of activity participation. These findings highlight the potential of using ontologies and learner modelling to enhance the personalization of educational content.

Table 6. Distribution of Personalized Content by Learner Cluster

Learner Cluster	Primary Content Type (50%)	Secondary Content Type (25%)	Tertiary Content Type (15%)	Other Content Type (10%)
Cluster 1	Reading Materials	Interactive Quizzes	Video Lectures	Case Studies
Cluster 2	Interactive Quizzes	Reading Materials	Video Lectures	Collaborative Projects
Cluster 3	Video Lectures	Interactive Quizzes	Reading Materials	Gamified Elements
Cluster 4	Video Lectures	Reading Materials	Interactive Quizzes	Case Studies

Table 6 shows the distribution of personalized content within the different clusters of learners, reflecting a strategic alignment with the specific preferences, characteristics, and behaviours of each group. For instance, Cluster 1 favours Reading Materials (50%), complemented by Interactive Quizzes (25%) and Video Lectures (15%). This configuration is consistent with the profile of this cluster, showing the most involvement with the platform and suggesting a preference for textual, in-depth material. Cluster 3, on the other hand, puts the focus on Video Lectures (50%), followed by Interactive Quizzes (25%) and Reading Materials (15%). This orientation is adapted to more passive visual learners, as videos can stimulate their involvement with a minimum of effort. The introduction of Elements Gamified (10%) in this cluster adds a ludic dimension, reinforcing motivation and engagement.

Based on ontological structures and learner clusters, content types are displayed in a differentiated format, reflecting a refined approach to personalized learning. By adapting learning resources to individual learning styles and preferences, this approach promotes deeper engagement and leads to more effective learning outcomes. What's more, the use of machine learning to analyze user behaviours and preferences enables the creation of personalized experiences that precisely meet the needs of each individual learner, improving overall learning effectiveness.

5.5. Learning Quality Assessment

To assess the impact of the adaptive model on learning quality, we compared learners' results before and after adaptation. The results, summarized in Table 7, show a significant improvement in learners' results after using the model.

Table 7. Learning Quality Assessment

Indicator	Before Adaptation	After Adaptation
Average Score (out of 20)	10.75	12.99
Success Rate	53.97%	70.86%

Table 7 clearly reflects the positive effect of the adaptive learning model on student performance. The average grade increased from 10.75 before adaptation to 12.99 after adaptation, representing a significant improvement. Moreover, the success rate, defined as the percentage of students obtaining a grade of more than 10, increased significantly, from 53.97% to 70.86%. This improvement indicates that the adaptation led to better understanding and performance on the part of the learners. These results indicate that adapting educational content based on learner profiles positively impacts performance, validating the effectiveness of the proposed model.

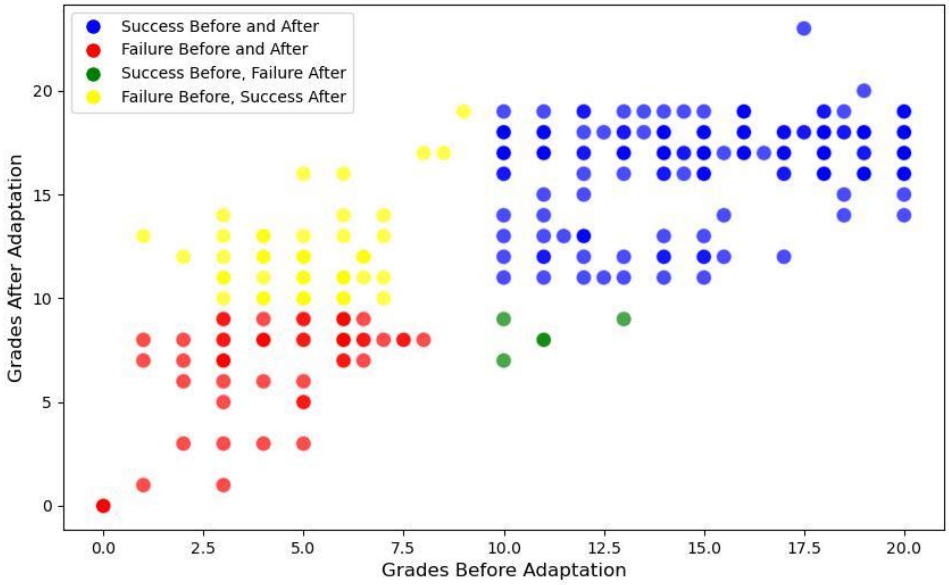

Figure 8. Student Grades Before and After Adaptation

Figure 8 presents the distribution of students' results before and after adaptation. The graph reveals that many students improved after adaptation, as indicated by the yellow dots (students who failed before adaptation but succeeded after). The green and red dots represent, respectively, students who succeeded before adaptation but failed after and students who failed both times. This suggests that while most students benefited from the adaptation, a few maintained or diminished their performance.

6. Discussion

The results highlight the need for a comprehensive strategy incorporating both clustering and ontological techniques simultaneously in personalized learning. In this case, the decision to use DBSCAN or K-means should be based on the distinguishing features of the learner's population and specific learning objectives. The use of ontologies also showed how it could enrich the learning experience through enhanced features and personalization. Heuristic-based clustering proved to be superior in forming learner clusters at the most appropriate level, with content being provided based on the level of engagement with the user's device and learning behaviour. This supports the hypothesis that density approaches to clustering are more appropriate for analyzing complex learner populations in mobile learning environments.

The analysis of device specifications also confirms that adaptive learning systems need to consider the device limitations of some users. While a larger percentage of learners have access to devices with the required RAM and screen size, some users still use less powerful devices, which can limit interaction with multimedia content. Bridging this gap by optimizing content, such as by providing less resource-intensive course materials, can improve learner engagement, whatever the device used.

The use of learner models, clustering, and ontologies for adaptive learning represents an important advance in the personalization of mobile learning. Mobile learning personalization techniques improve learner results, while the development of complementary techniques enables the portability and generalization of this approach to different platforms and online courses.

The results of our study support previous research highlighting the importance of clustering techniques and learner modelling in the personalization of digital education environments. For example, Adnan et al (2020) showed that the performance of M-learners could be improved by weighting behavioral and contextual features in classification models, a conclusion reinforced by our results showing improved learner results through learner clustering. Similarly, the integration of ontologies to improve adaptive learning reflects the findings previously reported by Jugo et al. (2016), who recommend semantic modelling to align educational content with learner profiles better. However, the difference with previous studies, which have often focused solely on behavioural data or profile characteristics, is that our approach integrates emotional and device-based contextual data, providing a more holistic learner model.

This research has some limitations, despite these contributions. The dataset used was limited to a specific Moodle course and institution, which may affect the generalizability of the results. Future studies should expand the dataset to include multiple courses and institutions and explore the integration of real-time emotional and engagement analytics to refine learner modelling further.

Theoretically, this study contributes to the mobile learning debates by proposing a framework for composite learner modelling, merging clustering, ontologies and contextual intelligence. Practically, it presents a scalable methodology that institutions can adopt to implement adaptive learning in mobile contexts. By linking our findings to other researchers' efforts in personalized learning, we hope this research will contribute to the broader purpose of making e-learning more inclusive, effective, and learner-focused.

7. Conclusion

This research presents an adaptive approach to M-learning that integrates machine learning and ontology-based modelling to enhance personalized learning experiences on the Moodle platform. Building on DBSCAN and K-means clustering, we classified learners according to their behavioural, contextual, and emotional characteristics, enabling the delivery of customized content. The integration of an ontology-based structure further enhances content appropriateness by aligning learning material with individual learner models. Results show that this approach improves performance, supporting M-learners with content adapted to their specific requirements and performance.

Based on our study, several recommendations can be made. Firstly, Moodle pedagogical designers should consider incorporating learner modelling techniques based on contextual and behavioural clustering to provide adaptive content. Institutions, on the other hand, could adopt modular ontologies to dynamically adapt content to learner needs, ensuring scalability and adaptability. Moreover, it is highly recommended to implement periodic updates of the learner model based on real-time activity logs to maintain the relevance of adaptive learning interventions. Finally, future implementations should incorporate continuous learner feedback mechanisms to refine personalization strategies and evaluate their effectiveness through measurable indicators such as learner engagement, user satisfaction and academic performance.

Future research should investigate the extensibility of this adaptive system in various educational contexts. Improvements in clustering techniques and ontological structures could enhance the accuracy of learner modelling. In addition, integrating real-time adaptation mechanisms and sentiment analysis could dynamically refine content recommendations in an e-learning platform such as Moodle. These advances will contribute to the continuous improvement of personalized M-learning, enabling a more effective and engaging learning environment for mobile learners.

Declarations

Author Contributions. Research was conceptualized by Mohamed DAOUDI in collaboration with Nour Eddine El Fezazi, who developed the methodology, carried out the formal analysis and initially drafted the document. Nour Eddine El Fezazi contributed the essential resources, while Ilham OUMAIRA supervised the research, ensuring its accuracy and validity. All authors have read and approved the published version of the article.

Conflicts of Interest. The authors declare no conflict of interest.

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