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Adaptive Mobile Crossword Application with Intelligent User Profiling Using Supervised Machine Learning

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Abstract: This study introduces Romooz, an Arabic-language mobile crossword application designed to address the limited adaptive personalization **in existing Arabic educational games. The system integrates supervised machine learning (ML) to perform intelligent user profiling and support adaptive mobile learning (m-learning). Real-time gameplay data—such as completion time, error count, hint usage, and scoring—are captured and used to classify learners into five pedagogically meaningful profiles: Novice, Basic Learner, Independent, Strategic Learner, and Expert. A dataset of 1,707 structured interaction records from 100 users over 800+ sessions was analyzed. Six supervised ML algorithms—K-Nearest Neighbors (KNN), Naive Bayes, Decision Tree, Support Vector Machine (SVM), Random Forest, and Multi-Layer Perceptron (MLP)—were trained using stratified 10-fold cross-validation. Random Forest and MLP achieved the highest accuracies (92.3% and 91.7%), confirming the robustness of ensemble and neural approaches in modeling learner behavior. Findings validate the feasibility of ML-powered adaptive content delivery, dynamic feedback, and culturally relevant Arabic m-learning environments.**

Keywords: *Adaptive Learning, Supervised Machine Learning in Education, User Profiling, Crossword, Arabic m-Learning.*

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I. INTRODUCTION

The integration of machine learning (ML) into intelligent educational systems has significantly reshaped how learners interact with digital content. Supervised ML techniques—such as decision trees, support vector machines (SVM), and neural networks—have played a pivotal role in empowering adaptive learning platforms to analyze user behavior, identify performance trends, and deliver personalized learning experiences. These adaptive mechanisms address the limitations of conventional rule-based systems, which often fail to respond to dynamic learner profiles, real-time performance data, and behavioral cues—thus limiting their adaptability in diverse educational contexts [1, 2, 3].

Recent research continues to affirm that data-driven personalization significantly enhances both learning outcomes and learner motivation, particularly in mobile and game-based educational environments. These effects are most pronounced when personalization is informed by rich interactional data—such as hint frequency, time-on-task, and error metrics—which provide deeper insights into learner behavior [4, 5]. As ML-integrated systems evolve, they increasingly support the development of scalable and intelligent user modeling frameworks, positioning them as a cornerstone of next-generation educational technologies.

Although recent advancements have accelerated the growth of mobile learning (m-learning) applications featuring gamification and artificial intelligence, many of these tools still lack robust adaptive personalization grounded in behavioral analytics. A notable example is Termbot by Hsu, Chan, and Yu [6], which employs a crossword-style interface combined with a chatbot to teach medical terminology. However, its adaptive scope is limited to content selection without incorporating learner modeling or behavioral classification. In contrast, Romooz sets itself apart by deploying a data-driven learner profiling system that classifies users into five pedagogically relevant categories based on detailed in-app behavioral data collected from over 1,700 gameplay sessions.

Bechtold's [7] SEEKH platform offers an innovative use of constraint satisfaction programming to generate educational crossword puzzles. While it presents a valuable contribution to automated content creation, it lacks a supervised learning

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component for learner modeling or adaptive content delivery. Similarly, the Smart Vocabulary App described by Sandberg, De Jong, and Van Rijn [8] implements basic adaptivity through repeated vocabulary testing, but it does not incorporate behavioral data or dynamic user profiling mechanisms. These limitations underscore the need for systems like Romooz, which combine educational gameplay with intelligent, data-driven user classification models to provide deeper personalization.

In the Arabic educational technology landscape, recent innovations have introduced artificial intelligence into mobile language learning tools. A notable example is the LLM-powered crossword system developed by Zeinalipour, Saad, Maggini, and Gori [9], which uses advanced models such as GPT-4-Turbo and LLaMA3 to transform Arabic instructional texts into interactive crossword puzzles. Their system is supported by a purpose-built dataset—Arabic-Clue-Instruct—containing over 50,000 entries to enable accurate clue generation and cultural relevance. While this approach marks a significant advancement in Arabic content automation and gamified learning, its scope is primarily linguistic and lacks adaptive personalization features such as user profiling or behavioral modeling. Similarly, Farhaoui, Herawan, Imoize, and Allaoui [10] proposed a smart Arabic language learning environment that leverages AI and data science for multilingual content retrieval. However, their system does not implement behavior-based learner classification or real-time personalization based on performance data. In contrast, Romooz introduces a more comprehensive adaptive learning framework by integrating supervised machine learning with gameplay metrics to profile learners and dynamically tailor crossword difficulty and feedback. This model bridges linguistic gamification with intelligent learner adaptation, offering a deeper and more responsive educational experience.

In contrast to prior systems, Romooz introduces a comprehensive adaptive learning framework that integrates Arabic-language crossword gameplay with a machine learning–based user profiling engine. The application employs six supervised classification algorithms—including Random Forest and Multilayer Perceptron—to analyze gameplay metrics such as response time, error rates, hint usage, and bonus scoring. These behavioral features are used to dynamically assign users to one of five pedagogically defined learner profiles. This profiling enables Romooz to adapt future content to each learner's evolving skill level, offering tailored educational experiences that support both engagement and personalized progression. Such integration of user modeling and real-time personalization represents a novel contribution to the field of Arabic intelligent educational games.

Adaptive learning games have gained prominence as effective tools for enhancing learner engagement and improving educational outcomes. By tailoring game elements—such as difficulty, feedback, and content pathways—based on user interaction data, these systems provide more meaningful and individualized learning experiences. ML, particularly classification and prediction techniques, lies at the core of these adaptive mechanisms. In m-learning environments, ML enables the capture and interpretation of real-time behavioral data—such as accuracy, time on task, hint usage, and response patterns—to inform intelligent decision-making and personalized intervention [4].

Recent studies highlight the pivotal role of user profiling in adaptive learning environments. Accurate classification of learners—based on behavioral indicators such as task completion time, hint dependency, and error frequency—enables systems to deliver tailored content, scaffold feedback, and optimize learning trajectories. For example, Pardos and Heffernan [11] and Verghis, et al. [12] emphasize that recognizing learner types (e.g., novice, hesitant, confident) can inform more effective sequencing and support strategies. However, many current educational systems lack the sophistication to adjust dynamically to evolving learner behavior or cognitive preferences, thereby limiting their potential for deep personalization.

This study introduces Romooz, a novel adaptive mobile crossword application designed to overcome the limitations of static educational games and the lack of behavioral personalization in Arabic mobile learning platforms. As part of the research, Romooz was conceptualized and developed to embed supervised machine learning (ML) techniques within an Arabic-language educational environment. The application delivers crossword puzzles across multiple thematic domains—including history, religion, culture, and science—while simultaneously logging fine-grained gameplay interaction data. This behavioral data is processed through various supervised ML classifiers to generate dynamic learner profiles that reflect users' performance patterns, cognitive tendencies, and learning progress. These profiles enable the system to adapt content in real time, offering personalized educational experiences aligned with individual learner trajectories. Accordingly, Romooz serves as a functional prototype for examining the role of supervised ML in advancing adaptive learning within Arabic m-learning ecosystems.

By employing a suite of supervised classification algorithms—including K-Nearest Neighbors (KNN), Naive Bayes (Gaussian), Decision Tree (CART), Random Forest (ensemble-based), Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP)—Romooz analyzes gameplay behaviors such as response latency, hint usage, and error frequency to construct adaptive learner profiles. These profiles inform real-time content adjustments tailored to each user's proficiency level, cognitive style, and historical performance. The system thus serves as a research-oriented platform for evaluating the effectiveness of supervised ML techniques in enhancing personalized learning within Arabic mobile educational environments.

Unlike static crossword applications, Romooz dynamically generates puzzles and continuously monitors learner performance across multiple behavioral dimensions—including error rates, word-level completion time, and clue interaction patterns. These metrics are aggregated to construct rich behavioral profiles, which serve as input features for supervised machine learning classifiers tasked with categorizing users into pedagogically meaningful proficiency

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levels. This adaptive mechanism is designed to enhance the learning experience by enabling real-time, personalized content progression grounded in intelligent behavioral modeling—thereby fostering deeper engagement and improved learning outcomes.

Building on these design principles and technical features, the study evaluates Romooz as an adaptive mobile crossword application that integrates supervised machine learning (ML) techniques to enable intelligent user profiling based on gameplay interaction data. The research specifically examines the classification performance of six supervised algorithms—K-Nearest Neighbors (KNN), Naive Bayes, Decision Tree, Random Forest, Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP)—in modeling learners according to behavioral performance patterns within Arabic-language educational content.

These foundations position Romooz as both a practical implementation and a testbed for examining how supervised machine learning techniques can inform adaptive behavior modeling in mobile learning. The following section reviews the role of ML in intelligent educational systems to contextualize this approach.

II. MACHINE LEARNING IN ADAPTIVE EDUCATIONAL SYSTEMS

Machine learning (ML) has fundamentally transformed digital learning environments by enabling systems to adapt dynamically to learners' behaviors, preferences, and performance trajectories. Within the broader spectrum of ML paradigms, supervised learning algorithms—including decision trees, K-nearest neighbors (KNN), support vector machines (SVM), and neural networks—have shown high efficacy in learner classification and adaptive content delivery. As demonstrated by Debeer et al. [2], adaptive digital tools significantly improve learning efficiency when user interaction data is harnessed for personalization. Similarly, Toomla and Hooshyar [13] highlight the importance of behavioral tracking frameworks in supporting self-regulated learning, emphasizing the value of real-time data in scaffolding learner autonomy. Together, these approaches support the development of intelligent educational systems capable of delivering personalized feedback and optimizing learning pathways based on evolving learner profiles.

Empirical evidence underscores the pedagogical benefits of machine learning (ML) in adaptive learning environments. ML-based personalization, particularly when guided by behavioral data such as hint frequency, error rates, and time-on-task, enables systems to respond dynamically to learner needs. As demonstrated by Lahza and Khosravi [14], leveraging such interactional analytics within digital learning platforms enhances instructional effectiveness and learner engagement. These insights are especially critical in m-learning contexts, where fine-grained behavioral data can be collected unobtrusively through user interfaces and utilized to support real-time adaptivity and personalized feedback.

In mobile-based educational environments, supervised ML models can capture and process user behaviors—such as task completion time, accuracy, and support-seeking patterns—transforming them into actionable learner profiles. Alzaza and Yaakub [15] highlighted students' growing awareness and expectations regarding mobile learning services, emphasizing the need for systems that adapt content based on real-time learner input. More recent work, such as Lahza and Khosravi [14], has shown how app-generated behavioral logs can be used to construct dynamic learner profiles and support adaptive instructional delivery.

Furthermore, adaptive mobile systems benefit from their capacity to unobtrusively capture micro-level behavioral data—such as clue-solving speed, error correction patterns, and difficulty preferences. These granular interaction metrics are particularly valuable in game-based learning environments like Romooz, where they enable fine-tuned learner modeling and personalized content adaptation based on real-time performance analytics [4, 14].

Recent studies also validate the pedagogical value of crossword-based educational systems in promoting engagement and knowledge retention. For example, Bosakova-Ardenska and Andreev [16] developed an educational game grounded in crossword mechanics to enhance learning in computer programming. Their system featured dynamic word selection and modular architecture to support personalized reinforcement. Likewise, Zeinalipour et al. [9] utilized large language models (LLMs) to automatically generate Arabic crossword puzzles from instructional texts. While these approaches contribute significantly to content automation and learner motivation, they lack behavior-driven adaptation or supervised user modeling.

This study builds on these insights by designing Romooz as a platform that merges supervised ML with Arabic crossword gameplay to support adaptive, learner-specific pathways in mobile learning environments.

III. USER PROFILING AND BEHAVIOR CLASSIFICATION

Accurate user profiling plays a central role in adaptive learning environments, enabling systems to tailor instruction, feedback, and progression pathways based on individual learner characteristics. Supervised machine learning offers a powerful mechanism for constructing such profiles by analyzing behavioral features captured during user interaction. Key indicators—such as average task completion time, error frequency, and hint reliance—serve as proxies for cognitive traits and engagement patterns [17, 18, 19].

Earlier work by Pardos and Heffernan [11] demonstrated how categorizing learners according to behavioral data can enhance scaffolded feedback and adaptive sequencing. Building on this, Huang and Chen [20] proposed a temporal graph-based profiling framework that links interactional learning data with performance prediction in massive open online courses, offering new pathways for behavior-aware adaptation in intelligent tutoring systems.

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The Romooz application operationalizes this concept by mapping gameplay behaviors—such as hesitation, confidence, and strategic decision-making—into five learner categories. Each user is profiled based on aggregated gameplay features, including response time, error rate, hint frequency, and task completion performance. To ensure robustness, the study adopts a multi-classification approach, employing multiple ML algorithms to cross-validate profile assignments, following best practices in predictive educational modeling as outlined in recent ensemble learning literature [21].

Additionally, the increasing demand for scalable and adaptive digital learning tools, especially in the wake of the COVID-19 pandemic, underscores the relevance of such profiling. Alzaza [22] emphasized the role of mobile learning platforms in maintaining instructional continuity during crises within the Arab educational context. Similarly, Li and Fan [23] highlighted how behavioral intention to adopt mobile learning is shaped by perceived usefulness and personalization capacity. Systems like Romooz, which combine mobile accessibility with intelligent profiling, are thus well-positioned to meet the evolving needs of learners in under-resourced or linguistically specialized contexts.

IV. METHODOLOGY

This study adopted a mixed-methods approach, combining iterative software development with supervised machine learning (ML) techniques. The methodology is structured around two core components: (1) the design and implementation of the Romooz adaptive crossword learning application, and (2) the collection, preprocessing, and classification of user interaction data using a suite of supervised ML algorithms.

➢ *System Design and Implementation of Romooz*

The Romooz application was developed in accordance with established educational software design principles that prioritize user-centered adaptability and functional usability in mobile learning (m-learning) environments [24]. In parallel, its game mechanics and interface elements were guided by best practices in educational game design, ensuring both pedagogical effectiveness and learner engagement [25].

As illustrated in Fig. 1, the user interface supports culturally contextualized Arabic crossword gameplay, designed to preserve linguistic structure and provide familiar content relevant to native speakers.

Fig. 1: Screenshots of Romooz Mobile Application

The development process of Romooz was guided by the Rapid Application Development (RAD) model, chosen for its iterative structure and alignment with user-centered educational software development. RAD emphasizes rapid prototyping, continuous user involvement, and flexible refinement cycles—features that are particularly well-suited to educational contexts where learning objectives, user preferences, and behavioral patterns evolve dynamically. This approach enabled the research team to adapt the application design based on real-time user feedback and interaction data, ensuring that Romooz remained both pedagogically relevant and functionally effective throughout its development lifecycle [26].

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As depicted in Fig. 2, the RAD model was applied in four key stages:

- *Requirements Planning:* Functional specifications were gathered based on pedagogical needs for Arabic-language learners, including the ability to track hint usage, time per puzzle, and accuracy.
- *User Design:* Prototypes were developed using Flutter, integrating user interface components with gameplay mechanics tailored for Arabic script and mobile usability.
- *Construction:* Core application logic was implemented, including integration with a supervised ML classification engine and local data logging capabilities.
- *Cutover:* The application was deployed in a controlled pilot environment for testing with real users, enabling iterative refinement based on interaction analytics and feedback.

This RAD-based process facilitated the iterative validation of both the adaptive game design and the ML infrastructure in a real mobile learning setting [24].

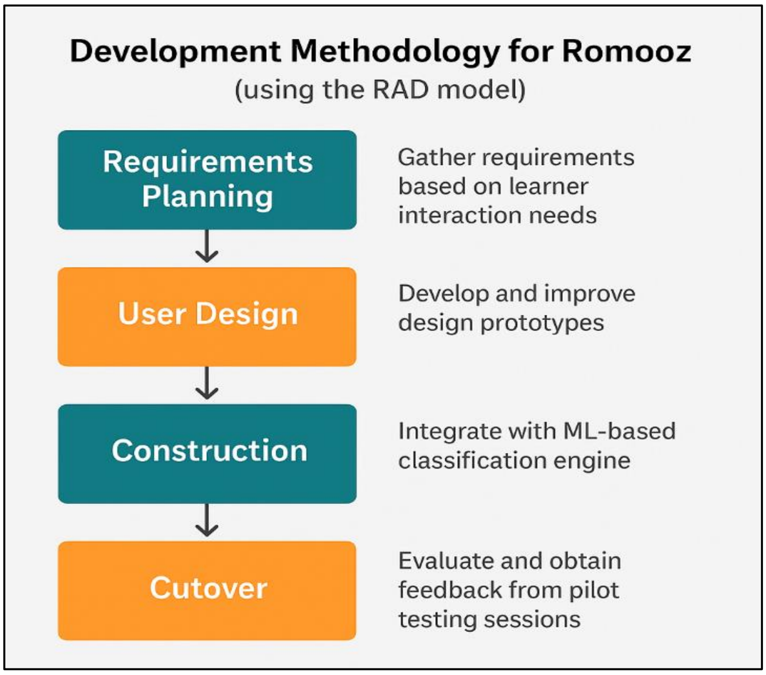

Fig. 2 Iterative Stages of the RAD-Based Development Process for Romooz

➢ *User Interaction Data Collection and Feature Design*

Each gameplay session was logged as a distinct record, capturing key performance metrics including total completion time, error count, hint usage (user-initiated and system-triggered), and bonus point rewards. Two gameplay difficulty levels—normal and advanced—were implemented, influencing hint penalties and scoring mechanisms.

Users completed between 5 and 15 crossword networks, with each network containing 6 to 12 Arabic-language words. These sessions were aggregated at the player level, resulting in 1,707 structured logs from 100 users and covering more than 8,000 unique word-level interactions.

Table 1 summarizes the structured features captured in each gameplay session log of the Romooz application. These variables include identifiers (e.g., user ID), categorical labels (e.g., assigned learner type), performance metrics (e.g., total completion time, number of errors, bonus points), and interaction indicators (e.g., hint requests, hint penalties, difficulty level). Collectively, these features provide a comprehensive behavioral representation of the player, forming the basis for subsequent machine learning–based classification and adaptive content personalization.

Table 1. Feature Descriptions in User Gameplay Logs

Feature	**Description**
user_id	Unique player identifier
Label (User Type)	Five user class labels (Novice, Basic Learner, Independent, Strategic Learner, or Expert)
timeTaken	Total time to solve one crossword (in minutes)
errors	Number of incorrect submissions
hints	Number of hint requests or system hints

hintPenalty	Score points lost due to hints
bonusPoints	Reward points for no-hint completion
level	Difficulty level of crossword (normal/advanced)

The selected sample size is supported by several methodological considerations:

- *Statistical Learning Requirements:* As [27] suggest, supervised machine learning tasks involving multi-class classification require at least 30–50 examples per class to ensure model robustness. With five learner classes and over 1,700 labeled entries, the dataset maintains a balanced class distribution.
- *Cross-Validation Readiness:* The dataset supports 10-fold stratified cross-validation—a widely accepted practice to reduce model variance, particularly in small-to-medium-sized datasets *[28]*. This allows each fold to maintain proportional class representation (~100 samples per fold).
- *Benchmark from Recent Literature:* Comparable studies in adaptive educational systems have utilized similar dataset sizes for model training and evaluation. For instance, Khosravi et al. (2020) employed over 1000 labeled learning sessions in evaluating personalized learner models, demonstrating the effectiveness of mid-scale datasets for adaptive profiling [29]
- *Behavioral Depth Per User:* Rather than increasing breadth with many users and few interactions, this study follows behavioral modeling guidelines that favor depth of interaction per user. Ten full-game sessions per user improve the granularity of learning behavior modeling, consistent with findings in self-regulated learning research that highlight the importance of repeated interaction traces for accurate user profiling [13].

This sample design ensures robust training, generalizability of results, and alignment with best practices in intelligent tutoring systems and educational data mining.

➢ *User Profiling Taxonomy*

Each user record was labeled with one of five behaviorally informed categories — Novice (N), Basic Learner (B), Independent (I), Strategic Learner (S), or Expert (E) — based on cumulative gameplay performance. These labels were informed by established user modeling frameworks in intelligent tutoring systems [30, 31], and reflect varying degrees of mastery, autonomy, and strategy use. The classification process utilized aggregated behavioral indicators such as average response time, error rates, hint usage, hint penalty, and bonus points.

To enable adaptive personalization in Romooz, this study implements a five-level user profiling taxonomy inspired by validated learner modeling frameworks in intelligent educational systems. The classification labels—Novice (N), Basic (B), Independent (I), Strategic (S), and Expert (E)—are grounded in prior literature on cognitive behavior modeling and student knowledge tracing.

The resulting taxonomy reflects the progressive development of user mastery and self-regulated learning capacity. As shown in Table 2, all labels were generated via expert-based heuristics and exploratory cluster analysis and validated for consistency across players [32, 4].

Table 2: Cognitive Profiling Taxonomy for User Classification with Supporting Literature

User Type (Label)	**Cognitive Characteristics**	**Supporting References**
Novice (N)	Limited task familiarity, frequent errors, high dependency on hints or extended time per item.	[11]**;** [33]**;**
Basic Learner (B)	Demonstrates partial understanding, reduced but persistent support-seeking behaviors.	[11]
Independent (I)	Performs tasks with moderate accuracy, low hint reliance, and efficient pacing.	[30]; [32]
Strategic (S)	Plans steps deliberately, demonstrates metacognitive awareness, and selects help effectively.	[34]; [4]
Expert (E)	Exhibits mastery-level performance with high accuracy, minimal delays, and almost no external support.	[30]; [31]

These classifications are derived from real-time features logged during gameplay, such as average time per clue, error rate, hint usage frequency, and difficulty level completion ratios. The approach aligns with contemporary perspectives on cognitive and behavioral learner modeling in adaptive educational technologies [32].

➢ *Data Preprocessing and Classification Framework*

Collected gameplay data were first cleaned by removing incomplete sessions or corrupted entries, normalizing continuous variables (e.g., timeTaken, hintPenalty), and one-hot encoding categorical fields such as level. Players whose records exhibited outliers or incomplete sequences were excluded from training. Features were then standardized using z-score normalization to ensure scale invariance across classifiers [35].

To evaluate predictive performance, six supervised classifiers—K-Nearest Neighbors (KNN), Naive Bayes, Decision Tree, Random Forest, Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP)—were implemented. These algorithms were selected for their proven effectiveness in modeling educational behavior across structured interaction datasets [36, 24]. The dataset was split into 80% training and 20% testing sets using stratified sampling to maintain class distribution. Each model was

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trained on the training set and evaluated using 10-fold cross-validation, a widely recognized technique for balancing bias and variance in classification tasks [37].

Performance was assessed using Accuracy, Precision, Recall, F1-Score, and confusion matrix visualization. To preserve ecological validity, no synthetic data augmentation was applied. Supplementary simulations were also conducted on a synthetic user profile to explore model generalization in unseen behavioral contexts.

V. RESULTS AND DISCUSSION

To assess the predictive effectiveness of different supervised machine learning algorithms in classifying learner profiles within the Romooz system, six distinct classifiers were employed. Each represents a unique computational paradigm, enabling a multifaceted evaluation of user behavior:

- *K-Nearest Neighbors (KNN)* is a non-parametric, instance-based classifier that predicts a user's class based on the majority vote from its k nearest neighbors, suitable for low-dimensional datasets where geometric similarity is meaningful [35].

- *Naive Bayes* is a probabilistic model based on Bayes' Theorem, assuming conditional independence between features. Its efficiency and robustness make it a common baseline in educational data modeling [36].

- *Decision Tree (CART) is* a recursive partitioning method that produces interpretable rules, valuable for explainable AI in education [35, 24].

- *Support Vector Machine (SVM)* is a discriminative classifier that maximizes the decision margin between classes, effective in high-dimensional spaces for modeling nuanced behavioral metrics [36].

- *Random Forest* is an ensemble of decision trees that enhances generalization and reduces overfitting, showing strong performance in educational classification tasks [24, 21].

- *Multi-Layer Perceptron (MLP)* is a feedforward neural network capable of modeling complex nonlinear relationships among features, widely used in adaptive learning systems [32, 35].

The diversity of these models covering distance-based, probabilistic, rule-based, ensemble, and neural paradigms ensures a robust comparative evaluation framework for user classification performance [24, 36].

➢ *Learner Profile Distribution*

Model predictions revealed a balanced distribution of users across the five predefined learner profiles, indicating consistent performance in learner classification. The distribution is detailed in Table 3.

Table 3. User Classification Distribution Across Five Learner Profiles

Lable	**No.**	**(%)**
Novice	283	16.58
Basic Learner	434	25.42
Independent	446	26.13
Strategic Learner	373	21.85
Expert	171	10.02

The majority of users (51.5%) were classified in the intermediate range (Basic Learner and Independent), suggesting strong potential for adaptive scaffolding mechanisms based on behavioral differentiation [11, 30]. The relatively low percentage of Expert users reflects the cognitive challenge posed by the system's design and highlights opportunities for refined progression strategies tailored to advanced learners [32].

This categorization enables Romooz to dynamically adjust future crossword content and feedback mechanisms according to the learner's evolving classification, thereby increasing engagement and instructional alignment. Such profiling has been shown to improve learning efficiency and user motivation in intelligent tutoring systems [4, 20].

These results validate that supervised machine learning models can accurately model user behavior within Arabic-language m-learning environments. Learner classification supports multiple layers of adaptivity, including:

- Adaptive gameplay sequencing (e.g., reduced complexity for Novice users),
- Dynamic feedback mechanisms (e.g., metacognitive hints for Strategic learners),
- Personalized progression paths that optimize the learner's zone of proximal development [32, 24].

Romooz thus functions not only as an interactive language-learning tool but also as a behavior analytics engine capable of driving intelligent, personalized learning trajectories through real-time data interpretation [4].

➢ *Classification Performance*

The six supervised models exhibited varying levels of accuracy and generalization. Table 4 presents a summary of their performance across standard evaluation metrics include Accuracy, Precision, Recall, and F1-score, computed on the test sets from each fold.

Table 4: Classification Performance of Supervised ML Models

Model	Accuracy	Precision	Recall	F1-Score
KNN	81.2%	0.80	0.79	0.795
Naive Bayes	84.6%	0.82	0.85	0.835
Decision Tree	88.5%	0.88	0.86	0.87
Random Forest	**92.3%**	**0.91**	**0.93**	**0.92**
(SVM)	90.0%	0.89	0.90	0.895
MLP	**91.7%**	**0.91**	**0.91**	**0.91**

The Random Forest algorithm achieved the highest overall accuracy (92.3%) and strongest F1-score (0.92), indicating its ability to generalize well across varying user interaction patterns. MLP Neural Networks and SVM models also demonstrated robust performance, with over 90% accuracy, making them viable options for intelligent user profiling.

In contrast, KNN yielded the lowest performance among all models (81.2%), likely due to its sensitivity to feature scaling and local data distribution. However, its simplicity and low computational cost make it a useful baseline.

The Decision Tree classifier provided a balance between interpretability and performance, achieving an 88.5% accuracy while remaining easy to visualize and explain—especially useful in educational settings where transparency in decisions is important [35, 24].

These findings reinforce previous studies showing the robustness of ensemble and deep learning methods in behavior classification [4, 32].

These findings demonstrate the feasibility and added pedagogical value of integrating ML in adaptive mobile games such as Romooz. The system's ability to classify users accurately across behavioral dimensions paves the way for: Dynamic content adjustment, Personalized feedback, and Targeted scaffolding strategies.

VI. CONCLUSION

This research explored the integration of supervised machine learning techniques into a custom-designed Arabic-language crossword application—Romooz—to support adaptive mobile learning. Through the collection and analysis of 1,707 gameplay records from 100 users across over 800 crossword sessions, the system successfully modeled user behavior and classified learners into five distinct profiles: Novice, Basic Learner, Independent, Strategic Learner, and Expert.

Six supervised ML classifiers were implemented—KNN, Naive Bayes, Decision Tree, SVM, Random Forest, and MLP—with Random Forest and MLP yielding the highest accuracy rates (92.3% and 91.7%, respectively). These findings confirm the viability of using ensemble and neural approaches to support intelligent user profiling in adaptive educational applications.

By offering personalized feedback, dynamic puzzle sequencing, and tailored learning pathways, Romooz enhances both learner engagement and instructional effectiveness. This research contributes to three key domains:

- *Developers:*

Demonstrates the technical feasibility of embedding intelligent profiling within lightweight, scalable mobile applications.

- *Educators:*

Offers insight into learners' cognitive and behavioral patterns, enabling data-driven pedagogical decisions.

- *Policymakers:*

Proposes a sustainable and culturally responsive model for Arabic-language educational technologies that can operate without heavy infrastructure demands.

Ultimately, Romooz showcases the potential of combining machine learning with localized mobile learning platforms to foster more inclusive, intelligent, and engaging learning experiences for Arabic-speaking learners.

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