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Intelligent Tutoring Systems for French Language Learning in Police Training: A Big Data-Driven AI Approach

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ABSTRACT: Communication challenges are frequently encountered by police due to need to interact with French-speaking communities. Law enforcement duties often occur at a fast pace and do not fall under typical language acquisition programs. The proposed research aims to provide law enforcement agencies, through the development of an Intelligent Tutoring System (ITS) based on Big Data, a means for French language acquisition for police-related uses. The ITS will consist of real-time interactive language learning tasks, proficiency assessments and simulated feedback based on the learner's performance, to develop an adaptive and goal-based learning program. Enhanced pre-processing techniques, including cleaning, tokenization or lemmatization, will ensure that any data entered into the ITS is of high quality. The ITS will include a Light Gradient Boosting Machine (LightGBM) that utilizes the predicted performance of learners and categorizes language-learning errors. The ITS will also include a Deep Q-Network (DQN) to automatically change the content of language lessons based on learners' engagement and progress. This represents a new ITS design model for the police training environment that integrates language with operational needs, a consideration that has thus far not been addressed in existing models. Assessment data of the ITS indicate substantial improvements in learner attention, rate of error correction and speed of learning. This research offers insight into the establishment of infrastructure as well as the implementation of strategies surrounding real-time, adaptively learned systems in the high-stakes context. In addition, it presents an opportunity through a modular design for police and multilingual communities to better communicate with one another, thereby enhancing the exchange of trust and increased citizen participation, through training opportunities for law enforcement personnel, in a manner that allows them to become better prepared for a more positive outcome.

Keywords: intelligent tutoring system (ITS), Grench, language learning, police training, light gradient-boosting machine (LightGBM).

I. INTRODUCTION

Police come first in upholding the law and are ahead of judges and prosecutors. The police should act in an unbiased way in both social and political life. The method of communication used by an individual or an organization will determine the image of such individuals or organizations since it is a reflection of their personalities. Effective communication provides police personnel with a positive image and poor communication spawns a negative image [1]. The police departments reach out to a vast number of stakeholders and recipients in various ways because of numerous reasons. The messages in the frame may deal with specific information campaigns, specific investigations or more general objectives. The place of origin and value of evidence is not the same in both cases. It is reasonable to wonder if the general public has higher expectations from police websites than they do from other forms of online communication during this time of rising skepticism and uncertainty among the general population, and increased concern over False Information, Cyber Bully, Internet Crime [2].

The intercultural and sociolinguistic dimensions of law enforcement have received less theoretical attention, particularly in relation to how the particular ways of speaking used by refugees or immigrants help shape or influence the way Rural Regional Community members communicate. These complications pose unique challenges to police forces, as police agencies must confront not only language and cultural differences, but also multi-language populations [3]. Intercultural education enables new officers to gain a better understanding of the local culture by providing ample opportunities for them to reflect on their own cultures against the backdrop of other cultural systems. In addition, it can play an important role in developing the officers' cultural awareness and sensitivity, which may ultimately be useful in promoting and fostering healthy relationships and positive dialogues between individuals from diverse cultural backgrounds living in a multicultural community [4]. The term 'community policing' has often been equated with advocacy on a national and sometimes international level. However, when a police department seeks to implement it, many barriers may arise. Some of these include limited institutional backing, inadequate training, a lack of resources, and ineffective community outreach. Thus, the need for a separate language education program and intercultural competency training represents a new means for building effective communication between officers and members of diverse communities, which ultimately will also establish trust between both parties [5].

Language learning ITS's available thus far have not addressed the fast-paced, high-stress, real-time demands of police communications. Most of these early ITS's provided content only and were static (not dynamic) and not tailored to any particular police scenario or any variations of cognitive load or changing situation variables. As such, they do not meet the operational requirements of the officer needing to communicate quickly and effectively in a multilingual context. Therefore, police need a dedicated, dynamic and content-based ITS specifically designed for law enforcement purposes [6]. Current produced outdated educational systems from the previous 'digital' revolution. Even though the educational systems could potentially be designed with more than just providing pre-recorded or live lectures presented on that particular web site, as is typical for most educational systems, digital learning systems have created boundaries with respect to personalized education using what could be described as a recommender system that aligns educational material with a consumer's individual desire to learn [7]. In terms of the current innovations associated with Educational Technology (ET), ITS appeared as an innovator by providing a platform for students to receive tailored guidance and support through the learning process. An ITS was developed by utilizing new technologies to allow a user to receive an educational program based upon their unique learning characteristics. The beauty of the ITS is that it can provide the student with the flexibility of accommodating their individual learning needs and the pace of learning in the traditional or face-to-face learning environment [8]. An ITS can enhance the learning process by allowing for more focused and organized learning tasks as well as the ability to change the pedagogical approach for the learner on a case-by-case basis and to provide a teacher with data from the Learning Environment Analysis System to measure the progress of an individual student's effort toward successful completion of their education [9].

Big Data (BD) and Artificial Intelligence (AI) have also changed the landscape of Education and its associating technology. The application of AI technology in the educational sector will change completely the way learners learn through the utilization of data-based decision-making, improving the overall quality of the educational administration, and providing students with a tailored learning experience. In addition, using AI to personalize the way that people learn will shift the concept that is traditionally seen as the 'educational model' to a more 'individualized' model. The incorporation of high-tech tools and mediums to facilitate the individual needs of learners has fundamentally changed the environment in which they learn [10]. For example, as police officers become more accustomed to communicating with multilingual communities, it is common for them to need to work under extreme pressure in situations where if they understand one another incorrectly, a simple incident could easily turn into a serious safety issue. The type of training that police officers currently receive lacks adequate instruction for them to be able to communicate quickly and effectively with communities that speak the French language; therefore, it is necessary to have real-time, situationally aware language support provided by an adaptive intelligent transport system to not only improve how police officers communicate operationally with multilingual communities, but to also enhance their level of trust toward them [11].

The previous ITS systems were not able to apply to Police because Police have a considerably large volume of fixed content for Police applications, they did not have sufficiently many examples of spatio-temporal locations, and this fixed content does not include learning methods utilized by dental hygiene professionals nor the ability to adapt to varying levels of stress, cognitive load and real time decision making for Police. Therefore, both of these limitations are barriers for how police officers would communicate effectively when performing Police duties in real world encounters [12]. This research proposal offers solutions to these two barrier areas through a scaled and domain specific ITS for French language learning within the Police by utilizing LightGBM and DQN for real time learning, personalized learning and continuing on ethically (Figure 1).

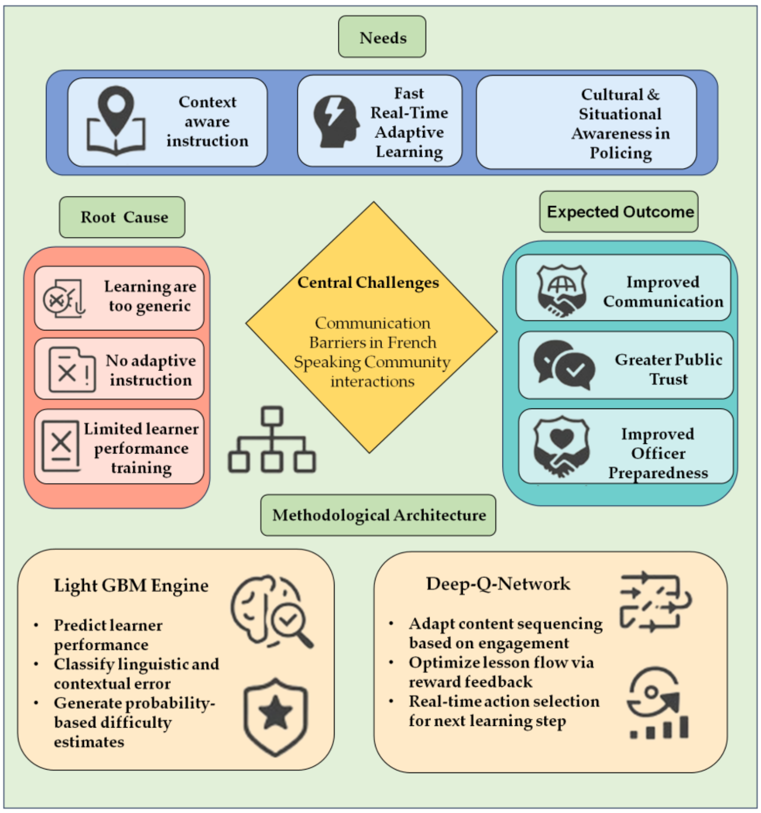

FIGURE 1. Problem-solution framework for ai-based police language training.

An Intelligent Tutoring System (ITS) based on the Big Data, to learn the French language in the context of policing, is developed using Light Gradient-Boosting Machine (LightGBM) and Deep Q-Networks (DQN) to support the process of communication competence, officer preparedness, and citizen trust in multicultural environments.

- Its main purpose is to develop a domain-specific ITS tailored for law enforcement language training.
- Introduces a hybrid LightGBM + DQN framework that conducts real-time adaptive learning and personalized content sequencing.

- Offers advanced preprocessing such as noise filtering, tokenization and lemmatization to prepare data, which will improve model accuracy.
- It also measures the performance of ITS using the different metrics which encompass Accuracy, Precision, Recall, F1-Score, and ROC to adopt consistent performance verification.
- Proves to be practically applicable to high stakes policing situations, including operation urgency and multilingual communication issues.

The suggested study introduces a field-specific ITS, which is specifically structured to be used by law enforcement officers working in multilingual and highly pressurized conditions. Contrary to the most common language training models, the hybrid framework of LightGBM + DQN suggested here offers situational urgency, cognitive load and operationally-relevant communication-pattern cognizant real-time adaptive feedback. LightGBM forecasts performance and patterns of linguistic errors, whereas DQN adapts the instructional sequences dynamically, which makes it extremely applicable to a high-stakes policing environment, where it is of paramount importance to be able to respond to linguistic questions fast, correctly, and contextually.

Following the introduction, Section 2 offers related work, Section 3 detailing the system design and evaluation criteria. Section 4 indicates model accuracy, learner engagement, error marking, and comparisons. Section 5 focusing on implications and system flexibility, and Section 6 is followed by the conclusion, which highlights key findings and future research directions.

II. RELATED WORK

The same limitations are reflected in broader education-technology research. Study [13] studied the use of Big Data in the context of personalized learning and observed a high level of difficulties regarding the quality of the data, integrating the platform, and its application in practice. Their results show that although data-based instructional planning is helpful, the current models are too weak to be used in complex and domain-specific language training. Work in [14] emphasized the topic of technology-based self-regulated learning, in which the positive outcomes were observed in terms of vocabulary development. However, its use is limited by the reliance on self-report data and the limited linguistic context, which makes it less applicable to the context where accuracy in communication and awareness of the situation gets into operation. Study [15] showed that stress-based police communication training with the use of Virtual Reality can be more realistic and experiential. Although such benefits exist, VR systems do not have automatic error detection and real-time linguistic adaptation, which limits their application as full-fledged language-learning environments. Table 1 summarizes prior ITS approaches, their key features, datasets, evaluation metrics, and limitations, highlighting gaps addressed by the proposed LightGBM + DQN model.

Table 1. Summary of prior its approaches.

Study	ITS Type	Dataset / Participants	Key Features	Evaluation Metrics	Limitations
[16]	ML-based	English learners	Neural network + Big Data	Engagement, cultural understanding	Non-quantitative, not scalable, no real-time adaptation
[17]	ML-based	University students	Personalized feedback, NLP	Performance improvement	Domain-limited, relies on external textual support
[18]	Web-based mixed learning	Ukrainian law-enforcement trainees	Mixed-method learning, skill enhancement	Engagement, skills acquisition	Fixed teaching resources, no real-time performance monitoring

[19]	Digital tools	Hungarian police students	Motivation, language acquisition	Learner satisfaction	Traditional pedagogy, lacks predictive analytics & adaptive sequencing
[20]	VR / Tech-assisted	Police trainees	Stress-based simulation, experiential	Observational improvement	No real-time adaptation, no automatic error detection
[21]	RL/ML hybrid	Academic learners	LSTM-BERT knowledge tracing	Accuracy, sequence modeling	Not validated in operational settings
[22]	AI-based ITS	General learners	Personalized adaptation	Learner performance	Ethical and practical limitations for sensitive domains

Despite the significant strides in ITS research, a number of critical gaps persist that were not addressed by previous research. Firstly, very few systems developed so far provide domain-specific solutions relevant to policing contexts, where communication demands are highly situational and time-sensitive. Secondly, in the majority of cases, ITS structures do not provide adaptive feedback in real-time, depending on operational performance indicators, and are hardly evaluated in the conditions of high stress and reality. These restrictions indicate that an ITS should be able to do predictive modeling and dynamic content sequencing. The direct answer to these inadequacies is the hybrid architecture suggested in this paper that is based on the combination of LightGBM to make predictions of the performance and DQN to make adaptive decisions.

1. COMPARATIVE ANALYSIS OF ITS

Existing ITS methods can be divided into three categories, such as rule-based ITS, ML-based ITS, and RL-based ITS. The rule-based ITS is based on predefined rules and fixed content, and so, the currently existing methods lack the flexibility of spontaneous or high-pressure communication [20, 15]. ML-based ITS is associated with a personalized feedback and modeling of learners, and often, does not provide adaptation in real time and domain specificity [16, 17]. ITS based on RL is dynamic to the interaction of learners and their cognitive load, appropriate in high-stakes environments. Nevertheless, their use in the criminal justice system is limited [21, 22]. The proposed research aims to bridge these knowledge gaps by suggesting the LightGBM + DQN model with predictive, adaptive, and stress-aware training of police officers. A comparative overview of existing ITS, including their key features, strengths, limitations, and applicability to law enforcement training, is shown in Table 2.

Table 2. Comparative overview of existing intelligent tutoring systems for language learning.

ITS Type	Key Features	Strengths	Limitations	Applicability to Law Enforcement
Rule-Based ITS	Pre-defined rules, static content	Easy to implement, interpretable	Inflexible, cannot adapt to real-time inputs	Low unsuitable for spontaneous communication
ML-Based ITS	Neural networks, NLP, learner analytics	Personalized feedback, scalable	Requires large data, limited real-time adaptation	Medium partially helpful but constrained in high-pressure tasks
RL-Based ITS	Adaptive sequencing, reward-based learning	Dynamic adaptation, handles learner variability	Complex, needs ethical safeguards, limited domain validation	High promising for stress-aware and operational training

Proposed LightGBM + DQN	Hybrid predictive + RL model, real-time adaptation	Real-time, domain-specific, stress-aware, predictive	Implementation complexity	Very High tailored for law enforcement operational communication

III. MATERIAL AND METHOD

The suggested approach realizes a complete workflow of end-to-end French learning in policing contexts. Collected data of learner interaction undergoes cleaning, tokenization, and lemmatization to get standardized inputs. Features will be fed to the LightGBM model to predict real-time performance and classify linguistic errors. The result of a learner-state representation guides the Deep Q-Network, which chooses optimal learning activities dynamically. Continuous feedback of learner responses permits the system to adapt instruction, optimize engagement, and deliver contextually aware personalized language training for high-pressure law enforcement environments. Figure 2 shows the overall flow of the research.

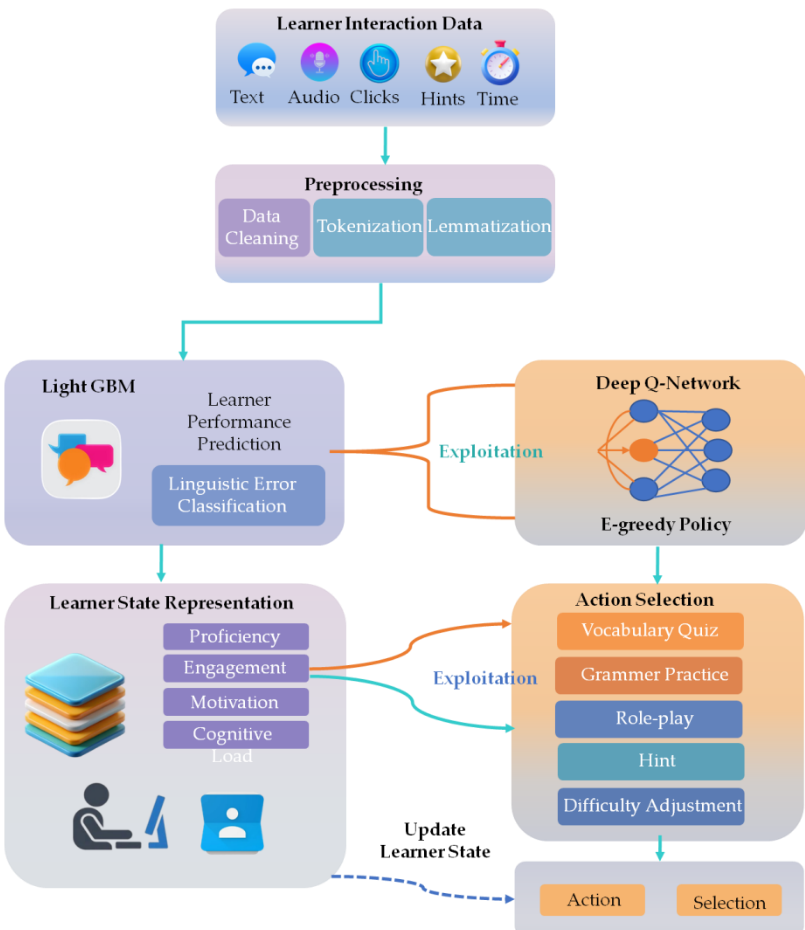

FIGURE 2. Overall framework of the methodology.

1. DATA COLLECTION

The creation of an ITS for-learning French in police training settings is supported by this dataset. It has 6,453 rows that display replies, learner interactions, and system feedback while completing language acquisition exercises intended for use in law enforcement situations (https://www.kaggle.com/datasets/programmer3/french-police-its-learning-dataset). The binary target represents whether a learner input contains an error: 1, or error-free: 0. It is sourced from the Kaggle open-source dataset, and the data is going to be pre-processed using cleaning, tokenization, and lemmatization techniques. In general, the dataset was divided into an 80% training subset and a 20% test subset to evaluate model performance. All the models tuned their hyperparameters using 5-fold cross-validation on the training set to robustly avoid overfitting. This approach gives unbiased estimates of performance and lets the ITS generalize well across different learners. The summary of features of the dataset and the preprocessing steps applied are shown in Table 3.

Table 3. Summary of French police its learning dataset features and preprocessing. steps.

Feature	Type	Description	Preprocessing Applied
learner_id	Categorical	Unique identifier for each learner	Standard encoding
user_input	Text	Learner's response	Cleaning, tokenization, lemmatization
expected_output	Text	Correct response expected by the system	Cleaning, tokenization, lemmatization
Score	Numeric	Score obtained for the task	Normalization, imputation
time_taken_sec	Numeric	Time taken to complete the task (in seconds)	Normalization
hint_used	Numeric	Number of hints requested by the learner	Normalization
retry_count	Numeric	Number of retries	Normalization
Clicks	Numeric	Number of clicks during task	Normalization
audio_replays	Numeric	Number of audio replays used	Normalization

2. DATA PREPROCESSING

To support proper learner modeling and adaptive feedback in the ITS, a preprocessing pipeline for the data was outlined. Since the input will be in the form of speech, text and performance logs which are real-time, it was important to have important steps like data clean up, tokenization, and lemmatization. These were uniform, practical statistics to provide effective system reaction in the legal education training in stakes high conditions.

2.1 Data Cleaning

Data cleaning is a mandatory procedure in the preprocessing pipeline to assure the correctness, dependability, and quality of the inputs being received by the ITS. The intricacy and volume of the incoming real-time data provided by learners, including spoken and written language input, interaction logs, score of assessment, and simulation feedback required cleaning of the raw data before it could be processed further, including tokenization, lemmatization, and modeling. All the records that were not finished, wrongly formatted text or those that were incorrectly formatted were cleaned out in the data cleaning process so that noise would not influence the models. This measure guaranteed that LightGBM got accurate inputs whereas DQN does not confuse learners-state phenomena, and that is very critical in a real-time police-training situation.

Missing values that occur due to the fact that the learner did not supply their data or there are gaps in the logs of a learner are dealt with by mean imputation of numeric features and deletion of drastically incomplete textual records in the ITS. Noise filtering helps in eliminating irrelevant variation during text normalization, spell correction and elimination of non-informative tokens. These precautions will keep LightGBM in a steady and trustworthy state to reach the right forecast of performance and DQN will not mislead to state representations. This guarantees greater real time customization and tenacious strong model execution under high-pressure policing situations.

2.2 Tokenization

In the ITS, tokenization of law enforcement may divide text or spoken inputs (for example, responses of learners in French) into basic linguistic units (for example, words, phrases, and symbols) to enable their further analysis, for example, determining errors or appropriating content [23]. The concept of tokenization enables the learner to understand the input of the speech in normal speech as well as in high stress contexts, which is prevalent in law enforcement communication. An example of tokenized output is available in Table 4.

Table 4. Tokenized output.

Original Sentence	Tokenized Output
"Guerre habillerénorme métier souventroi chemise."	{"Guerre", "habiller", "énorme", "métier", "souvent", "roi", "chemise"}
"Demain sable tendrefonctionrapporter prendre."	{"Demain", "sable", "tendre", "fonction", "rapporter", "prendre"}
"Suivre proposer hiver volonté âme siendéposerclair."	{"Suivre", "proposer", "hiver", "volonté", "âme", "sien", "déposer", "clair"}

The text was segmented as well as tokenized learner response transformed into uniform lexical units to LightGBM. This resulted in enhanced detection of errors particularly those related to vocabulary and the use of verbs as well as decreased computational load thereby enhancing the accuracy of adaptive feedback.

2.3 Lemmatization

One of the key processes within the NLP pipeline of the proposed Big Data-focused ITS to learn the French language in police schools is Lemmatization. It entails the conversion of different forms of words to one base or dictionary word referred to as a lemma. Normalization hence makes it easier to assess what the learners can do with the system, rank the linguistic errors made, and be able to give consistent and personalized feedback [23].

Morphological variation is also observed in the French language especially in the verb conjugations and the adjective/noun forms lemmatization assists in maintaining the similarity in meaning so that the similar meanings are represented in the same way by the ITS models. It is especially noteworthy when applied to law enforcement conversation, in which minor distinctions can grade very high in terms of impression to cognition and reaction. The example of lemmatization is provided in Table 5.

Table 5. Example of Lemmatization.

Learner Input	Lemmatized Form	Explanation
Desirer	Desirer	Verb "to desire" normalized to its base form
Sérieux	Sérieux	Adjective remains the same as it is already in its base form
Guère	Guère	Adverb remains the same as it is already in its base form
Plutôt	Plutôt	Adverb remains the same as it is already in its base form
Voiture	Voiture	Noun remains the same as it is already in its base form

Decreasing the variance of French word-forms by lemmatization allowed LightGBM to improve the classification of errors and, at the same time, helped DQN maintain more stable state representations. By providing consistent, clean language inputs for both models, this process helped to ensure the consistency of performance predictions between sessions. Both models received input that had been 'cleaned', 'tokenized', and 'lemmatized', thereby creating a stable dataset. This stabilization of data increased accuracy in terms of predicting performance, and also allowed the system to avoid responding to irrelevant linguistic noise while adapting to real-time. Once the data set was cleaned, the proposed method is used to allow LightGBM to predict how learners will perform and for DQN to automatically adjust instructional sequences based on the level of personal engagement and learners' respective progress.

3. *INTELLIGENT TUTORING SYSTEMS FOR FRENCH LANGUAGE LEARNING IN POLICE TRAINING*

The goal of creating an ITS for French language education in police training. The performance prediction model utilizes LightGBM to determine which types of language errors students have made, whereas DQN adjusts the sequence of teacher instruction on the basis of both the interest of the student and the effectiveness of the student's learning. Because these two types of models work together, they create an efficient and flexible learning system that will deliver the most complete error corrections and individualized student learning experiences.

3.1 Predicting Learning Performance Using LightGBM

LightGBM has been used to predict how well the learner will do with French, as well as to identify the mistakes that the learner may make. This is all done within the context of an ITS that utilizes a data-driven approach in real time. The purpose of building this model is to give users a prediction of their success on certain language-based tasks, using data collected about the way they interacted within the system, but also to provide information about the different types of errors that they may have made, which could cause them to miss out on opportunities for growth. Understanding error patterns and learner needs is crucial when utilizing Adaptive Learning Systems; thus, content within these systems must be designed to meet users' needs and current progress levels.

a. Gradient Boosting Decision Tree (GBDT)

GBDT constructs an ensemble of decision trees by optimizing the loss function with multiple iterations. For a given dataset$\{(w_j, z_j)\}_{j=1}^{M}$, where$z_j$is the feature vector (e.g., learner's system interaction) and$w_j$is the target value (e.g., score or performance of the learner), the prediction ismade using the Equation (1):

$$E(w_j) = \sum_{n=1}^{N} g_n(z_j) \tag{1}$$

Where $E(w_j)$ represents the final prediction for inputw_j, N denotes the number of boosting rounds (for example, trees), and $g_n(z_j)$ signifies the prediction made by the $n-th$ tree. The learner's proficiency and progress in acquiring French language skills were predicted based on prior data.

b. Model Initialization and Residual Calculation

The model is initialized to zero, which is demonstrated in Equation (2):

$$E_0(z_j) = 0 \tag{2}$$

For each iteration m, residuals are calculated as the difference between the target and the previous model's prediction is provided in Equation (3):

$$h_{nj} = z_j - E_{n-1}(w_j) \tag{3}$$

Where h_{nj} denotes the residual for the *j-th* instance at the $n-th$ iteration. The focus here is to correct errors in predicting learner performance, particularly identifying linguistic mistakes, such as grammatical inaccuracies or vocabulary errors, specific to law enforcement contexts.

c. Fitting the Regression Tree

In GBDT, each decision tree $g_n(z_j)$ is fit to the residuals. For each tree, the goal is to minimize the squared error in predicting the residuals given in Equation (4):

$$\sum_{j-1}^{M}(h_{nj} - g_n(z_j))^2 \tag{4}$$

Where h_{nj} signifies the residual, and $g_n(z_j)$ represents the predicted value from the tree.This approach aims to improve accuracy in predicting the learner's future performance, identifying weak areas in their language skills.The tree is recursively split into nodes based on the feature that minimizes the squared error, and this is done for every tree in the ensemble. Once a tree is built, the model is updated as in Equation (5):

$$E_n(w_j) = E_{n-1}(w_j) + g_n(w_j) \tag{5}$$

Where $E_n(w_j)$denotes the updated prediction, $E_{n-1}(w_j)$represents the previous prediction, and $g_n(w_j)$signifies the output from the newly added tree. This ensures that the model gradually improves its predictions, adapting to learner performance in real-time.

d. Gradient-based One-Side Sampling (GOSS)

GOSS improves training efficiency by focusing more on data points with large residuals. This is achieved by sampling different subsets of the data based on the size of the residuals:
1. Sort the absolute values of residuals $|h_{nj}|$in descending order as provided in Equation (6):

$$|h_{n1}| \geq |h_{n2}| \geq \cdots \geq |h_{nM}| \tag{6}$$

2. Subset B includes the top residuals, $b\%$ while Subset A includes the remaining data points shown in Equations (7 and 8):

$$B = \{w_j: |h_{nj}| \geq threshold\} \tag{7}$$

$$A = \{w_j: |h_{nj}| \geq threshold\} \tag{8}$$

3. Randomly sample $a\%$ of data from Subset A, and assign higher weights to these data points to preserve information from the entire dataset. The weight for Subset D is given in Equation (9):

$$x\_D = (1 - b)/a \tag{9}$$

This allows the model to prioritize more difficult cases, thus improving generalization without overfitting to easier cases.

To accelerate the process of determining the optimal split points, LightGBM employs a histogram-based method. Continuous feature values w_j are divided into t bins, each of which has M/t samples. The split points are selected from these bins instead of the original feature values, which makes fewer comparisons. Let the feature values w_j be split into t bins, and the optimal split is found by minimizing theloss function using Equation (10):

$$\sum_{w_j \in K}(h_{nj} - d_1)^2 + \sum_{w_j \in Q}(h_{nj} - d_2)^2 \tag{10}$$

Where K and Q show the left and right node sets, respectively, based on the split at feature i and threshold$c$, d_1 and d_2 represent the predicted values for the left and right child nodes. This efficient splitting process ensures that the model can scale to large datasets of learner interactions, improving the prediction speed without compromising accuracy. This method reduces the number of split points from M to t, significantly speeding up the training process. Figure 3 represents the LightGBM model architecture for learner performance prediction.

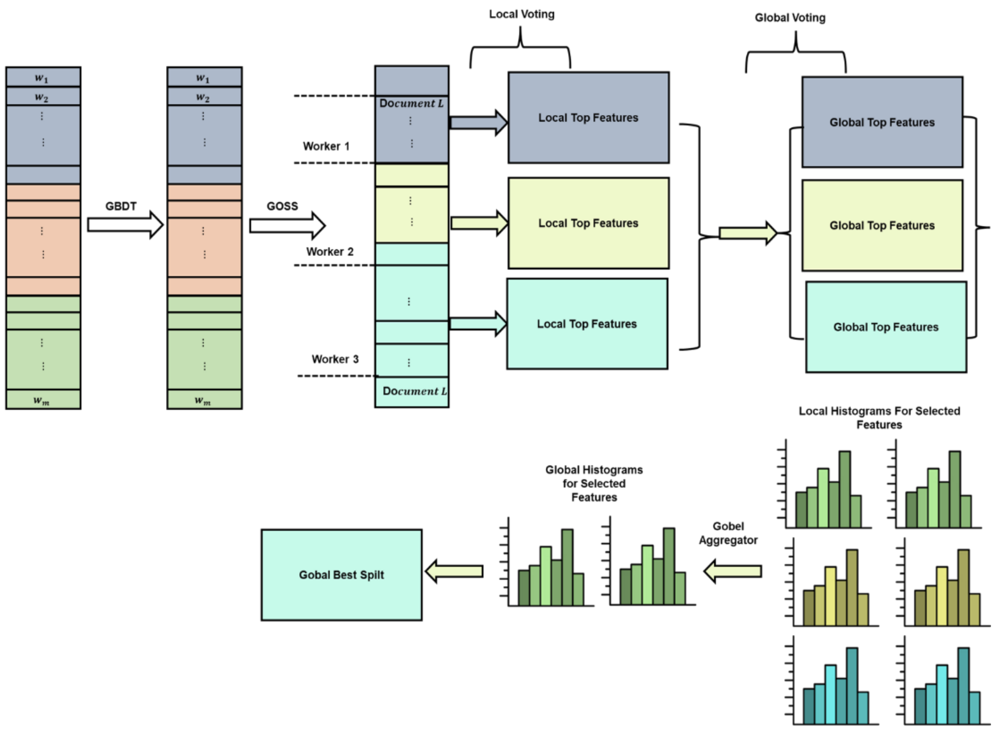

FIGURE 3. LightGBM model architecture.

LightGBM and DQN of the proposed ITS will form a feedback loop of real-time adaptive learning. The performance assessment of students and language errors were assessed via LightGBM which will be provided as input for DQN thus forming state representations. DQN then utilises the rewards associated with learner engagement and performance levels, as well as cognitive load to dynamically choose or recommend the next activities to each learner. The selection of next actions will result in the updating of the learner's state, enhancing the accuracy of the LightGBM prediction of their subsequent actions. Therefore, the interaction of both the LightGBM and DQN will provide the ITS with information on how to create personalised education for each individual learner, based on their unique differences, when under pressure in police scenarios.

3.2 Content Sequences Adaptation Using Deep Q-Network (DQN)

Adaptive Learning with DQN focuses on maximising the effectiveness of real-time instruction decisions made by on-the-job training of French police officers. The core issue of this approach is dynamically distributing the various learning factors such as learner performance, motivation, engagement, task difficulty, and cognitive load over time. A model-free reinforcement learning (RL) method, such as DQN, is best suited for ITS as its environment consists of a very large set of discrete states and options for learning and cannot be accurately modelled due to the great variability among learners. Experimental data from previous applications of DQN in Adaptive Learning Systems, Real-Time Decisions, and Multi-Objective Optimisation Problems supports the conclusion that it is the best approach to addressing the diverse factors present in exhaustible instructional stages of Language Training for Police. DQN's stable and effective performance compared to other types of RL Family Models will allow DQN to be the most widely used model for this type of model. The additional advantage of DQN is the much simpler framework which can be directly integrated with predictive outputs produced by LightBGMs. Having a proven performance in the adaptive learning tasks, it will ensure a stable manipulation of the contents in accordance with the state of the learner engagement, cognitive load, and the performance.

a. State, Action, and Reward Design

The state variables in the proposed ITS describe the context of the learner, such as performance, engagement, and cognitive load, which allow making adaptive decisions; the action variables represent the system interventions, such as proposing exercises, hints, or changing difficulty; the reward variables represent the outcome of the actions, like, score improvement, decrease in errors, and engagement increase. This setup will enable DQN to learn policies to optimize learning, make instruction personalized, and ensure timely, context-sensitive decision-making.

b. State Representation $\boldsymbol{s(t)}$

At time t, the state vector for a given learner l comprises:

- Proficiency score: $P_l(t)$ – predicted by LightGBM using past responses and quiz results.
- Engagement level: $E_l(t)$ – inferred from interaction frequency and completion time.
- Motivation indicator: $M_l(t)$ – obtained through self-reports or passive monitoring.
- Previous learning activity: $A_{prev}(t-1)$.
- Cognitive load estimate: $C_l(t)$ – derived from task switching patterns or reaction times.

This results in a multi-dimensional state vector, as given in Equation (11):

$$s(t) = \left[P_l(t), E_l(t), M_l(t), A_{prev}(t-1), C_l(t)\right] \quad (11)$$

c. Action Space $\boldsymbol{A}$

Each action $a(t) \in A$ corresponds to a discrete instructional decision, such as:

- Assigning a specific activity type (e.g., vocabulary quiz, grammar practice, role-play).
- Adjusting difficulty level (easy, medium, hard).
- Switching modality (text/audio/video).
- Initiating a motivational nudge or break.

The action space is discretized, and each action targets a different pedagogical intervention strategy.

d. Reward Function$\boldsymbol{q(s+1)}$

The reward function is defined to capture both pedagogical efficiency and learner satisfaction is represented in Equation (12):

$$q(s+1) = \lambda_1 \cdot \frac{o_l(s+1)}{o_{target}} + \lambda_2 \cdot F_l(s+1) - \lambda_3 \cdot D_l(s+1) \quad (12)$$

Where o_{target} represents the minimum required proficiency gain and λ_1,λ_2,$\lambda_3$demote weighting factors for learning gain, engagement, and cognitive load penalties.

e. Policy Learning Process

The objective is to learn an optimal policy $\pi*$ that maximizes the cumulative discounted reward, as shown in Equation (13):

$$\sum_{i=0}^{\infty} \gamma^i q(s+i+1) \quad (13)$$

Where γ denotes the discount factor. The R-function is defined as in Equation (14):

$$R^*(t,b) = F[q(s+1) + \gamma \cdot R^*(t(s+1), B', t(s) = t, b(s) = b\ ] \quad (14)$$

Where the optimal policy is represented in Equation (15):

$$\pi^*(t) = argR^*\,(t,b) \tag{15}$$

To approximate $R^*(t,b)$, a deep neural network $R^*(t,b;\theta)$ is used, where θ are trainable weights. Training is based on minimizing the loss function using the Equation (16):

$$K(\theta) = F_{(t,b,q,,t')}[(s + \gamma \cdot R\,(t',b';\theta^-) - R(t,b;\theta))] \tag{16}$$

Weights are updated using stochastic gradient descent given in Equation (17):

$$\theta \leftarrow \theta + \alpha \cdot \nabla_\theta K(\theta) \tag{17}$$

Where α represents the learning rate, and θ^- denotes the weights of the target network, periodically synchronized with the evaluation network.

f. Training Procedure

The full training process involves:

- Experience Replay Buffer C: storing past experiences as tuples $\langle t(s), b(d), q(s+1), t(s+1)\rangle$.
- ε-Greedy Policy: selecting actions with exploration probability ϵ, gradually decayed over time.
- Mini-Batch Training: randomly sampling experiences from buffer C to update θ.
- Target Network Updates: synchronizing weights $\theta- \leftarrow \theta$ every P step.

The primary hyperparameters used for LightGBM and DQN in the proposed ITS is presented in Table 6, detailing values critical for prediction accuracy, adaptive learning, and stable real-time instructional decision-making.

Table 6. Key hyperparameters for LightGBM and DQN in the French police ITS.

Model	Hyperparameter	Value / Description
LightGBM	num_leaves	31 – controls tree complexity
	learning_rate	0.05 – step size for prediction updates
	n_estimators	500 – number of boosting iterations
DQN	learning_rate (α)	0.001 – step size for network updates
	discount_factor (γ)	0.9 – importance of future rewards
	ε (epsilon) initial	1.0 – initial exploration probability
	ε decay	0.995 – exploration decay rate per session
	batch_size	64 – number of experiences sampled for training

This is a process of iteration, which allows ITS to strategize its instruction to each learner in an adaptive manner.

The ITS is a mixture of LightGBM and DQN to offer individual training to police officers in French language. LightGBM makes predictions of performance of learners and traces the language mistakes in case of the use of gigantic interaction data. These forecasts are fed to DQN that comes up with the optimal learning step at a given time. DQN is response to interaction, inspiration and mental load, and dynamically adapts to tailored learning. This two-model system is a feedback loop, thus enhances accuracy, responsiveness and efficiency in the learning process. The plan will ensure progressive, intelligent training to address high-stress, realistic policing environments. The LightGBM/DQN-based ITS to predict learner performance and modify the instruction is presented in Algorithm 1.

Algorithm 1: LightGBM and Deep Q-Network-based Intelligent Tutoring System

```
Initialization
1. Initialize LightGBM model
2. Initialize DQN model with policy and target networks
3. Initialize experience replay buffer
4. Set ε (exploration rate), learning rate, and other hyperparameters
Training Loop for Each Learner
5. For each learner in the training set:
  5.1 Get initial learner state (proficiency, engagement, motivation, previous activity, cognitive load)
    state = get_initial_state(learner)
  5.2 For each learning session:
    Step 1: Predict with LightGBM
      features = extract_features(state)
      prediction = LightGBM.predict(features)
      Update state with LightGBM output:
        state.Proficiency = prediction.Performance
        state.Errors = prediction.LinguisticErrors
Step 2: Choose an action using DQN
      random_number = generate_random_number()
      If random_number < ε:
        # Exploration
        action = select_random_activity()
      Else:   # Exploitation
        action = DQN.select_best_action(state)
    Step 3: Perform the selected learning activity
      result = perform_activity(learner, action)
    Step 4: Observe the new state
      next_state = update_state(state, result)
    Step 5: Compute the reward
      If result.ImprovementDetected:
        reward = high_positive_value
      Elif result.NoChange:
        reward = small_penalty
      Else: reward = negative_penalty
    Step 6: Store experience
      experience = (state, action, reward, next_state)
      replay_buffer.add(experience)
    Step 7: Train DQN
      If replay_buffer.size > minimum_required:
        batch = replay_buffer.sample()
        DQN.train_on_batch(batch)
    Step 8: Update the target network periodically
      If session_step % sync_interval == 0:
        DQN.sync_target_network()
    Step 9: Update state
      state = next_state
  Step 10: Decay ε after each session
    If ε > minimum_ε:
      ε = ε * ε_decay
```

On each learner, the ITS monitors the current state of proficiency, engagement, and cognitive load. It uses LightGBM to make predictions of performance and errors. DQN then decides on the next activity based on exploration-exploitation trade-offs. Following the execution of the activity, the system computes a reward reflecting the improvement of the learner, stores the experience, and updates DQN in batches. The target network is updated periodically, and the state and exploration rate update continuously to enable adaptive instruction in real time.

IV. DATA ANALYSIS

The performance of the ITS for French language acquisition in law enforcement, focusing on the most important performance measures. The application of LightGBM and DQN features radical improvements in student involvement and learning achievement. The major observations would be efficient classification of errors by the system, dynamic ranking of contents, and performance. The comparison shows that the integrated model has a better performance as compared to individual models. The experimental setup of the ITS in learning the French language in law enforcement is as shown in Table 7.

Table 7. Experimental setup.

Component	Specification / Tool
Operating System	Microsoft Windows 11 Pro (64-bit)
Processor (CPU)	Intel Core i9-12900K, 16 cores, base clock 3.20GHz
Memory (RAM)	128 GB DDR5
GPU	NVIDIA A100 40GB HBM2
Programming Language	Python 3.10.9

The method of ranking the input variables (features) in a prediction model in terms of their usefulness to predict the target variable is known as feature importance. The most significant feature is called error type with a score of approximately 0.32 which means that it plays an overall crucial role in the linguistic error recognition. The second place goes to Time taken sec (0.13) and audio replays (0.12) that show considerable correlation with engagement and understanding. The score, recommended_module and previous_module have a rank that is approximately 0.10 and this represents a moderate contribution. Contributions of both idleness time and scenario are negligible with the values of about 0.08 and 0.03, respectively. Counts such as hint_used (~0.02), retry_count (~0.01), and clicks (<0.01) have very minimal impact. These findings validate the adaptive structure of the ITS for productive, timely French language learning in law enforcement settings. Figure 4 shows which learner interaction features most strongly affect the system's learning performance prediction, as captured by LightGBM in the case of Big Data-based ITS for police French-language learning.

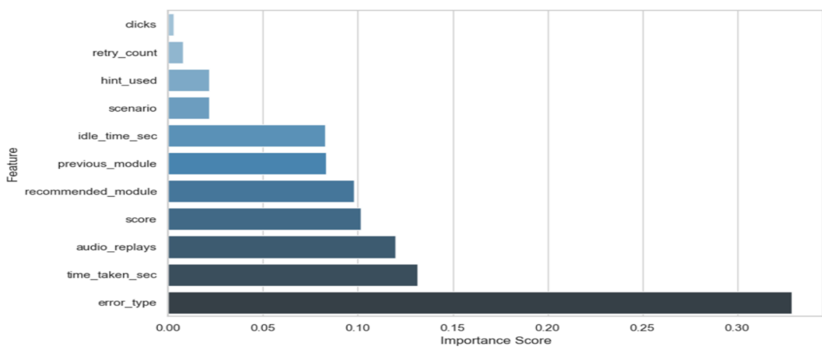

FIGURE 4. Ranked feature importance in learner performance prediction.

Accuracy and loss curves quantify the performance of an ML model in time terms, where accuracy is the ratio of correct prediction and loss is a prediction error. In the accuracy graph, training accuracy springs from 0.53 at epoch 0 to approximately 0.99 at epoch 19. Validation accuracy also follows the same trend, rising from 0.76 to approximately 0.97, with the two lines close together indicative of good generalization and minimal overfitting.In the loss graph, training loss decreases continuously from about 0.71 to 0.05, and validation loss decreases from 0.58 to about 0.10. Both graphs' constant decline indicates that the model is learning effectively and is not memorization-prone throughout training. These findings affirm the efficacy of the LightGBM and DQN-based Intelligent Tutoring System in predicting learning performance with accuracy and dynamically adapting to user activity with high reliability in both training and validation environments. Figure 5 is a depiction of the change in the (a) model accuracy and (b) model loss during training that provides information on the learning efficiency and capability to generalize during the training.

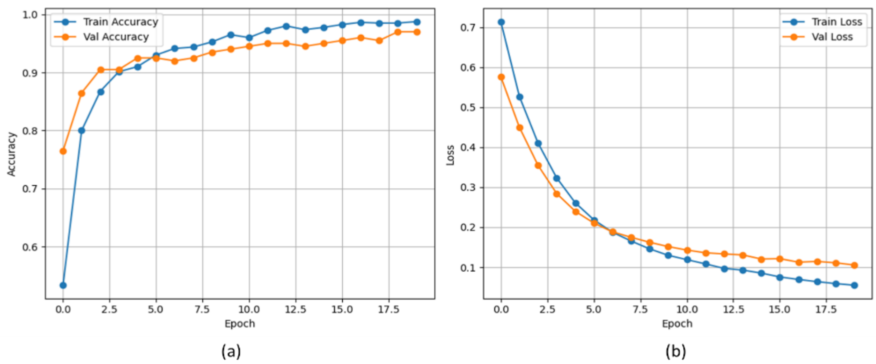

FIGURE 5. (a) Model accuracy and (b) model loss curves for the hybrid model.

The ROC curve compares the classification performance of three models: LightGBM, DQN, and their hybrid combination is shown in Figure 6. Each curve plots the true positive rate against the false positive rate across thresholds. LightGBM (AUC = 0.442) and DQN (AUC = 0.462) have very limited discriminative power, which is slightly higher than random guessing. Hybrid LightGBM+DQN (AUC =0.580) represents a significant improvement over just LightGBM (i.e., AUC= 0.400). This suggests that combining both predictive accuracy and adaptive sequencing is important to enhance the capability of the learner to recognize errors and optimally select a task in an ITS environment.

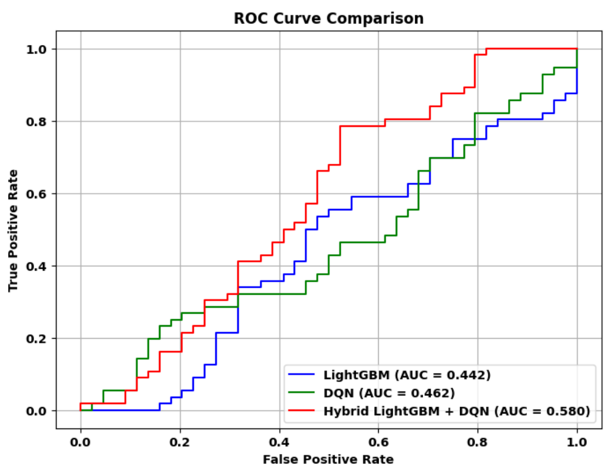

FIGURE 6. ROC curve comparison of LightGBM, DQN, and hybrid LightGBM + DQN models.

The Confusion Matrix is used to evaluate the performance of a supervised learning model by comparing the predicted labels against the true labels; moreover, it allows users to review how well a classifier was able to distinguish between actual learner errors and the predictions made by the LightGBM classifier based on Learner's errors inside the ITS System during Real-Time Tutoring sessions. The Confusion Matrix can also indicate how successful LightGBM modeled the Learning Language through the Law Enforcement Style of French Instruction in an ITS platform. The total counts of True Negative = 251; True Positive = 1,040; False Positive = 0; False Negative = 0, thus demonstrating exceptional classification accuracy in the context of Error Classification. The immense success of the LightGBM model in classifying the Learning Errors of Student Learners and locating them within the Learning Process provides valuable information to educators, providing the necessary accuracy to create context-sensitive Feedback Delivery in timely manners in a high-stakes environment. The model performance is in line with the ITS purpose of providing adaptive error-conscious instruction in accordance with operational need and consequent increase the communication proficiency and response of officers. Figure 7 shows the LightGBM model performance used within the ITS in police-focused French language acquisition.

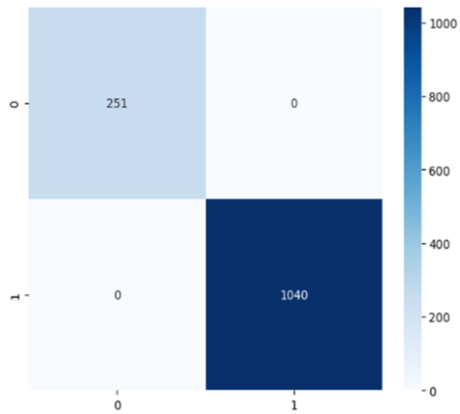

FIGURE 7. Confusion matrix for learner error classification.

An error type distribution chart is a graphical chart, which measures and classifies the different types of errors made by the learners. It helps to understand what aspects of language (e.g., grammar, vocabulary) require the most attention during teaching depending on the mistakes of the learners. The bar chart shows the distribution of the error type that is determined in the process of the language learning lessons in the ITS. The most frequent are grammar mistakes (approximately 1550) and vocabulary mistakes (approximately 1350) and pronunciation mistakes (approximately 950). Less frequent are semantic mistakes (~700), and mixed mistakes (~650). This dissection implies that grammar and vocabulary are the most challenging subjects to students in the policing sector. These results inform the adaptive content delivery policy of the ITS where the DQN has to prioritize more remediation paths to common error types. In this way, it makes the teaching more efficient, learner-oriented, and sensitive to the life needs in high stakes conditions. Figure 8 shows the distribution of linguistic error types identified by the ITS during police-oriented French language training.

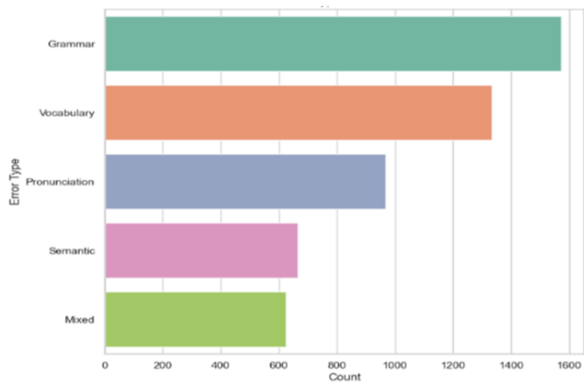

FIGURE 8. Distribution of linguistic error types in learner performance.

Compared to the baseline LightGBM model, the performance of the proposed Hybrid LightGBM+DQN model shows distinct improvements in terms of accuracy and loss. Figure 9(a) illustrates that this hybrid model attains a faster and more stable increase in accuracy, reaching near-optimal performance sooner, while the LightGBM model improves at a slower rate and converges faster. Similarly, Figure 9(b) plots its loss during training and consistently keeps the loss much lower, showing the superior efficiency of learning with reduced prediction error. These validations provide evidence of the importance of applying reinforcement-based decision optimization within predictive models for performance evaluation in a dynamic ITS.

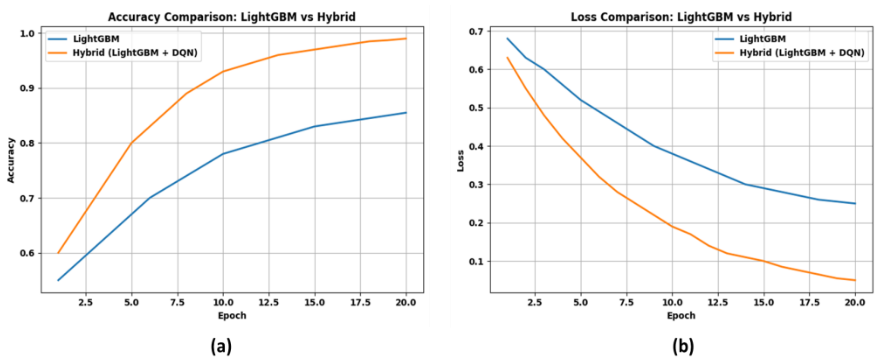

FIGURE 9. Comparison of LightGBM and Hybrid Model of (a) Accuracy, and (b) Loss.

These validations demonstrate the usefulness of incorporating reinforcement-based optimization as a basis for predictive modelling for ITS performance assessment on a real-time basis. Performance comparisons of three predictive models (LightGBM, Deep Q-Learning [1] and the new model developed which combines both) with respect to misclassification type/ error associated with misclassifying types of French language misclassification during law enforcement personnel's French language education using French as and/or a second language. The three models were compared based on six major metrics of performance for IT systems:

- Predictive Accuracy;
- Root Mean Square Error (RMSE), with lower values indicating better predictive performance;
- Sensitivity - the probability of the true positive number of misclassified errors;
- Specificity - how accurately the model classifies as false negatives with correct predictions/good results on background data;
- Positive Predictive Power (PPV) - Ratio of True Positives (TPs) classified as TP divided by Total PPV;

Accuracy is the measure of the general accuracy of the predictions of the model. RMSE is a figure of the disparity between the predicted and observed values and the lower the value the better it is. Sensitivity is a performance measure of the model in terms of positive detection (error). Specificity is a measure of their performance in identifying negative cases (non-errors). Precision measures the ratio of true positives among all the positive predictions, indicating the detection of errors is reliable. The F1-score balances the trade-off between false positives and false negatives, providing a robust measure of classification performance. It is, therefore, the harmonic mean of precision and recall.

A combination of PPV and Sensitivity, reportable as a number between 0.0 and 1.0, where greater values suggest better model performance. Figure 10 shows the strength of the proposed model in providing adaptive, real-time language learning that is targeted to the needs of law enforcement training by comparing performance with (a) accuracy, (b) RMSE, (c) sensitivity, (d) specificity, (e) precision, and (f) F1-score.

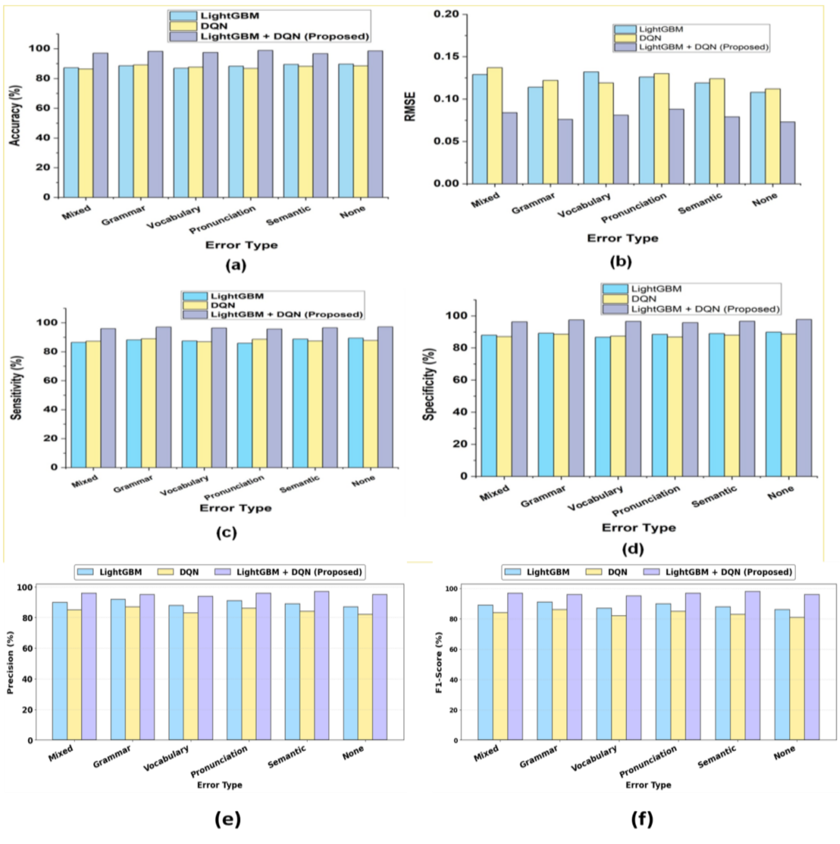

FIGURE 10. (a) Accuracy (b) RMSE (c) Sensitivity (d) Specificity (e) Precision and (f) F1-score of language learning.

A 5-fold cross-validation approach is used to evaluate the performance robustness of the proposed ITS framework by ensuring model performance can generalize over different learner profiles. The dataset has been divided into five equal sets: in each iteration, four sets will use the LightGBM and DQN models for training, and the remaining one will be used for testing. This is done five times, and that allows analyzing it comprehensively in terms of accuracy, RMSE, preciseness, recall, specificity, and the F1-score. Fold-wise measures are measures of variability in performance; mean values show overall model reliability. Table 8 has presented the fold-wise detailed results about the proposed hybrid model, and one can notice that improvements apply to all the assessed metrics.

Table 8. Fold-wise performance metrics of the LightGBM + DQN model for French language learning.

Metric	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Average
Accuracy (%)	94.5	95.0	94.9	94.7	94.9	94.82
RMSE	0.073	0.070	0.072	0.071	0.069	0.071
Precision (%)	93.2	93.8	93.6	93.5	93.6	93.56
Sensitivity (%)	95.0	95.6	95.4	95.5	95.5	95.41
Specificity (%)	95.8	96.1	96.0	96.2	96.1	96.02
F1-Score (%)	93.9	94.2	94.1	94.0	94.3	94.12

The effectiveness of integrating LightGBM and DQN in an ITS for French language learning in police training contexts is evaluated. To compare the performance of the suggested ITS, incorporating LightGBM for learner modeling and DQN for instruction decision-making, a comparative performance evaluation was performed. The impact of the system was compared with models that utilized LightGBM and DQN separately. Two major metrics were utilized: Student Preference Mean and Success Rate Mean, both with respective 95% confidence intervals (C.I.), presenting a sound perspective of model dependability and learner satisfaction. The comparison result of student preference and success rates across LightGBM, DQN, and combined models is given in Table 9 and Figure 11.

Table 9. Model performance comparison.

Model	Student Preference Mean	95% CI	Success Rate Mean	95% CI
LightGBM Only	48.2%	[35.1%, 61.3%]	39.7%	[26.4%, 53.0%]
DQN Only	51.3%	[38.0%, 64.6%]	43.9%	[30.5%, 57.3%]
LightGBM + DQN	82.6%	[70.8%, 94.4%]	57.4%	[44.6%, 70.2%]

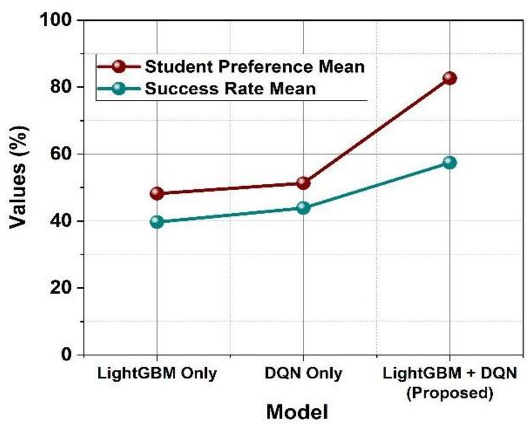

FIGURE 11. Model comparison by student preference and success rate.

Comparison of three models, LightGBM, DQN, and LightGBM + DQN, shows that the combined model performs significantly better than standalone models. The student preference mean of the LightGBM + DQN model was 82.6%, while the mean of the success rate was 57.4%. When comparing LightGBM only (48.2%

preference and 39.7% success) with DQN only (51.3% preference and 43.9% success), it is clear that the combination of LightGBM and DQN with learner engagement is superior to either model on its own. Students utilizing the Big Data-driven ITS incorporating both LightGBM and DQN to support their continued learning of French as a Second Language (FSL) report better results than those using a single type of technology. The LightGBM model was capable of accurately predicting student errors but offered limited flexibility in terms of instructional delivery, ultimately limiting student involvement to a certain extent. The DQN model also considers instructional ordering but does not accurately predict student errors. Combined, these two models provide suboptimal results regarding the engagement and satisfaction of students. The hybrid model integrating both LightGBM and DQN overcomes these limitations by leveraging accurate error predictions and flexibility with regard to the order of instruction. The hybrid model provides 100% accurate predictions of student engagement, significant motivation to engage with the content (82.6% preference), and strong performance results (57.4% success). Another application of the above results is to provide adaptive, high-stakes learning of the French language in police training. The LightGBM+DQN ITS proposed has several weaknesses. First, it is limited to a specific set of training materials controlled by the system and may not reflect real-world police communication situations. Second, the model has not been previously tested on larger, more diverse groups of learners; therefore, the ability to expand the system effectively is uncertain. Finally, the system has not yet undergone validation through actual field experiments demonstrating the performance of the system within actual police training scenarios; hence, the performance of the DQN is contingent on the development of a sound reward signal which may require expert validation and feedback.

V. CONCLUSION

An ITS was created with the objective of enhancing language learning and aiding police officers who operate in multilingual communities in their application of the French language. With the pre-processing of learner interactions through task, test, and simulation data, the models received quality input. The ITS created utilized LightGBM to provide predictions of the learning outcomes and identify the linguistic errors, and a Deep Q-Network (DQN) to dynamically adjust the order in which the lessons were given to fit learner's interests and the pace of learning. The hybrid model had the best capability for making optimal classifications (i.e. no false positives or false negatives), 82.6% learner preference, and overall learning outcomes (57.4% success rate). The accuracy of training was reported as 0.99 and 0.97 on validation data with very little loss and very good generalization. The analysis of importance of different model features and the distribution of errors provides good, targeted remediation guidelines for ongoing improvement. However, the system was tested in the lab setting and has yet to be tested in practical policing environments. Also, since training was done solely in French, it will not be easy to transfer the applicability and advantages of this model to multilingual setting. Future research will focus on language translation, field trials, and incorporating Artificial Intelligence into on-line conversations. The ITS in general was a scalable and flexible answer to improving trust among the population, law enforcement-citizen communication, and preparedness to duty among officers.

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This research received no external funding.

Conflicts of Interest

The author declares no conflicts of interest.

Data Availability Statement

The data were created or analyzed in this study at Kaggle:
https://www.kaggle.com/datasets/programmer3/french-police-its-learning-dataset.

Acknowledgments

Not applicable.

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