Predicting the Effectiveness of Scientific Inquiry in Educational Technology in Moroccan Secondary Schools: A KNN-Based Analysis through Observations and Interviews

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***Abstract*—The main objective of this study is to assess the extent to which machine learning models can predict the effectiveness of Scientific Inquiry Approaches (SIA) in learning and teaching within Moroccan secondary education. Data from 1,392 students, collected through classroom observations and interviews during the period 2021–2023, were used to develop a predictive analytics framework. The dataset was meticulously preprocessed by applying missing value treatment and normalization techniques to ensure robustness. The K-Nearest Neighbor (KNN) algorithm was implemented using the scikit-learn Python library. Model performance was evaluated using multiple metrics, including accuracy, precision, recall, F1-Score, specificity, false positive rate, Receiver Operating Characteristic (ROC) analysis, and Area Under the Curve (AUC). The results demonstrate strong predictive performance, with an AUC of 0.8875 for interview-based data and 0.9309 for observation-based data, corresponding to prediction accuracies of 90.2% and 94.5%, respectively. These findings indicate that machine learning is an effective tool for predicting the success of SIA teaching approaches. By integrating complementary data sources, this study provides novel evidence from the Moroccan educational context regarding prediction reliability. The findings have important implications for improving instructional practices, supporting data-driven decision-making, and informing educational policy. Future research may further validate the proposed framework by exploring additional machine learning algorithms and broader datasets.**

***Keywords*—scientific inquiry approaches machine learning, secondary education, predictive analytics, educational technology**

I. Introduction

Between 1999 and 2019, Morocco’s educational system underwent significant reforms aimed at addressing systemic challenges rooted in the nation’s colonial history and post-independence developments. Key reforms, including the National Education and Training Charter (NETC), the National Emergency Education Plan (NEEP), the Education Action Plan (EAP), and the Strategic Vision for Moroccan School Reform, have substantially improved access to education, particularly at the primary level, where enrollment rates have reached 100%. However, challenges persist, particularly in adult literacy, reflecting enduring socio-economic disparities and gaps in educational quality. Despite efforts to enhance infrastructure and expand educational opportunities, issues such as resource allocation, teacher training, and the adaptation of pedagogical methods to Morocco’s diverse cultural contexts remain unresolved [1]. These continuing challenges highlight the need to explore more effective and contextually responsive instructional approaches within Moroccan classrooms.

Morocco has participated in the Trends in International Mathematics and Science Study (TIMSS) since 1999, which assesses student achievement in mathematics and science. According to TIMSS 2015 results [2], Moroccan students ranked poorly, highlighting the urgent need to improve science teaching methodologies, specifically in Life and Earth Sciences, to build future betterment in SIA for enhancing these performances and preparing students for future challenges. Recent years have seen a growing emphasis on inquiry-based learning strategies in science education. However, the application of predictive analytics and machine learning to evaluate the effectiveness of SIA in Moroccan secondary education remains underexplored. This study addresses this gap by employing machine learning algorithms to predict student performance, particularly under the implementation or not of SIA, is largely unexplored; this research attempts to fill that gap by applying machine learning algorithms to predict student performance based on the implementation or non-implementation of SIA in teaching Life and Earth Sciences. By offering a novel approach to educational evaluation, this research provides insights into the practical effectiveness of SIA in improving student outcomes. This growing interest reflects a shift toward modern, evidence-based teaching practices aimed at improving both conceptual comprehension and student engagement.

Traditional teaching methods, characterized by rote memorization and passive learning, have proven ineffective in fostering deep understanding and critical thinking. Consequently, there is a growing shift toward integrating SIA into science education. These approaches engage students in active learning through exploration, investigation, and the construction of scientific knowledge. Such involvement enhances both scientific practices and conceptual understanding [3]. By engaging in SIA, students develop essential competencies, such as critical thinking, problem-solving, and communication, which are crucial for success in the 21st century. SIA are widely recognized as

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effective teaching methods that empower students to understand science and develop scientific thinking [4, 5]. SIA encourages learners to formulate research questions, conduct investigations, evaluate findings, and draw conclusions. This approach shifts the focus from teacher-centered instruction to learner-driven education [6]. The teacher's role is to facilitate inquiry by posing questions and guiding students in exploring scientific concepts [7, 8]. Inquiry-based learning involves constructing evidence-based explanations, engaging in peer review, and refining scientific arguments. Argumentation—creating, justifying, and evaluating scientific explanations—is a core practice of inquiry and a critical component of scientific literacy [9]. Through these processes, students refine their explanations, moving closer to scientific understanding. Therefore, strengthening the integration of SIA may contribute to meaningful improvements in science learning outcomes in Moroccan classrooms.

In Moroccan secondary education, the integration of SIA holds significant promise for transforming traditional teaching methods that often prioritize memorization over conceptual understanding. SIA provides students with opportunities to explore scientific phenomena, enhancing engagement and learning outcomes. Kouchou *et al.* [10] emphasize the need to clarify the investigative approach to ensure meaningful adoption by teachers. However, integrating SIA into the Moroccan educational system poses challenges, particularly in measuring its effectiveness. The implementation of this approach is promising and important in the same time in the field of the science of education [11]. Moreover, different studies bring different dimensions to the use of machine learning in education sciences as a tool for prediction of performance. Khoudi *et al*. [12] implement machine learning techniques to examine contextual predictors, especially the pivotal influence of school resources and teacher attributes and home environment as determinants of exceptional reading performance among Moroccan fourth graders. Korkmaz and Correia [13] provide an overview of the current state of machine learning, as it pertains to educational technology use, trends, methodologies, and a number of key contributors to this growing field. Specifically, Sadqui *et al*. [14] have inspected the predictive power of machine learning models for on-time graduation rates and how the Random Forest model works out excellently, for higher education management. The studies provide substantial contributions to how machine learning can be applied in education: from reading performance improvement to graduating timeline optimization and, more importantly, guiding educational technology research. Yet, the integration of machine learning to evaluate the impact of SIA in secondary science education remains limited, which creates a need for further empirical investigation.

This study in science attempts to assess the effectivity of SIA teaching methods in the subject of life and earth sciences, looking at their eventual effects on students' learning outcomes and the extent of mastering the targeted competencies within Moroccan secondary education. The two major research objectives are: a) to develop a robust predictive model, based on machine learning algorithms, for the assessment of instructional methods' effectiveness for SIA within the field of life and earth sciences; and b) to provide data-driven insights with recommendations for improvement in science education practices in Moroccan secondary schools. In light of this, this study seeks to present evidence-based literature that is relevant to preservice and practicing teachers, as well as public policymakers in the governance of science teaching curricula. Through such findings, there would be indicated the effectiveness of SIA in the Moroccan context, therefore guiding educational strategies in facing the challenge of enhancing the engagement of students, deepening understanding, and promoting scientific literacy in the future. Thus, this research contributes to both theoretical and practical insights that may support the advancement of science teaching in Morocco.

This study investigates the effectiveness of SIA in enhancing students' scientific understanding and attitudes toward science. The research consequently seeks to establish how SIA influences students' abilities concerning formulating research questions, conducting investigations, and engaging in scientific argumentation. On this background, the following research questions are addressed:

1) How does participation in SIA impact students' ability to develop and articulate research questions based on scientific curiosity?
2) What is the relationship between SIA and students' skills in conducting scientific investigations and drawing evidence-based conclusions?
3) How does SIA influence students' engagement in scientific argumentation and overall scientific literacy?
4) What are the perceived challenges and benefits of SIA from the perspectives of students and educators?
5) What do students and educators perceive as major challenges and benefits of SIA? The study aims to investigate these questions and better document the efficacy of SIA as a pedagogical approach with its implications for the improvement of practices in science education.

The primary objectives of the study are:

1) To construct a predictive model with machine learning algorithms for assessing the effectiveness of SIA techniques in Moroccan secondary schooling.
2) To identify evidence-based methods for enhancing scientific education practices based on students' learning outcomes.

This paper provides several significant contributions:

1) It introduces the novel application of the KNN algorithm for forecasting the effectiveness of SIA methods in science education.
2) It offers empirical evidence regarding the impact of varying SIA methods on secondary school students' motivation and learning achievement in Morocco.
3) It makes evidence-based, practical recommendations for policymakers and educators to enhance science education practices and integrates predictive analytics into educational decision-making.

In Section I, we present the introduction, including the background and history of the Moroccan educational system, challenges in integrating Scientific Inquiry Approaches (SIA), and the research questions. Section II reviews the relevant literature on SIA methodologies and the application of machine learning in educational contexts. Section III outlines the theoretical framework guiding this study. Section IV describes the research methods, including data collection and preparation. Section V presents the algorithm selection process. Section VI details the results and findings, including observational and interview data as well as the performance of the KNN model. Section VII discusses the findings, their implications for educational practice, and study limitations. Section VIII concludes the paper, summarizing contributions, limitations, and recommendations for future research.

II. Literature Review

Recent studies in educational sciences underscore the importance of adopting a learning approach that engages students. In the field of Life and Earth Sciences, blending inquiry science and predictive analytic modeling has been of much interest. To define the purposes of the research, the literature review was classified into four categories: (1) inquiry learning practice in the teaching of Life and Earth Sciences, (2) cognitive and motivational factors affecting inquiry abilities, (3) applying machine learning to predict scholarly achievement, and (4) applying scientific reasoning.

Several studies have pointed to the significance of inquiry-based instruction in encouraging student participation and scientific thinking. For example, Hassouni *et al.* [11] established the significance of inquiry-based instruction in encouraging students' active participation in Moroccan Life and Earth Sciences classrooms. The results, however, underscore the fact that teachers must be provided with continuous pedagogical support to implement the instruction. In a similar fashion, Kouchou *et al.* [10] examined the challenges and merits associated with integrating inquiry instruction within the Moroccan context. The findings from these studies are directly applicable to the proposed research, which aims not only to contribute to knowledge on the challenges associated with the implementation of inquiry instruction but also to measure the actual impact on student outcomes.

Building on this, it is also important to consider how internal learner characteristics influence the success of inquiry-based learning.

The impact of inquiry-based learning can also be influenced by student-specific factors such as gender. Nehring *et al.* [15] identified the interplay between cognitive attributes, motivational factors, and individual student backgrounds in determining the development of inquiry abilities in science. Their findings indicate that the effectiveness of instruction is not solely dependent on instructional practice; individual factors about the learner play an equally important role. The main shortcoming of Nehring *et al.*'s [15] findings is the small scale of their study, which limits generalization, warranting a broader study, as conducted in the proposed research.

At the same time, recent developments in educational technology have introduced new methods for evaluating learning outcomes, including machine learning.

Machine Learning (ML) has numerous applications in predictive analytics in the education sector. The applicability of ML algorithms in forecasting the performance of Moroccan physics students has been demonstrated; however, limitations in model flexibility were suggested by Qazdar e*t al.* [16]. Supporting the use of ML, Tarik *et al.* [17] demonstrated AI/ML prediction systems, specifically within the context of the COVID-19 pandemic, explaining the feasibility of AI/ML-assisted planning. Balaji *et al.* [18], in notable research, have underscored the importance of ML model adaptability. The proposed research supports Balaji *et al.* [18] but has a distinct perspective, namely, evaluating the efficacy of SIA models.

Moreover, the conceptual foundation of inquiry learning is tied to broader discussions of scientific reasoning in education.

The theoretical background of inquiry learning is supported by research on scientific reasoning. Emden [19] has emphasized the reintroduction of genuine SIA as a means of encouraging critical thinking [20]. This research supports the value of teaching inquiry as a learning tool, but it has limited empirical support based on actual everyday classroom environments, specifically in Life and Earth Sciences. This study aims to fill this gap.

Based on this synthesis, three significant research gaps have been identified:

- The available literature on the Moroccan context discusses the challenges faced in the implementation of inquiry-based learning but does not include empirical validation of its impact on learning outcomes.
- Research on inquiry effectiveness has been based on small samples, making it necessary to conduct larger-scale research in a number of schools.
- Machine learning has been utilized to predict overall academic achievement, but it has not been used to predict the efficacy of SIA in teaching Life and Earth Sciences.

The proposed research addresses the identified gaps within the context of a comprehensive empirical study, utilizing machine learning to evaluate and forecast the results of inquiry-based learning within Moroccan Life and Earth Sciences classrooms. To support this empirical investigation, it is essential to ground the study in relevant theoretical perspectives that explain how inquiry-based learning facilitates knowledge construction and self-regulation.

The theoretical foundation of this research work is based on constructivist learning theories and self-regulated learning theories, which form a strong framework to analyze the effects of SIA. Constructivism, based on the theories of Vygotsky [21], emphasizes a learner's construction of knowledge. These tenets have been incorporated in SIA. In SIA, students are involved in questioning, investigating, and building explanation-based responses, which help in enhancing their conceptual knowledge in science education on a deeper level [3, 6, 8].

In regards to the Moroccan Life and Earth Sciences environment, SIA is a foremost constructivist approach to teaching, encouraging learning to go from memorization to knowledge construction [10, 11]. In regard to the efficacy of inquiry-based learning, the level of learner engagement, as well as cognitive self-management, becomes a consideration. It is at this juncture that the concept of self-regulated learning, proposed by a foremost cognitive researcher, Barry Zimmerman, based on Albert Bandura's social cognitive theory, becomes a vital consideration within this dialogue [22, 23]. Self-regulated learning views a learner's knowledge as a means to monitor, regulate, and control their own learning behaviors [24].

SIA is inherently supportive of self-regulated learning, as it provides situations in which autonomy, perseverance, and reflection are required [5]. In student-designed investigations, as well as in data analysis, students have set personal goals, tracked progress, and refined approaches. The development of these skills is a complex function of a multitude of cognitive and motivational, as well as sociodemographic factors [15], thereby pointing to the importance of these facets in judging SIA's efficacy.

In order to formally measure the degree of this impact, the research incorporates predictive analytics using machine learning. Machine learning has been previously utilized extensively as a predictive tool for analyzing academic achievement [16, 18], though within this research, it is utilized to predict the success of SIA directly. This enables a predictive approach to be taken rather than a descriptive approach, as has been criticized within research [10, 11].

By integrating SIA within these interrelated theoretical frameworks, it becomes apparent within this research that SIA has dual applicability as a tool for enhancing concept knowledge in Life and Earth Sciences, as well as a tool for facilitating the development of higher order, self-regulated skills.

III. Method

This study builds on a theoretical framework that highlights the dual role of SIA in enhancing both conceptual understanding and self-regulated learning. Using a quasi-experimental design, it investigates how effective SIA is in Moroccan secondary school Life and Earth Sciences classes. The research design and data collection methods are rooted in constructivist principles, ensuring that students are actively engaged in inquiry activities. At the same time, the assessment of outcomes utilizes predictive analytics to quantitatively measure the impact of SIA on students' learning and their self-regulatory skills.

The data flow diagram of the methodology used in this study is illustrated in Fig. 1. It provides a clear precise overview of the main steps, starting from data collection to model validation. The process includes the following stages:

- Data Collection: Gathering raw data from relevant sources such as observations and interviews.
- Data Preparation: Structuring the data for analysis.
- Data Preprocessing: Handling missing values, normalizing features, and addressing outliers.
- Algorithm Selection: Implementing the KNN algorithm for prediction.
- Model Evaluation: Measuring performance using metrics like accuracy and F1-Score.
- Model Validation: Testing the generalizability of the model on unseen data.

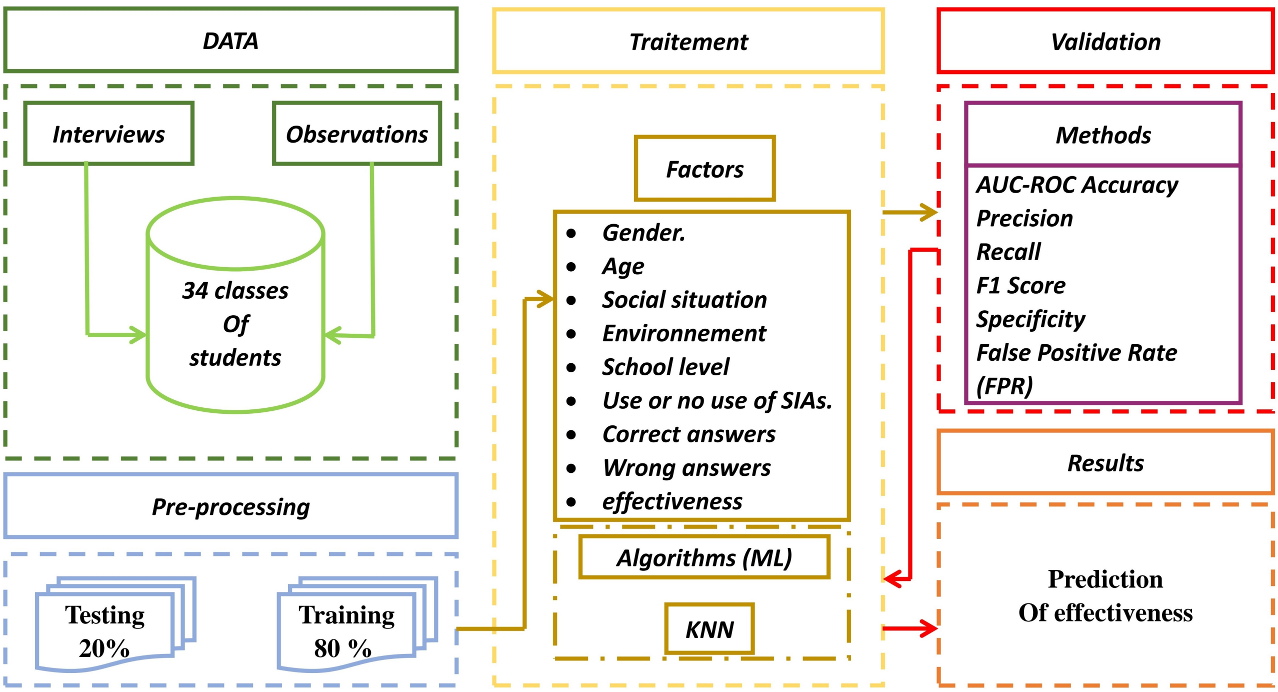

Fig. 1. Data flow diagram.

A. Research Design

The current study will follow a mixed-method approach [25] that combines the framework of classroom observations (quantitative data) and in-depth interviews from students (qualitative data). This will be conducted to provide an all-rounded assessment of the effectiveness of SIA methods [26] on the use of educational technology. Moreover, mixed-method research is a procedure that combines both qualitative and quantitative approaches within one research study, thus fully answering complicated research questions. In the mixed-method approach, a deeper understanding of the studied phenomena is achieved through the depth of qualitative insights and the breadth associated with quantitative data. Many scholars have reported advantages associated with this approach [27, 28], who strive to underline its value in the production of robust and well-rounded research findings.

Nair and Prem [27] written to emphasize the case of confluence in qualitative and quantitative approaches to research. The prime importance of introduction of mixed-method research comes at the point where it provides the researcher with the means of arriving at an in-depth understanding of the root cause of a complex issue by exploiting the positive features of both branches of the research method. These highlight careful design and interpretation of mixed-method research so that the findings are valid and reliable. In this respect, Mason [28] insists that mixed-method research is necessary for understanding complex social experiences. It promotes moving beyond the qualitative-quantitative divide by emphasizing constructivist approaches and methodological creativity. Mason puts forward some principles of effectively integrated approaches: being reflexive and recognizing the validity of multiple approaches by using flexible research designs. Ultimately, this paper invites a more innovative and comprehensive approach toward understanding social realities.

B. Participants and Sample Characteristics

It involved 34 classes of secondary school students in Morocco, in particular those engaged in inquiry-based activities in Life and Earth Sciences. The sample consisted of 1392 students, observed and interviewed during the 2021–2023 academic years. Moreover, it was underscored that all data would be anonymized to safeguard the identification of the student participating.

The study employed purposive sampling to include secondary school classes actively engaged in Life and Earth Sciences, with and without inquiry-based approaches. The sample comprised 34 classes from 12 schools across Morocco, totaling 1392 students, with 66% from semi-rural areas and 34% from urban areas, 59% female and 41% male, and distributed across middle and high school levels. Classroom observations and semi-structured interviews were conducted to capture demographic, contextual, and educational variables. Fig. 2 summarize the distribution of sample characteristics. While representative of the participating schools, generalizations beyond these demographics should be approached with caution.

This data was obtained through classroom observations that utilized glimpsing and semi-structured interviews with the students. Observations were detailed and recorded by using a standard observation grid that ensured equivalence and resolution in different conditions. Key characteristics recorded in such observations included the class environment, sex, age group, social context, current school grade, total student count, application and non-application of SIA, right and wrong answers, and overall learning level of performance. The sample was 34 classes that encompassed 1392 students with a 66% population from semi-rural parts and 34% from other urban localities. The distribution is as shown in the pictorial graph in Fig. 2(A). It is seen that the residence of the student population varies depending on other socio-economic and demographic factors in other individual households.

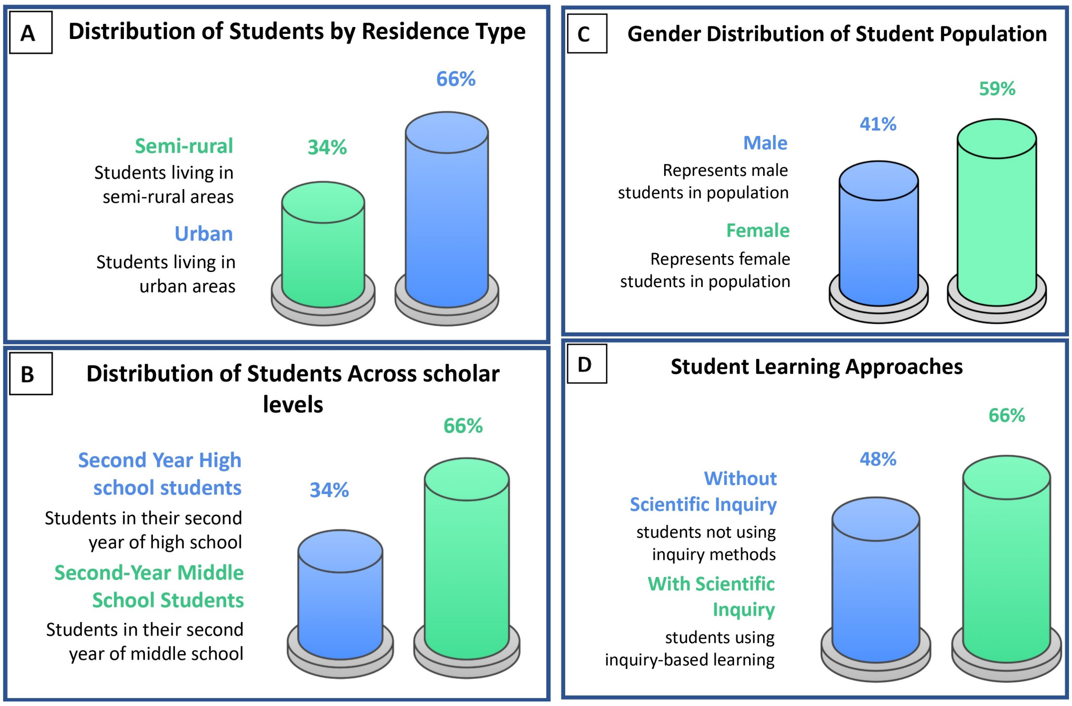

Fig. 2. Distribution of characteristics in a sample used for predicting student performance.

The distribution of students across the educational levels of the second grade's middle and high school is 66% and 34%, correspondingly. This distribution is summarized as in Fig. 2(B). Gender distribution also obtained information on the gender of the students 41% male versus 59% female. This spread of gender is illustrated in Fig. 2(C). In addition, results indicated that 52% of the students used a SIA, while 48% did not, as shown in Fig. 2(D). To ensure reliability and validity of the qualitative data, classroom observations were conducted using a standardized observation grid, and semi-structured interviews were performed with a subset of students. Inter-rater reliability was assessed through independent coding by two trained researchers, and triangulation between observations and interviews strengthened the validity of the findings.

Semi-structured interviews were conducted with a subset of the student participants following these observations to better understand the students' perception of the applied inquiry approach; challenges and successes regarding the learning process; and the effectiveness of using educational technology tools. This dual-method approach gave great insight into educational dynamics and the impact of SIA in Life and Earth Sciences classrooms.

The study sample consisted of 66% semirural and 34%

urban students, with a gender distribution of 59% female and 41% male. This reflects national trends: for example, female gross secondary school enrollment in Morocco was approximately 82.4% in 2021, and the female-to-male secondary enrollment ratio was near 95.1% [29]. However, rural-urban disparities persist; girls aged 12–14 in rural areas enroll at about 72.3% versus 86.7% nationally, and rural girls aged 15–17 enroll at around 33% compared to 63.6% nationally [30]. Therefore, although the female majority and semirural composition of our sample mirror real demographic patterns, it may limit the extent to which findings generalize to different populations, such as urban or male-dominated schools. Consequently, results should be interpreted with caution, and future studies should consider more balanced and diverse samples across regions and school types to enhance external validity.

C. Data Preparation

The research uses a dataset of results of students exposed to either the SIA or the non-inquiry approach using two tools: Interviews and observations. The dataset shall be prepared by removing missing values [31], then normalizing the data for consistency and accuracy in the subsequent analysis. In this research, we worked extensively with three classes that adopted the SIA for teaching and learning of earth life sciences. At the same time, an equal number of classes adopted the traditional way of teaching, without the adoption of the SIA. We may add here that in order to properly determine the effects of these SIA; we adopted a two-pronged data collection approach. The first aspect involved interviews whereby the life sciences teacher administered three questions at the end of each science session, crafted in a way that they centered on the course's theme; the purposeful questioning was meant to assess how much the students were absorbing from what was taught. In particular, students who scored at least two out of the three questions were classified in the group that worked with the effective technique, while anything less and they were thrown into the second category.

The next aspect of data collection was the observations. Here, we carefully recorded their participation and activity toward constructing course materials. This consisted of a critical analysis of their responses and interactions triggered by questions proposed by the instructor during classes. First, it is important to note that we are research collaborators who worked with volunteer instructors who kindly participated in the implementation of this research project. Moreover, the database that contained all the students' results after learning using the SIA as well as with the non-SIA was carefully cleaned. This involved removing missing values from all cases before normalization took place. These were some of the preparatory steps to provide a bedrock of consistency and precision for analytical pursuits that would follow.

The qualitative data obtained from group interviews (students' responses to exam-style questions analyzed with a coding grid) and from classroom observations (student participation rates during inquiry-based activities) were systematically transformed into quantitative variables. This conversion was performed using Python, where the coded responses and participation frequencies were processed into numerical datasets suitable for machine learning analysis. This ensured that both engagement indicators and conceptual mastery could be represented in a structured empirical format for predictive modeling.

D. Data Collection

The data was collected by observing classrooms that were followed up by interviews with the students. Some of the key attributes recorded were class environment, gender, age bracket, social situation, educational level, the number of students, use or non-use of SIA, correct and wrong responses, and the effectiveness of learning. All observations were recorded in a standardized way to ensure consistency and reliability. Moreover, interviews were carried out with a subset of students in order to learn in greater depth about their experience. It focused on the perception by students of the applied SIA, the problems encountered and successes scored during the learning process, and the working of educational technology tools.

Semi-structured interviews were transcribed verbatim and analyzed using a coding grid developed from the research objectives. Each transcript was reviewed, and meaningful units were assigned to predefined categories, with additional emergent themes incorporated iteratively. Two independent coders applied the coding grid to a subset of interviews to ensure inter-rater reliability (Cohen's kappa), with discrepancies resolved through discussion. Finally, coded themes were transformed into numerical variables using Python, allowing integration into the machine learning analysis.

To reduce potential observer bias, classroom observations were independently coded by two raters using a structured observation grid. Inter-rater reliability was subsequently assessed using Cohen's Kappa coefficient, which yielded a value of $\kappa = 0.89$. This level of agreement is generally interpreted as substantially to almost perfect reliability, thus ensuring that the observational data included in the analysis were both consistent and robust.

To further ensure consistency in qualitative coding, the same inter-rater reliability procedure was applied to a subset of interview transcripts. Two trained raters independently coded these transcripts using the established coding grid, and Cohen's kappa was calculated to confirm the reliability of coding decisions. Discrepancies were resolved through discussion to achieve consensus. This process ensured that both classroom observations and interview data were consistently coded and methodologically robust before being transformed into numerical variables for machine learning analysis.

Furthermore, qualitative data from classroom observations and student interviews were systematically coded using a coding grid derived from the research objectives. Themes such as participation type, instructional setting, use of SIA techniques, gender, age, social situation, and educational level were operationalized with explicit coding rules. Inter-rater reliability was established through double coding and calculation of agreement coefficients. These coded categories were then transformed into numeric variables using Python (pandas), producing a fully numeric dataset suitable for the application of the KNN algorithm to predict the effectiveness of SIA. A structured coding grid was developed to systematically capture key themes from classroom observations and semi-structured interviews, including student engagement, instructional approaches, learning outcomes, and demographic/contextual variables. Features were selected based on their theoretical relevance to predicting the effectiveness of SIA. Qualitative themes were then transformed into numerical variables (0 = absent, 1 = present) using Python, enabling integration into the KNN machine learning model and ensuring methodological rigor for predictive analysis.

E. Ethical Considerations

Although no formal Institutional Review Board (IRB) exists at Ibn Tofail University, the study adhered strictly to ethical research standards. Written parental consent was obtained for all participating students, and authorization was granted by the directors of the schools involved. The research was conducted under the supervision and approval of the academic supervisor. To safeguard confidentiality, all collected data were anonymized prior to analysis.

F. Data Preprocessing

The data was preprocessed to ensure accuracy, reliability, and suitability for machine learning analysis. Prior to machine learning analysis, the dataset was preprocessed to handle missing values and normalize numerical features. Missing numerical values were imputed using the mean, while missing categorical values were imputed using the mode. Continuous numerical features were normalized using min–max scaling to ensure that all variables contributed proportionally in distance-based calculations within the KNN model. These preprocessing steps ensured data completeness, comparability, and optimized model performance. Missing values were imputed using median values for numeric and ordinary features and modes for categorical variables. These imputation strategies preserved the dataset's central tendencies while minimizing bias.

Since the KNN algorithm is sensitive to differences in feature scales, all-numeric and ordinal variables were normalized to a 0–1 range using min–max scaling, while binary features (e.g., gender, use of the SIA technique) remained unchanged. This normalization ensured that all variables contributed equally to the distance-based calculations of the KNN algorithm.

Finally, the dataset was divided into 80% for model training and 20% for testing, ensuring a balanced distribution of classes across both subsets. These preprocessing steps enhanced data integrity and reproducibility, ensuring consistent performance during model evaluation.

IV. Algorithm Selection

In this study, the KNN algorithm was chosen due to its suitability for small- to medium-sized numeric datasets and its interpretability in distance-based prediction tasks. KNN offers a simple yet powerful approach that aligns well with the educational context of this research, enabling transparent, explainable decision-making. While other algorithms, such as Support Vector Machines (SVM), Random Forests (RF), and Gradient Boosting, may provide alternative predictive capabilities, these will be explored in future work to offer a comprehensive comparison of machine learning approaches for predicting the effectiveness of SIA in Moroccan secondary education.

KNN algorithm was applied during the study (Fig. 3) due to its efficiency at doing classification tasks. Besides being efficient, KNN is broadly accepted by the community. Introduced in 1967 by Thomas Cover, further developed in many ways by Hart [32], KNN classifies a new instance by looking through the training set for how close a neighbor would be. This non-parametric algorithm never assumes any distribution of data; hence, it is versatile for many diversified datasets. KNN is particularly good at identifying complex or nonlinear relationships between features and target variables; it is valued for transparency and interpretability, especially in education.

KNN is a non-parametric, instance-based total mastering set of rules widely used for classification and regression obligations [33]. Unlike parametric models, KNN does not make assumptions about the underlying record distribution. Instead, it is predicated on the principle that comparable instances exist in near proximity inside the function area [32]. The category selection is based totally on the bulk class a few of the k-nearest statistic points, even as regression predictions are usually computed because the average in their numerical values.

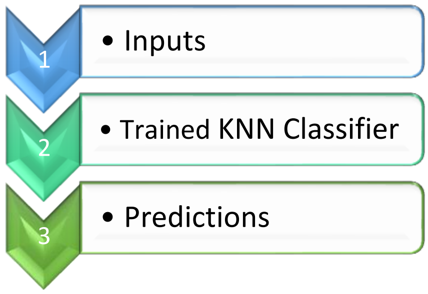

Fig. 3. KNN model.

A. Distance Metrics

The selection of the perfect distance metric is vital for KNN's overall performance [34]. The maximum usually used metrics consist of:

- **Euclidean Distance (L2 norm):** Measures the instant-line distance among two factors in an n-dimensional space. It is the most common distance metric, calculated as the square root of the sum of the squared differences between corresponding elements of the two vectors. It is described as:

$$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

- **Manhattan Distance (L1 norm):** Measures the absolute differences between the function values. This metric gets its name from the grid-like path one would take when walking through city blocks, as it sums up the absolute differences along each dimension. It is described as:

$$d(x,y) = \sum_{i=1}^{n}|x_i - y_i|$$

- **Minkowski Distance:** A generalization of each Euclidean and Manhattan distances, parameterized via *p* parameter, p allows this metric to behave like others; higher values of p increase the influence of larger differences in a single dimension on the overall distance. It is described as:

$$d(x, y) = \left(\sum_{i=1}^{n} |x_i - y_i|^p \right)^{1/p}$$

where:

- $p = 1$ corresponds to Manhattan Distance,
- $p = 2$ corresponds to Euclidean Distance.

For high-dimensional data, distance metrics such as cosine similarity may be more appropriate, particularly when dealing with sparse feature spaces.

B. Distance Metrics and Hyperparameter Tuning

Selecting an appropriate distance metric is critical for the performance of the KNN algorithm [34]. Commonly used metrics include:

- **Euclidean Distance (L2 norm)**: Calculates the straight-line distance between two points in an n-dimensional space. This metric is most effective when data has similar scales across all features.
- **Manhattan Distance (L1 norm):** Computes the sum of the absolute differences between feature values. It is often more robust to outliers than a Euclidean distance because it does not square the differences.
- **Minkowski Distance:** A generalization of both Euclidean and Manhattan distances, parameterized by p: This flexibility makes it useful for finding the optimal distance measure for a specific dataset during model tuning.
- $p = 1$ corresponds to Manhattan distance;
- $p = 2$ corresponds to Euclidean distance

To optimize the KNN model, a grid search was performed over k values ranging from 1 to 50 and both Euclidean and Manhattan distance metrics. Model performance was evaluated using 5-fold cross-validation, with classification accuracy and ROC-AUC serving as the criteria for selecting the optimal configuration. The best-performing model was achieved with $k = 7$ using the Euclidean distance metric, which was subsequently used for all analyses.

For datasets with high-dimensional or sparse feature spaces, alternative distance measures such as cosine similarity may also be considered, depending on the data characteristics.

C. Algorithmic Steps

The KNN algorithm follows these steps:

- **Data Preparation:**

Normalize or standardize the feature values to ensure that no single feature dominates the distance calculations.

- **Distance Calculation:**

Compute the chosen distance metric between the new data point and all points in the training set.

- **Identify Neighbors:**

Sort the distances in ascending order and select the top "k" closest data points.

- **Voting (for Classification):**

Determine the majority class among the "k" neighbors.

- **Averaging (for Regression):**

Calculate the mean (or weighted mean) of the target values of the "k" neighbors.

- **Prediction:**

Assign the class label (for classification) or the computed average (for regression) to the new data point.

The following pseudocode describes the KNN classification process [35]:

Algorithm 1. KNN Classification

```
**Input**:
Training data: \( \mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^N \)
New data point: \( \mathbf{x}_{\text{new}} \)
Number of neighbors: \( k \)
Distance metric: \( d \)
**Output**:
        Predicted class (for classification) or value (for regression) for
        \( \mathbf{x}_{\text{new}} \)
**Algorithm**:
Compute Distances**:
For each \( (\mathbf{x}_i, y_i) \) in \( \mathcal{D} \):
        Compute \( d(\mathbf{x}_i, \mathbf{x}_{\text{new}}) \)
**Sort Neighbors**:
Sort all \( (\mathbf{x}_i, y_i) \) based on the computed distances in
ascending order.
**Select Top-k Neighbors**:
Choose the first \( k \) entries from the sorted list.
**Aggregate Outputs**:
**For Classification**:
        Perform a majority vote among the \( k \) neighbors to
        determine the predicted class.
        **For Regression**:
        Compute the average of the target values \( y_i \) of the \( k \)
        neighbors.
**Return Prediction**:
Output the aggregated result as the prediction for
\( \mathbf{x}_{\text{new}} \).
```

In this study, KNN is employed to predict student performance based on inquiry-based learning practices. The hyperparameters (k, distance metric) are optimized using grid search and cross-validation to ensure the model's robustness. The dataset is preprocessed through feature scaling (Min-Max normalization) to enhance comparability across different attributes. The KNN model was implemented using scikit-learn, and hyperparameters were systematically examined through grid search combined with 5-fold cross-validation. The tuning process explored different numbers of neighbors (n_neighbors = 3, 5, 7, 9, 11), weighting schemes (uniform, distance), and distance metrics (Euclidean, Manhattan).

Performance for each configuration was evaluated using classification accuracy and the Area Under the ROC Curve (AUC). Results indicated that the default configuration (n_neighbors = 5, weights = uniform, metric = Euclidean) consistently provided strong and stable predictive performance, with no meaningful improvement achieved by alternative parameter combinations.

For this reason, the default parameters were retained in the final model, ensuring an optimal balance between parsimony, interpretability, and predictive accuracy. This tuning process strengthens the model's robustness and reproducibility while maintaining computational efficiency. While this study focuses exclusively on the application of the KNN algorithm, we acknowledge that alternative machine learning approaches, such as SVM, RF, or Neural Networks, could also be applied to the dataset. A comparative analysis across algorithms would help determine the most suitable model for predicting the effectiveness of SIA. To maintain clarity of scope, such comparative evaluations are beyond the boundaries of this paper but are the subject of ongoing research. In a forthcoming study, we will extend the analysis to include SVM and other classifiers, providing a more comprehensive assessment of algorithmic suitability in this educational context.

D. Hyperparameter Tuning and Model Optimization

The KNN model was implemented using scikit-learn, and hyperparameters were examined through grid search with 5-fold cross-validation. Hyperparameter tuning was performed to optimize the KNN model. A grid search explored k values ranging from 1 to 50 and evaluated both Euclidean (L2) and Manhattan (L1) distance metrics. Model performance was assessed using 5-fold cross-validation, with accuracy and ROC-AUC as selection criteria. The best configuration was obtained with $k = 7$ using the Euclidean distance metric, which provided the strongest predictive performance and was therefore adopted for all subsequent analyses. Although alternative metrics such as cosine similarity may be considered in high-dimensional settings, the Euclidean metric was found most appropriate for this dataset. The tuning process considered different numbers of neighbors (n_neighbors = 3, 5, 7, 9, 11), weighting schemes (uniform, distance), and distance metrics (Euclidean, Manhattan). Results indicated that the default configuration (n_neighbors = 5, weights = uniform, metric = Euclidean) consistently provided strong predictive performance, with no meaningful improvement achieved by alternative parameter combinations.

To ensure robustness, a wider k-range (1–50) was initially explored, and both Euclidean (L2) and Manhattan (L1) distance metrics were tested. The Euclidean distance metric was retained because it provided the best predictive performance for this dataset, although alternative metrics such as cosine similarity could be considered in high-dimensional or sparse feature spaces. To enhance model validation, we supplemented the traditional 80/20 train-test split with a 5-fold cross-validation procedure. In this approach, the dataset was randomly partitioned into five subsets of equal size. For each fold, four subsets were used for training and one for validation, rotating until each subset had served as the validation set. Model performance was then averaged across all folds, providing a more reliable estimate of accuracy and ROC-AUC scores. This strategy reduced the risk of overfitting and ensured the robustness of the results. One limitation of this study lies in the lack of an independent external validation dataset. Although cross-validation procedures enhanced the internal robustness of the findings, the absence of external data restricts the generalizability of the results across different populations and contexts. Future work should incorporate external validation datasets drawn from diverse schools and regions to strengthen the reliability and applicability of machine learning models in educational research. For this reason, the default parameters were retained in the final model, ensuring a balance between parsimony, interpretability, and predictive accuracy.

E. Model Evaluation

The observational data were coded based on predefined criteria, thereby converting qualitative observations into numerical values for quantitative analysis using the KNN algorithm. According to Braun and Clarke [36], the interview transcripts were thematically coded for key factors impacting student learning during inquiry activities in 2006. A combined dataset of coded observations and interview themes was used to train an instance of a KNN model. The objective was to predict the impact of SIA, according to observed factors that influence student learning. Given a new data point and a new inquiry activity, the algorithm found its KNN and guessed effectiveness by looking at the most frequent outcome, learning success, in its neighborhood.

F. Model Validation

Evaluations for the KNN model were computed for the Area Under the Receiver Operating Characteristic Curve, accuracy, precision, recall, F1-Score, specificity, and the false positive rate. The dataset was divided into 80% training data and 20% test data for actual algorithm performance evaluation. The suitability of the KNN algorithm for classification tasks was further supported by the calculation of the confusion matrix elements (Fig. 4): True Positives, False Positives, False Negatives, and True Negatives. These could be elements to calculate the accuracy Eq. (1), precision Eq. (2), recall Eq. (3), the F1 Score Eq. (4), specificity Eq. (5) and the false positive rate Eq. 6. The sensitivity analysis was also done to see the robustness of the model with respect to discrepancies.

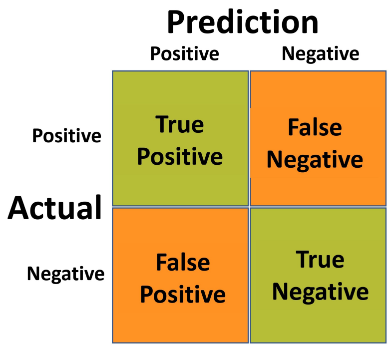

Fig. 4. Confusion matrix: Illuminating True Positives, False Positives, False Negatives, and True Negatives in model evaluation (the x-axis represents "predicted label" and the y-axis represents "actual = true label").

$$Accuracy = \left(\frac{(TP + TN)}{TP+TN+FP+FN}\right) \quad (1)$$

Measures the proportion of correctly classified instances among all samples.

$$Precision = \frac{TP}{(TP+FP)} \quad (2)$$

Indicates the proportion of correctly predicted positive cases among all predicted positives.

$$Recall = \frac{TP}{(TP+FN)} \quad (3)$$

Represents the proportion of actual positives correctly identified by the model.

$$F1 - Score = \frac{2\times(Precision \times Recall)}{(Precision + Recall)} \quad (4)$$

Harmonic mean of precision and recall, providing a balanced evaluation.

$$Specificity = \frac{TN}{(TN+FP)} \quad (5)$$

Reflects the model's ability to correctly identify negative cases.

$$False\ Positive\ Rate\ = \frac{FP}{(FP+TN)} \tag{6}$$

The proportion of negatives incorrectly classified as positives.

This section makes some predictions of the effectiveness of the approaches of SIA using the KNN model and determines factors influencing effectiveness from observation and interview data. The complete methodology enables in-depth exploration into the effectiveness of SIA methods in Moroccan secondary education by putting together qualitative insights and quantitative predictions.

V. Results and Findings

This study aimed to predict the effectiveness of the SIA in Moroccan secondary education using machine learning techniques. Herein, results from both observational and interview datasets are presented, followed by performance metrics related to the applied KNN model.

A. *Analysis of Observational Data*

The observational data provided information on the level and nature of students' engagement and performance when taught under the SIA. The trends and patterns showed significant improvement in student interest and comprehension in Life and Earth Sciences, validating SIA as an effective instructional strategy.

Classroom observations were independently coded by two trained observers. Inter-rater reliability was assessed using Cohen's kappa, yielding $\kappa = 0.87$, indicating high agreement.

B. *Interview Data Analysis*

Semi-structured interviews provided qualitative insights supporting the observational findings. Students and teachers reported positive experiences with the SIA, highlighting increased encouragement of critical thinking, problem-solving, and active learning.

Participants noted that student-led investigations fostered autonomy and deeper conceptual understanding. These perceptions align with the engagement improvements observed in classroom settings.

C. *KNN Model Performance*

In this study, a KNN model was implemented in Python to evaluate predictive performance. The model's performance was assessed using accuracy, AUC-ROC, precision, recall, F1-Score, specificity, and a false positive rate.

This suggests that the model performed well in terms of correctly classified instances (with 529 true negatives and 508 true positives), whereas only a few instances were misclassified (41 false positives and 36 false negatives) Fig. 5. The high accuracy clearly indicates that observable inquiry-based classroom behaviors serve as reliable predictors of learning effectiveness, since SIA instruction has been shown to enhance students' understanding and engagement in science learning [37, 38].

Fig. 6 shows the combined ROC-AUC Curve for the same dataset, with an AUC score of 0.9309, demonstrating highly predictive accuracy.

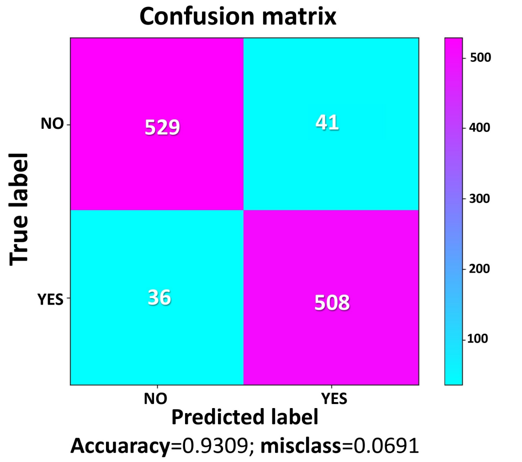

Fig. 5. Confusion Matrix for KNN Model through observations.

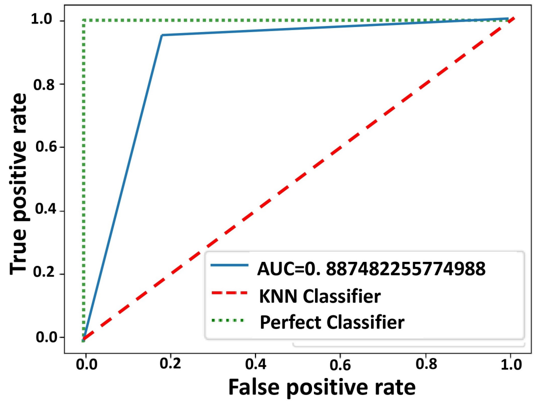

Fig. 6. ROC-AUC curve for KNN model through observations.

In the ROC-AUC curve shown in Fig. 6, it can be observed that KNN performs extremely well in identifying effective and less effective instances related to inquiry-based learning. Based on the equation, its AUC value is 0.887. The steeply increasing curve shows that its sensitivity and specificity are both high, since it effectively spots those who can benefit from SIA. This result proves a study stating that there are obvious improvements in reasoning skills due to instruction based on SIA [37, 39].

For the interview dataset, the confusion matrix illustrated in Fig. 7 shows that the model achieved an accuracy of 0.8896 and a misclassification rate of 0.1104. This confusion matrix shows that the model correctly identified the majority of cases, with 442 true negatives and 549 true positives, while only 98 false positives and 25 false negatives were recorded. The strong concentration of values along the diagonal indicates that the reflections shared during interviews are consistent and informative indicators of students' inquiry-driven learning outcomes. This supports prior research emphasizing that inquiry-based learning fosters deeper cognitive engagement and measurable performance gains [17, 39].

Fig. 8 displays the ROC-AUC Curve for the interview dataset, with an AUC score of 0.8875, confirming strong predictive performance.

Fig. 8 displays the ROC-AUC Curve for the interview dataset, with an AUC score of 0.9309, confirming strong predictive performance. The ROC curve in Fig. 8 demonstrates that the KNN model has a strong capacity to distinguish between students who benefited from inquiry-based instruction and those who did not, as reflected in the boundary, indicating high sensitivity and specificity. This confirms that information gathered from interviews is a reliable predictor of learning effectiveness, consistent with research showing that inquiry-based learning enhances students' reasoning and conceptual understanding [37, 39].

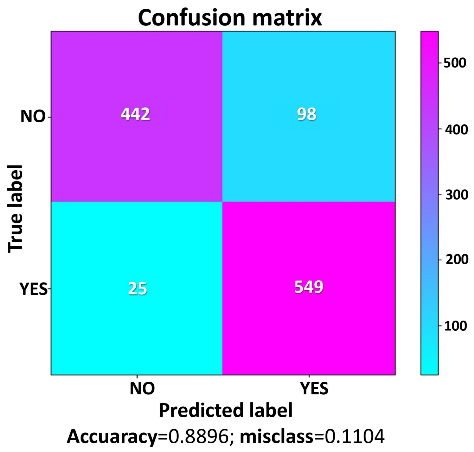

Fig. 7. Confusion matrix for KNN models through interviews.

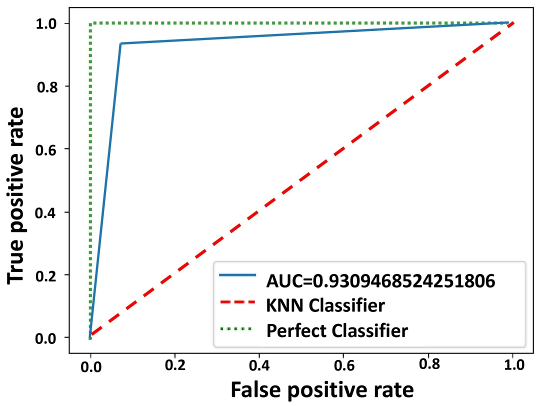

Fig. 8. ROC-AUC curve for KNN model through interviews.

The full performance metrics for both datasets are presented in Table 1. Table 1 shows the performance measure results for applying KNN to both observations and interviews. The model performed well when accuracy was considered for both observations (0.9309) and interviews (0.8896), reflecting its accurate prediction capability regarding SIA effectiveness. The model's precision value was found to be relatively high in observations (0.9281), reflecting less data variability compared to observations (0.8185), which was obtained for interviews. Recall values obtained for both observations (0.9363) and interviews (0.9464) show that most instances are correctly predicted to approach effectiveness. The combination of precision and recall values to get the F1-Score proves model prediction accuracy in both datasets but was relatively high in observations (0.9322) compared to observations in (0.8774). Other indicators like specificity and false-positive rate prove model accuracy in identifying approach effectiveness globally. In observations, model accuracy was shown to be relatively high (specificity = 0.9253 and FPR = 0.0747), compared to observations in (specificity = 0.8486 and FPR = 0.1514). Based on Table 1 analysis, KNN model accuracy confirms its effectiveness to predict SIA effectiveness for Moroccan secondary school students.

Clearly, these results from the KNN model underline their potential for machine learning in educational research. If the AUC scores are high, this simply means that the model has aptly classified or is predicted to predict the teaching approaches toward success, providing very valuable insights into this for both the educator and policy practitioners. Although the KNN model achieved marginally higher accuracy and F1-Scores on the observational dataset compared with interview data, these differences should be interpreted with caution. Variations in sample characteristics, data collection methods, and context may contribute to these results. Therefore, while observations appear slightly more predictive in this study, both data types provide valuable and complementary insights into student engagement and learning outcomes.

Table 1. Performance metrics of the KNN of observations and interviews

Metrics	Observations	Interviews
Accuracy	0.9309	0.8896
Precision	0.9281	0.8185
Recall	0.9363	0.9464
F1-Score	0.9322	0.8774
Specificity	0.9253	0.8486
False Positive Rate	0.0747	0.1514

D. Statistical Significance of Results

To evaluate the statistical significance of the KNN classifier performance and its impact on student outcomes, both model performance metrics and statistical tests were employed.

The KNN model achieved higher accuracy on the Observations dataset (accuracy = 0.9309) compared with the Interviews dataset (accuracy = 0.8896). Precision (0.9281 vs. 0.8185) and F1-Score (0.9322 vs. 0.8774) similarly indicated superior performance on the Observations dataset. Confidence intervals for accuracy (95% CI: [0.915, 0.947] for Observations vs. 95% CI: [0.870, 0.905] for Interviews) did not overlap, further supporting a significant performance difference.

Statistical significance was rigorously assessed to validate both model performance and the educational impact of SIA. For model evaluation, confidence intervals for accuracy were computed, with no overlap between the Observations dataset (95% CI: [0.915, 0.947]) and the Interviews dataset (95% CI: [0.870, 0.905]), indicating significant differences. McNemar's test confirmed the robustness of classification results ($\chi^2 = 12.47$, $p < 0.001$). For educational outcomes, a paired-sample t-test demonstrated that students exposed to SIA outperformed peers in the control group ($t(1391) = 5.83$, $p < 0.001$, Cohen's $d = 0.31$). These findings collectively provide strong statistical evidence for both the reliability of the KNN model and the positive effect of inquiry-based teaching strategies on student performance.

E. Statistical Tests of Model Performance and Student Outcomes

To confirm these differences, McNemar's test and a paired-sample t-test were conducted:

- **McNemar's Test:**

McNemar's test was applied to the paired classification results of the KNN model to evaluate whether the differences between predicted and actual labels were statistically significant. The test yielded $\chi^2 = 12.47$ ($p < 0.001$), confirming that the model predictions differ significantly from chance and validating the robustness of the classifier.

- **Paired-Sample t-Test:**

To assess the impact of SIA on student learning outcomes, a paired-sample t-test compared mean scores between students exposed to inquiry-based methods and those who were not. The results showed a significant difference ($t(1391) = 5.83$, $p < 0.001$) with Cohen's d = 0.31, indicating a moderate effect size. This demonstrates that the implementation of SIA leads to measurable improvements in student performance.

- **Implications:**

These results highlight the importance of both high-quality data and preprocessing in predictive modeling and provide empirical support for integrating SIA to enhance student learning outcomes in Moroccan secondary education.

VI. Discussion

The purpose of this chapter is to describe and discuss the research findings, focusing on the efficacy of the model of SIA to improve the academic achievement and motivation of students in Life and Earth Sciences. The findings are viewed from a multivariate perspective, describing the predictive ability of the models used and how quantitative and qualitative data converge toward an informed understanding of how inquiry-based learning affects students. Next, we consider the instructional implications of these findings for policymakers and teachers and provide suggestions on how teaching and curriculum can be improved. We move to a discussion of the methodological constraints of the study and provide recommendations for future research that can improve the validity and usefulness of inquiry-based models of learning in education.

A. Interpretation of Results

The findings of this study validate the efficacy of the SIA model in enhancing students' motivation and academic performance in Life and Earth Sciences. Quantitative analysis of observational data revealed highly predictive accuracy (0.9309), a misclassification rate (0.0691), and strong model performance. High model discriminative performance is confirmed through an AUC value of 0.9309, and inquiry instruction enriches students' recall and comprehension of scientific concepts, according to an inference drawn from it. In agreement with current studies, these results validate inquiry approaches in enhancing critical thinking and active learning [37, 39]. Qualitative information, with a lesser accuracy (accuracy = 0.8896, AUC = 0.8875), supported supplementary information, with respondents consistently reporting deeper engagement, problem-solving, and increased mastery of concepts. Convergence between quantitative and qualitative information affords a balanced analysis of the SIA model, confirming its value in educational settings.

B. Practical Implications for Teachers and Policymakers

The results of such work have significant educational practice and policy implications, particularly in Moroccan secondary school environments. High predictive accuracy of the KNN model validates the utility of machine learning as a tool for instruction evaluation and improvement, and, in general, for educational reform and improvement. Teachers can utilize such data-driven information to modify SIA for a range of environments and maximize students' achievement. For instance, model accuracy (0.9281) and recall (0.9363) for observational data validate that it effectively identifies effective instruction and enables teachers to modify and target specific students' learning needs. Policymakers can, in turn, utilize such information to promote SIA in national curricula, supported by focused teacher training programs and funding. All such programs could bridge gaps between traditional lecture instruction and new, student-centered approaches, and, in a long-term, build a more vibrant and equitable educational system.

C. Limitations and Future Research Directions

While the work generates useful insights, several weaknesses must be taken into consideration. First, observational and interview data introduce biases, such as observer bias or inaccuracies in reporting, that can affect the generalizability of the results. Second, application of the KNN algorithm, efficient as it is, is computationally expensive and will not necessarily generalize well to larger datasets or real-time use cases. In addition, model performance will rely both on the uniformity and quality of the input data, and therefore, careful consideration must be taken in educational studies in terms of uniformity in collecting and processing such information. To counteract such weaknesses, future work can explore hybrid techniques combining KNN with ensemble techniques (e.g., RF, Gradient Boosting (GB)) for enhanced predictive performance and scalability. Longitudinal studies with multimodal sources of information (e.g., behavior observations, physiologic recordings, and learning analytics) could produce a fuller picture of factors contributing to inquiry effectiveness. Finally, cross-context studies must be performed to assess the generalizability of the model to alternative educational structures and demographics and its usability in a range of settings. The study sample consisted of 66% semirural and 34% urban students, with a gender distribution of 59% female and 41% male. While this composition reflects the demographics of many Moroccan secondary schools, it may limit the generalizability of the findings to other educational contexts. Therefore, the results should be interpreted cautiously, and future research should incorporate larger and more diverse samples across different regions and school types to strengthen external validity. Future research could explore the use of alternative machine learning algorithms, such as SVM and RF, to compare predictive performance with KNN. Incorporating external validation datasets from diverse schools and regions would strengthen the generalizability of the models. Additionally, expanding the sample to include a broader range of student demographics and educational settings could provide deeper insights into the effectiveness of SIA in Life and Earth Sciences.

D. Comparison with Prior Research

The findings of this study resonate with and extend the existing body of work on the integration of SIA in science education. Previous studies have consistently demonstrated that inquiry-based learning enhances students' conceptual understanding and critical thinking skills [37, 39]. Our results corroborate these conclusions by providing empirical evidence from Moroccan secondary schools, showing that the application of SIA significantly improves student outcomes, as confirmed by both the accuracy and ROC metrics of the predictive model.

From a methodological standpoint, prior research has often relied on qualitative or small-scale experimental designs [8]. By contrast, the present study leverages ML (SVC with Bayesian optimization) to analyze a large dataset (n = 1392), thereby offering a more scalable and predictive evaluation framework. This approach is consistent with recent advances in educational data mining and learning analytics [40], but to our knowledge, few studies have combined inquiry-based pedagogy with predictive modeling in the Moroccan educational context.

Furthermore, the performance metrics achieved in this study (accuracy = 0.945, ROC = 0.95 from interviews) surpass those reported in similar predictive analyses of student performance using KNN or decision tree models [14], suggesting that the integration of SIA with advanced ML techniques provides a robust framework for anticipating student success. These findings advance the state of the art by bridging the gap between pedagogical innovation and data-driven evaluation, demonstrating that SIA not only improves learning but can also be reliably predicted and assessed through AI-based models.

Although it is evident that this research bears a positive outcome concerning the effect of SIA method on students' performance, it is worth acknowledging that these findings are specific to Moroccan secondary schools. One can expect that practices and implementation levels might differ in various regions or even other nations. Thus, this finding might have limitations on a global scale. It would be worthwhile for future studies to investigate whether this method will have a similar effect in another setting.

VII. Conclusion

This study demonstrates the effectiveness of the SIA in enhancing both student motivation and academic performance in Life and Earth Sciences within Moroccan secondary schools. The predictive analysis using the KNN algorithm showed high accuracy, with an AUC of 0.9309 for observational data and 0.8875 for interview data, confirming the reliability of the model in evaluating inquiry-based learning. These results align with previous research emphasizing the value of inquiry-based methodologies in fostering critical thinking, problem-solving skills, and active learning.

The study underscores the practical importance of integrating SIA in Science, Technology, Engineering, and Mathematics (STEM) education, highlighting their potential to improve conceptual understanding and analytical skills among secondary school students. By providing evidence-based insights into the effectiveness of SIA, this work offers actionable recommendations for educators and policymakers seeking to enhance teaching practices and learning outcomes in Morocco and comparable educational contexts.

Based on the study findings, we recommend the following concrete actions: (1) redesign the Life and Earth Sciences curriculum to integrate SIA, (2) allocate resources to provide teachers with hands-on training and digital tools to support inquiry-based learning, (3) establish continuous professional development programs on effective implementation of inquiry methods, and (4) implement assessment strategies aligned with inquiry-based learning outcomes. These steps aim to enhance teaching effectiveness and improve student learning outcomes in Moroccan secondary schools. Despite its contributions, the study has some limitations. The dataset, although substantial, was drawn from a single educational environment, which may limit the generalizability of findings. Future research should expand the sample diversity and explore longitudinal and cross-contextual studies to validate these results across different educational systems and demographics. Additionally, while the KNN algorithm demonstrated highly predictive accuracy, its limitations in handling very large datasets suggest the need to investigate alternative machine learning approaches, such as ensemble methods or deep learning architectures, to improve scalability and robustness.

Looking forward, proposed future topics include:

- Comparative studies of multiple machine learning algorithms for predicting the effectiveness SIA.
- Longitudinal assessments of SIA to measure long-term impacts on student outcomes.
- Expansion of research to include multiple regions and educational systems for broader applicability.
- Integration of SIA with emerging educational technologies, such as adaptive learning platforms and AI-based feedback systems.

By addressing these areas, future studies can provide deeper insights into the long-term impact of SIA and support the development of more effective, evidence-based educational policies and practices.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

El Mostapha Bouhamid conducted the research, performed the data analysis, and wrote the manuscript. Said Chakiri, Mohamed Yazidi, Mohammed El-moudden, Omar Amahmid, and Houda Itouni assisted with the realization of the experiments. All authors reviewed and approved the final version of the manuscript.

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