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ORIGINAL

Design and Implementation of an Adaptive Tutoring System for Enhanced E-Learning

Diseño y aplicación de un sistema de tutoría adaptativo para mejorar el aprendizaje electrónico

Atmane EL HADBI[1], Mohammed Hatim RZIKI[1], Yassine JAMIL[1], Zaynab AMMARI[2], Mohamed Khalifa BOUTAHIR[3,4], Hamid BOURRAY[5], Driss EL OUADGHIRI[1]

[1]Laboratory of AI, Faculty of Sciences, Moulay Ismail University of Meknes, Morocco.
[2]Research Laboratory Management, Finance, Digitization and Applied Statistics (MaFDeSA), Management Sciences, Abdelmalek Essaâdi University, Tanger, Morocco.
[3]National School of Artificial Intelligence and Digital Berkane, Morocco.
[4]Engineering science and technology laboratory, IDMS Team, Faculty of Sciences and Tech niques, Moulay Ismail University of Meknes, Errachidia, Morocco.
[5]Systems Theory and Computer Science Team, Faculty of Sciences, Moulay Ismail University of Meknes, Morocco.

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Corresponding author: Atmane EL HADBI

ABSTRACT

The increasing offer of new information and communication technologies has changed the educational field, e-learning emerged as an important complement to traditional face-to-face education and often a good alternative in many contexts. This shift has been emphasized by global challenges such as the COVID-19 pandemic, which highlighted the importance of remote learning platforms and their effectiveness in such situations. However, many challenges such as the costs and the need for personalized and interactive learning environments remain an obstacle. To address these issues, adaptive e-learning systems and Intelligent Tutoring Systems (ITS) are increasingly being developed and given support by education communities and governments. These systems aim to adapt content to the learner's cognitive abilities and individual learning styles, for better understanding and retention. This paper explores the design and development of an adaptive ITS, which integrates Artificial Intelligence and data analytics to provide better learning experience. This paper puts the light on the role of adaptive hypermedia in educational interactions, analyzing its key features and how they can be leveraged to enhance learning outcomes. By incorporating learning success metrics, our study provides a comprehensive perspective on the potential of ITS to revolutionize adaptive and personalized e-learning systems, driving significant improvements in both learner engagement and achievement.

Keywords: E-learning; Intelligent Tutoring Systems; Personalized E-learning; Adaptive E-learning; Digital Transformation; Adaptive Tutoring Systems; ATS; Data Analytics; User Experience.

RESUMEN

La creciente oferta de nuevas tecnologías de la información y la comunicación ha cambiado el ámbito educativo, surgiendo el e-learning como un importante complemento a la educación presencial tradicional y, a menudo, como una buena alternativa en muchos contextos. Este cambio se ha visto acentuado por retos mundiales como la pandemia de COVID-19, que puso de relieve la importancia de las plataformas de aprendizaje a distancia y su eficacia en tales situaciones. Sin embargo, muchos retos, como los costes y la necesidad de entornos de aprendizaje personalizados e interactivos, siguen siendo un obstáculo. Para hacer frente a estos problemas, las comunidades educativas y los gobiernos están desarrollando y apoyando cada vez más los sistemas de aprendizaje electrónico adaptativo y los sistemas de tutoría inteligente (STI). El objetivo de estos sistemas es adaptar los contenidos a las capacidades cognitivas y los estilos de aprendizaje individuales del alumno, para mejorar su comprensión y retención. Este artículo explora el diseño y desarrollo de un STI adaptativo, que integra Inteligencia Artificial y análisis de datos para proporcionar una mejor experiencia de aprendizaje. Este trabajo arroja luz sobre el papel de los hipermedios adaptativos en las interacciones educativas, analizando sus características clave y cómo pueden aprovecharse para mejorar los resultados del aprendizaje. Mediante la incorporación de métricas de éxito en el aprendizaje, nuestro estudio ofrece una perspectiva completa sobre el potencial de los STI para revolucionar los sistemas de e-learning adaptativos y personalizados, impulsando mejoras significativas tanto en el compromiso del alumno como en sus logros.

Palabras clave: E-Learning; Sistemas de Tutoría Inteligentes; E-Learning Personalizado; E-Learning Adaptativo; Transformación Digital; Sistemas de Tutoría Adaptativos; ATS; Análisis de Datos; Experiencia de Usuario.

INTRODUCTION

Over the past decade internet usage has expanded all over the globe and impacted all industries, including the field of education. This expansion opened the door to e-learning which has become increasingly prevalent in education community. During the COVID-19 pandemic, E-learning became crucial supplement to traditional classroom teaching, highlighting the growing importance of flexible and accessible online learning platforms.

Educational organizations worldwide were suddenly faced with the challenge of transitioning from face-to-face learning to fully online or hybrid models. Many students struggle with a lack of engagement and a disconnect between the learning materials and their personal learning styles. The need for more interactive and personalized learning environments is evident.

In the past years, there has been a growing interest in adaptive learning systems and Intelligent Tutoring Systems (ITS), which aim to address these challenges by adapting educational content to each learner's individual needs and cognitive abilities. These systems use Artificial Intelligence (AI) and rely on data analytics to personalize learning materials based on the student's learning preferences, enhancing both comprehension and retention.

In this paper, we share the design and implementation of an adaptive ITS that aims to create an engaging and personalized e-learning experience. By incorporating analytics, user experience metrics and heat maps, ITS adjusts the experience to each learner's unique needs. We also explore how adaptive hypermedia can enhance educational interactions, providing more effective learning pathways for students and facilitating the teaching process for educators. Our study demonstrates how ITS can significantly improve both learner engagement and academic achievement, offering a glimpse into the future of personalized and adaptive e-learning systems.

Adaptative Tutoring Systems: A Brief Overview

Adaptive Tutoring Systems (ATS) refer to educational platforms that rely on artificial intelligence, data analytics, and user engagement key indicators to deliver personalized learning experiences to learners. Unlike basic tutoring systems, ATS can adapt to each learner's unique personality traits, adjusting content, pace, and teaching methods dynamically to better engage the learner and guarantee better learning outcomes. These systems are able to identify learning patterns, offering tailored support such as additional exercises or alternative explanations. This personalized approach makes learning more efficient and engaging by addressing each student's strengths and weaknesses.

Traditional education relies on delayed feedback through tests and exams. ATS can analyze student responses and give immediate help or guidance. This real-time feedback and intervention helps student's correct mistakes immediately, reinforcing understanding and improving retention. Additionally, Adaptive Tutoring Systems can adapt the difficulty level of tasks, ensuring that students are neither overwhelmed nor bored, thereby maintaining an optimal learning curve.

ATS systems are way more scalable and flexible than traditional tutoring systems, they are an ideal solution for diverse educational environments. ATS are suitable for individual learners at home and large classrooms, these systems can accommodate different learning speeds and styles without the need for one-on-one human instruction.

Through student interaction and engagement measurement, ATS becomes better over time, providing more and better recommendations and modifications to improve learning outcomes. With the ability to completely change the way students engage with and assimilate knowledge in the digital age, these systems mark a major advancement in the use of technology to facilitate individualized learning.

Fundamental Concepts

The core of ATS is the idea of personalizing the learning experience. These systems assess a learner's prior knowledge, learning style, pace, and progress to provide individualized content. Personalization ensures that learners engage with material at the right level, avoiding frustration or boredom so as to get the best outcomes.

Personalization and Individualization

The knowledge base of an ITS contains the subject matter expertise that learners are expected to acquire. This knowledge is typically organized into a structured format, allowing the system to assess the learner's current understanding and provide targeted guidance.

Real-Time Feedback and Assessment

Adaptive Tutoring Systems assess learner performance as they engage with educational content. They provide right away feedback. In contrast to traditional learning systems that offer static assessments, ATS evaluates performance dynamically and can adapt to reinforce areas where learners struggle.

Learner Modeling

ATS relies on sophisticated learner models, which are representations of a student's knowledge, skills, preferences, and goals. These models are continuously updated based on interaction data. The system uses this evolving learner model to adapt content and provide appropriate learning experience.

Content Adaptation and Sequencing

Another important aspect of ATS is its ability to change the order and form of educational content presentation. The system helps in choosing what content should be suggested to the learner next, depending on what the learner knows at this point. Such an adaptive content sequence enables the learners to progress on the level of mastery and acquire knowledge as they start with the simple concepts and move on to the more advanced topics.

Cognitive and Metacognitive Support

Adaptive Tutoring Systems do not only concern themselves with the content but they also help in aiding the cognitive and metacognitive process. These encourage learners to engage in metacognition by encoding their understanding, trying to anticipate their outcome or by recommending learning strategies. Such features can enhance learner's self-regulation skills which are fundamental in learning throughout life.

Scalability and Flexibility

One-on-one human tutoring is hard to scale but adaptive teaching systems can. While the ability to provide such scale particularly useful in online education platforms and corporate training environments, ATS could also be designed for a wide variety of subjects, educational levels, and learner demographics.

Data-Driven Insights for Educators

Data generated by Adaptive Tutoring Systems can provide information for teachers to observe how students are faring, to discover what students have not learned, and to change their instruction. Insights obtained from here can influence the teacher in both classroom-based and distance learning environment decisions to combine a human process with an AI tutoring system. The Architecture of Adaptive Tutoring System was presented on the following figure 1.

Architecture of Adaptive Tutoring

Domain Model

The domain model contains the knowledge to be taught. This knowledge is represented using Artificial Intelligence techniques (production rules, semantic networks, frames, etc.).

This model is produced using a knowledge base relating to the domain to be taught. In some systems, the pedagogical rules used to manage a learning session are also represented in this model.

User Model

This Model contains information about the learner's knowledge (level), profile (personal traits), goals and preferences. This model is a key component of any adaptive hypermedia system.

Interaction Model

This model represents the interaction between the user and the system.

It is this model that has to make decisions such as 'When is the right time to provide directions? or 'How far should we let the user go down the wrong path?

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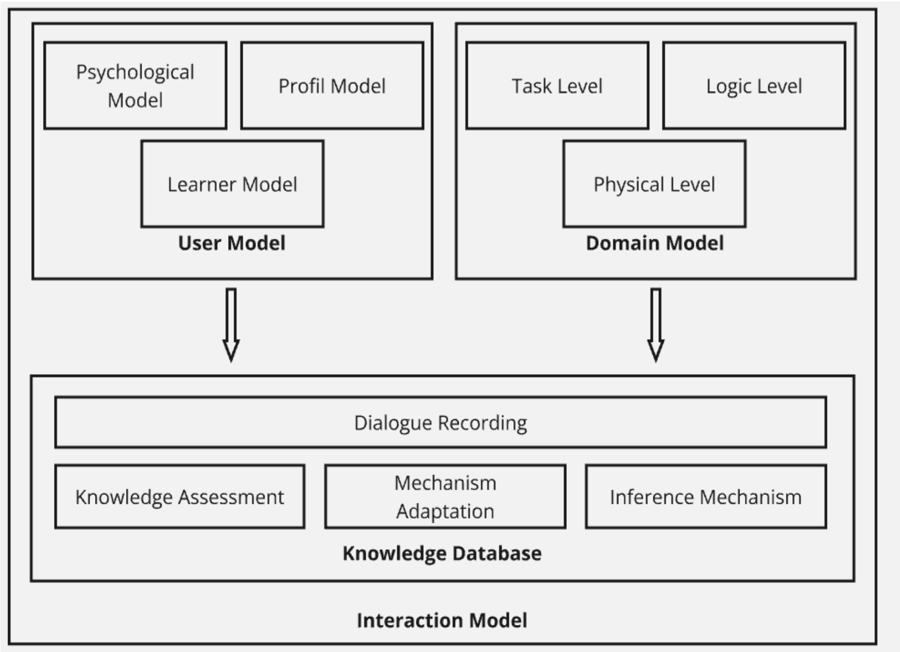

Figure 1. Architecture of an adaptative system
Source: Benyon D. R, 1993.

Design of an Intelligent Tutoring System (ITS)

After making a literature research of Intelligent Tutoring systems and examination of how and ITs works and interacts with the end user. The next stage is to put the light on architecture of ITS and how they could be implemented.

Bellow the details of how the ITS will be designed and how its components should behave.

Intelligent Tutoring System: Design

System Architecture

A typical architecture is called a client-server architecture, in which the server manages data processing, storage, and adaptive logic while the client communicates with the system via a user interface.

Key Components:

- Client:
    - UI/UX Layer: Web or mobile application where learners interact with the system.
    - Presentation Logic: Delivers the course material (videos, text, quizzes, etc.), captures user inputs, and sends data to the server.
    - Data Visualization: Displays learner progress and recommendations using dashboards.
    - Server:
    - Business Logic Layer: Includes modules for learning management, content adaptation, and feedback.
    - Machine Learning Engine: Utilizes learner data to generate personalized recommendations.
    - Content Repository: Stores the educational materials, quizzes, and other learning assets.
    - Learner Model: Stores and tracks individual learner profiles, history, and performance metrics.
    - Database: Centralized storage for all system data (e.g., user profiles, learning outcomes, etc.).

- Middleware:
    - API Gateway: Facilitates communication between clients and the server, managing requests and responses.
    - Authentication & Authorization: Ensures secure access to system resources.

- AI Algorithms:
    - Knowledge Tracing: Predicts what a student knows based on their interaction with the material (e.g., Bayesian networks or deep learning models).

   - Recommendation System: Suggests the next best learning activity based on student data.
- Natural Language Processing (NLP): Understands student queries and provides automated support.

Client-Server Interaction Flow

The system operates on a standard request-response model, in which requests are sent to the server by the learner's device, which acts as the client. The server then processes the request and makes any necessary adaptations before responding.

- User Interaction with UI: The learner interacts with the system (e.g., accessing a quiz or learning material).
- Data Submission to Server: Learner responses and actions (e.g., quiz answers, time spent) are sent to the server for processing.
- Processing on Server: The server processes the learner's data using the ML engine to adapt learning content based on the learner's model.
- Response to Client: Adapted content and progress feedback is sent back to the client, which updates the user interface accordingly.

Sequence Diagram

Below is a sequence diagram representing the interaction between the learner (client) and the server, with the system adapting learning content dynamically:

Figure 2. Sequence Diagram of client server interactions.

Adaptive Learning Flow

In order to provide a personalized experience, the adaptive learning engine dynamically modifies information based on the learner's profile and progress. The most suitable learning path is recommended by the Machine Learning Engine based on the learner's past interactions.

Key Steps:

Learner Performance Monitoring: The system tracks metrics like quiz scores, time spent on tasks, and engagement levels.

Adaptation Logic:

If a learner is struggling, easier content or additional practice may be recommended.

For high-performing learners, more challenging materials are served.

Personalized Feedback: The system provides real-time feedback based on learner performance, identifying areas of improvement or suggesting alternative learning paths.

Data Flow Diagram

The Data Flow Diagram (DFD) below shows the movement of data between system components:

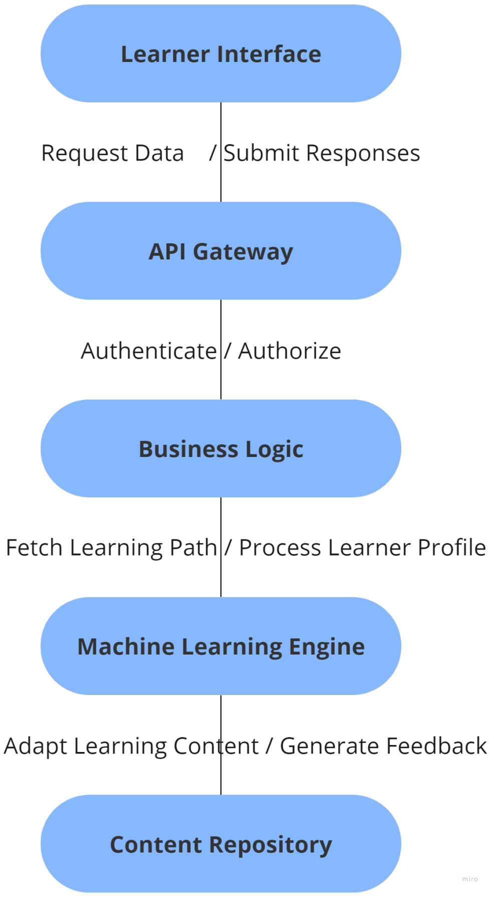

Figure 3. Data Flow Diagram

Machine Learning Models

Knowledge Tracing: Uses algorithms like Bayesian Knowledge Tracing (BKT) or Deep Knowledge Tracing (DKT) to predict learner knowledge levels.

Collaborative Filtering: Recommends content based on the behavior of similar learners.

Clustering: Identifies groups of learners with similar learning habits for tailored content recommendations.

Technology Stack

- Frontend (Client-Side):
    - HTML/CSS/JavaScript: For rendering the user interface.
    - React/Vue.js/Angular: For building interactive web applications.
    - Mobile SDKs (iOS/Android): For native mobile applications.

- Backend (Server-Side):
    - Python/Node.js/Java: For implementing the server-side logic.
    - Django/Flask/Express: Backend frameworks to manage routing and requests.
    - TensorFlow/PyTorch: Machine learning libraries for adaptive learning algorithms.
    - PostgreSQL/MySQL: Database for storing user profiles, learning content, and analytics.
    - Redis: For caching frequently accessed data.

- APIs & Microservices:
    - RESTful API for communication between the client and server.
    - OAuth2/JWT: For user authentication and secure access to resources.

Deployment Considerations

Cloud Hosting: Utilize cloud providers (e.g., AWS, Azure) for scalability and reliability.

Containerization: Use Docker and Kubernetes for easy deployment and scaling.

CDN (Content Delivery Network): Deliver content efficiently to users across different geographical locations.

With the help of this technological implementation, educators may create a solid Intelligent Adaptive Tutoring System that offers students individualized support and content. Scalability is guaranteed by the client-server architecture, and the system's continuous learner adaptation is ensured by the application of machine learning models.

Constraints of Implementation and Usage of Intelligent Tutoring Systems

Technical Complexity

Development Challenges: Developing an ITS requires advanced technical expertise in artificial intelligence, machine learning, and cognitive psychology. Integrating these diverse fields to create an effective system can be highly complex.

Infrastructure Requirements: ITS often require robust technological infrastructure, including high-performance servers, reliable internet connectivity, and up-to-date hardware and software, which may not be readily available in all educational settings.

Cost Factors

High Initial Investment: The cost of developing and implementing an ITS can be significant. This includes expenses related to software development, hardware procurement, and ongoing maintenance.[31]

Training Costs: Educators and administrators need training to effectively use ITS, which adds to the overall cost of adoption.

Data Privacy and Security

Student Data Protection: ITS collect and analyze vast amounts of student data to personalize learning experiences. Ensuring the privacy and security of this sensitive information is a major concern.

Compliance with Regulations: Implementing ITS requires adherence to various data protection regulations, which can vary by region and pose additional compliance challenges.[32]

Scalability Issues

Adapting to Different Learning Contexts: ITS need to be scalable and adaptable to various educational contexts and learner needs. Creating a system that works well across different subjects, age groups, and learning environments can be challenging.

Resource Allocation: Scaling up ITS to serve large numbers of students effectively requires substantial resources, including server capacity, technical support, and continuous system updates.

Pedagogical Limitations

One-Size-Fits-All Approach: Despite their ability to personalize learning, some ITS may still struggle to address the unique needs of every learner, particularly those with special educational needs.

Teacher Integration: Successful implementation of ITS requires seamless integration with traditional teaching methods. This can be difficult if teachers are resistant to change or lack the necessary skills to incorporate technology into their teaching practices.

Usability and Accessibility

User Interface Design: The usability of ITS can significantly impact their effectiveness. Poorly designed interfaces may frustrate students and teachers, reducing the system's overall impact.

Accessibility Issues: ITS must be designed to be accessible to all students, including those with disabilities. Ensuring compliance with accessibility standards is essential but can be technically challenging.

Assessment and Feedback Challenges

Accurate Assessment: ITS rely on algorithms to assess student performance and provide feedback. Ensuring that these assessments are accurate and reliable is critical, but it can be difficult to achieve.

Timeliness of Feedback: Providing timely and constructive feedback is crucial for student learning. ITS must be designed to deliver feedback promptly, which requires efficient data processing and analysis capabilities.

By addressing these constraints, developers and educators can work towards creating more effective and widely accessible Intelligent Tutoring Systems that enhance learning outcomes for all students.

Educators with tools to optimize their teaching strategies. As we embark on this transformative journey, it is imperative to strike a balance between technological innovation and the preservation of the human-centric elements that make education a profoundly enriching experience.

CONCLUSION

By tailoring the educational experience, Adaptive Tutoring Systems (ATS) have made a substantial advancement in the field of e-learning. These systems may dynamically adjust to the particular requirements and preferences of each learner by integrating Artificial Intelligence (AI) and data analytics. This enhances

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engagement, retention, and learning results. Real-time feedback, cognitive support, and material customization are used to make sure that students advance at their own speed while successfully addressing their unique strengths and shortcomings.

The main elements of ATS—learner modeling, content sequencing, and machine learning algorithms—have been emphasized in this research. These elements cooperate to offer an adaptable and scalable educational solution. With the growing trend of education systems shifting to digital platforms, particularly after major worldwide shocks like the COVID-19 pandemic, Advanced Teacher Support (ATS) is a crucial instrument for guaranteeing that students receive high-quality instruction in a variety of contexts.

Notwithstanding the manifold benefits, obstacles like expense, intricacy of technology, and privacy issues about data persist. It will be essential to address these problems if ATS are to be widely used in formal and informal learning settings. With continued advancements in artificial intelligence and digital technologies, adaptive learning systems will become more and more important in reshaping education to become more efficient, inclusive, and learner-focused.

REFERENCES

1. Michalas, A., & Vretaros, P. (2023). Protecting medical emergency personnel through a framework for verifiable and privacy-preserving cross-border collaboration. ICT Systems Security and Privacy Protection, 82-94. https://doi.org/10.1007/978-3-031-54288-6_5

2. Shraim, K. (2024). Artificial Intelligence (AI)-Powered Tutoring Systems: Exploring Their Potential to Reduce Dropout Rates in E-Learning. In A. K. M. Azad & M. K. Hasan (Eds.), Artificial Intelligence in Education: Toward a Better Future (pp. 255–275). Springer. https://doi.org/10.1007/978-3-031-54288-6_15

3. Kulkarni, S., & Ogata, H. (2020). Intelligent Tutoring Systems: Opportunities and Challenges in E-Learning. Educational Technology & Society, 23(3), 34-45.

4. Smith, A., & Johnson, B. (2021). The Impact of Intelligent Tutoring Systems on Student Learning. Journal of Educational Technology Research, 15(2), 123-145.

5. Brusilovsky, P., & Millán, E. (2007). User Models for Adaptive Hypermedia and Adaptive Educational Systems. In P. Brusilovsky, A. Kobsa, & W. Nejdl (Eds.), The Adaptive Web: Methods and Strategies of Web Personalization (pp. 3-53). Springer.

6. Shute, V. J., & Zapata-Rivera, D. (2012). Adaptive Educational Systems. In P. J. Durlach & A. M. Lesgold (Eds.), Adaptive Technologies for Training and Education (pp. 7-27). Cambridge University Press.

7. De Jong, T., & van Joolingen, W. R. (1998). Scientific Discovery Learning with Computer Simulations of Conceptual Domains. Review of Educational Research, 68(2), 179-201.

8. Baker, R. S. J. d., & Inventado, P. S. (2014). Educational Data Mining and Learning Analytics. In Learning Analytics (pp. 61-75). Springer.

9. Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). Intelligence Unleashed: An Argument for AI in Education. Pearson Education.

10. Pane, J. F., Steiner, E. D., Baird, M. D., Hamilton, L. S., & Pane, J. D. (2017). Informing Progress: Insights on Personalized Learning Implementation and Effects. RAND Corporation.

11. Cloude, E. B., Carpenter, D. D., Choe, E. K., & Lee, D. (2022). Multimodal Learning Analytics to Quantify Student Behaviors in Complex Digital Learning Environments. Computers & Education, 176, 104352.

12. Stamper, J., & Koedinger, K. R. (2022). Enhancing LLM-Based Feedback: Insights from Intelligent Tutoring Systems and Learning Sciences. arXiv.

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AUTHORSHIP CONTRIBUTION

Conceptualization: Atmane EL HADBI, Mohammed Hatim RZIKI, Yassine JAMIL, Zaynab AMMARI, Mohamed Khalifa BOUTAHIR, Hamid BOURRAY, Driss EL OUADGHIRI.

Data curation: Atmane EL HADBI, Mohammed Hatim RZIKI, Yassine JAMIL, Zaynab AMMARI, Mohamed Khalifa BOUTAHIR, Hamid BOURRAY, Driss EL OUADGHIRI.

Formal analysis: Atmane EL HADBI, Mohammed Hatim RZIKI, Yassine JAMIL, Zaynab AMMARI, Mohamed Khalifa BOUTAHIR, Hamid BOURRAY, Driss EL OUADGHIRI.

Research: Atmane EL HADBI, Mohammed Hatim RZIKI, Yassine JAMIL, Zaynab AMMARI, Mohamed Khalifa BOUTAHIR, Hamid BOURRAY, Driss EL OUADGHIRI.

Methodology: Atmane EL HADBI, Mohammed Hatim RZIKI, Yassine JAMIL, Zaynab AMMARI, Mohamed Khalifa BOUTAHIR, Hamid BOURRAY, Driss EL OUADGHIRI.

Project management: Atmane EL HADBI, Mohammed Hatim RZIKI, Yassine JAMIL, Zaynab AMMARI, Mohamed Khalifa BOUTAHIR, Hamid BOURRAY, Driss EL OUADGHIRI.

Resources: Atmane EL HADBI, Mohammed Hatim RZIKI, Yassine JAMIL, Zaynab AMMARI, Mohamed Khalifa BOUTAHIR, Hamid BOURRAY, Driss EL OUADGHIRI.

Software: Atmane EL HADBI, Mohammed Hatim RZIKI, Yassine JAMIL, Zaynab AMMARI, Mohamed Khalifa BOUTAHIR, Hamid BOURRAY, Driss EL OUADGHIRI.

Supervision: Atmane EL HADBI, Mohammed Hatim RZIKI, Yassine JAMIL, Zaynab AMMARI, Mohamed Khalifa BOUTAHIR, Hamid BOURRAY, Driss EL OUADGHIRI.

Validation: Atmane EL HADBI, Mohammed Hatim RZIKI, Yassine JAMIL, Zaynab AMMARI, Mohamed Khalifa BOUTAHIR, Hamid BOURRAY, Driss EL OUADGHIRI.

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Drafting: Atmane EL HADBI, Mohammed Hatim RZIKI, Yassine JAMIL, Zaynab AMMARI, Mohamed Khalifa BOUTAHIR, Hamid BOURRAY, Driss EL OUADGHIRI.