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Innovative Decision Support System for Academic and Scientific Output Management: An AI-Based Approach for Algerian Higher Education Institutions

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✦ Dedication ✦

To my tender mother, **Saida**, whose love, strength, and faith have been the pillar of my journey. You are my refuge and my greatest source of inspiration. May God bless you with health and happiness. Thank you for standing by my side with infinite tenderness, even during my moments of weakness and illness.

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✦ Dedication ✦

As a token of my love, appreciation, and deep gratitude, I dedicate this work:

✨ To the memory of my beloved father, who always believed in me. May God the Almighty grant him His mercy and welcome him into His vast paradise. You remain alive in my heart and present in each of my successes.

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Abstract:

The objective of the platform developed in this project is to enhance both the efficiency and modernity of academic output management in higher education. It enables instructors to submit lectures, handouts, dissertations, and articles via a dedicated interface. The integration of intelligent data processing techniques allows the system to automatically identify and recommend the most suitable reviewers based on the research field, title, and abstract of the submitted work. Reviewers are provided with a personal workspace where they can accept or decline review requests and easily provide feedback. The chair or scientific director can monitor submissions in real time, approve proposed reviewers, and oversee the various stages of the review process. Automating these time-consuming tasks has been shown to improve processing speed, enhance the accuracy of reviewer recommendations, and increase the transparency of scientific governance.

Keywords: Digital Platform, Submission System, Intelligent Data Processing, Reviewer Recommendation, Research Field, Abstract Analysis, Review Management, Scientific Governance, Workflow Automation, Real-Time Tracking, Peer Review, Academic Publishing, Knowledge Management, K-Means, TF-ID.

Résumé

L'objectif de la plateforme développée dans le cadre de ce projet est d'améliorer l'efficacité et la modernité de la gestion des résultats académiques dans l'enseignement supérieur. Elle permet aux enseignants de soumettre des cours, des documents, des thèses et des articles via une interface dédiée. L'intégration de techniques intelligentes de traitement des données permet au système d'identifier et de recommander automatiquement les évaluateurs les plus appropriés, sur la base du domaine de recherche, du titre et du résumé du travail soumis. Les évaluateurs disposent d'un espace de travail personnel où ils peuvent accepter ou refuser des demandes d'évaluation et fournir facilement un retour d'information. Le président ou le directeur scientifique peut suivre les soumissions en temps réel, approuver les évaluateurs proposés et superviser les différentes étapes du processus d'évaluation. Il a été démontré que l'automatisation de ces tâches fastidieuses améliore la vitesse de traitement, la précision des recommandations des évaluateurs et la transparence de la gouvernance scientifique.

Mots-clés : Plate-forme numérique, système de soumission, traitement intelligent des données, recommandation des évaluateurs, domaine de recherche, analyse des résumés, gestion des évaluations, gouvernance scientifique, automatisation des flux de travail, suivi en temps réel, évaluation par les pairs, édition universitaire, gestion des connaissances, K-Means, TF-ID.

الملخص

تهدف المنصة المطورة في هذا المشروع إلى تبسيط وتحديث إدارة المخرجات الأكاديمية في التعليم العالي، فهي تمكن الأساتذة من تقديم محاضراتهم، وأوراقهم البحثية، وأطروحاتهم، أو مقالاتهم بسهولة عبر مساحة مخصصة . بفضل دمج تقنيات المعالجة الذكية للبيانات مثل (k-means وTF-IDF) ، يقوم النظام بعملية البحث والتوصية بالمراجعين الأنسب، اعتمادًا على مجال البحث وعنوان العمل وملخصه، بما يضمن دقة وملائمة التوصيات . يستفيد المراجعون من مساحة شخصية لقبول أو رفض طلبات المراجعة وتقديم تعليقاتهم بسهولة، بحيث يمكن لرئيس القسم أو المدير العلمي تتبع الطلبات المقدمة في الحال والموافقة على المراجعين المقترحين وإدارة المراحل المختلفة لعملية المراجعة من خلال أتمتة هذه المهام المستهلكة للوقت، وتحسين المنصة، وسرعة المعالجة، ودقة التوصيات، وشفافية الحوكمة العلمية .

الكلمات المفتاحية: منصة أكاديمية – المعالجة الذكية للبيانات - دعم القرار - توصية آلية - التعليم العالي- k-means - TF-IDF.

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List of abbreviations and acronyms:

AI: Artificial Intelligence

DSS: Decision Support Systems

DL: Deep Learning

ML: Machine Learning

SLM: Scientific Literature Mining

NLP: Natural Language Processing

ALS: Techniques like Alternating Least Squares

DB: Database

SVM: Support Vector Machines

PCA: Principal Component Analysis

UL: Unsupervised learning

SL: Supervised learning

SSL: Semi-supervised learning

RS: Recommendation System

CF: collaborative filtering

TF-IDF: Term Frequency-Inverse Document Frequency

SVM: Support Vector Machines

CDM: Conceptual Data Model

SQL: Structured Query Language

HTML: Hyper Text Markup Language

CSS: Cascading Style Sheets

General introduction

In a global context marked by the acceleration of scientific production and the rapid evolution of digital technologies, higher education institutions are increasingly called upon to adopt innovative tools to optimize the management of their academic and scientific activities. The valorization of research, the evaluation of intellectual output, and strategic decision-making regarding publication and scientific support have become central challenges in ensuring the quality and visibility of the knowledge being produced.

In the face of these challenges, Artificial Intelligence (AI) emerges as a promising solution for automating complex processes, supporting academic actors in their decision-making, and enhancing the efficiency of management systems. Decision Support Systems (DSS), powered by AI techniques, enable the analysis of large volumes of data, the identification of relevant patterns, and the provision of context-aware recommendations.

From this perspective, this thesis proposes the design and implementation of an intelligent system to support the management and valorization of scientific output, specifically tailored for higher education institutions in Algeria. This system aims to facilitate the submission, evaluation, and tracking of scientific publications, integrating functionalities based on machine learning and process personalization.

This work is structured around several key areas: a literature review on DSS and their integration into the academic domain; an analysis of the needs and specificities of the Algerian context; a system design using software engineering tools; and finally, a technical implementation that demonstrates the feasibility and relevance of the proposed solution.

Through this research, we aim to contribute to the optimization of academic governance and enhance the quality of scientific processes within Algerian universities.

Chapter I: Introduction to the AI and Decision Support System

I.1 Introduction

Given the significant increase in academic production and the increasing complexity of decisions that must be made in higher education, decision support systems (DSS) are emerging as essential tools for supporting performance management, resource optimization, and strategic planning. Incorporating artificial intelligence (AI) methods into these systems makes it easier to evaluate large amounts of data, produce relevant suggestions, uncover hidden patterns, and simplify intricate decision-making procedures. In this regard, the creation of a cutting-edge decision support system centered on the administration of scholarly and scientific output is a component of a dynamic, technologically and strategically driven effort to improve university governance. As a result, this chapter offers a thorough literature analysis on the core ideas of AI and DSS [1].

The purpose of this first chapter is to lay forth the conceptual and theoretical foundations of the study. It lays out the basic concepts that underpin discussions about artificial intelligence, decision assistance, and scientific output control. The chapter describes the main DSS categories and architectural components, looks at how these technologies are currently being used in academia, and offers a general architecture for developing a new AI-based DSS. It also provides a succinct overview of the current state of affairs to highlight the unique contribution of the proposed prototype.

Furthermore, a crucial first stage in every creative design process is system analysis. In addition to finding unmet requirements, this helps us understand the approaches, designs, and constraints of previous solutions. Many tools have been created in the field of academic management, but few of them fully leverage artificial intelligence's potential to support strategic decision-making [2]. As a result, our study offers a strong basis for our methodology, permits the avoidance of duplication, and suggests a system that is more adapted to the current issues of academic management, performance, and quality [3].

I.2 A General Overview of Artificial Intelligence

I.2.1 Definition of Artificial Intelligence

Artificial Intelligence (AI) is the branch of computer science dedicated to creating systems capable of performing tasks that typically require human intelligence. These tasks include reasoning, learning, problem-solving, perception, and language understanding. John McCarthy, one of the founding figures of AI, defined it as "the science and engineering of making intelligent machines" [4].

In contemporary applications, artificial intelligence (AI) refers to a variety of tools and methods that let computers analyze enormous volumes of data, recognize patterns, and adjust to novel circumstances with little assistance from humans. AI has emerged as a key component of digital transformation across industries, from digital assistants to autonomous cars and medical diagnostics.

I.2.2 AI Applications in Scientific Research

Artificial intelligence (AI) plays an increasingly important role in modern scientific research. Its ability to process and analyze large amounts of complex data, identify hidden patterns, and optimize decision-making processes makes it a powerful tool for many disciplines. Here are the key areas where AI is changing research methods and results:

- **Automated Data Analysis and Pattern Recognition**

AI, particularly through machine learning and deep learning, enables researchers to process massive datasets efficiently. For example, in genomics, AI helps identify mutations and patterns in DNA sequences. In physics and astronomy, AI processes telescope data to detect celestial objects or phenomena that might be missed by traditional analysis [5].

Example: AI has been used by CERN to analyze data from the Large Hadron Collider, improving the detection of rare particle collisions [6].

- **Scientific Discovery and Hypothesis Generation**

AI can assist in generating new scientific hypotheses by discovering correlations and causal relationships in existing datasets. Some AI systems are even capable of proposing new theories or research directions [7].

Example: IBM's Watson has been used in cancer research to recommend potential treatments and even suggest new research questions based on published literature [8].

- **Scientific Literature Mining (SLM)**

  SLM techniques facilitate knowledge discovery, improve information retrieval, and support summarization of scientific documents. They have been particularly impactful in biomedical research, materials science, and environmental exposure studies [9] [10].

Example: COVID-19 Open Research Dataset (CORD-19) was mined using AI to extract relevant medical knowledge during the pandemic reference.

- **AI for Simulation and Modeling**

AI enhances simulations by improving accuracy and reducing computation time. In environmental sciences, AI helps simulate climate systems, while in material sciences, it predicts new compound structures and properties.

Example: DeepMind's AlphaFold predicts the 3D structures of proteins with unprecedented accuracy, aiding drug development and molecular biology [11].

- **Robotics and Automation in Laboratories**

AI-powered robots and lab systems can perform repetitive experimental procedures, measure results, and adapt protocols based on real-time data. This is especially valuable in fields like chemistry and biology where high-throughput screening is essential.

Example: AI-driven robotic chemists are capable of autonomously conducting hundreds of experiments daily and modifying them based on outcomes [12].

I.2.3 AI Models and Techniques

The principal models and techniques of IA are summarized in the following:

I.2.3.1 Machine Learning

Machine Learning (ML) is a subfield of Artificial Intelligence that enables systems to learn from data and improve their performance without being explicitly programmed. ML algorithms can detect patterns, make decisions, and predict outcomes. Key types include supervised learning, unsupervised learning, and reinforcement learning. ML is widely applied in fraud detection, recommendation systems, and data analysis [13].

I.2.3.2 Deep Learning

Deep Learning is a specialized branch of machine learning that uses multi-layered neural networks (deep neural networks) to model complex patterns in large datasets. It excels in tasks such as image recognition, speech processing, and language understanding. Architectures like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are common [14].

I.2.3.3 Neural Networks

Neural Networks are computational models inspired by the human brain, consisting of interconnected layers of artificial neurons. They are capable of approximating complex functions and are used in pattern recognition, prediction, and classification. Their ability to handle non-linear relationships makes them effective in scientific data analysis [15].

I.2.3.4 Natural Language Processing (NLP)

Natural Language Processing is a field of AI focused on enabling machines to understand, interpret, and generate human language. It combines computational linguistics with machine learning and deep learning. NLP applications include machine translation, sentiment analysis, text summarization, and scientific literature mining [16].

I.2.5 Difference between AI, Machine Learning (ML), and Deep Learning (DL)

Artificial Intelligence (AI), a term introduced by Stanford professor John McCarthy in 1955, is defined as "the science and engineering of making intelligent machines." Initially, much research focused on programming machines to perform specific tasks cleverly, such as playing chess, but modern AI increasingly emphasizes machines that can learn and adapt in ways that resemble human learning.

However, Machine Learning (ML) is a subfield of AI that concentrates on enabling computer systems to improve their perception, reasoning, knowledge, or behavior through experience and data. It draws upon various disciplines, including computer science, statistics, psychology, neuroscience, economics, and control theory. ML encompasses several learning paradigms: in supervised learning, the system learns from labeled data (for instance, identifying dog breeds from labeled images); in unsupervised learning, it uncovers patterns in unlabeled data, such as predicting the next word in a sentence without prior labels; and in reinforcement learning, an agent learns to perform sequences of actions that maximize cumulative rewards, such as winning a game, by exploring strategies without explicit instructions.

Furthermore, Deep Learning (DL), a subset of ML, involves large, multi-layer artificial neural networks that process information in a manner inspired by the hierarchical organization of neurons in the human brain. DL has become one of the most successful approaches in ML, offering superior generalization from limited data and scaling effectively to large datasets and computational resources. Unlike traditional algorithms, where explicit instructions dictate behavior, much of the functionality in modern AI systems emerges from data-driven learning processes; a paradigm shift often referred to as "Software 2.0," as coined by Stanford alumnus Andrej Karpathy [17].

The relationship between these concepts can be visualized hierarchically as follows (figure 1.1):

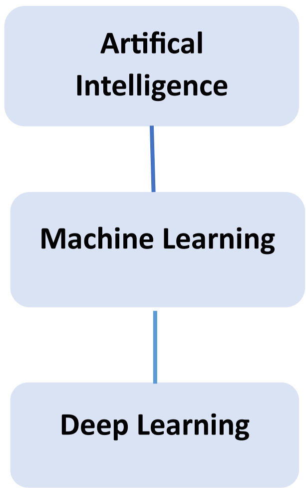

Figure 1.1: Hierarchical Relationship Between Artificial Intelligence, Machine Learning, and Deep Learning.

I.2.6 Artificial intelligence and science data management

Artificial intelligence (AI) is revolutionizing scientific data management by automating the processing and analysis of large amounts of information. Through its learning and pattern detection capabilities [18].

AI facilitates the discovery of new knowledge, accelerates research and improves decision-making. It allows for more efficient, accurate and rapid data management, while posing ethical and regulatory challenges to be taken into account [19].

Artificial intelligence (AI) is now a major technological revolution, profoundly transforming many sectors. AI brings together a set of theories, methods and technologies that allow machines to simulate certain human cognitive abilities such as learning, problem solving, perception or understanding of natural language [20].

Artificial intelligence (AI) is an area of computer science aimed at creating systems capable of mimicking certain human abilities such as perception, reasoning, planning or learning. AI is now booming thanks to advances in computing power, the accessibility of massive data (big data) and the evolution of algorithms. In the context of higher education and research, AI provides powerful tools for analyzing scientific outputs, facilitating strategic decision-making and automating various administrative and academic tasks [21].

Among the many branches of AI, several stand out for their particular usefulness in the field of academic and scientific production management. These include machine learning (ML), natural language processing (NLP) and expert systems:

1.2.6.1 Machine Learning (ML)

It is a machine learning method that allows a system to improve itself from the data. It is particularly used for classifying publications, predicting performance indicators and identifying trends in academic production [22].

1.2.6.2 Natural language processing (NLP)

Natural language processing (NLP) is a subfield of artificial intelligence that is concerned with the automatic understanding of human language by computers [23].

NLP allows a machine to understand, analyze, and generate human language. It is essential for analyzing scientific texts, summarizing documents, and automatically extracting information [24].

1.2.6.3 Expert Systems

These are computer systems that simulate the reasoning of a human expert in a specific field. In the academic world, they can be used for decision-making support in evaluating the quality of publications, managing scientific committees or providing strategic direction to research [25].

These technologies complement each other to help institutions enhance their scientific output, anticipate research developments and optimize their governance.

I.3 Decision Support Systems (DSS)

I.3.1 Definition

Decision Support Systems (DSS) are integral tools designed to enhance decision-making processes within organizations by leveraging data analysis and expert knowledge [26]. These systems facilitate the interpretation of complex data, enabling users to make informed decisions more efficiently. The effectiveness of DSS is contingent upon their design, which includes a robust database, analytical models, and user-friendly interfaces, ensuring that decision-makers can access and utilize relevant information effectively [27].

I.3.2 Typologies of DSS

- **DSS driven by data**

  These systems focus on accessing and analyzing large data sets to facilitate decision making. They use data analysis to generate information from stored information [28].

- **DSS driven by documents**

This type uses documents and unstructured data to provide the information needed for decision-making, integrating different document formats [29].

- **DSS driven by Knowledge**

Often referred to as expert systems, these systems use knowledge bases to provide recommendations and information, thus improving decision-making through expert knowledge (Power, 2003).

- **DSS driven by communication:**

These systems facilitate communication and collaboration between users, often incorporating technologies that support group decision-making processes. (Fernando & Baldelovar, 2022).

- **DSS driven by the model:**

These systems use quantitative models to simulate scenarios and predict outcomes, often referred to as model-oriented DSS or calculation-oriented DSS [30].

I.3.3 Architecture of a Decision Support System (DSS)

A decision support system is based on a modular architecture composed of several interdependent layers, which allow the collection, processing, analysis and restitution of information useful for decision-making. The classic architecture of a DSS generally includes the following four components:

- **The Database (Base De Données)**

It contains all the information necessary for decision-making: internal data (research activities, publications, projects) and external data (bibliographical databases, international indicators). It is often based on a data warehouse (data warehouse) and can be automatically fed by various sources [31].

- **The basis of models (Model Management Module):**

It includes analysis and processing tools: statistical models, optimization, simulation or artificial intelligence algorithms. These models can be used to explore scenarios, make predictions, or detect patterns useful for decision-making [32].

- **The knowledge base (base de connaissance):**

It integrates expert rules, feedback or machine learning systems to enrich recommendations. This is where AI techniques such as expert systems, decision trees or supervised and unsupervised learning can come in [33].

- **User Interface (L'interface utilisateur):**

This is the layer visible to the user (decision-maker, laboratory manager, academic administrator). It presents the results in the form of dynamic reports, interactive dashboards, visualizations or alerts. It also allows you to interact with models and data to explore different scenarios. (Bendib, s.d.).

- **Interactions between modules:**

• The decision-maker interacts via the interface, which queries the model base and database.

• Models access data to produce results, often enriched by the knowledge base.

• The visualization of results then guides the decision-maker to informed action.

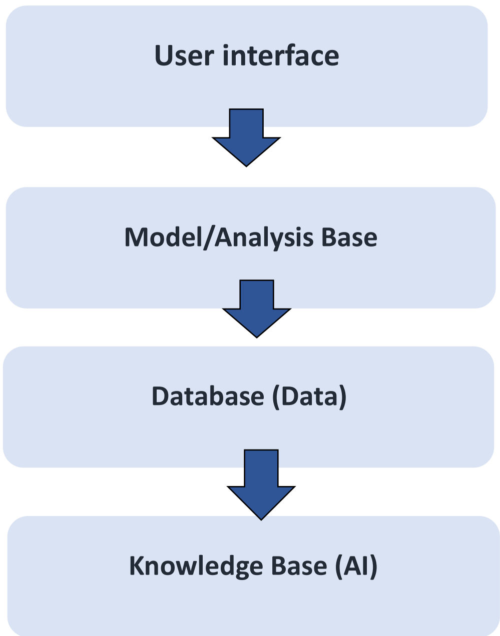

Figure 1.2: Architecture of a decision support system.

I.3.4 Role of DSS in university governance

Decision support systems (DSS) play a crucial role in university governance by providing leaders and managers with powerful tools to improve strategic and operational decision-making. These systems enable the extraction [34]. analysis, and presentation of relevant data from various institutional sources, thus facilitating planning, resource management, performance monitoring, and evaluation of university programs, and have a positive impact on the performance of universities [35].

I.4 Motivation for Integrating AI into Decision Support Systems

The pressing need to integrate artificial intelligence (AI) into Decision Support Systems (DSS) stems from several core motivations. First, AI enables the handling of vast, heterogeneous datasets, structured and unstructured; at high velocity and scale, far beyond the capabilities of traditional DSS. This capacity allows systems to uncover hidden patterns, generate predictive insights, and support data-driven decision-making.

Second, AI enhances DSS functionality through advanced analytics. Through predictive and prescriptive modeling, AI-driven DSS can forecast trends, simulate scenarios, assess risks, and recommend optimal actions, empowering decision-makers to act proactively rather than reactively.

Third, AI improves user interaction and system usability. Integration of natural language processing (NLP) and intelligent agents enables conversational interfaces and personalized recommendations, reducing cognitive load and increasing trust and satisfaction.

Fourth, there is a significant drive to improve decision quality and operational efficiency. AI-powered DSS reduce human error and bias, enhance consistency, and automate routine tasks, yielding measurable improvements in speed, accuracy, and cost effectiveness.

Fifth, the real-world context, including rapidly evolving markets, increased data complexity, competitiveness, and governance demands, has propelled the adoption of AI-enhanced DSS across industries.

Finally, emerging concerns around AI transparency, accountability, and trust have sparked interest in explainable AI (XAI). By incorporating interpretability into DSS, organizations can mitigate algorithm bias, foster human–AI collaboration, and ensure responsible decision-making.

I.5 AI for decision support

Artificial intelligence (AI) plays a central role in modern decision support systems, particularly through three key functions: recommendation, scoring and prediction. In the context of higher education institutions, these technologies make it possible to process large amounts of data from scientific production, academic performance or student trajectories.

I.5.1 Recommendation systems

Recommendation systems use historical and behavioral data to suggest relevant actions. For example, they can suggest strategic research areas, scientific collaborations or targeted publications to a researcher based on his or her profile. This facilitates a better focus of efforts and improves the visibility of academic work [36]. In the following, we propose several illustrative instances of domain application in which recommendation systems can be employed:

- In the e-commerce field, platforms such as Amazon and Flipkart employ recommendation systems to enhance user experience and drive sales by suggesting products tailored to individual customers' purchase histories, browsing behavior, and the preferences of similar users. By leveraging user behavior data, these systems deliver personalized product recommendations that increase user engagement, satisfaction, and ultimately, revenue [37].
- The integration of recommendation systems within the online education sector has been a significant development, with the primary function of these systems being to suggest educational resources, courses, and learning paths that are tailored to individual learners' interests, skill levels, and prior activities. Platforms such as Coursera and edX utilise these systems to personalise learning experiences, thereby enhancing engagement and optimising learning outcomes. By taking into account the unique characteristics of each learner, including their preferences, behaviours, and learning styles, these systems seek to facilitate more effective, adaptive, and engaging educational experiences [38]
- In the context of media streaming services, such as Netflix and Spotify, recommendation systems meticulously analyse viewer or listener habits to

propose content that is aligned with the user's preferences, thereby enhancing user satisfaction and retention.

- Social media platforms, including Instagram and Facebook, utilise recommendation techniques to suggest new friends, groups, or content based on users' interactions and social networks.
- In the field of healthcare, the implementation of personalised recommendation systems has emerged as a significant development. These systems are designed to support healthcare professionals by offering tailored treatment options that are aligned with the individual profiles, medical histories, and prevailing clinical guidelines of each patient. The overarching objective of this initiative is to enhance patient outcomes.
- In the domain of travel and tourism, services such as Booking.com and Airbnb employ recommendation systems to suggest destinations, accommodations, or travel packages, informed by users' historical bookings and preferences.
- Financial institutions and investment platforms implement recommendation algorithms to personalize financial advice, portfolio management, or credit product offerings, enhancing client satisfaction and trust.
- In the context of recruitment and job platforms, such as LinkedIn, recommendation systems have been developed to suggest job opportunities, professional connections, or skill development resources. These recommendations are based on an analysis of users' profiles and career trajectories.
- Finally, within the gaming industry, platforms such as Steam utilise data analytics to recommend video games and in-game content, with these recommendations being based on gameplay patterns and peer behaviours. This process serves to enhance the gaming experience and promote community engagement. The wide range of applications under discussion demonstrates the versatility of recommendation systems and their critical role in optimising user experience across a variety of sectors.

These diverse applications illustrate the versatility and critical role of recommendation systems in optimizing user experience across a multitude of sectors.

I.5.2 Scoring

It allows entities (teachers, projects, publications, laboratories) to be evaluated and classified according to defined criteria such as scientific impact, productivity or strategic relevance. This mechanism helps decision-makers set priorities, allocate resources fairly and recognize the most outstanding performance [39].

I.5.3 Prediction

Prediction uses machine learning algorithms to anticipate future developments. This can be the trajectory of a researcher, the success of a project or the emergence of new scientific trends. By integrating these predictive capabilities, institutions can adopt proactive governance that is better aligned with research and innovation dynamics [40].

Prediction is a critical process that involves inferring future outcomes based on historical and current data, employing scientific methods. It serves as a foundation for decision-making across various fields, including engineering, data science, and computer science. The nuances of prediction encompass various methodologies and mathematical frameworks, which are essential for accurate forecasting [41].

I.6 Applications of AI in Higher Education

AI embodies the expertise of instructors by simplifying essential teaching tasks and addressing them within the educational field:

- **Addressing Faculty Shortages**

In cases where universities lack expert instructors, AI that encapsulates faculty expertise can enhance their effectiveness. Research indicates that providing high-quality curricula and online educational materials to less experienced faculty can improve students' academic performance.

- **Meeting Diverse Student Needs**

Even highly skilled instructors sometimes struggle to meet the diverse educational needs of their students. Universities may train instructors in differentiated instruction, and AI can support this by delivering core content, essential teaching skills, and better assessment data to instructors.

- **Teaching Beyond Academic Content**

In addition to academic content, deep learning and non-cognitive skills play a crucial role in academic outcomes and students' lives. AI that embodies the expertise of instructors enhances their ability to help students develop essential skills.

- **Maximizing Instructor Value**

Expert instructors are invaluable resources in the education system, and ensuring every student receives excellent instruction requires simplifying innovations and unique teaching aspects through AI.

- **Reducing administrative burdens:**

AI applications can alleviate instructors' workloads by handling administrative tasks like grading exams and assessing assignments, allowing instructors to dedicate more time to research and curriculum development [42].

I.7 Conclusion

In summary, this first chapter has laid the conceptual and technological groundwork essential for understanding the role of Artificial Intelligence (AI) and Decision Support Systems (DSS) in enhancing the strategic management of scientific production within higher education. By exploring key definitions, theoretical models, and existing academic practices, we have established a comprehensive framework that guides the rest of this work.

Building on this foundation, the next chapter will focus on Machine Learning and Recommendation Systems, examining their principles, techniques, and relevance in designing intelligent solutions for academic environments.

Chapter II: State of the Art and Proposal

II.1 Introduction

In today's era of information overload, Machine Learning (ML) has become essential for uncovering meaningful patterns and preferences within large, complex datasets. By employing techniques such as collaborative filtering to analyze user–item interactions, content-based models to extract and compare item features, and advanced neural architectures for deep representation learning, ML enables systems to generate intelligent, personalized predictions and suggestions.

Recommendation systems, a key application of ML, convert passive data into proactive guidance by tailoring content, products, and services to individual user needs. Methods like matrix factorization uncover latent affinities between users and items, while deep models (e.g., autoencoders, multilayer perceptrons, and transformers) capture higher-order relationships to deliver more nuanced recommendations. Emerging approaches, such as reinforcement learning, further enhance these systems by modeling recommendations as sequential decision problems that optimize long-term user satisfaction.

By continuously learning from both explicit feedback (e.g., ratings) and implicit signals (e.g., clicks or dwell time), ML-driven recommendation systems adapt in real time to evolving user behavior and contexts. This adaptability boosts personalization, engagement, and retention, making recommendation engines a cornerstone of modern AI-powered platforms.

This chapter offers a comprehensive exploration of the ML principles underpinning recommendation systems, examining core algorithmic paradigms, from collaborative and content-based filtering to deep learning and reinforcement learning, and evaluating their impact on adaptive, intelligent decision support.

II.2 Machine Learning

In this section, we provide a concise overview of machine learning, outlining its fundamental principles, key methodologies, and primary applications. We then examine the main algorithmic paradigms that enable systems to learn from data and support intelligent decision making.

II.2.1 Introduction to Machine Learning

Throughout history, humans have continually invented tools to ease their daily lives. These tools have evolved over time, driven by human ingenuity and technological advancement. Among the most significant innovations of the digital age is Machine Learning (ML), a subfield of Artificial Intelligence (AI) that focuses on developing algorithms capable of learning from data and improving their performance without being explicitly programmed [43].

One of the earliest and most influential definitions of machine learning was introduced by Arthur Samuel (1959), who described it as:" The field of study that gives computers the ability to learn without being explicitly programmed" (Samuel, 1959).

Samuel's work on a self-learning checkers-playing program marked one of the first real-world applications of machine learning and highlighted its potential.

In the context of the big data revolution, machine learning plays a crucial role by providing tools that allow computers to analyze massive volumes of data, detect patterns, and make informed decisions. This process reduces the need for constant human supervision and enables systems to adapt and improve over time [44].

A more formal and widely accepted definition is provided by Tom M. Mitchell (1997):

"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E." (Mitchell, 1997).

This definition frames machine learning as a measurable and empirical process, emphasizing that learning is demonstrated through performance improvements based on experience.

Today, machine learning underpins a wide array of applications, including image and speech recognition, natural language processing, medical diagnosis, financial forecasting, recommendation systems, and autonomous systems. As such, it is regarded as a foundational pillar of modern intelligent technologies.

II.2.2 The relationship between ML and AI

Artificial Intelligence (AI) is the overarching field that encompasses various techniques for enabling machines to simulate human intelligence. One of its most prominent subsets is Machine Learning (ML), which allows systems to learn from data and improve their performance autonomously. Within ML lies Deep Learning (DL), which relies on artificial neural networks to process complex patterns. In this hierarchy, AI is the foundation, ML builds upon it, and DL further specializes in data-driven learning [45].

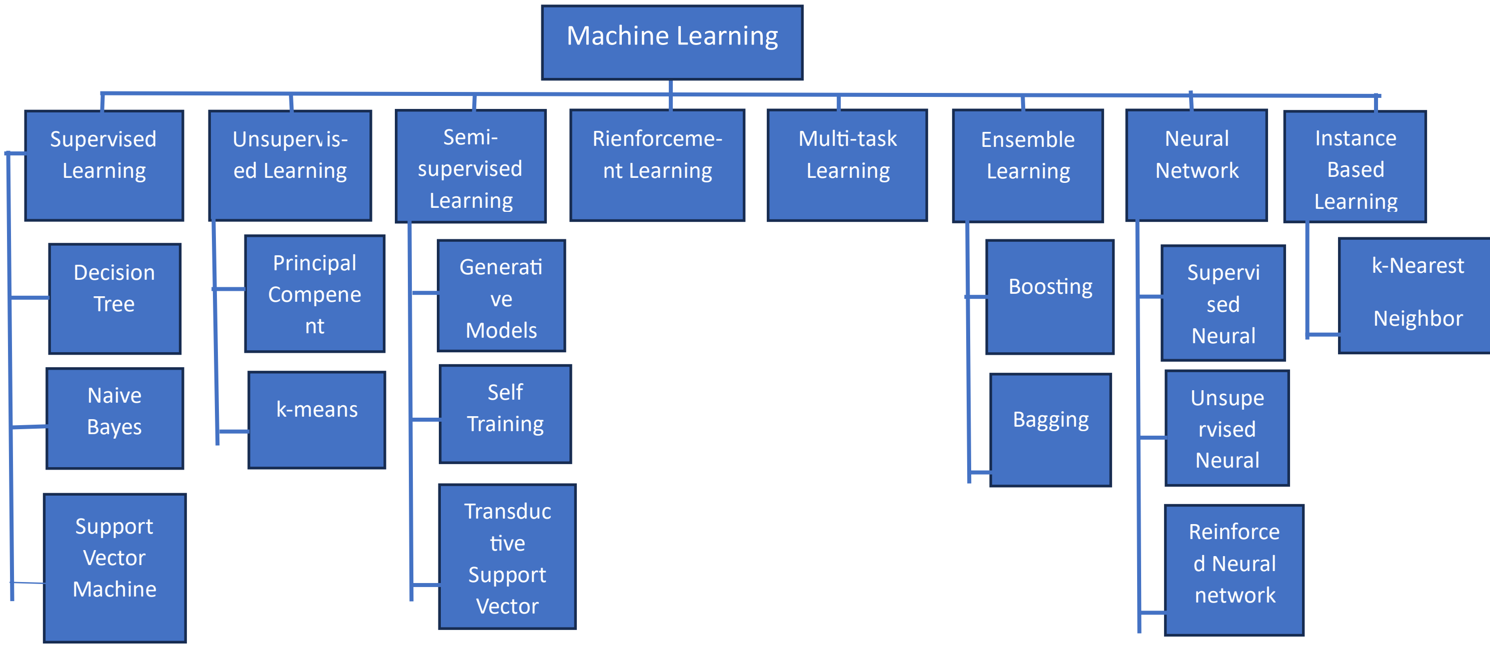

Figure 2.1: Type of machine learning

II.2.3 Taxonomy of machine learning

Various algorithms are used in machine learning to address data issues. Data scientists frequently emphasize that there isn't a single, universally applicable algorithm that is ideal for resolve an issue. The type of problem you want to solve, the quantity of variables, the model that would work best for it, and other factors all influence the type of methode used [46].

Here is a brief overview of some of the most widely used machine learning (ML) algorithms. There are three main categories in which machine learning models fall:

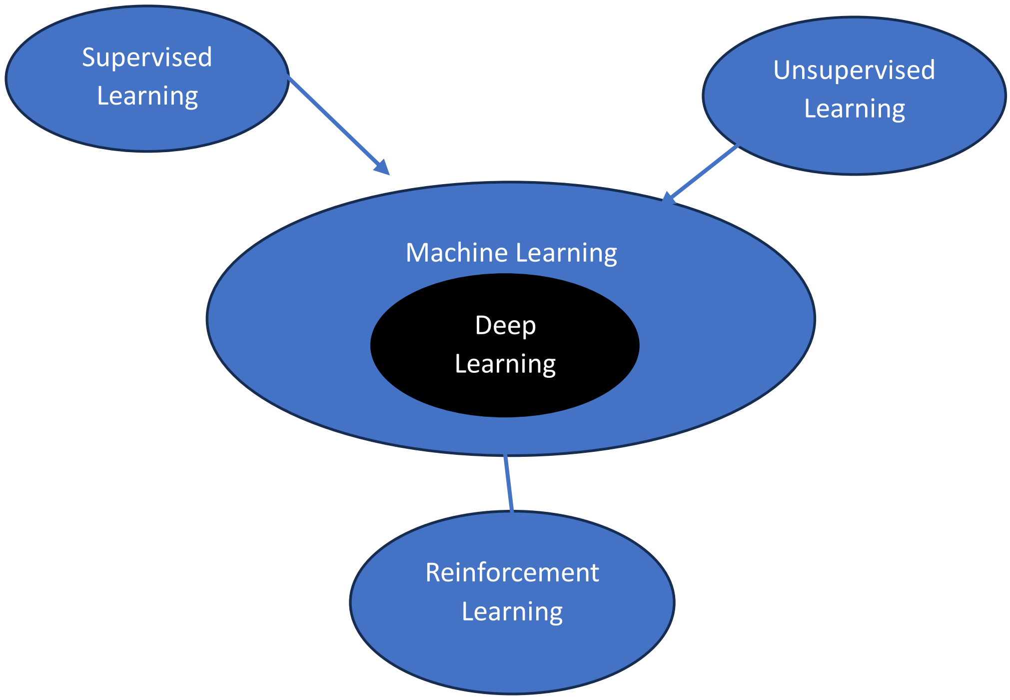

Figure 2.2: Machine Learning and Deep Learning: Taxonomy of Types.

II.2.3.1 Supervised Learning

By supervised learning from a large number of training examples, each of which has a label indicating its ground-truth output, supervised learning approaches build predictive models. Despite the remarkable success of existing methodologies, it is important to emphasize that the high expense of the data-labeling process makes it challenging to obtain robust supervision information, such as entirely ground-truth labels, in many activities [47].

The first of the four machine learning models is supervised learning. The machine learns by example in the supervised learning algorithms. The supervised learning models are made up of pairs of data called "input" and "output," where the desired value is labeled for the output. It is assumed that the machine's purpose is to distinguish between a marguerite and a thought. Our binary input data pair will be able to distinguish between the picture of a marguerite and the image of a thought. We hope the machine will select the marguerite. Therefore, the image of the marguerite will be recognized beforehand as the desired outcome [48].

The system gathers all of these training data over time and puts them in correlation using an algorithm. He then starts to find similarities, differences, and other logical aspects until he is able to provide the answer to a question on his own. That's the same method used when a child is given a set of problems with clear answers and is then asked to demonstrate his work and explain the reasoning behind it [49].

II. 2.3.2 Unsupervised learning

Machine learning is expanding quickly, following big trends like Big Data and the larger data science area. The most popular methods for both supervised and unsupervised learning were found by a systematic evaluation of 84 academic publications published between 2015 and 2018. The most commonly used and discussed supervised techniques were Naïve Bayes, Decision Trees, and Support Vector Machines (SVM). The most popular methods for unsupervised learning were Principal Component Analysis (PCA), Hierarchical Clustering, and K-means Clustering. As machine learning technologies continue to advance, the review also underlined the increasing significance of ensemble approaches and reinforcement learning, pointing to their potential as important fields for further study [50].

Among unsupervised learning techniques, K-Means is one of the most widely used clustering algorithms. It aims to partition a dataset into K distinct, non-overlapping clusters, where each data point belongs to the cluster with the nearest mean (also called the centroid).K-Means is widely used in recommender systems, for example to:

- Group similar users based on behavior or preferences.
- Cluster items to suggest similar content.
- Enhance scalability by applying content-based or collaborative filtering within clusters.

However, its performance depends on the correct choice of K, and it may not perform well with non-spherical clusters or when data is not well-separated [51].

Unsupervised learning (UL) is a kind of automatic learning that relies just on input data and lacks corresponding output variables. In this kind of learning, algorithms are left to their own mechanisms to find and present the interesting structure of the data; neither the teacher nor the algorithm receives the proper response [52].

The answers that are sought to be predicted are not found in the data games. Here, the algorithm makes use of an unidentified data game. The system is then asked to generate its own responses. In this way, she offers answers based on data grouping and analysis [53].

II. 2.3.3 Semi-supervised learning

Semi-supervised learning (SSL) is a machine learning technique that leverages a limited set of labeled data alongside a much larger pool of unlabeled data during the training process [54].

Positioned between supervised learning (which depends solely on labeled data) and unsupervised learning (which uses only unlabeled data), SSL seeks to enhance model accuracy while minimizing the expense and effort associated with extensive data annotation [55].

II.2.4 Advantages and disadvantages of machine learning algorithms

II.2.4.1 Advantages

The principals' advantages of machine learning are:

- **Automation and Increased Efficiency:** Machine learning algorithms enable the automation of complex tasks, the rapid processing of large volumes of data, and more efficient real-time decision-making [56].
- **Discovery of Hidden Patterns:** They can uncover subtle trends, patterns, and correlations within data, supporting innovation, service personalization, and process optimization [56].
- **Flexibility and Adaptability:** Machine learning models easily adjust to new data types and constantly evolving environments, making them valuable across various sectors such as finance, healthcare, and cybersecurity [56].
- **Accurate Predictions:** Supervised algorithms, in particular, can provide reliable, real-time predictions; provided they are trained on relevant and well-structured data [57].
- **Reduction of Human Error:** By automating repetitive or technically demanding tasks, machine learning reduces the risk of human error and frees up time for higher-value activities [57].

II.2.4.2 Disadvantages

The principal disadvantages of machine learning are the following:

- **Dependence on Large and High-Quality Data:** Machine learning algorithms require vast amounts of reliable, unbiased, and well-structured data to function effectively. The processes of collecting, preparing, and cleaning such data are often time-consuming and costly [58].
- **High Technical and Operational Costs:** Developing, training, and running machine learning models demand significant computational and hardware resources, which can result in substantial financial investment [58].
- **Difficulty in Interpreting Results:** Models, particularly those based on deep learning, can produce outputs that are difficult to interpret, posing a challenge in fields where transparency is critical.
- **Bias and Data Quality Issues:** Biases present in training data can lead to unfair or incorrect decisions, making it essential to implement rigorous validation and monitoring mechanisms.
- **Risk of Overfitting or Underfitting:** A model may overfit the training data (becoming too specific) or underfit (being too simplistic), both of which hinder its ability to generalize effectively to new data.
- **Ethical and Privacy Concerns:** The use of sensitive data raises issues related to privacy, information security, and compliance with legal frameworks such as the GDPR.
- **Social Impact:** Increased automation may lead to job displacement in certain sectors and reduce human interaction in the workplace [58].

II.3 Recommendation systems

II.3.1 Definition

[Burke, 2002] defend recommendation systems as: "any system that produces individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options" [59].

In other words, recommendation systems suggest relevant or interesting items to a user by filtering the valuable information to find the most relevant items. These systems are widely used in various fields such as e-commerce, streaming services, social media, e-learning, etc.

II.3.2 Objective

The general goal of recommendation systems is to produce significant and customized suggestions of items like products, services, etc., for a particular group of users. Some specific goals of recommendation systems include:

- Enhancing the quality of user experience.
- Maximizing performance by focusing on key metrics as time taken for navigation and search.
- Achieving efficient handling of large amounts of data beyond the levels possible with manual processing.
- Data filtering becomes automated, so that information management can be handled more efficiently [60].
- User is guided; new items become easier to discover due to tailored suggestions being provided.

II.3.3 Recommendation System Categories

RSS belong to 6 categories: collaborative filtering, content-based, utility-based, demographic-based, knowledge-based, and hybrid-based. among which the most popular ones are content-based and collaborative filtering. A short description of these categories is provided below.

- **Collaborative-Filtering Recommendation Systems**

Collaborative filtering is probably the oldest and most popular method of recommender systems. It came into existence in the mid-1990s due to projects like GroupLens and MovieLens. The system works on the assumption that users who liked the same items in the past are likely to have similar tastes about new items as well [61]. In the beginning, users of collaborative filtering systems were open-employed, visiting a website with an expectation of instantly getting suggestions from the system. As the web evolved, these systems began to get embedded in the background and started to modify website content like ranking news pieces or recommending products, without any explicit user action [62]. Collaborative filtering can be classified into two categories of algorithms: memory-based algorithms and model-based algorithms:

- **Memory-based collaborative filtering**

Memory-based CF algorithms leverage the complete or a subset of user-item data for making predictions. Every user belongs to a cluster of like-minded individuals. By spotting the so-called neighbors of an emerging user (or active user), a forecast about preferences on new items for him or her can be made. The community-based CF algorithm a common memory-based CF algorithm utilizes the following steps: compute the similarity or weight w i, j which shows distance, correlation, or weight between two users or two items I and j; generate a prediction for the active user by taking the weighted average of all ratings of the user or item on a specific item or user or apply simple weighted average When top-N recommendation is the task to be performed first find k most similar users or items nearest neighbors after computing similarities then aggregate neighbors to get top-N most frequent items as output [63].

- **Model-based collaborative filtering**

From a probabilistic perspective, this approach forecasts an unobserved rating using the user data to learn and infer a model [64]. Model-based methods look at the utility matrix with the ratings users give to find links in the data. This step uses machine learning and data mining ways, like regression and clustering, to check the list of top-k recommendations [65].

- **Content-Based Recommendation Systems**

  Content-based approaches try to construct a user profile in order to anticipate ratings on items that the user has not seen before. Successful content-based techniques make use of tags and keywords. The utility of content-based filtering is usually measured by heuristic function, for example, the cosine similarity metric. Content-based filtering can be applied in numerous instances, where the values of features can be easily extracted. Content-based filtering tends not to be used in instances where the values of features have to be manually entered; manageable for small datasets but, when thousands of new products are being added daily, this task becomes impossible Since the suggested recommendations are user-specific, content-based filtering does not require data from other users. As a result, these methods expand the system to accommodate several users. Since this system simply needs to analyze the items and user profile to provide recommendations, content-based filtering is user-independent. Content-based filtering does not suffer from cold-start problems, in contrast to collaborative filtering. Before a sizable user base gives a rating, new products or items are recommended. Filtering based on content has a number of shortcomings. First off, the recommendation won't be accurate if there isn't enough information in the content to accurately differentiate products. These methods necessitate extensive domain expertise. Second, because content-based systems have to align the attributes of goods and profiles, they only provide a certain amount of originality [66,67].

- **Demographic-Based Recommendation Systems**

By classifying users according to demographic characteristics, demographic RSs are able to produce recommendations. Demographic RSs are particularly helpful when there is a shortage of product information. The goal of demographic RSs is to address and resolve the issues of cold-start and scalability. To generate suggestions, this system uses user attributes like demographic data (i.e., recommend products based on age, gender, language, etc.) [68]. The main benefit of demographic filtering RSs is that, with just a few observations, they may produce findings quickly and easily. Additionally, these methods lack user ratings, which are crucial for content-based and collaborative filtering strategies. Filtering methods based on demographics have a number of drawbacks. For instance, given the security and privacy concerns, collecting user data in its whole is unfeasible. Second, the system is compelled to suggest the same item to users with similar demographic profiles because demographic filtering is primarily based on user interests. The stability vs. plasticity dilemma, which refers to the difficulty of changing a client profile when preferences change, is another difficulty.

- **Hybrid-Based Recommendation Systems**

Hybrid systems are combining two or more techniques to obtain better performance. Their main target is to eliminate the drawbacks of the individual ones. Some of the combination strategies are discussed next. Figure 1 shows various hybrid strategies:

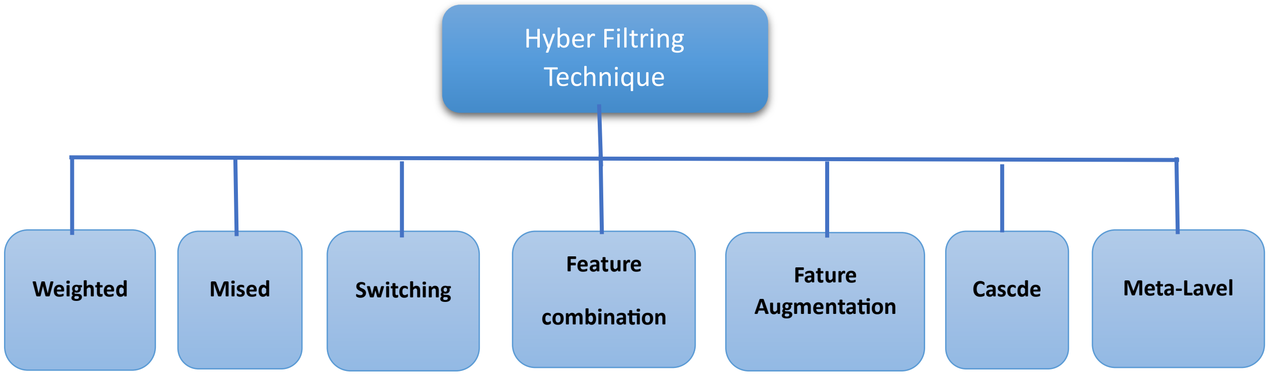

Figure 2.3: Hybrid filtering strategies.

According to Burke (2002), hybrid recommender systems can be implemented using various combination strategies, including [69]:

- **Weighted Hybrid:**
  Combines the results from multiple recommendation techniques by assigning each a numerical weight. The final score is a weighted average of the outputs. Example: A 70% weight on collaborative filtering and 30% on content-based.
- **Switching Hybrid:**
  Dynamically selects one recommendation method depending on the situation (e.g., amount of data available, user type, or context).
  Example: If a user is new (cold start), use content-based; otherwise, use collaborative filtering.
- **Mixed Hybrid:**
  Presents recommendations from multiple systems simultaneously.
  Example: A list that includes both user-similarity-based and content-based suggestions.
- **Feature Combination:**
  Combines features from different sources into a single model. For instance, using content features (e.g., genre, keywords) together with collaborative ratings in one algorithm.
- **Cascade Hybrid:**

Applies one recommender system first, then uses another to refine the results. *Example:* Use content-based to filter a candidate list, and then collaborative filtering to rank it.

- **Feature Augmentation:**
  Uses the output of one recommender as an input feature for another. *Example:* Collaborative filtering generates a user profile that is then used by a content-based model.
- **Meta-Level:**
  The Meta-Level hybrid approach involves using the model generated by one recommendation technique as the input to another. Rather than combining raw recommendations or scores, this method passes learned models (e.g., a user profile or decision tree) between systems.

  For instance, a content-based recommender may first build a user profile based on item features. This profile is then used by a collaborative filtering system to find similar users or make final predictions. The strength of this strategy lies in its ability to transfer learned knowledge in a structured form across different recommendation paradigms.

  This method is particularly useful when the secondary system benefits from richer, abstract representations generated by the first algorithm.

II.3.4 Advantages and disadvantages of different recommendation approaches

Table 2.1 summarizes some of the advantages and disadvantages of various filtering techniques [70].

Filtering Approach	Avantages	Disadvantages
Content-Based Filtering	Recommendations are generated by analyzing the item's attributes and the user profile. Therefore, this type of filtering does not require the calculation of user similarity. It is possible to recommend new products even in cases where there is not enough information from other consumers. This approach offers the flexibility to quickly adjust recommendations if the user's interests change, while also protecting user privacy because the user can receive recommendations without sharing their selections [70].	A effective recommendation system necessitates a substantial quantity of data, including user profiles and item descriptions that are well-structured. This kind of filtering, nevertheless, could run into the problem of over-specialization by suggesting things that are already defined in the user's profession [70].
Collaborative Filtering	Large user spaces are a good fit for Collaborative Filtering (CF) algorithms, which provide a varied person-alized list. Furthermore, domain knowledge is not required for the first recommendation phase. They have the option to suggest pertinent products to a user even if the information is outside of their area of expertise [70].	One of the main issues facing Collaborative Filtering (CF) is the cold-start problem, which makes it challenging to recommend things that were not encountered during the training phase. Large datasets become more complex, necessitating the computation of similarity indices for numerous users. Furthermore, the recommendation system may be impacted by the sparsity of real-world data [70].

Hybrid Filtering	Combining several filtering approaches can optimize the recommendation system and produce useful results. Furthermore, it lessens disadvantages in comparison to employing a single strategy [70].	Due to the use of multiple filtering algorithms, hybridization results in significant implementation costs and complexity (both spatially and temporally) [70].
Demographic-Based	use demographic data, such as location, gender, and age, to categorize users and provide suggestions. helpful when there is little preference data. Simple to put into practice [71].	that preferences are shared by users with similar demographics, which may not be the case. restricted in its ability to capture dynamic preferences or individual behavior [71].
K-Means Clustering	Allows grouping similar users or items into clusters without prior labeling. Improves scalability and efficiency by reducing recommendation scope within meaningful clusters. Suitable for unsupervised learning tasks [72].	requires predefinition of the number of clusters (K). Performance may degrade if data is not well-separated or clusters are not spherical. Sensitive to initial centroid selection and may converge to local optima [72].

Table 2.1 : Advantages and disadvantages of different filtering approaches.

II.4 Problem Statement

In an era defined by the exponential growth of scientific output and the swift advancement of digital technologies, higher education institutions face mounting pressure to efficiently manage and valorize their research activities. Traditional administrative and evaluation processes struggle to keep pace with the volume and complexity of academic data, leading to suboptimal strategic decisions regarding publication venues, funding allocation, and researcher support. Although Decision Support Systems (DSS) enhanced with Artificial Intelligence (AI) offer the potential to automate data-intensive tasks, uncover latent patterns, and deliver context-aware recommendations, existing solutions often remain confined to proof-of-concept prototypes or lack integration into day-to-day academic workflows. Consequently, there is a critical need to develop and evaluate AI-driven DSS that can bridge this gap; providing scalable, user-centric, and semantically rich support for research management, evaluation, and strategic planning within universities.

II.5 Related works

To position our proposed approach within the broader field of reviewer recommendation systems, we present a comparative examination of several influential works from the existing literature table 2.2). These systems illustrate a range of conceptual and technical strategies, from early content-based models to recent advances in graph learning and neural architectures. By analyzing their core principles, underlying data assumptions, and distinctive contributions, this overview highlights both common trends and methodological divergences across the field. Our own approach is included in this comparison to better illustrate how it aligns with and differs from existing solutions. This synthesis offers valuable insights into the strengths, limitations, and applicability of various approaches to reviewer assignment.

Work	Year	Methodology	Data type	Special features	Lien
A Recommender System of Reviewers and Experts	2016	Content-based filtering (cosine similarity, indexation)	Keywords, author profiles	Based on semantic similarity between article and reviewer	[85]
A Proactive Decision Support System	2021	Heterogeneous networks (TCRRec), multi-level graphs	Citation network, topics, reviewers	Proactive system combining several relationship graphs	[86]

Perceiving Conflict of Interest Experts Recommender	2022	Profile and history-based filtering, conflict management	Author data, co-publications	Takes conflicts of interest (CoI) into account in the recommendation	[87]
Large-Scale Study on Code Reviewer Recommendation	2018	RevFinder, Naive Bayes, empirical study	History of code reviews (GitHub, Gerrit)	Comparative study on a large open source dataset	[88]
RevGNN: Contrastive Graph Learning for Reviewer Rec.	2024	GNN + Negative sampling + contrastive learning	Authors and publications graph	Self-supervised learning for improved precision	[89]
Our work	2025	K-means clustering + TF-IDF weighting	Abstracts of articles, keywords, reviewers' profiles	Recommendations based on similarity of automatically extracted themes	(Unpublished)

Table 2.2: Comparison between my work and previous studies.

The comparative analysis highlights key differences in the design and applicability of reviewer recommendation systems. Traditional content-based methods offer simplicity and ease of implementation but lack the ability to capture deeper contextual or relational information. Graph-based approaches, though more accurate, demand complex data and higher computational resources. Ethical considerations, as addressed in conflict-aware systems, add value but may reduce scalability. Domain-specific solutions, such as those for code review, provide useful insights but have limited generalizability. In contrast, our TF-IDF and K-means-based approach offers a practical middle ground; balancing thematic relevance with efficiency and interpretability. It is especially suitable for academic settings with limited resources, where scalable and content-driven reviewer recommendations are needed.

II.6 Hybrid TF-IDF and K-Means Clustering for Reviewer Recommendation

With the rise of scientific research and the increasing volume of academic output, the process of selecting reviewers (scientific evaluators) represents a real challenge for higher education institutions and research organizations. This process generally relies on human intervention, which can lead to:

- Delays in appointing suitable reviewers,
- A certain degree of subjectivity or bias,
- difficulties in ensuring alignment between the reviewer's area of expertise and the subject of the work to be evaluated.

To address these issues, it has become essential to design an intelligent system capable of:

- Automating the selection of reviewers based on objective scientific criteria.
- Ensuring the match between the reviewer's research field and the subject of the work.
- Epeeding up the recommendation process and reducing administrative workload.

II.6.1 Proposed solution

The proposed system employs a content-based recommendation strategy in which reviewer suggestions are generated by assessing the semantic similarity between manuscript features and reviewer profiles. Instead of relying on historical user behavior and interaction data, this approach directly compares the textual and metadata attributes of submissions, such as keywords, abstracts, and topic models, with the documented expertise of potential reviewers. Focusing on intrinsic content characteristics ensures that reviewer assignments are driven by subject-matter alignment, improving recommendation accuracy and minimizing dependence on user interaction histories.

To enhance this process, our proposed solution employs a hybrid approach that integrates Term Frequency-Inverse Document Frequency (TF-IDF) with K-means clustering, executing TF-IDF feature extraction prior to clustering to recommend suitable reviewers. By first transforming manuscript texts into weighted vector representations, TF-IDF highlights the most discriminative terms and down-weights common language, ensuring that K-means operates on a semantically rich feature space. This arrangement was selected because TF-IDF's precise feature weighting complements K-means' ability to partition documents into coherent thematic clusters. Reviewer profiles are then matched to these clusters based on their publication records, enabling the system to suggest reviewers whose expertise aligns closely with the manuscript's content. The hybrid model thus combines robust textual representation and efficient unsupervised grouping to deliver accurate, interpretable reviewer recommendations.

Furthermore, our system provides the following features:

1. **Prediction Module:** The proposed prediction system relies on the Logistic Regression algorithm, a widely used supervised machine learning technique designed to estimate the likelihood that a given instance belongs to a particular class, such as "accept" or "reject" in the context of manuscript evaluation. To make this prediction, various features are extracted from each submission, including document length, word count, and textual characteristics represented through TF-IDF weighted vectors. These features serve as inputs to the model, which computes a weighted sum of the variables and applies the sigmoid activation function to transform this output into a probability score ranging from 0 to 1 (or equivalently, 0% to 100%). This probability reflects the model's estimation of the likelihood that a submission should be accepted or rejected. By providing a quantitative and objective assessment based on content features, the system offers valuable support to editors and reviewers, complementing human judgment and enhancing the transparency and consistency of the decision-making process. Moreover, the model can be continuously improved as new data become available, allowing for adaptive learning and performance refinement over time.
2. **Scoring Mechanism for Reviewer Recommendation:** Cosine Similarity is employed to compute a similarity score that quantifies the degree of alignment between the feature vector of the submitted document and those of potential

reviewer profiles. This metric evaluates the angle between the two vectors in a high-dimensional space, capturing their semantic proximity regardless of absolute vector magnitude. A score closer to 1 indicates a strong overlap in research interests and expertise between the reviewer and the manuscript's subject matter, while values approaching 0 suggest little to no thematic correspondence. By providing a normalized measure of relevance, Cosine Similarity enables the system to objectively assess and rank reviewers based on their topical fit to each submission.

II.6.1.1 Why use TF-IDF and K-means?

The TF-IDF Allows the texts of academic papers, especially the title and the abstract, to be represented numerically, highlighting the importance of terms present in a document relative to the entire corpus. This representation facilitates comparison between works.

Moreover, the K-means allows previous works to be grouped into homogeneous clusters based on thematic or disciplinary criteria, which helps the system recommend reviewers with experience in similar topics. As part of the developed recommendation system, the K-means algorithm plays a central role in classifying academic papers according to their research field.

Each submitted paper (course, dissertation, article) is represented numerically by calculating TF-IDF weights on its title and abstract. These numerical vectors reflect the thematic content of the paper.

The K-means is then applied to these representations in order to:

- Group papers with similar research fields into distinct clusters.
- Form homogeneous clusters where the papers share similar themes or specialties (e.g., artificial intelligence, Arabic literature, cybersecurity, etc.).

Thus, when a new author submits a paper, the system:

- Calculates the corresponding TF-IDF vector.
- Identifies the closest cluster (research field) using K-means.
- Selects reviewers who have already reviewed papers in the same field.

II.6.1.2 Objective of the proposed method

The proposed method aims to design an intelligent system for recommending academic reviewers, based on:

- Text analysis of academic works (title and abstract) using the TF-IDF algorithm to convert the scientific content into a numerical representation that accurately reflects the subject of the work.
- Clustering of previous works into homogeneous groups (clusters) according to their research domains using the K-means algorithm.
- Identification of the most suitable reviewers by selecting those who have experience in evaluating works within the same scientific field as the new submission.

The main objectives are to ensure:

- The alignment of the reviewer’s expertise with the subject of the academic work.
- The provision of an objective and accurate recommendation.
- Faster assignment of reviewers with reduced manual effort.

II.6.1.3 Advantages of the proposed method

The proposed method offers several significant advantages, including:

- **Accuracy and objectivity:** By relying on text analysis and the classification of previous works, the system ensures that the recommended reviewers have direct relevance to the field of the new work.
- **Speed and efficiency:** The system automatically and rapidly filters suitable reviewers without requiring extensive manual intervention, thereby accelerating the review process.
- **Scalability:** The system can be further developed to incorporate additional criteria such as:
    - The reviewer’s evaluation history,
    - The quality of their previous reviews,

- Or even their current availability.

- **Reduction of bias:** Recommendations are based on automated analysis rather than personal connections or subjective decisions, thus enhancing transparency.

II.6.2 TF-IDF (Term Frequency–Inverse Document Frequency)

TF-IDF is a numeric statistic that reflects how important a word is to a document in the collection or corpus The TF-IDF value increases proportionally to the number of times when a word appears in the document but it is offset by the frequency of the word in the corpus which helps to control the fact that some words are more common than others the frequency term means the raw frequency of a term in a document where the term regarding inverse document frequency is a measure of whether the term is common or rare across all documents in which it can be obtained by dividing the total number of documents by the number of documents containing the term[74].

- **Term Frequency (TF):** Measures how frequently a term occurs in a document.

$$TF(t,d)=\frac{Number\ of\ times\ term\ t\ \ appears\ in\ document\ d}{Total\ number\ of\ terms\ in\ document\ d}$$

- **Inverse Document Frequency (IDF):** Measures how important a term is across the corpus. It reduces the weight of commonly used terms and increases the weight of rare terms [76].

$$IDF(t) = log\left(\frac{N}{1-df(t)}\right)$$

Where:

- N = Total number of documents in the corpus.
- $df(t)$= Number of documents containing the term t.

This score helps to highlight words that are more relevant to specific documents.

II.6.3 K-Means Algorithm

The K-Means algorithm is a widely used unsupervised learning technique for partitioning a dataset into *K* distinct, non-overlapping clusters. Each cluster is represented by its centroid (the mean of all points in the cluster). The algorithm proceeds as follows:

1. **Initialization**

   Randomly select K data points from the dataset as initial centroids *{μ1,μ2 ,…,μK}*. Where the μi is the centroids.

2. **Assignment Step**

   For each data point xix_ixi, assign it to the cluster whose centroid is closest in Euclidean distance:

$$C(i) \leftarrow \arg_{j\,\epsilon\{1,\ldots K\}} \ \min ||x_i - u_j||^2$$

3. **Update Step**

   After all points have been assigned, recompute each centroid as the mean of points assigned to that cluster:

$$u_{j\leftarrow \frac{1}{|C_j|}} \sum_{i:c(i)} x_{i,} \quad j=1,\ldots,K$$

$$where\ C_j = \{x_i | c(i) = j\} is\ the\ set\ of\ points\ in\ cluster\ j$$

4. **Convergence Check**

Repeat Steps 2 and 3 until one of the stopping conditions is met:

- Cluster assignments no longer change, or
- Centroids move by less than a small threshold ϵ\epsilonϵ, or
- A maximum number of iterations is reached.

When implementing K-Means, several considerations influence both its efficiency and effectiveness. Such as:

- **Initialization Strategy:** The choice of initial centroids can affect convergence speed and solution quality. Common strategies include random selection, k-means++ (which spreads out initial centroids), or multiple random restarts with best outcome chosen.
- **Distance Metric:** Euclidean distance is standard, but other metrics (e.g., cosine distance) may be used depending on the feature representation.

- **Scalability:** For large datasets, variations such as Mini-Batch K-Means process small random subsets in each iteration to reduce computation time.
- **Convergence Guarantees:** K-Means is guaranteed to converge to a local minimum of the within-cluster sum-of-squares objective, but not necessarily the global minimum.

II.7 conclusion

This chapter explores the fundamentals of machine learning-based recommendation systems, with a particular focus on content-based approaches and machine learning algorithms. The proposed solution is introduced as an intelligent technique that efficiently converts textual input into numerical vectors, allowing for the computation of similarity scores between reviewer profiles and research topics. This proposition forms the backbone of a reviewer recommendation system that assigns documents to relevant experts based on their fields of specialization and research interests. By integrating this solution into our project, we have taken a significant step toward building an intelligent and efficient system that enhances the academic evaluation process. Consequently, this chapter lays the groundwork for exploring more advanced techniques in the following sections.

Chapter III: System Design and Modeling

III.1 Introduction

Designing a robust and intelligent system requires a structured and thoughtful approach that transforms conceptual ideas into a functional technological solution. In this chapter, we move from the theoretical groundwork laid in previous sections to the concrete development of a system architecture tailored to the needs of academic and scientific management within Algerian higher education institutions.

This phase is crucial, as it defines the overall structure, behavior, and user interaction pathways of the proposed AI-based Decision Support System (DSS). Through a detailed analysis of functional and non-functional requirements, this chapter outlines the technical specifications, software architecture, and data management models necessary for successful implementation.

Furthermore, this chapter introduces design tools and methodologies, including Conceptual Data Model (CDM) and system modeling techniques, to visualize system behavior and user interactions. By doing so, we ensure that the final product is not only technologically sound but also aligned with the expectations and workflows of its end users: research managers, faculty members, and institutional leaders.

III.2 Objectives of the System

The major aim of the proposed system is to build an intelligent Decision Support System (DSS) applicable to the management and appraisal of academic and scientific outputs in Algerian higher education institutions. The system shall be designed as a comprehensive solution based on Artificial Intelligence to respond effectively to the challenges arising from the increasing volume of research publications and consequent aggravation of peer review processes, data-driven academic management requirements, and decision facilitation needs. This will further enhance reviewer selection along with institutional research activities' quality and visibility.

The specific objectives include:

- **Automating the Management of Scientific Production:**
  To centralize and organize academic documents such as research articles, theses,

and technical reports, enabling institutions to access and monitor their research portfolio efficiently.

- **Enhancing the Review Process through AI Techniques:**
  To integrate Natural Language Processing (NLP) and Machine Learning (ML) models, particularly TF-IDF and cosine similarity in order to recommending suitable reviewers based on content relevance and expertise.
- **Supporting Academic Decision-Makers:**
  To provide university administrators and scientific councils with tools for evaluating researcher performance, identifying strategic research directions, and making evidence-based decisions.
- **Improving Transparency and Objectivity:**
  To minimize human bias in reviewer selection and performance evaluation by applying algorithmic, criteria-based methods.
- **Ensuring Scalability and Future Integration:**
  To design a flexible system architecture that can be scaled and integrated with national academic databases and publication repositories in the future.

By fulfilling these objectives, the system will contribute to raising the quality of scientific research management in Algerian universities and fostering a more transparent, data-driven, and collaborative research ecosystem

III.3 General system architecture

The system consists of (figure 3.1):

- A web server.
- A database that gathers information about the system's stakeholders.
- Three main areas for the system's stakeholders: administrators (President/editor)- Author – Reviewer.

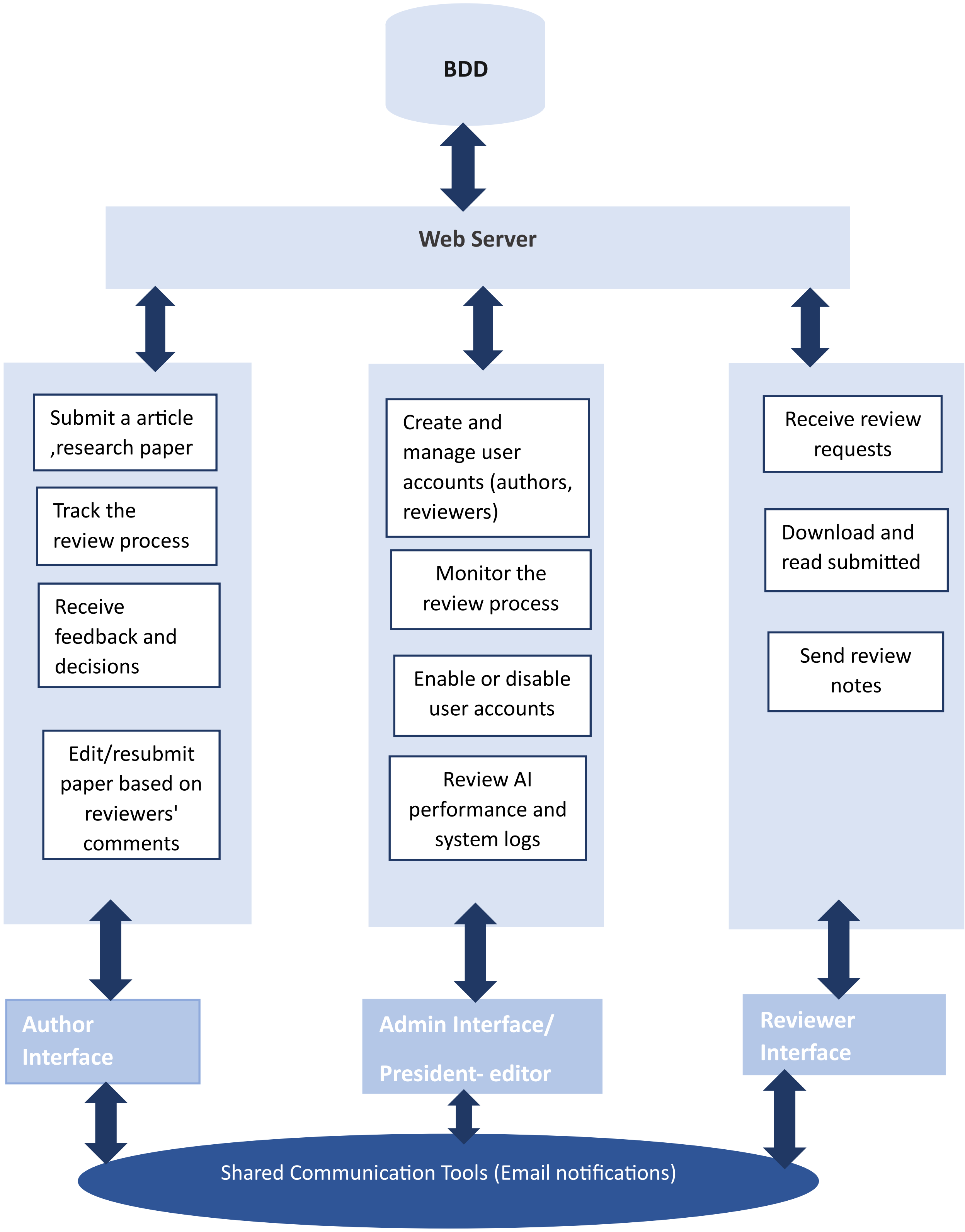

Figure 3.1: global system architecture

III.4 Data Structure

The database allows for storing and retrieving information related to the various actors of the system. It also enables the tracking and analysis of their communication history for monitoring purposes.

Therefore, it serves as the backbone for all the information available within our system.

III.4.1 The Data Dictionary

N°	Code	Meaning	Type
01	Id_Auteur	Author ID	Integer(9)
02	Nom_Auteur	Author Last Name	varchar(255)
03	Prenom_Auteur	Author First Name	varchar(255)
04	Username_Auteur	Full username (author)	varchar(255)
05	Email_Auteur	Author's Email	varchar(255)
06	Mot_Auteur	Author's password	varchar(255)
07	Sexe_Auteur	The author's gender	varchar(255)
08	Departement	Department of (Author, President, Reviewer)	varchar(255)
09	Affilation	Affiliation of (Author, president, Reviewer)	varchar(255)
10	Pays	Country of (Author,precident , reviewer)	varchar(255)
11	Domaine_de_recherche	Research area of (Author,precident , reviewer)	varchar(255)
12	Grade	Author's academic rank	varchar(255)
13	Anciannete	Number of years, Length of experience(Author,precident , reviewer)	varchar(255)
14	Naissance_Auteur	Author's date of birth	Date
15	Telephone_Auteur	Author's phone number	Integer(255)
16	Date_inscription	The date of user registration(Author,precident , reviewer)	Timestamp
17	AcceptAdmin_Auteur	Author's Account Acceptance	varchar(255)
18	Verification	Email verification (the code)	varchar(255)
19	Id_Precident	President Identifier	Integer (9)
20	Nom_precident	President's name	varchar(255)
21	Prenom_Precident	President's first name	varchar(255)
22	Username_Precident	Full username (president)	varchar(255)
23	Naissance_Precident	President's date of birth	Date
24	Telephone_Precident	President's phone number	Integer (10)

25	AcceptAdmin_Precident	Acceptance of the precident account	varchar(255)
26	ID_reviewer	Reviewer ID	Integer (9)
27	Nom_reviewer	Reviewer's name	varchar(255)
28	Prenom_reviewer	Reviewer's first name	varchar(255)
29	Username_reviewer	Full username of reviewer	varchar(255)
30	Email_reviewer	Email of reviewer	varchar(255)
31	Mot_reviewer	The reviewer password	varchar(255)
32	Sexe_reviewer	Reviewer's gender	varchar(255)
33	Naissance_Reviewer	Reviewer's date of birth	Date
34	Telephone_Reviewer	Phone number	Integer (9)
35	acceptAdmin_Reviewer	Accept a reviewer	varchar(255)
36	Id_Accepter	Acceptance Identifier	Integer (10)
37	TypeRessource	Resource types (courses, articles, etc.)	varchar(255)
38	IdRessource	Resource identifier	varchar(255)
39	Score	The score number	Double
40	PourcentageAccepter	Acceptance percentage	Double
41	PourcentageReject	Rejection rate	Double
42	Mode	Reviewer status (same affiliation, other affiliation)	varchar(255)
43	Decision	The decision to review for courses, articles...	varchar(255)
44	Remarque	Reviewer’s remark on courses, articles, etc.	varchar(255)
45	Code_adm	Administrator ID	Integer (10)
46	Nom_Adm	Admin Name	varchar(255)
47	Mot_Adm	Admin password	varchar(255)
48	Id_Article	ID of article	Integer (10)
49	Titre	The title of the article, course, book...	Varchar(255)
50	Specialite	The author's specialty	Varchar(20)
51	Resumer	The summary of the article, course, book..	Text
52	Nom_file	File name	Varchar(255)
53	Envoyer	Send the article, course, book...	Varchar (255)
54	Id_Confirence	Confrence identifier	Integer (10)
55	Id_Cours	Course ID	Integer(10)
56	Id_file	File identifier	Integer(10)
57	Description_file	The file description	Varchar(20)
58	Type	File types	Varchar (255)
59	Id_livre	Book identifier	Integer (10)
60	ID_memoire	Memory identifier	Integer (10)
61	Id_Notification	Notification Identifier	Integer(10)
62	EnvoyerNotification	Send a notification	Integer(10)

63	ReceptionNotification	Receiving notifications	Integer(10)
64	Notification	The notification content	Text
65	Activite	Responsable of notification	Varchar (255)
66	DateEnvoyer	The date of sending	Date
67	IdPrifile	Profile identifier	Integer(10)
68	Id_Remarque	Note identifier	Integer(10)
69	Description	The content of the remark	Text
70	IdviewFile	Identificateur de	Integer(10)
71	Id_editeur	Identificateur de editeur	Integer(9)
72	Nom_editeur	editor Last Name	Integer (10)
73	Prenom_editeur	editor First Name	Varchar(255)
74	Username _Editeur	Username pf editor	Varchar(255)
75	Sexe_editeur	Sex editor	Varchar(255)
76	Naissance_Editeur	The editor's date of birth	Date
77	Telephone_editeur	Phone number of editeur	Integer(10)
78	Mot_editeur	The editor's password	Varchar(255)

Table 3.1: The Data Dictionary.

III.4.2 Conceptual Data Model (CDM)

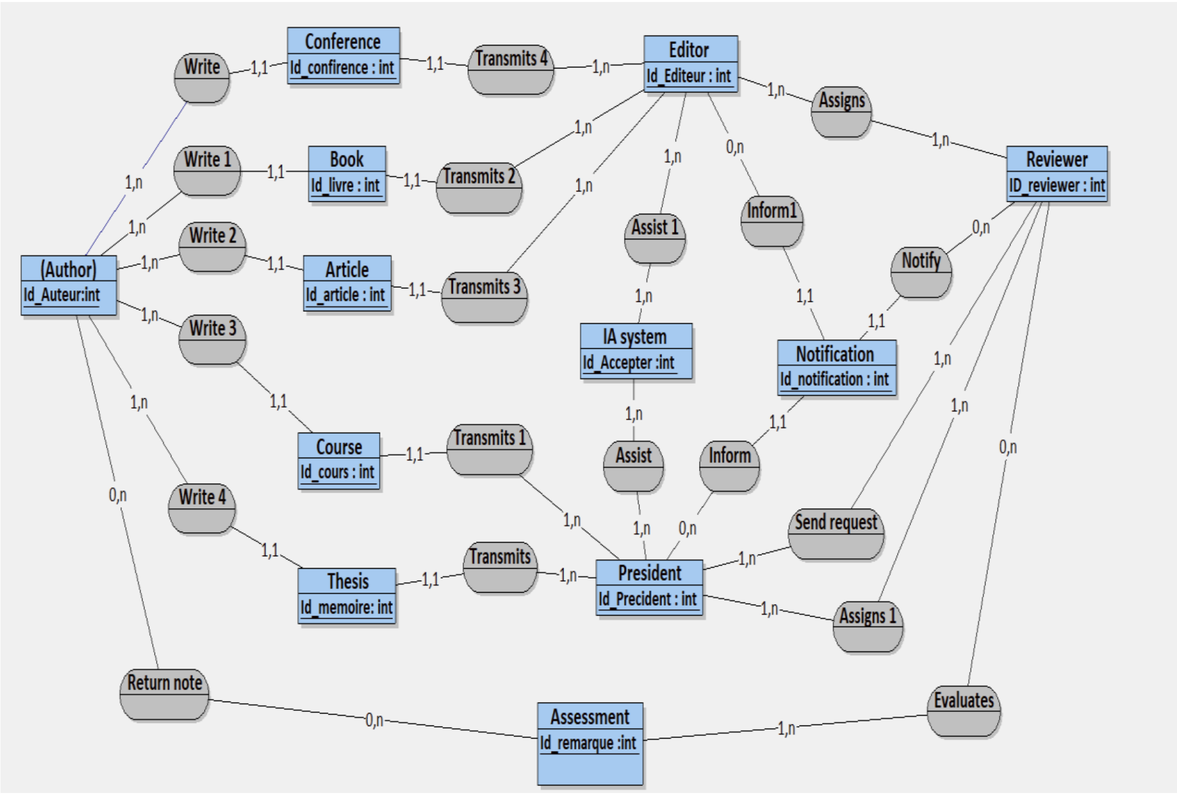

Figure3. 2: Conceptual Data Model (CDM).

III.4.3 List of entities

Entity	Identifier	Attributes
Author	Id_Auteur	-ID_auteur -prenom_Auteur -Sexe_Auteur - Email_Auteur -Nom_Auteur -Username_Auteur -Sexe_Auteur -Affilliation - Mot_Auteur -Departement - Domaine_de_recherche - Pays - Domaine_de_recherche - Grade -Anciannete - Naissance Auteur -Telephone_Auteur - Date_inscription - acceptAdmin_Auteur - verification
Precident	Id_Precident	- Id_Precident -Nom_Precident -Prenom_Precident -Username_Precident - Email_Precident - Mot_Precident - Sexe_Precident - Departement - Affilliation - Pays - Domaine_de_recherche - Grade - Anciannete -Naissance_precident - Telephone_Precident - Date_inscription - acceptAdmin_Precident - verification
Reviewer	Id_Reviewer	- Id_Reviewer - Nom_Reviewer - Prenom_Reviewer Username_Reviewer - Email_Reviewer - Mot_Reviewer - Sexe_Reviewer - Departement - Affilliation - Pays - Domaine_de_recherche - Grade - Anciannete Naissance_Reviewer - Telephone_Reviewer - Date_inscription - acceptAdmin_Reviewer - verification
Editor	Id_Editeur	- Id_Editeur - Nom_Editeur - Prenom_Editeur Username_Editeur

		- Email_Editeur - Mot_Editeur - Sexe_Editeur - Departement - Affilliation - Pays - Domaine_de_recherche - Grade - Anciannete Naissance_Editeur - Telephone_Editeur - Date_inscription - acceptAdmin_Editeur - verification
Course	Id_Cours	- Id_Cours - IdAuteur - Dicision - Titre - Specialite - Resumer - Nom_file - Date
Book	Id_Livre	-Id_Livre -IdAuteur -Dicision -Titre -Specialite -Resumer -Nom_file -Date
Article	Id_Article	-Id_Article -IdAuteur -Dicision -Titre -Specialite -Resumer -Nom_file -Date
Thesis	Id_Memoire	-Id_Memoire IdAuteur -Dicision -Titre -Specialite -Resumer -Nom_file -Date
conference	Id_Confirence	-Id_Confirence -IdAuteur -Dicision -Titre -Specialite -Resumer -Nom_file -Date
Notification	Id_Notification	-Id_Notification EnvoyerNotification

		-ReceptionNotification -Notification -Activite -Dateenvoyer
Assessement	Id_Remarque	-Id_Remarque -IdRessource -IdREviewer -Description -Date -TypeRessource
IA System	Id_Accepter	-Id_Accepter -IdReviewer -IdPrecident -TypeRessourse -IdRessource -Score -PourcentageAccepter -Mode -PourcentageReject -Decision -Remarque

Table 3.2: List of entities.

III.4.4 List of relationships

Relationship	**Collection**	**Cardinality**
Write	Author Conference	1,n 1,1
Write 1	Author Book	1,n 1,1
Write 2	Author Article	1,n 1,1
Write 3	Author Course	1,n 1,1
Write 4	Author Thesis	1,n 1,1
Return note	Author Assessment	0,n 0,n
Transmits	Precident Thesis	1,1 1,n

Transmits 1	Precident Course	1,1 1,n
Transmits 2	Editor Book	1,1 1,n
Transmits 3	Editor Article	1,1 1,n
Transmits 4	Editor Conference	1,1 1,n
Assist	Editor IA System	1,n 1,n
Assist 1	President IA System	1,n 1,n
Inform	Notification Precident	1,1 0,n
Inform 1	Notification Editor	1,1 0,n
Notify	Notification Reviewer	0,n 1,1
Assigns	Reviewer Editor	1,n 1,n
Assigns 1	Reviewer Precident	1,n 1,n
Send request	Reviewer President	1,n 1,n
Evaluates	Reviewer Assessment	1,n 0,n

Table 3.3: List of relationships.

III.4.5 Relational Logical Data Model

Author (**Id_auteur**,Nom_Auteur, Prenom_Auteur, Username_Auteur , Email_Auteur , Mot_Auteur , Sexe_Auteur , Departement , Affilliation ,Pays, Domaine_de_recherche , Grade , Anciannete , Naissance_Auteur , Telephone_Auteur , Date_inscription , acceptAdmin_Auteur ,verification_)

Conference **(Id_confirence ,**Dicision ,Titre , Specialite , Resumer, Nom_file ,

Date_,#Id_auteur , #Id_Editeur)

Book (**Id_livre** ,_Dicision ,Titre, Specialite , Resumer , Nom_file ,Date , #Id_auteur , #Id_Editeur)

Article (**Id_article** , Dicision , Titre , Specialite , Resumer , Nom_file , Date , #Id_auteur , #Id_Editeur)

Course (**Id_cours** ,_Dicision , Titre , Specialite , Resumer , Nom_file , Date__, #Id_auteur , #Id_precident)

Thesis (**Id_memoire** ,_Dicision , Titre , Specialite , Resumer , Nom_file , Date , #Id_auteur,#Id_precident)

Editor **(Id_editeur ,** Nom_Editeur , Prenom_Editeur , Username_Editeur , Email_Editeur ,Mot_Editeur , Sexe_Editeu , Departement , Affilliation , Pays , Domaine_de_recherche , Grade ,Anciannete , Naissance_Editeur , Telephone_Editeur, Date_inscription , acceptAdmin_Editeur ,verification)

President (**Id_precident ,** Nom_Precident , Prenom_Precident , Username_Precident , Email_Precident ,Mot_Precident , Sexe_Precident , Departement , Affilliation , Pays , Domaine_de_recherche , Grade , Anciannete , Naissance_precident , Telephone_Precident , Date_inscription , acceptAdmin_Precident , verification)

Assessment (**Id_remarque,** IdRessource, IdREviewer , Description ,Date , TypeRessource)

IA_system (**Id_accepter ,** IdReviewer , IdPrecident , TypeRessourse , IdRessource , Score ,PourcentageAccepter , Mode , PourcentageReject , Decision , Remarque)

Notification (**Id_notification ,** EnvoyerNotification , ReceptionNotification , Notification ,Activite ,Dateenvoyer , # Id_Editeur , #Id_precident , #Id_reviewer)

Reviewer (**Id_reviewer ,** Nom_Reviewer , Prenom_Reviewer , Username_Reviewer ,Email_Reviewer , Mot_Reviewer , Sexe_Reviewer , Departement , Affilliation , Pays ,Domaine_de_recherche , Grade , Anciannete , Naissance_Reviewer , Telephone_Reviewer , Date_inscription , acceptAdmin_Reviewer , verification)

Return_note (**Id_auteur , id_remarque**)

Assist (**Id_precident , Id_accepter**)

Assist_1 (**Id_editeur , ID_accpter**)

Assigns (**Id_reviewer , Id_Editeur**)

Assigns_1 (**Id_precident , Id_reviewer**)

Send_request (**Id_precident , id_reviewer**)

Evaluates (**Id_reviewer , Id_remarque**)

III.5 Functional Analysis

In this section, our goal is to identify the various actors in the system and the functionalities of each actor.

III.5.1 Specification of system spaces and functionalities

There are three main actors: the administrator, the author, and the reviewer, and each actor has a set of features.

In the following table, we will summarize the features of each actor:

Actor	Role
Administrator (President, editor)	• Log in to the website • Log out of the website • Register users (reviewers and authors) • Delete a user account • Access the administration dashboard • Review submitted articles • Assign reviewers to submitted articles
Author	• Register on the website • Log in to the website • Log out of the website • View and edit their profile • Submit a new article with attachments • Track the submission status (pending, accepted, rejected) • Submit a revised version
Reviewer	• Register or log in to the website • Accept or decline a review request • Download the articles assigned for evaluation • Submit comments or feedback • Propose a decision (accept or reject the article)

Table 3.4: Functionalities of each system actor.

III.5.2 Specification of common tools

The common features among the actors involved in our system are:

- **Authentication Interface:**
  The system offers a secure authentication interface that allows users to log in using their email address and password. A registration feature is also available based on the selected role (Author, Reviewer, or President). Upon registration, a confirmation email is automatically sent to the user in order to validate their email address and activate their account.
- **User Profile Management:**
  Each user has a personal area that allows them to view and modify their information.
- **Notification System:**
  The system includes a real-time notification mechanism to inform users about important actions. For example, the president is notified when a reviewer accepts a review request. Similarly, in the reviewer's space, an alert indicates that an article has been sent to them by the president for evaluation.
- **Tableau de bord personnalisé:**
  Selon le rôle de l'utilisateur, un tableau de bord dynamique est affiché. Il permet d'accéder rapidement aux fonctions principales, comme le suivi des articles soumis, les demandes d'évaluation.
- **Search Engine:**
  To simplify navigation and access to information, an integrated search engine allows users to quickly find an article.

III.5.3 Administrator Area

The administrator area provides privileged access to essential management features of the system. Administrators can log in to the platform using secure credentials and log out when their session ends. They have the ability to register new users, including both reviewers and authors, and to delete user accounts when necessary. Through the administration dashboard, administrators can monitor overall system activity, manage user data, and maintain system integrity. Additionally, they are responsible for reviewing article submissions and assigning reviewers to each submitted paper, ensuring a fair and structured evaluation process.

III.5.4 Reviewer Area

The reviewer space enables registered reviewers to actively participate in the article evaluation process. Upon registering or logging into the platform, reviewers can securely access their personal dashboard.

Reviewers receive review requests from the system, which they can accept or decline based on availability or expertise. Once a request is accepted, the reviewer can download the assigned article and any related documents.

After thoroughly evaluating the submission, the reviewer can submit detailed comments or feedback through a dedicated form. These insights help the author enhance the quality and clarity of the article.

Finally, the reviewer must propose a decision, such as acceptance or rejection, based on the article's scientific contribution and relevance. The system then aggregates reviewers' decisions and displays the overall evaluation result to the author in the form of a percentage score (e.g., 75% accepted,25% reject), giving a clear and quantified overview of the article's evaluation status.

III.5.5 Author Area

The author space allows users registered as authors to interact with the platform independently and seamlessly. The author can register on the site, securely access their personal space through protected authentication, and log out at any time.

Once logged in, the author has access to an interface that enables them to view and edit their personal profile. They can also submit a new article through a dedicated form, attaching the necessary files.

After submission, the author can track the processing status of their article in real-time (pending, accepted, rejected) through an interactive dashboard. In case a revision is requested, the author has the opportunity to submit a corrected version of their work, taking into account the feedback provided by the reviewers.

II.6 Conclusion

Chapter III: System Design and Modeling

In this chapter, we carried out the detailed design of the decision support system for managing and enhancing scientific production in the context of higher education. This phase allowed us to structure the functional and organizational architecture of the platform by defining the various user roles (Administrator, Author, Reviewer, and President) along with their responsibilities and interactions.

We modeled the system’s main features using the Conceptual Process Model (CPM) and represented the data structures through the Conceptual Data Model (CDM). This model helped identify the main entities, their attributes, and the relationships between them. Additionally, a data dictionary was established to define the content, type, and role of each data element processed within the system.

This design phase thus represents a crucial step toward ensuring a consistent and efficient implementation of the solution, which will be addressed in the following chapter dedicated to the development and technical implementation of the platform.

Chapter IV: Implementation

IV.1 introduction

After completing the design phase of the system, this chapter marks the beginning of the implementation stage, which constitutes the final part of this thesis and aims to showcase the work that has been carried out. To this end, we will begin by specifying the development environment and the tools used to build our system. We will then present the interfaces and functionalities of our system.

IV.2 Software Environment and Programming Languages

The development of the intelligent decision support system was carried out using a combination of programming languages and software tools tailored for web development, machine learning, and data management. These choices were made to ensure interoperability, performance, and ease of deployment.

IV.2.1 Programming Languages

- **PHP:**
  PHP is a general-purpose scripting language especially suited for web development. It runs on the server side and is often embedded in HTML to create dynamic web pages. In this project, PHP was used in conjunction with XAMPP for handling some database operations during early prototyping [74].
- **Python 3.11:**
  Python is a high-level programming language widely used in artificial intelligence and machine learning due to its re adability , large community support, and rich set of scientific libraries such as Scikit-learn, Pandas, and NumPy [75].
- **SQL (Structured Query Language):**
  Used to manage relational data within MySQL, facilitating the storage, retrieval, and management of structured data such as articles, reviewers, and evaluation records [76].
- **HTML, CSS, JavaScript:**
  These core web languages were used to build the front-end of the platform.

HTML provides the structure, CSS defines visual style, and JavaScript adds interactivity [77].

IV.2.2 Development Tools and Software Environment

- **Visual Studio Code:**
  A flexible and lightweight code editor supporting Python, PHP, and front-end development with Git integration [78].
- **Flask (Python Framework):**
  Used for building RESTful APIs and connecting the machine learning model to the user interface [79].
- **XAMPP:**
  Local development environment including Apache and MySQL, used to host PHP scripts and manage MySQL [80].
- **Scikit-learn:**
  A comprehensive machine learning library in Python, widely used for tasks such as text similarity, clustering, and classification. In the context of this project, it played a central role in transforming text data into numerical vectors using TF-IDF (Term Frequency-Inverse Document Frequency), grouping similar articles or reviewers using K-Means clustering, and computing cosine similarity to recommend relevant reviewers or research content. Its integration ensured efficient processing and analysis of textual and structured academic data [81].
- **Pandas & NumPy:**
  Python libraries for efficient handling and analysis of structured numerical and textual data [82][83].
- **Bootstrap**:

  A popular open-source front-end framework used to develop responsive and visually consistent web interfaces. It was employed in this project to design clean, mobile-friendly pages and to streamline UI/UX components, such as forms, buttons, and navigation bars [84].

IV.3 System Interfaces and Functionalities

In this section, we present the main interfaces of the developed system. Each screenshot is accompanied by a detailed explanation of its function and contribution to the decision-making process within the academic context.

IV.3.1 Home page Interface

The homepage represents the main entry point for users into the system. It includes a simplified list of essential options such as login and account registration (figure 4.1). The interface is designed in a simple and practical manner that considers user experience, providing clear guidance toward the next step; whether it is signing up or directly accessing the personal dashboard

Figure 4.1: Homepage Interface.

IV.3.2 User Registration Interface

This interface (figure 4.2) allows a new user to register by entering their personal information, including first name, last name, email, and password. The user must also select its role form the following: Author, President, Editor, or Reviewer. After submitting the registration form, a confirmation code is sent to the provided email address. The user must enter this code to verify their account and activate their access to the platform.

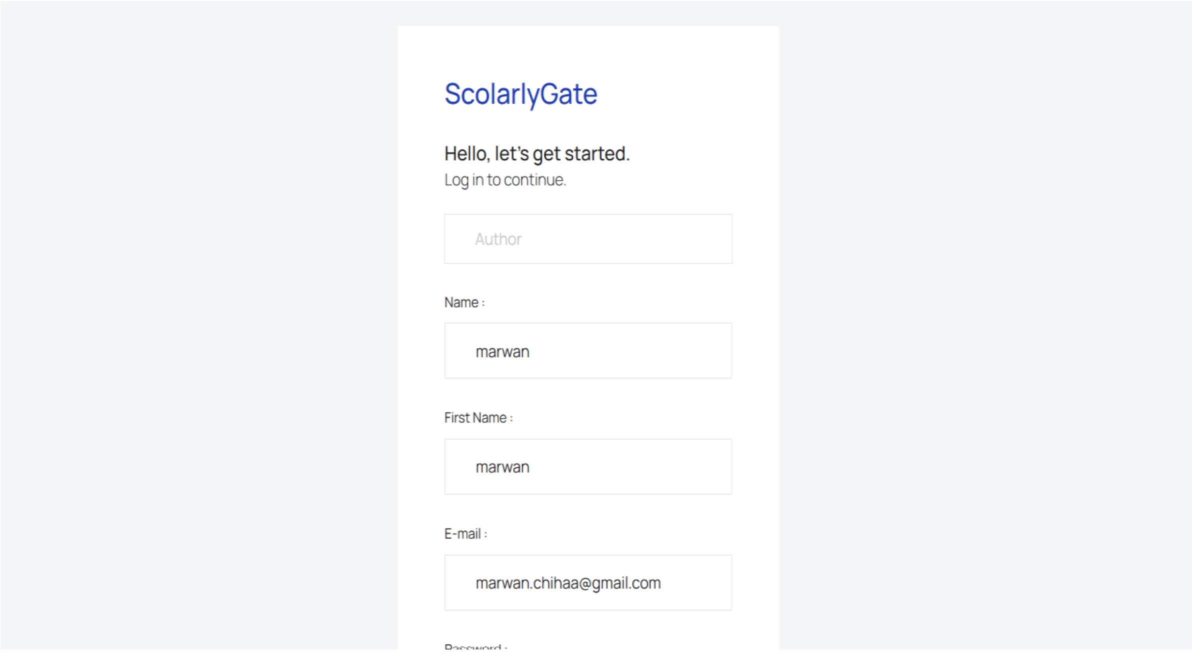

Figure 4.2: User Registration Interface.

- **Email Confirmation Code Sent Notification :**

This interface (figure 4.3) confirms that the email confirmation code has been successfully sent to the user's email address. The user is now required to check their email and enter the code to complete the registration process.

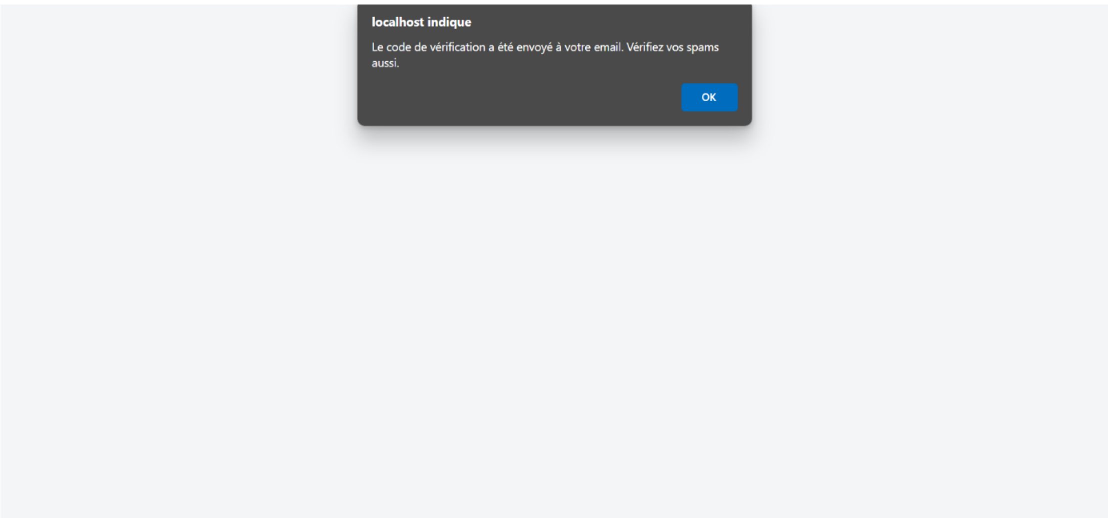

Figure 4.3: Email Confirmation Code Sent Notification.

IV.3.3 Login Interface

This is the main access point to the system (figures 4.4 and 4.5), where users (authors, reviewers, administrators, editor) enter their credentials (username and password). The authentication system ensures secure and confidential access to the platform.

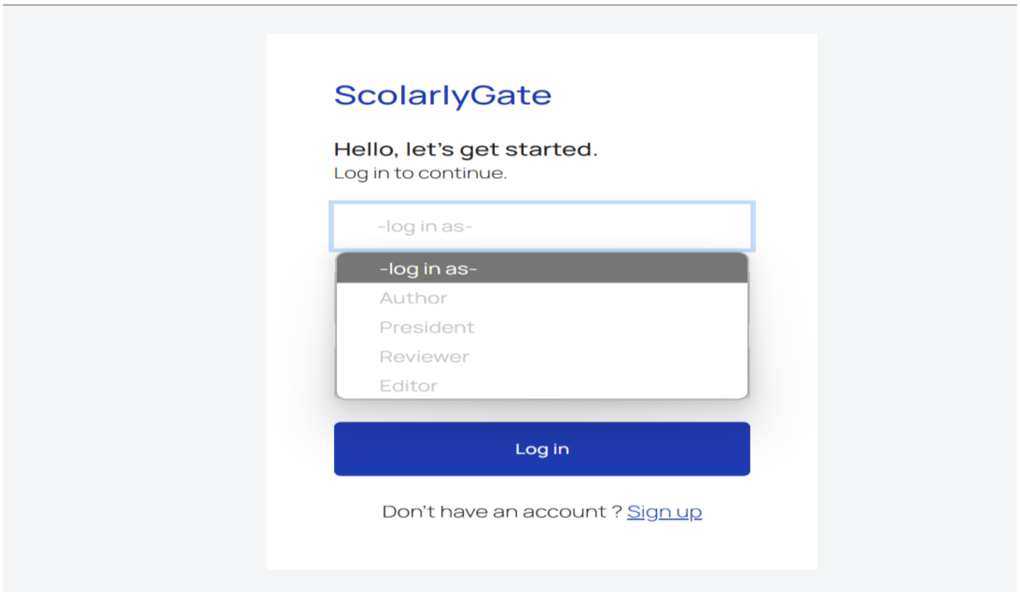

Figure 4.4: Login Interface To choose the role.

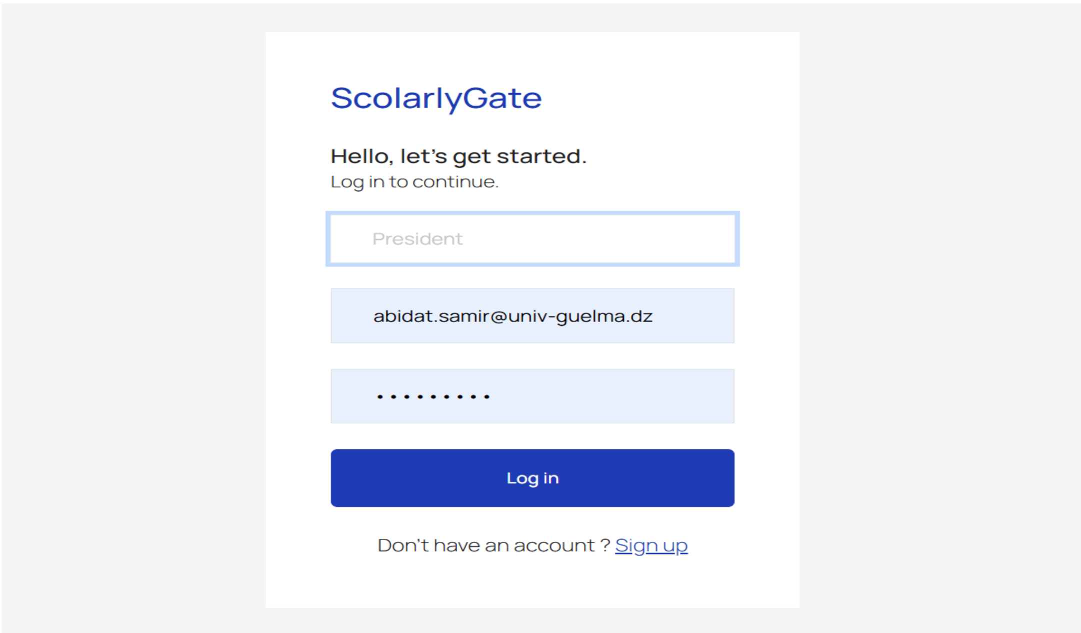

Figure 4.5: Login Interface

IV.3.4 Administrator Dashboard Interface

The figure 4.6 displays the system administrator's dashboard interface, which provides full control over the platform's operations. It is designed to support the academic workflow by enabling the editor to manage users and oversee the review process efficiently.

The administrator has access to the following core features:

- ✓ Registering new users (authors and reviewers).
- ✓ Deleting user accounts when necessary.
- ✓ Reviewing submitted articles for validity and completeness.
- ✓ Assigning appropriate reviewers to each submission based on the system's AI recommendations.

This interface plays a critical role in maintaining the quality and organization of the peer review workflow and aligns with the system's goal of intelligent academic decision support.

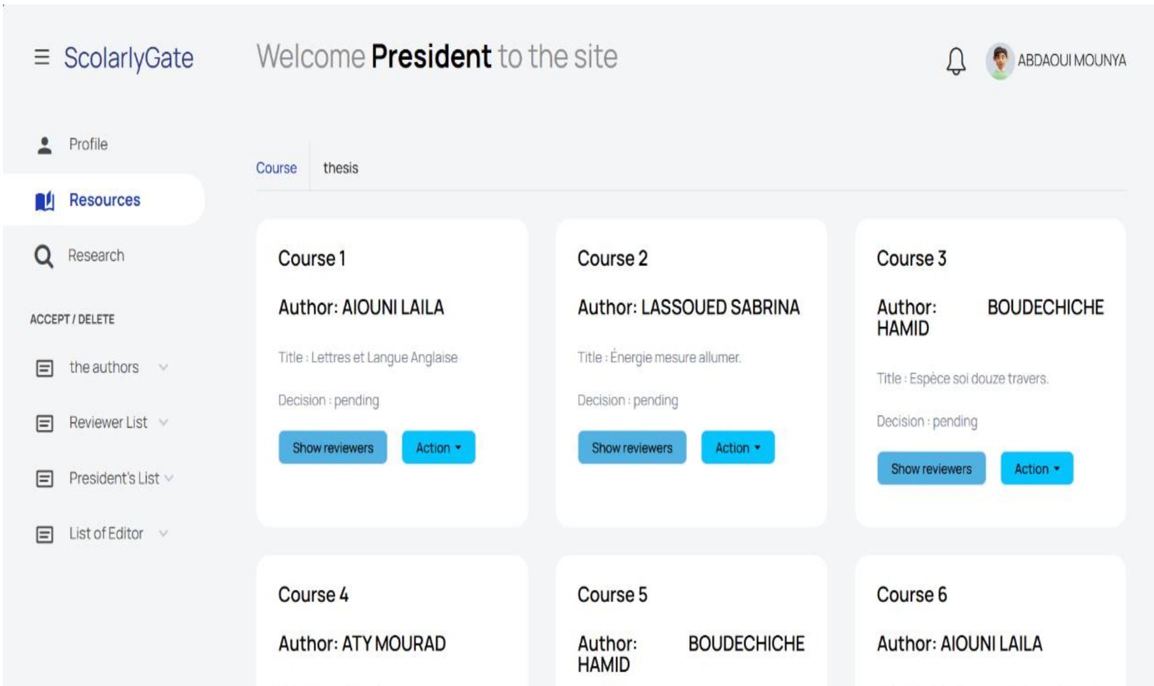

Figure 4.6: Administrator Dashboard Interface.

- **Reviewer Recommendation Interface:**

Once an article is submitted, the system uses the TF-IDF and Cosine Similarity and/or K-means algorithms, according to the user's choice, to suggest a list of appropriate reviewers (figure 4.7).

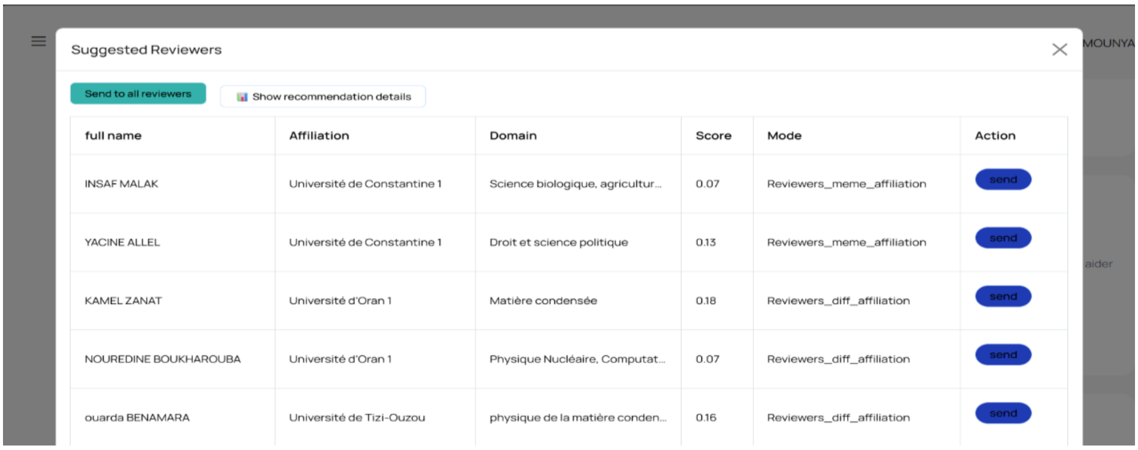

Figure 4.7: Reviewer Recommendation Interface.

- **Reviewer Matching Scores Based on Subject Relevance:**

This interface (figure 4.8) displays a list of potential reviewers along with a relevance score that indicates how closely each reviewer's expertise matches the subject of the submitted article. The score is calculated based on keyword similarity and domain overlap between the author's submission and the reviewer's profile. A score higher than 0.5 indicates that the reviewer is highly relevant to the topic, helping the administrator select the most appropriate evaluators and ensure accurate, subject-aligned peer review.

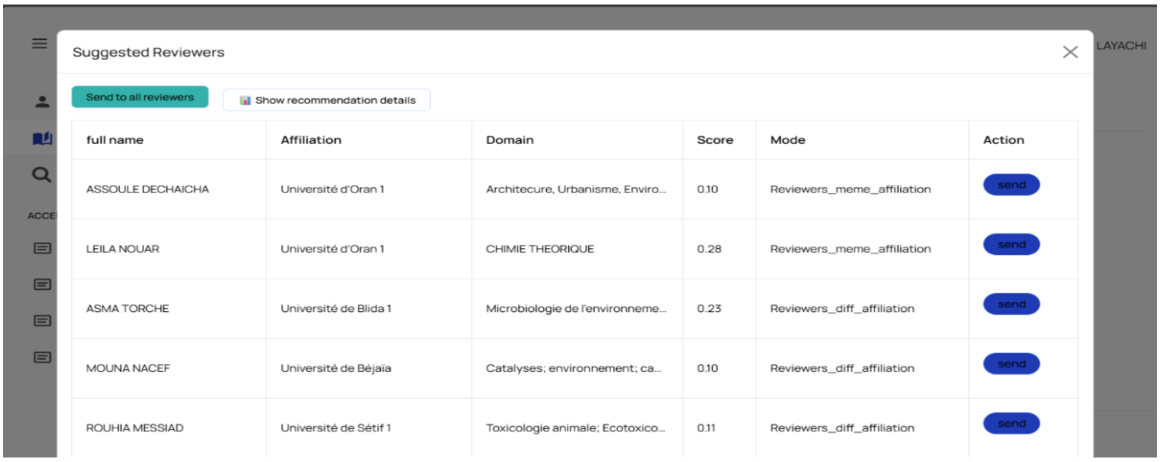

Figure 4.8: Reviewer Matching Scores Based on Subject Relevance.

- **Reviewer Assignment with Institutional Diversity:**

This interface (figure 4.9) enables the administrator to assign reviewers to a submitted article. The system supports selecting two reviewers; one from the same institution as the author and another from a different institution. This approach aims to ensure a balanced evaluation, reduce bias, and enrich the review process with diverse academic perspectives.

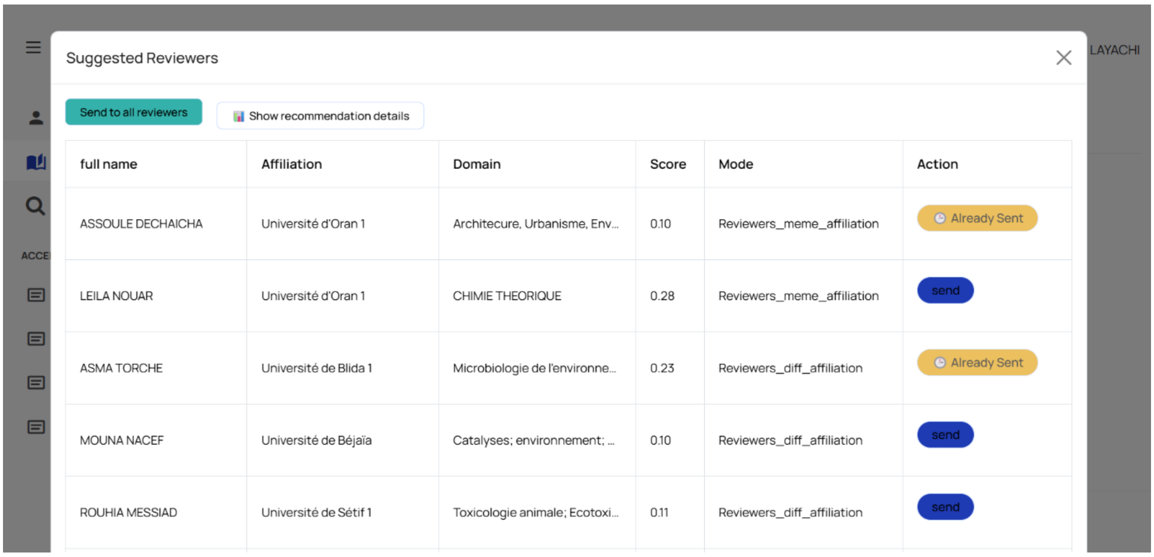

Figure 4.9: Reviewer Assignment with Institutional Diversity.

- **Dynamic Reviewer Filtering Based on Institutional Affiliation:**

In this interface (figure 4.10), the administrator assigns reviewers to an article while ensuring institutional diversity. Once a reviewer accepts the evaluation request, the system automatically hides other reviewers from the same institution, preserving the requirement of selecting two reviewers from different universities. For example, if a reviewer from the author's university accepts, only reviewers from other institutions remain visible to the admin, and vice versa. This mechanism helps maintain neutrality and reduce bias in the peer-review process.

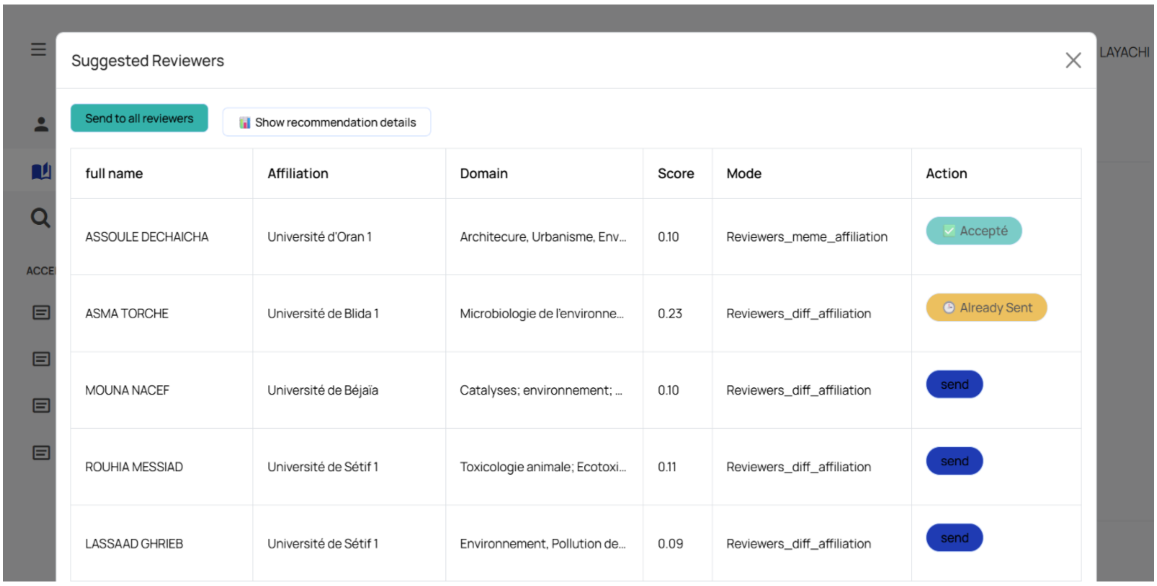

Figure 4.10: Dynamic Reviewer Filtering Based on Institutional Affiliation.

- **Filtered Reviewer List – One Internal and One External:**

This interface (figure 4.11) demonstrates the system's dynamic filtering of reviewers based on institutional affiliation. Once a reviewer accepts the review request, the platform retains only two reviewers eligible for assignment: one from the same university as the author and another from a different institution. This ensures a balanced peer-review process with both internal and external academic perspectives.

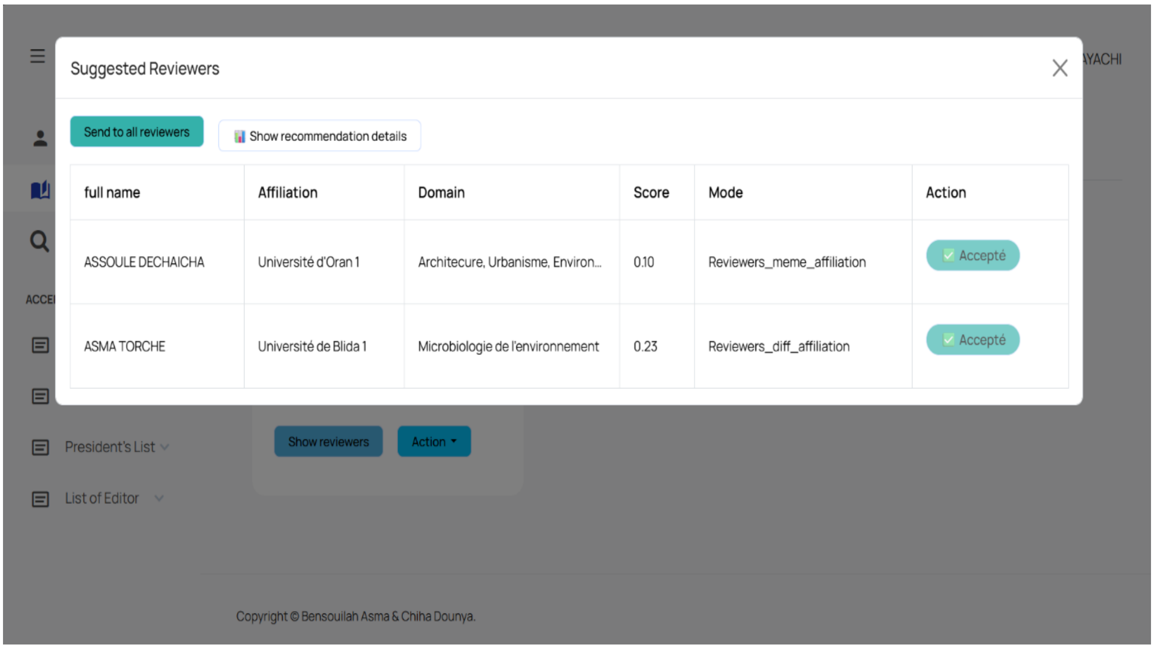

Figure 4.11: Filtered Reviewer List – One Internal and One External.

- **Managing User Registrations and Accounts:**

This interface (figure 4.12) allows the president to manage user accounts. He can validate the registration of new reviewers or authors, as well as delete existing accounts when necessary (figure 4.13). This functionality ensures that only verified and authorized users can access the platform.

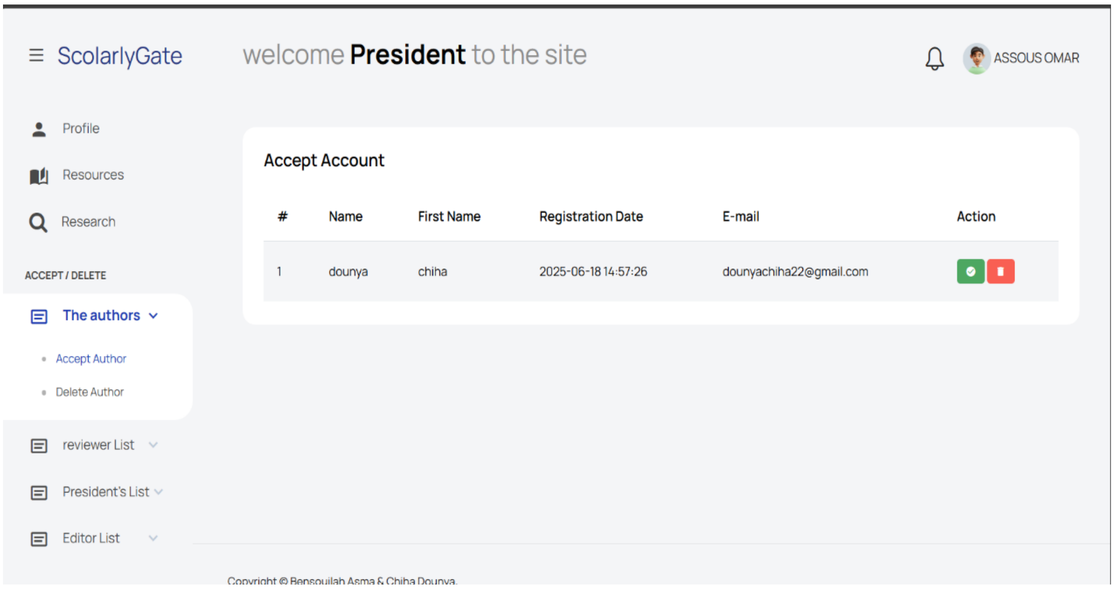

Figure 4.12: Managing User Registrations and Accounts.

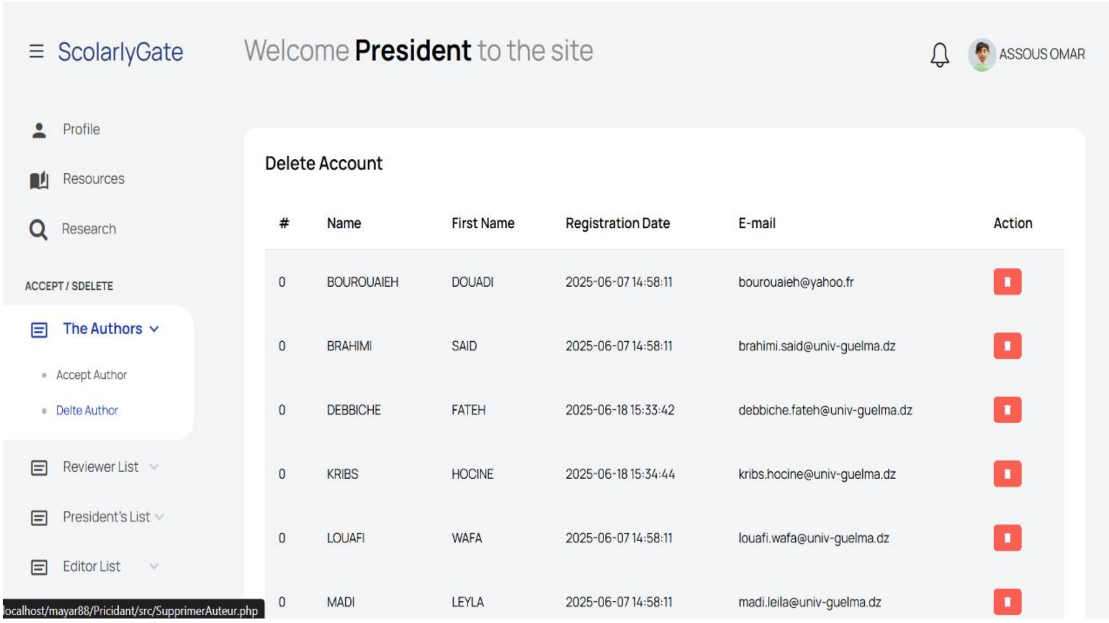

Figure 4.13: delete accounts.

IV.3.5 Author Dashboard

The Author Dashboard is the main interface designed for users with the role of "author" or researcher. It provides access to a set of essential tools that allow the author to manage their scientific contributions within the platform (figure 4.14).

The main functionalities available in this interface include:

- ✓ Viewing and updating their personal profile information (name, email, research field, etc.).
- ✓ Submitting new research articles along with metadata such as title, abstract, keywords, and PDF attachments.
- ✓ Tracking the status of each submission in real time (e.g., pending review, accepted, rejected).
- ✓ Uploading a revised version of an article based on reviewer feedback.

This dashboard facilitates the researcher's workflow by ensuring a smooth submission process and clear communication with reviewers and editorial staff

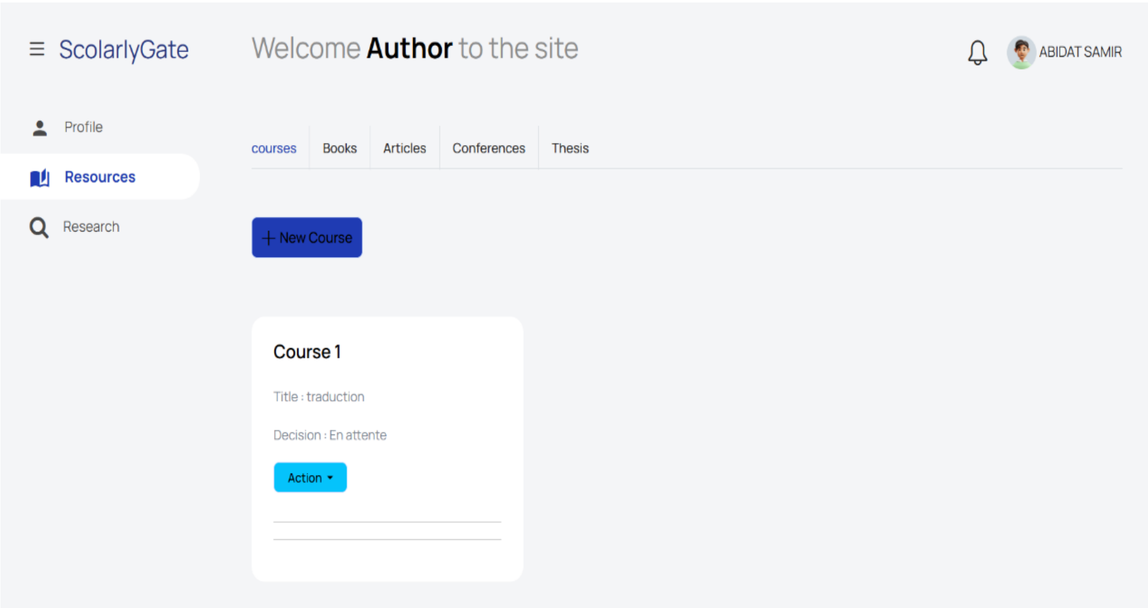

Figure 4.14: Author Dashboard.

- **User Profile Editing Interface:**

This interface(figure 4.15) allows the user to view and update their personal information, such as name, email address, institutional affiliation, and password. It ensures that users can maintain accurate and up-to-date data in the system, which is essential for proper identification and communication throughout the platform.

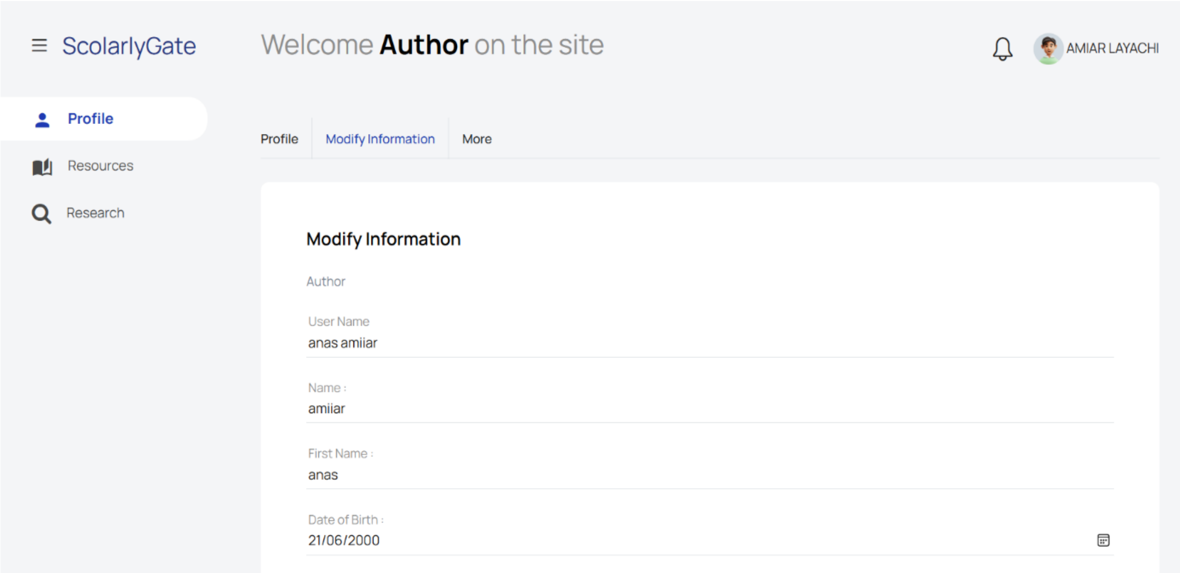

Figure 4.15: User Profile Editing Interface.

- **Article Submission Interface:**

This interface (figure 4.16) allows researchers to submit scientific articles by entering metadata such as the title, abstract, field, and uploading the PDF file. The collected information feeds the recommendation engine that suggests suitable reviewers.

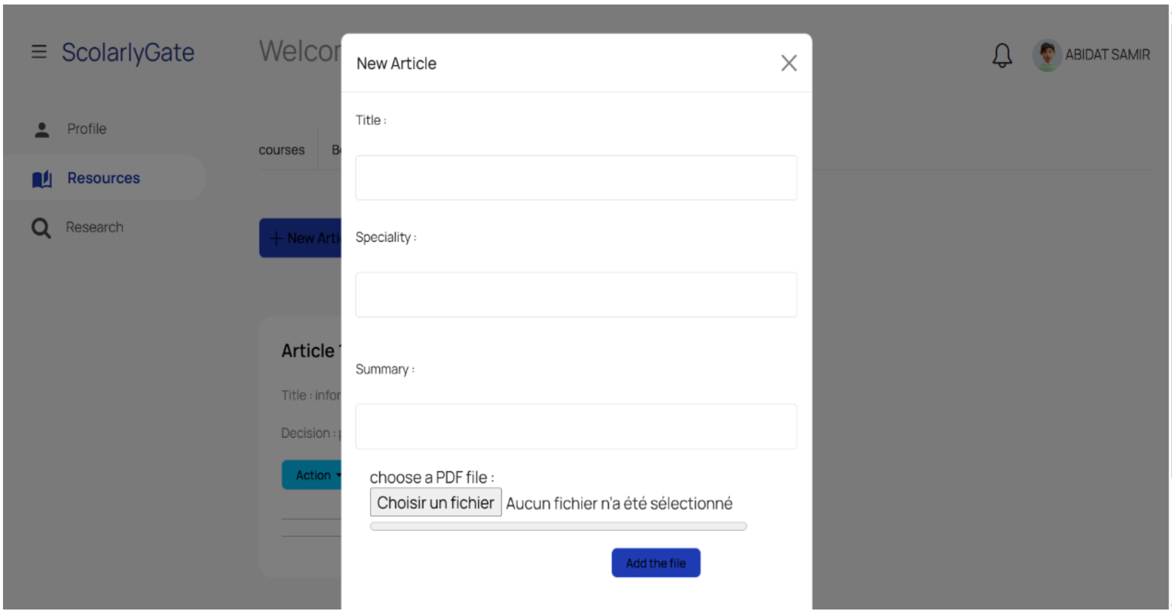

Figure 4.16: Article Submission Interface.

- **Research Interface:**

This interface (figure 4.17) allows users to search for existing research articles within the platform. The search can be performed using keywords, titles. This feature enables authors and reviewers to explore relevant academic work, enhance their own research quality, and avoid duplication.

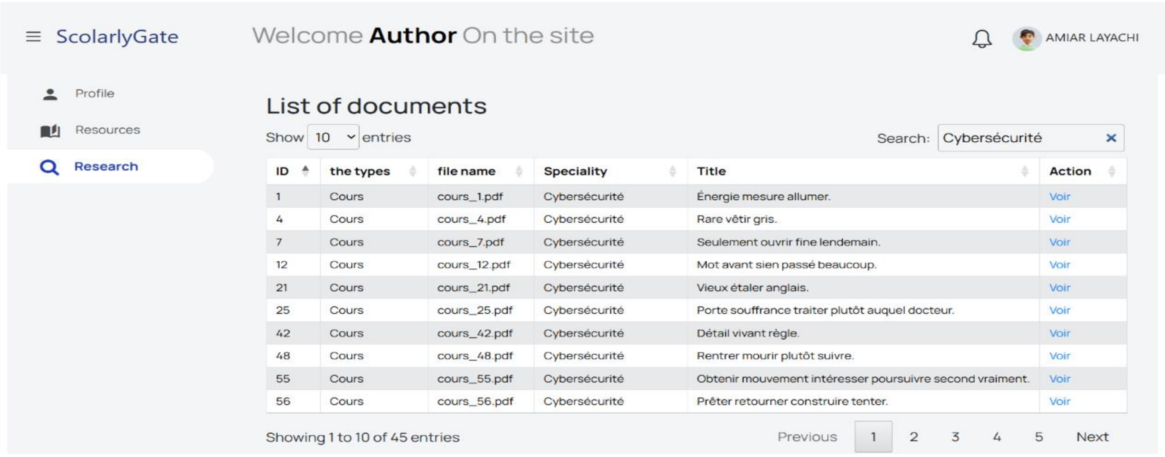

Figure 4.17: Research Interface.

- **Article Submission Interface with Mandatory Abstract Field:**

This interface (figure 4.18) allows users to submit a new article, book, or research topic to the platform. A mandatory abstract field must be completed before submission is accepted. This requirement ensures that every submission includes a concise summary of its content, which is essential for indexing, reviewer assignment, and general comprehension by readers.

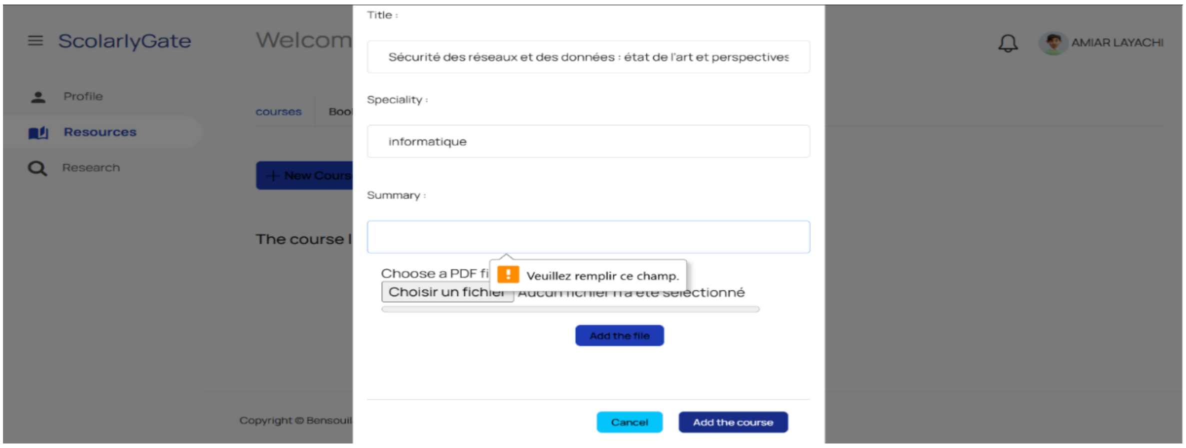

Figure 4.18: Article Submission Interface with Mandatory Abstract Field.

- **Author Dashboard – Published Works Overview:**

This interface (figure 4.19) allows the author to view a summary of their academic contributions, including the total number of published books, lessons, articles, and dissertations. It offers a quick and clear overview of their output within the platform.

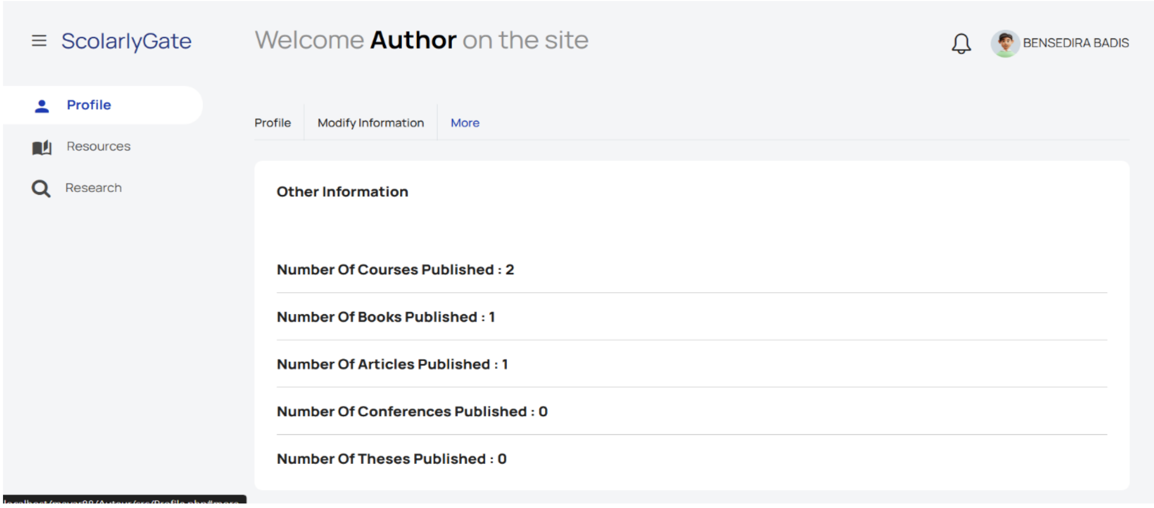

Figure 4.19: Author Dashboard – Published Works Overview.

- **Logout Confirmation Interface:**

This interface (figure 4.20) appears when the user chooses to log out from the system. This step is essential to protect user data and maintain system integrity.

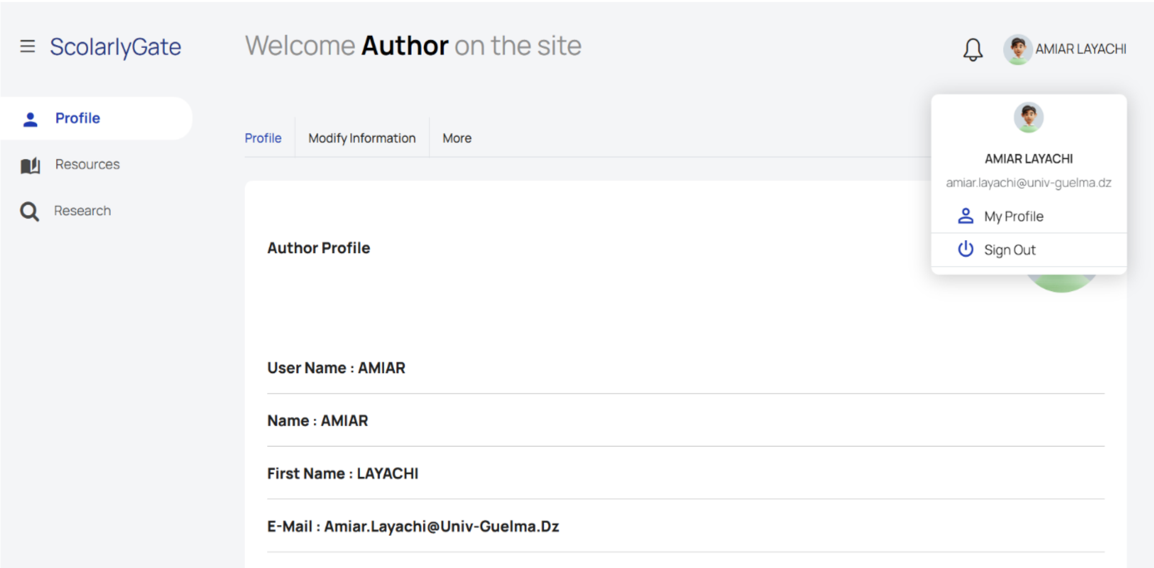

Figure 4.20: Logout Confirmation Interface.

- **Author View – Dual Acceptance Probabilities by Reviewer Affiliation:**

This interface (figure 4.21) displays two separate acceptance probabilities for the author: one derived from the comment of the reviewer from the same university, and another based on the reviewer from a different university. This dual display provides the author with a balanced view of the feedback, considering both internal and external academic perspectives.

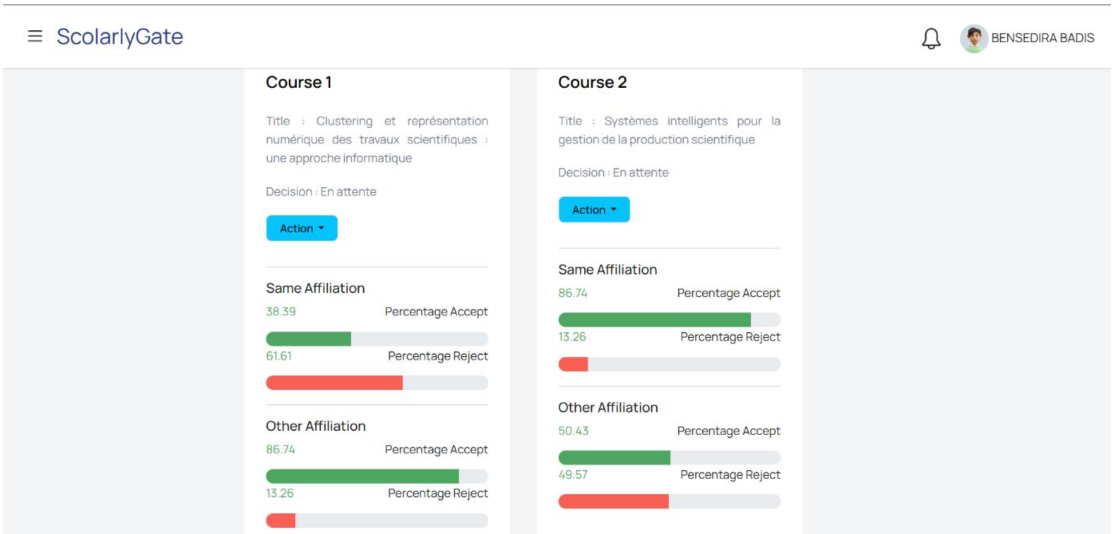

Figure 4.21: Author View – Dual Acceptance Probabilities by Reviewer Affiliation.

IV.3.6 Reviewer Dashboard

The Reviewer Dashboard is the dedicated interface for reviewers, enabling them to manage their peer-review tasks efficiently. It offers a comprehensive set of tools to support the academic evaluation process (figure 4.22).

The main features include:

- ✓ Accepting or declining a review invitation, after reviewing the article's title and research field.
- ✓ Downloading the full PDF version of the assigned article for thorough evaluation.
- ✓ Submitting structured feedback or comments regarding the article's content, methodology.
- ✓ Proposing a decision to either accept or reject the article.

This interface enhances the peer-review experience by promoting clarity, transparency, and structured communication between reviewers and the editorial team.

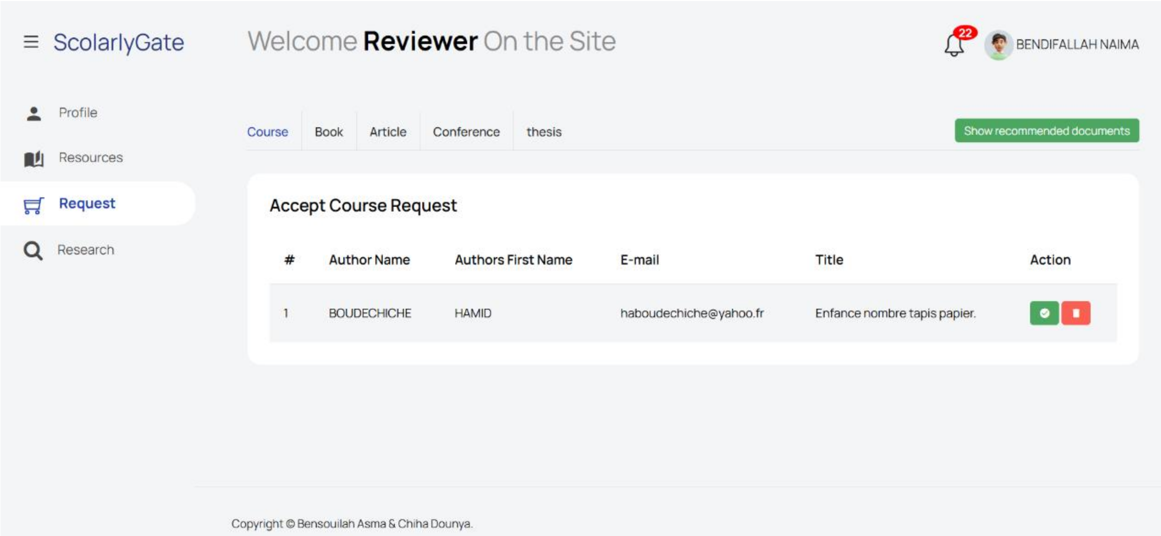

Figure 4.22: Reviewer Dashboard.

- **Automatic Decision Probability Based on Reviewer Comments:**

When a reviewer submits a comment on a research article, the system automatically analyzes the content and importance of the comment using a machine learning model (figure 4.23). Based on this analysis, it displays an estimated probability of acceptance. This feature supports the decision-making process by offering a predictive insight derived from the content of the feedback.

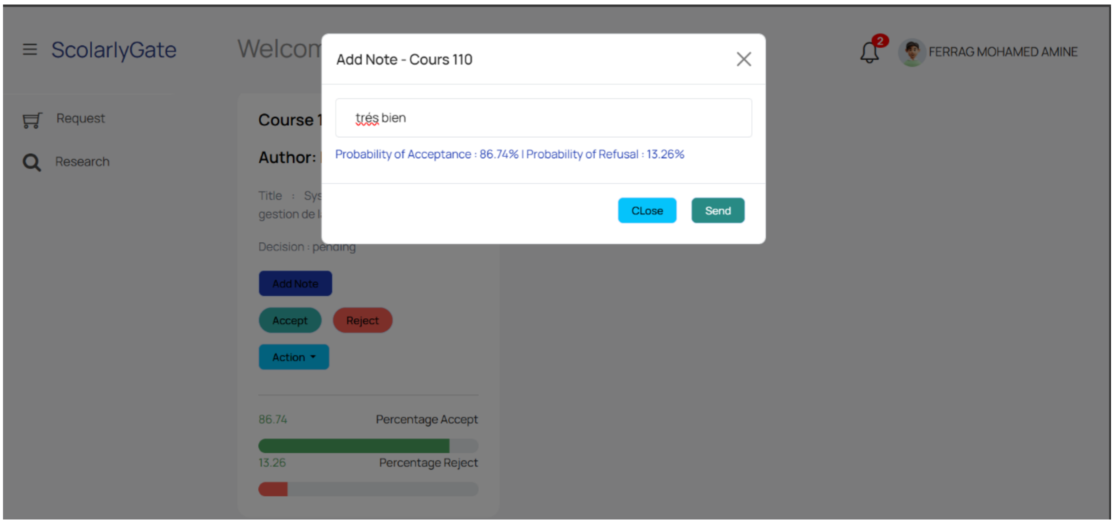

Figure 4.23: Reviewer Comment Interface and Acceptance Probability.

- **Reviewer Comment Display After Submission:**

This interface (figure 4.24) shows how the reviewer's comment is displayed after submission. The comment is stored and instantly sent to the author, allowing them to review the feedback.

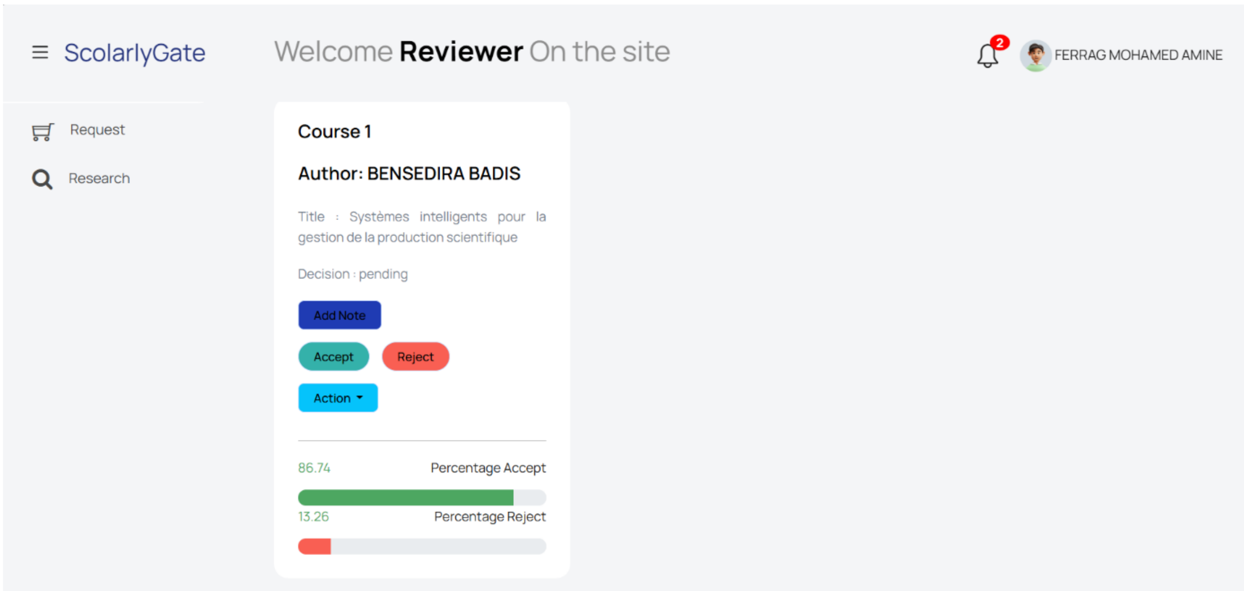

Figure 4.24: Reviewer Comment Display After Submission.

- **Notification Interface for Reviewers:**

The system includes a real-time notification mechanism (figure 4.25). When an administrator assigns a paper to reviewers, a notification appears on their dashboard, informing them of the new task with a direct link to access the review form.

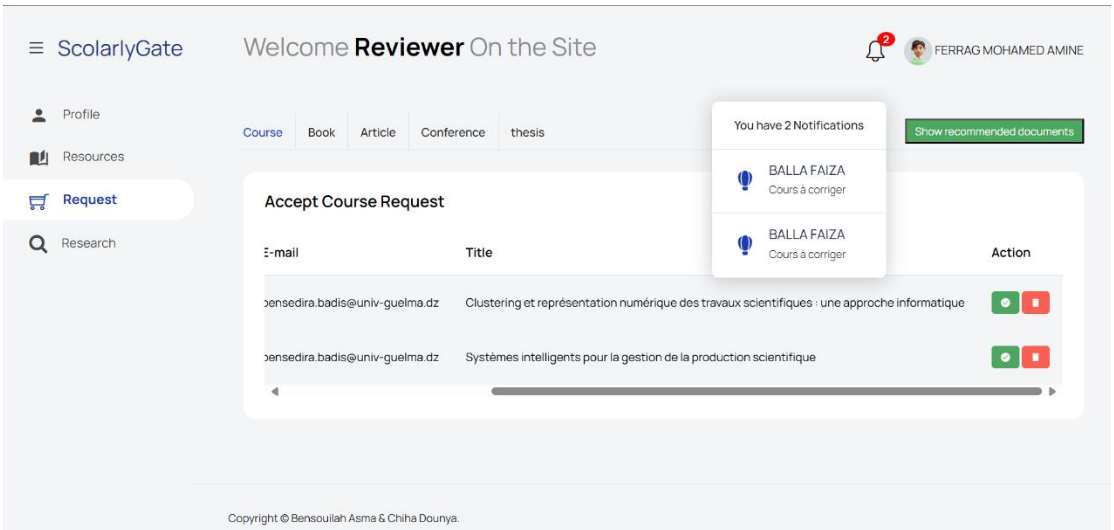

Figure 4.25: Notification Interface for Reviewers.

- **Bulk Review Request Acceptance Interface:**

This interface (figure 4.26) allows the reviewer to accept all review requests at once, without having to handle each request individually.Only articles for which the reviewer has a matching score greater than 0.5 are displayed, ensuring that the reviewer evaluates only works that align with their area of expertise. If no article exceeds this threshold, the list appears empty.

Figure 4.26: Bulk Review Request Acceptance Interface.

IV.3.7 Editor Space

This space is dedicated to the editor, who has similar functionalities to the president, but with a more focused scope (figure 4.27). The editor is specifically responsible for managing articles, books, and conferences, while the president oversees courses and academic dissertations. This separation of roles ensures clearer task distribution and better content organization.

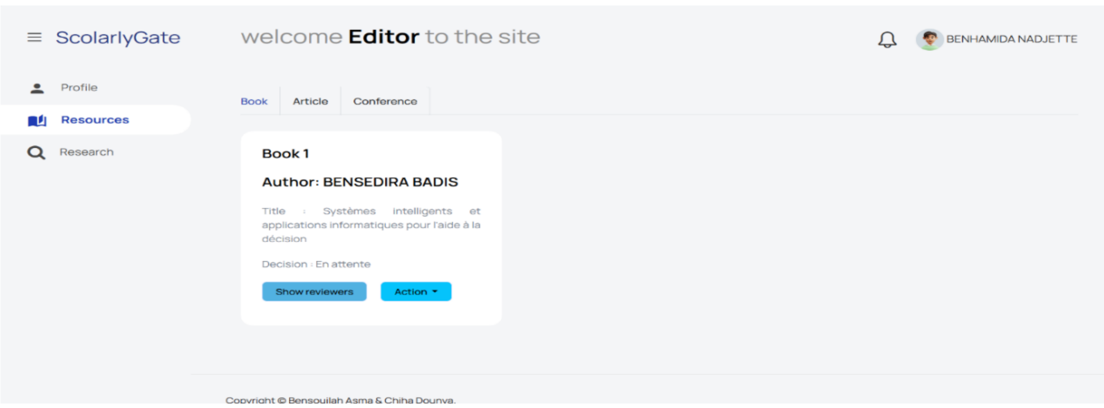

Figure 4.27: Editor Space.

IV.4 Obtained results

In this section, we present the empirical outcomes of our intelligent decision support platform following its implementation and preliminary evaluation.

Criteria	**K-Means**	**TF-IDF**	**Hybrid (TF-IDF + K-Means)**
Method type	Clustering algorithm (unsupervised learning)	Term weighting algorithm	Combination of vector representation and clustering (unsupervised hybrid approach)
Objective	Group documents into clusters	Represent documents as numeric vectors to enable similarity calculations	Associate documents with clusters after vector transformation to improve the relevance of recommendations
Recommendation time in the model	0.0093 Seconds	0.106 seconds	0.1375 seconds
Time similarity in the model	0 Seconds	0 seconds	0 seconds
Time similarity average	0,0011 Seconds	9,3363 seconds	0,087 seconds
Time similarity max	0,13 Seconds	31,0459 seconds	0,13 seconds
Time similarity min	0 seconds	0,7009 seconds	0,053 seconds
standard deviation	0,0103 seconds	4,7103 seconds	/
total number of reviewers proposed	same affiliation:2 difference affiliation:12	14	14

Table 3.1: Result obtained.

Table 4.1 demonstrates that the hybrid TF-IDF + K-Means approach offers a balanced trade-off between accuracy and efficiency. While TF-IDF provides comprehensive coverage of potential reviewers, its similarity computations introduce significant latency and performance variability, rendering it impractical for interactive use. In contrast, K-Means achieves exceptionally low response times but exhibits clustering biases that can limit the diversity and relevance of recommendations.

The hybrid model, however, maintains full reviewer coverage and semantic fidelity, owing to TF-IDF's discriminative feature representation, while preserving near real-time performance comparable to K-Means clustering. Its moderate overhead stays within acceptable limits for user responsiveness, confirming that the combined technique effectively leverages the strengths of both constituent methods and is well suited for practical deployment in academic peer-review recommendation workflows.

IV.5 Conclusion

In this chapter, we presented how the decision support system operates for managing and evaluating scientific output. We began by introducing the development tools and environment used to implement the system. We then explained the application's various interfaces, tailored to specific user roles (author, reviewer, administrator). Several screenshots of the platform were included to illustrate the system in action. This practical implementation demonstrates the feasibility of deploying the proposed model in a real-world academic setting.

General Conclusion and future works

The present work seeks to address the growing challenges of managing and enhancing scientific output within Algerian higher education institutions by proposing an intelligent, AI-based decision support system. In an era marked by rapid digital transformation, the development of such systems has become essential to streamline publication processes, reinforce research evaluation, and promote a culture of transparency and efficiency in academic environments.

Our approach began with a thorough assessment of the institutional context and prevailing difficulties, followed by a detailed needs analysis to define the key functional and technical specifications of the platform. The resulting system integrates intelligent components such as reviewer recommendation algorithms and tools for tracking and managing scientific evaluations, all while ensuring an intuitive user experience adapted to different academic roles.

The implementation and preliminary testing of the system highlighted its potential to to improve significantly the organizational workflow, facilitate decision-making, and support the scientific community through practical, AI-driven functionalities. The results reinforce the relevance of adopting intelligent systems to modernize academic governance and valorize research output on a national scale.

Nevertheless, due to technical and time constraints, several promising features could not be implemented within the current scope. Future development could include the integration of a predictive model capable of estimating the publication success of scientific contributions based on content analysis, thematic focus, and methodological rigor. Additionally, the use of blockchain technology could provide a robust framework for securing intellectual property rights, thereby enhancing trust and traceability. Finally, implementing an automated module to detect academic misconduct, such as plagiarism or fraudulent authorship, would further strengthen the scientific integrity of the academic ecosystem.

In conclusion, this project constitutes a foundational step toward a more intelligent and transparent academic management system in Algeria. We hope it contributes to fostering a research environment built on innovation, responsibility, and technological advancement, and that it inspires further exploration and implementation of AI in academic and scientific governance.

Future Work:

Building on the foundational prototype developed in this study, several avenues for future enhancement are evident:

1. **Predictive Publication Success Model**

Integrate machine learning–based predictive analytics to estimate the likelihood of manuscript acceptance. By combining content features (e.g., topic relevance, methodological rigor) with historical publication outcomes, the system would be able **to** provide authors and editors with early guidance on optimal target journals and necessary revisions.

2. **Blockchain-Enabled Provenance and IP Management**

Leverage blockchain technology to create an immutable ledger of submissions, reviews, and authorship claims. This would enhance intellectual property protection, ensure transparent audit trails, and bolster trust among stakeholders by preventing unauthorized modifications or disputes over contribution.

3. **Automated Misconduct Detection**

Develop an AI-driven module for detecting academic integrity violations, including plagiarism, data fabrication, and fraudulent authorship. Natural-language processing and stylometric analysis could flag anomalies in writing style or similarity to existing texts, while metadata consistency checks would identify possible conflicts of interest or duplicate submissions.

4. **Advanced Semantic Analysis and Topic Modeling**

Extend the current TF-IDF and K-Means framework with deep learning techniques, such as transformer-based embeddings and hierarchical topic models, to capture nuanced semantic relationships and evolving research trends, thereby improving the precision of reviewer recommendations and thematic reporting.

5. **Interactive Dashboards and Real-Time Monitoring**

Design and implement dynamic visual analytics dashboards that allow administrators and researchers to monitor key performance indicators (e.g., submission turnaround times, reviewer load balancing, citation impact) in real time, facilitating timely interventions and data-driven governance.

6. **User-Centered Feedback Loops**

Incorporate mechanisms for continuous user feedback, via rating of reviewer recommendations and system usability surveys, to refine algorithms, adapt to evolving institutional needs, and ensure sustained user engagement.

7. **Scalability and Integration with National Repositories**

Architect the platform for horizontal scalability and interoperability with national research information systems (e.g., institutional repositories, grant management platforms). This will enable seamless data exchange, reduce redundancy, and foster a unified ecosystem for Algerian academic governance.

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