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**AI-Based Recommendation System for Selecting
Suitable Training Courses for Students (AIRSS)**

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Abstract

This study aims to develop an intelligent recommendation system predicated on advanced artificial intelligence ways to support Saudi university graduates in concluding training courses that align with their academic backgrounds and career aspirations. The significance of the system lies in its capability to help graduates in navigating the vast range of online knowledge platforms and making informed opinions that meet the demands of the original labor request.

The proposed system analyzes druggies' textual inputs, analogous as their educational interests and chops, and matches them with course descriptions using Natural Language Processing (NLP) ways. To enhance recommendation performance, the system employs multiple text representation styles, including TF- IDF and BERT, combined with similarity dimension approaches analogous as cosine similarity and Euclidean distance to induce substantiated and applicable course recommendations.

Experimental results deemonstrate that the BERT model combined with cosine similarity provides more accurate and meaningful recommendations compared to other approaches, as it effectively captures semantic connections between handbooks.

The system is anticipated to meliorate educational decision- timber, reduce the time and trouble demanded for career drug, and promote invention in digital knowledge surroundings. likewise, it contributes to the development of intelligent educational systems aligned with modern trends in AI- driven knowledge.

Keywords:

Artificial Intelligence, Natural Language Processing, Recommendation Systems, Course Recommendation, BERT, TF- IDF, Cosine Similarity, Personalized Learning

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List of Abbreviations

AI — Artificial Intelligence

NLP — Natural Language Processing

AIRSS — AI-Based Recommendation System for Selecting Suitable Training Courses for Students and Graduates

TF-IDF — Term Frequency–Inverse Document Frequency

BERT — Bidirectional Encoder Representations from Transformers

ML — Machine Learning

DL — Deep Learning

RS — Recommendation Systems

CBR — Content-Based Recommendation

CS — Cosine Similarity

ED — Euclidean Distance

LMS — Learning Management System

IR — Information Retrieval

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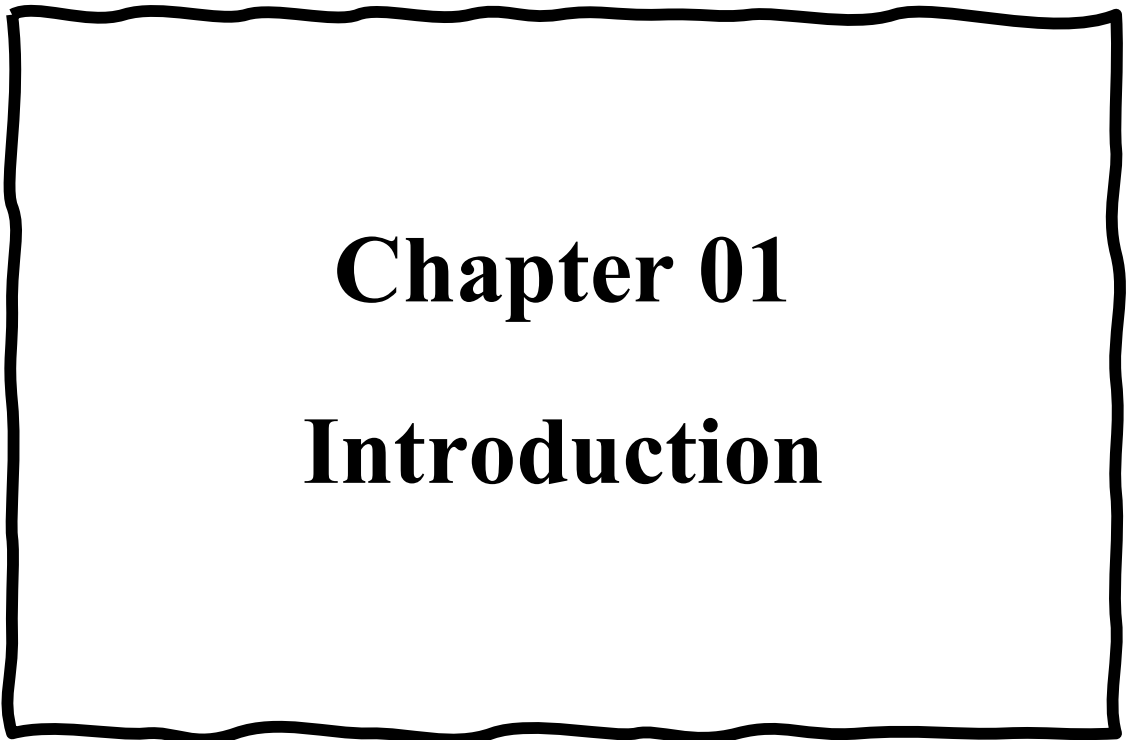
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Chapter 01

Introduction

1.1 Background of the Study

The education and training sector has witnessed rapid-fire development in recent times due to the adding reliance on digital technologies and the wide vacuity of learning platforms. This changeover has led to a significant expansion in the number and diversity of training courses across various fields and specializations. As a result, scholars and graduates are now presented with precious openings to enhance their chops and align themselves with the evolving demands of the labor request.

This growth also reflects a shift toward lifelong knowledge, where individualities continuously seek to meliorate their knowledge and professional capabilities. still, despite these advantages, the rapid-fire expansion of available courses has introduced a major challenge concluding the most applicable training options. The cornucopia of choices, variations by course quality, and differences in learning objects make it delicate for stoners to identify courses that align with their interests, chops, and career pretensions.

This challenge becoames more pronounced in surroundings where structured academic or career guidance is limited. In Saudi Arabia, multitudinous scholars still calculate on traditional approaches analogous as manual searching or general recommendations when concluding training courses. These styles constantly warrant personalization and may not directly reflect individual preferences or capabilities, which can lead to ineffective knowledge issues and poor decision-timber.

In this terrain, Artificial Intelligence (AI) technologies have surfaced as effective results to support educational decision-timber. Recommendation systems have shown strong eventuality in assaying user data and furnishing substantiated suggestions. By exercising Natural Language Processing (NLP) ways, these systems can exercise textual information and measure the similarity between user inputs and course descriptions to identify the most applicable training options.

To address these challenges, this study proposes the AIRSS system, an AI-predicated recommendation system designed to help scholars and graduates in concluding suitable training courses. The system integrates multiple text representation ways, including TF-IDF and BERT, along with similarity measures analogous as cosine similarity and Euclidean distance, to induce accurate and personalized recommendations.

likewise, the system supports multiple recommendation models and provides both unified and model-specific interfaces, allowing for effective comparison and evaluation of different approaches.

The proposed system is anticipated to meliorate the quality of educational decision-timber, reduce the time and trouble demanded for course selection, and enhance alignment between stoners' chops and labor request conditions.

1.2 Problem Definition

College graduates in Saudi Arabia face a significant challenge in concluding applicable training courses due to the vast vacuity of educational platforms and the diversity of course content and specializations. While this variety provides precious openings, it also creates confusion and query, constantly leading to deficiently informed opinions that do not align with graduates' academic interests or the evolving demands of the original labor request.

In addition, utmost being quest tools warrant effective personalization capabilities, as they do not sufficiently anatomize stoners' preferences, chops, and background information. As a result, these systems give generalized recommendations that may not directly reflect individual conditions.

This limitation reduces the effectiveness of academic and career guidance and increases the time and trouble demanded to identify suitable training openings. Likewise, the absence of intelligent recommendation systems contributes to a gap between available training options and factual user conditions, which may negatively impact skill development and career readiness among graduates.

- Therefore, the problem addressed in this study can be epitomized in the following question.

How can Artificial Intelligence (AI) ways be used to give individualized course recommendations that help Saudi university graduates in opting training courses aligned with their career pretensions and professional conditions?

1.2.1 Study Questions

This study aims to answer the following main exploration question. Grounded on this main question, the study seeks to address the following sub-questions.

- To what extent can gladden-grounded recommendation systems support graduates in making effective and informed training opinions?
- How can Natural Language Processing(NLP) ways be applied to dissect stoner interests and match them with descriptions of available online training courses?
- How do substantiated and interpretable recommendations contribute to enhancing stoner experience and adding satisfaction with the proposed AIRSS system?

- What's the impact of the proposed AIRSS system on reducing the time and trouble needed for graduates to identify suitable training courses?

1.2.2 Study Hypothesis

This study hypothesizes that the proposed intelligent recommendation system(AIRSS) will significantly ameliorate the applicability and felicity of training course recommendations for Saudi university graduates compared to traditional or homemade course selection styles.

Likewise, it's hypothecated that the integration of advanced textbook representation ways, similar as BERT, combined with similarity dimension styles(e.g., Cosine Similarity and Euclidean Distance), will enhance the delicacy and effectiveness of the recommendation process.

1.3Study Objectives

This study aims to develop an intelligent recommendation system that supports Saudi university graduates in making accurate and effective training opinions. This ideal can be achieved through the following.

- To help graduates in opting for training courses that align with their interests, chops, and career paths.
- To reduce the time and trouble I needed to manually search for suitable training courses.
- To enhance the quality of academic and career guidance using Artificial Intelligence (AI) ways.
- To dissect druggies' textual data using Natural Language Processing (NLP) styles in order to induce accurate and individualized recommendations.
- To apply advanced textbook representation ways, similar as TF- IDF and BERT, combined with similarity measures (e.g., Cosine Similarity and Euclidean Distance) to ameliorate recommendation delicacy.
- To design and develop multiple system interfaces, including model-specific and unified interfaces, to enable effective comparison between different recommendation approaches.
- To support universities and training institutions in developing intelligent advising systems for scholars and graduates.

- To contribute to the advancement of smart education and substantiated learning systems.

1.4 Study Contribution

Former studies have made significant benefactions to the development of AI- grounded recommendation systems in educational surroundings. Several crucial benefactions can be epitomized as follows

- Oubalahcen et al.(2023) handed a comprehensive review of artificial intelligence ways used ine-learning recommendation systems, pressing their capability to deliver substantiated literacy pathways grounded on stoner geste
- and preferences.
- Salim et al.(2025) emphasized the part of substantiated course recommendation systems in Massive Open Online Courses (MOOCs), particularly in enhancing availability, inclusivity, and learner engagement through gusto.
- driven data analysis.
- Tolety and Prasad(2022) proposed a cold-blooded recommendation approach that combines cooperative filtering and content- grounded filtering, achieving bettered performance compared to traditional styles ine-learning surroundings.
- Mentec(2023) introduced resolvable recommendation systems, emphasizing the significance of translucency and stoner commerce in perfecting trust, effectiveness, and decision- making processes.
- Pazzani and Billsus(2007) handed foundational perceptivity into content- grounded recommendation systems, explaining how stoner biographies and point features are employed to induce individualized recommendations.

Overall, these studies inclusively demonstrate the significance of personalization, delicacy, explainability, and rigidity in recommendation systems. still, there remains a need for systems that integrate advanced textbook representation ways, similar as BERT, with effective similarity measures to give more accurate and environment- apprehensive recommendations.

1.5 Significance of the Study

The significance of this study can be examined from academic, practical, and societal perspectives, as outlined below:

1.5.1 Academic Significance

This study contributes to the existing literature on educational recommendation systems by fastening content-predicated approaches and integrating Natural Language Processing (NLP) ways for textual data analysis. It incorporates advanced text representation styles, analogous as TF-IDF and BERT, to enhance the understanding of user inputs and course descriptions.

Likewise, the study integrates multiple similarity measures, including Cosine Similarity and Euclidean Distance, to estimate and compare different recommendation approaches. This integration improves the delicacy and connection of recommendations by landing both syntactic and semantic connections within textual data.

Accordingly, the study provides a comprehensive frame for developing further effective and personalized recommendation systems in educational surroundings.

1.5.2 Practical Significance

The practical significance of this study lies in the development of the proposed intelligent recommendation system (AIRSS), which is designed to help graduates in opting suitable training courses grounded on their interests, chops, and career pretensions.

The system reduces reliance on traditional homemade hunt styles and general recommendations by furnishing substantiated suggestions using AI ways. By exercising TF-IDF, BERT, Cosine Similarity, and Euclidean Distance, the AIRSS system enhances decision-making effectiveness and improves stoner experience by delivering accurate and applicable recommendations.

In addition, the system offers multiple model-specific interfaces as well as a unified interface, allowing druggies to compare different recommendation models and better understand their performance.

1.5.3 Societal Importance

From a societal perspective, this study supports the advancement of substantiated literacy and professional development through the operation of intelligent technologies. It contributes to preparing graduates to meet the dynamic conditions of the labor request, particularly in the environment of rapid-fire digital metamorphosis.

also, the study aligns with the objects of Saudi Vision 2030 by promoting the integration of Artificial Intelligence in education and training systems. By enhancing graduates' readiness and supporting skill development, the proposed system contributes to erecting a knowledge- grounded frugality and fostering sustainable societal growth.

1.6 Scope of Research

This study is limited to a defined compass that outlines its boundaries and focus, icing clarity, consistency, and validity of the disquisition issues. The compass of the study can be epitomized as follows.

1. Target Group

The study focuses on university graduates in the Kingdom of Saudi Arabia, as it aims to support them in concluding applicable training courses aligned with their career paths. This group represents a pivotal member that can significantly benefit from intelligent recommendation systems.

2. Thematic compass

The study is concerned with recommendation systems in the educational sphere, specifically fastening on course recommendation processes. It aims to support the selection of suitable training courses and programs that match stoners' interests, chops, and career pretensions.

3. Specialized compass

The study adopts a content-predicated recommendation approach, exercising Natural Language Processing (NLP) ways to anatomize textual data. It integrates advanced text representation styles analogous as TF- IDF and BERT, along with similarity measures including Cosine Similarity and Euclidean Distance, to induce personalized recommendations.

In addition, the system supports multiple recommendation models and provides both model-specific interfaces and a unified interface, enabling comparison between different approaches.

4. Data Scope

The study relies on textual data that includes stoners' interests, chops, and course descriptions. This data are used to develop and estimate the proposed AIRSS system, furnishing a meaningful base for understanding user conditions and perfecting recommendation quality.

1.7 Research Gap

A review of former studies in the field of educational recommendation systems reveals several important gaps that have n't been adequately addressed.

First, utmost being studies primarily concentrate on general pupil populations within formal educational surroundings. Limited attention has been given to university graduates and their specific requirements in opting applicable training courses aligned with their career paths. This limitation reduces the applicability of being systems to real- worldpost-graduation challenges.

Second, numerous recommendation systems have been developed without sufficient consideration of original educational and socio- profitable surrounds. In particular, there's a lack of systems acclimatized to the Saudi labor request and its evolving conditions. Ignoring similar contextual factors may lead to less applicable and ineffective recommendations.

Third, there's a conspicuous gap in the operation of Natural Language Processing (NLP) ways, especially in assaying textual stoner inputs to induce individualized recommendations. This highlights the need for systems that can effectively reuse and understand stoner- generated textbooks.

Furthermore, numerous being systems fail to adequately separate between stoner biographies, similar as academic backgrounds, specializations, and particular interests. This limitation reduces the system's capability to give precise and meaningful recommendations.

In addition, limited disquisition has explored the integration of advanced text representation models, analogous as BERT, with multiple similarity measures (e.g., Cosine Similarity and Euclidean Distance) to meliorate recommendation delicacy and semantic understanding.

Research Contribution Motivation

These gaps punctuate the need for an intelligent, environmentally apprehensive recommendation system that focuses on graduates, leverages advanced NLP ways, and aligns with original labor request conditions.

Consequently, this study proposes the AIRSS system, which integrates TF-IDF and BERT with similarity dimension styles to give substantiated, accurate, and environment-apprehensive training course recommendations.

1.8 Operational Definitions

To this study, the following terms are defined operationally.

- **Intelligent Recommendation System(AIRSS)**

An AI- grounded system designed to give individualized training course recommendations for graduates by assaying their textual inputs, including interests, chops, and preferences, using advanced Natural Language Processing (NLP) ways.

- **Content- Grounded Recommendation**

A recommendation approach that suggests particulars grounded on the similarity between point features and stoner preferences, without counting on data from other druggies.

- **TF- IDF (Term frequency – Inverse Document frequency)**

A statistical system used to transfigure textual data into numerical vectors by measuring the significance of words within a document relative to a collection of documents.

- **BERT (Bidirectional Encoder Representations from Mills)**

A deep literacy model used for advanced textbook representation, able of understanding the contextual meaning of words within a judgment, which enhances semantic analysis in recommendation systems.

- **Cosine Similarity**

A fine measure used to determine the similarity between two vectors by calculating the cosine of the angle between them, where advanced values indicate lesser similarity.

- **Euclidean Distance**

A fine measure used to calculate the distance between two vectors in a multidimensional space, where lower values indicate advanced similarity.

1.9 Study Organization

The remainder of this thesis is organized as follows.

Chapter 1 introduces the exploration background, problem description, exploration questions, objects, thesis, significance of the study, compass, and crucial delineations. It also provides an overview of the overall structure of the thesis.

Chapter 2 presents the theoretical background and affiliated work, covering crucial generalities similar as Artificial Intelligence (AI), Natural Language Processing (NLP), and recommendation systems. It also reviews former studies and identifies the exploration gap.

Chapter 3 describes the proposed methodology of the AIRSS system. It explains the dataset, data preprocessing way, and textbook representation ways, including TF-IDF and BERT. It also presents similarity dimension styles similar as cosine similarity and Euclidean distance used for generating recommendations.

Chapter 4 presents experimental results and discussion. It evaluates the performance of the system and compares different approaches to demonstrate the effectiveness of the proposed recommendation system.

Chapter 5 concludes the thesis by recapitulating the crucial findings and benefactions. It also provides recommendations for unborn work and implicit advancements to the system.

Chapter 02

Background and Related Work

2.1 Introduction

This chapter presents the abecedarian generalities related to Artificial Intelligence (AI), recommendation systems, and Natural Language Processing (NLP). Understanding these generalities is essential for establishing a solid theoretical foundation for the proposed study.

In addition, this chapter reviews former studies in the field of AI-grounded recommendation systems, particularly those applied in educational surrounds and course selection. This review helps in relating the strengths and limitations of being approaches, as well as pressing current exploration gaps.

The chapter aims to make a comprehensive theoretical background that supports the design and development of the proposed AIRSS system. It also provides a clear link between being exploration and the proposed result by relating the gaps addressed in this study.

From this perspective, establishing a strong theoretical foundation is pivotal for icing the effectiveness, delicacy, and applicability of the proposed recommendation system.

2.2 Artificial Insights (AI)

Artificial Intelligence (AI) refers to the capability of machines to pretend to be mortal intelligence processes, similar as literacy, logic, and decision- timber. It has become one of the most transformative technologies in ultramodern education due to its capability to replicate intelligent mortal gusto and automate complex tasks.

In educational surrounds, AI is extensively used to enhance literacy guests and support intelligent decision-making systems. It enables the analysis of large volumes of data and the birth of meaningful perceptivity, which can be employed to ameliorate the quality and effectiveness of educational processes (Russell & Norvig, 2021).

Likewise, AI plays a critical part in the development of recommendation systems by assaying stoner data and generating substantiated suggestions. These systems influence AI ways to understand stoner preferences, prognosticate requirements, and give applicable recommendations.

In this study, AI serves as the foundational technology for the proposed AIRSS system, enabling the generation of accurate and individualized training course recommendations grounded on druggies' textual inputs and behavioral patterns.

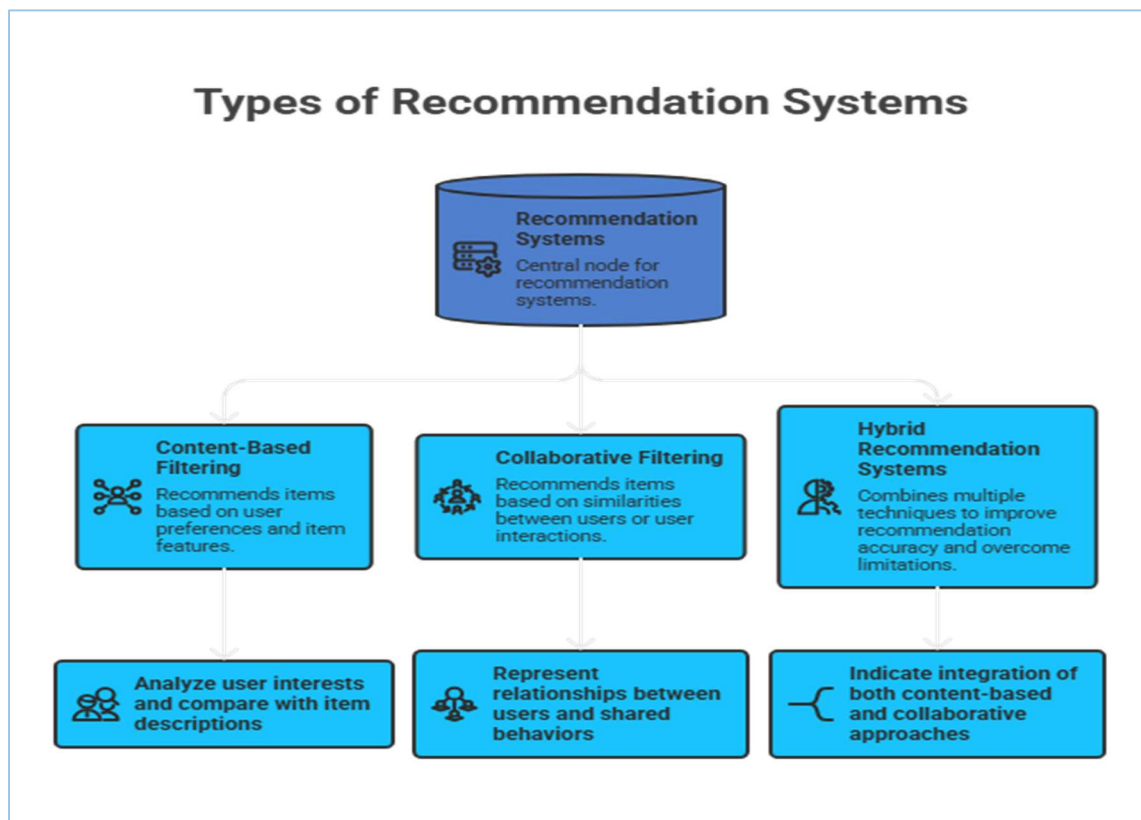
2.3 Recommendation Systems

Recommendation systems are intelligent systems designed to suggest applicable particulars to druggies grounded on their preferences, gusto.

, and commerce history. These systems play a pivotal part in simplifying decision-making processes, especially in surroundings characterized by a large number of available options.

In educational surrounds, recommendation systems are extensively used to suggest courses, training programs, and literacy coffers. Their operation enhances substantiated literacy by helping druggies identify suitable openings aligned with their interests and career pretensions.

Figure 1: Types of Recommendation Systems



This figure illustrates the main types of recommendation systems, including content- predicated, collaborative filtering, and cold- thoroughbred approaches.

Among the various approaches, content- predicated recommendation systems calculate on assaying user preferences and matching them with point descriptions. This approach is particularly suitable for educational surroundings where user data may be limited(Pazzani & Billsus, 2007). It enables the system to capture individual interests and give applicable recommendations.

In distinction, cold- thoroughbred recommendation systems combine multiple ways, analogous as content- predicated and collaborative filtering, to meliorate delicacy and overcome the limitations of individual approaches (Tolety & Prasad, 2022). Integrating multiple styles can lead to farther robust and reliable recommendation issues.

In this study, the proposed AIRSS system adopts a content- predicated approach enhanced with advanced Natural Language Processing (NLP) ways, including TF- IDF and BERT, along with similarity dimension styles to induce accurate and personalized course recommendations.

2.4 Natural Language Processing (NLP)

Natural Language Processing(NLP) is a fundamental branch of Artificial Intelligence that focuses on assaying and understanding textual data. It enables machines to interpret mortal language in a meaningful way, allowing systems to prize perceptivity and support intelligent decision- timber.

In the terrain of recommendation systems, NLP plays a critical part in processing user inputs and course descriptions. By applying NLP ways, the system can more understand user preferences and directly match them with applicable traening content. This enhances the system's capability to deliver substantiated and meaningful recommendations.

Among the used ways, TF- IDF is employed to transform textual data into numerical representations predicated on the significance of words within a document. This approach helps in relating significant terms and lodging useful features from text data.

In addition, similarity measures, particularly cosine similarity, are used to estimate the degree of similarity between user input and course descriptions. This enables the system to rank courses according to their connection and alignment with user interests. The integration of text representation ways analogous as TF- IDF and advanced models like BERT, combined with similarity calculations, significantly improves the delicacy and quality of recommendations.

Figure 2: Intelligent Training Course Selection Process

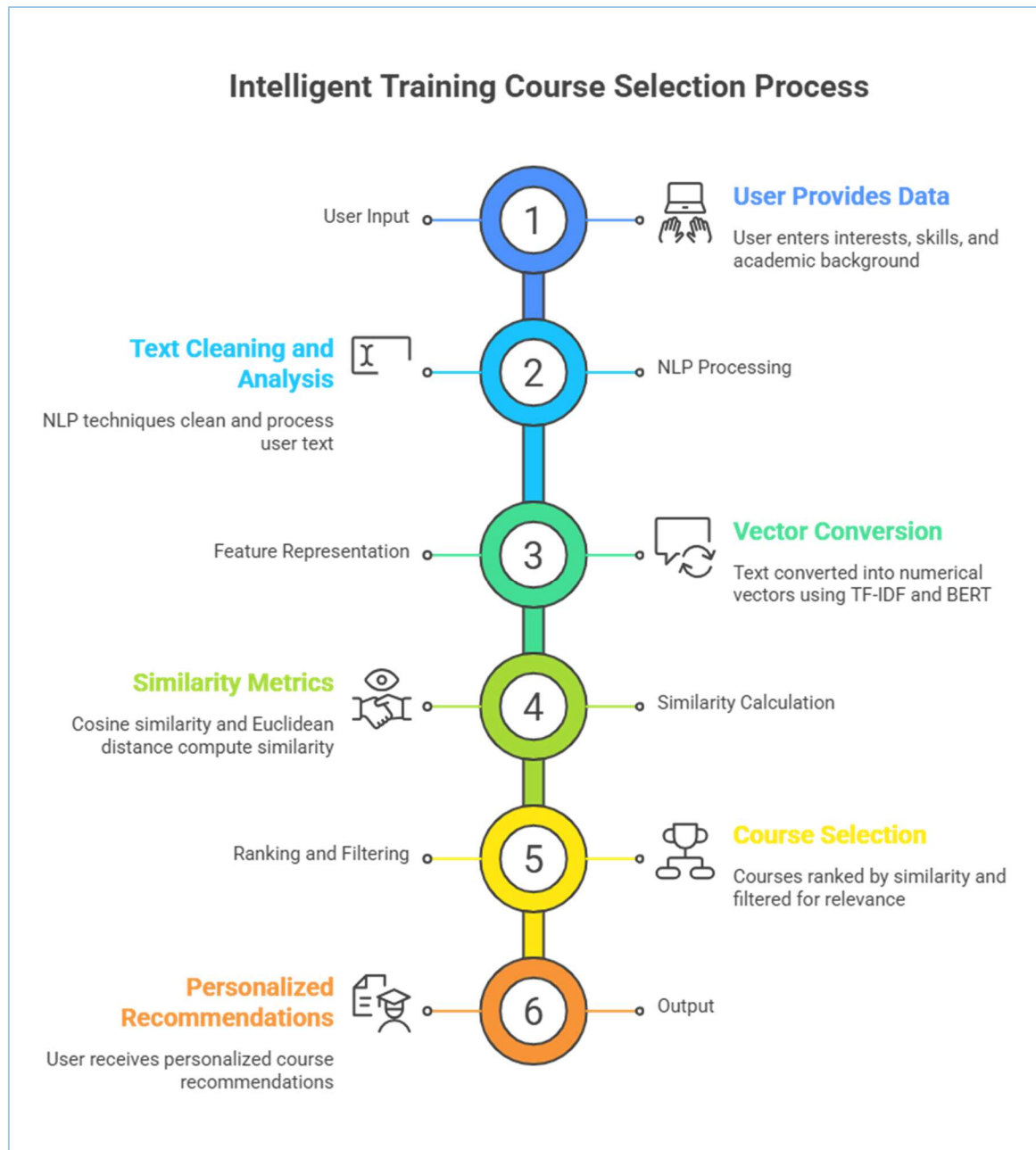


Figure 2 illustrates the overall workflow of the intelligent training course selection process. It shows how user input is collected and reused using NLP ways, followed by converting text into numerical vectors through point representation styles analogous as TF- IDF and BERT. The system also computes similarity using distance criteria, ranks the courses, and generates personalized recommendations.

This process demonstrates a structured and effective channel that transforms user textual data into practicable recommendations, enhancing user experience and supporting informed decision-timber.

This figure outlines in the general preparation of brilliantly preparing course determination. It illustrates how the customer gives input in the frame of erudite interface, how the system analyzes this input exercising NLP strategies, and how it produces a positioned list of recommended courses grounded on applicability.

The critic accepts that this preparation reflects a orderly and productive approach to changing customer input into important proffers, in this manner upgrading decision- timber and customer involvement.

2.5 Related Work

Several studies have explored the operation of artificial intelligence- grounded recommendation systems in educational surroundings, reflecting the growing significance of intelligent results in ultramodern literacy systems.

Akbar et al.(2023) demonstrated that recommendation systems can enhance decision- making processes and meliorate user satisfaction by effectively assaying user preferences. This highlights the critical part of understanding user interests in perfecting system performance. also, Cha et al.(2024) showed that AI-predicated systems support multiple stages of course selection, including searching, assessing, and final decision- timber, indicating the comprehensive part of AI in guiding stoners throughout the entire process.

In addition, Tani et al.(2021) emphasized the significance of recommendation systems in supporting lifelong knowledge and aligning educational choices with labor demands. This alignment is essential for perfecting graduates' readiness for employment. Likewise, Mentec(2023) stressed the significance of soluble recommendation systems in enhancing user trust and translucence, which are pivotal factors for adding user acceptance of AI- driven results.

Outbalance et al.(2023) handed a comprehensive review of artificial intelligence ways used ine- learning recommendation systems, offering precious perceptivity into the diversity of being approaches. Likewise, Salim et al.(2025) mooted recent advancements in substantiated

knowledge and linked several disquisition gaps in recommendation systems for MOOCs, which supports the need for further development in this area.

also, Tolety and Prasad(2022) proposed an cold- thoroughbred recommendation system that combines content- predicated and collaborative filtering ways, achieving significant advancements in performance and delicacy. This suggests that integrating multiple approaches can enhance system effectiveness. Lops et al.(2019) also talked over recent trends in content- predicated recommendation systems, specifically in manual representation and explainability, which are directly applicable to this study.

the foundational work of Pazzani and Billsus(2007) provides the theoretical base for content- predicated recommendation systems, supporting the abstract frame of the proposed AIRSS system.

2.6 Summary of Previous Studies

Table 2- 1 presents an structured summary of the most applicable former studies in the field of educational recommendation systems. It highlights the artificial intelligence ways used in each study, along with their pivotal contributions and connection to the proposed AIRSS system.

Organizing former studies in a irregular format facilitates clearer comparison and deeper understanding of being approaches. As shown in Table 2- 1, former disquisition has employed a wide range of ways, including content- predicated filtering, collaborative filtering, crossbred styles, and Natural Language Processing(NLP). These approaches have demonstrated strong effectiveness in perfecting decision- timber, enhancing user satisfaction, and supporting personalized knowledge surroundings.

The diversity of these styles reflects the rapid-fire- fire elaboration of recommendation systems and their adding significance in the educational sphere. Several studies emphasize the benefits of combining multiple ways to meliorate recommendation delicacy, while others concentrate on explainability and translucence to enhance user trust and system acceptance.

Despite these advancements, certain limitations remain. multitudinous being systems do n't adequately address the specific conditions of university graduates, particularly in aligning recommendations with original labor request conditions. In addition, limited attention has been given to using textual data for generating personalized recommendations.

To address these gaps, the proposed AIRSS system adopts a content- predicated recommendation approach supported by NLP ways. It utilizes TF- IDF and BERT for text representation, along with similar measures analogous as cosine similarity and Euclidean distance, to give accurate and personalized course recommendations adapted to user interests.

Table (2-1): Summary of Previous Studies Related to Educational Recommendation Systems

#	Reference	Title	Authors	Study Summary	Methodologies / Techniques	Contribution to AIRSS
1	Akbar et al. (2023)	The Role of Artificial Intelligence-Based Recommendation Systems in Selection of Courses for Students	Akbar, Z.; Sopandi, E.; Badruzzaman, B.; Khalik, M. F.	Examines the role of AI-based recommender systems in supporting course selection, focusing on user satisfaction and decision-making effectiveness.	Quantitative Survey, Descriptive Analysis	Confirms the effectiveness of recommender systems in improving educational decision-making, aligning with AIRSS objectives.
2	Cha et al. (2024)	The Impact of AI-Based Course-Recommender System on Students' Course-Selection Decision-Making Process	Cha, S.; Loeser, M.; Seo, K.	Explores how AI-based systems support different stages of decision-making (search, evaluation, selection).	Qualitative Method, Thematic Analysis	Supports AIRSS as an intelligent assistant during evaluation and selection stages.
3	Tani et al. (2021)	Recommendation Systems and AI Solutions Guiding Open (Life-Long) Learning	Tani, P. et al.	Links recommender systems with lifelong learning and labor market needs.	AI-based Matching, Recommender Systems	Supports AIRSS focus on lifelong learning and career-oriented recommendations.
4	Mentec (2023)	Explainable Job Recommender Systems for Recruiters and Consulting Companies	Mentec, F.	Focuses on explainable systems and improving user trust and transparency.	NLP, Semantic Similarity, Explainable AI, Advanced Text Representation	Supports explainability and transparency in AIRSS.

5	Oubalahcen et al. (2023)	The Use of AI in E-Learning Recommender Systems: A Comprehensive Survey	Oubalahcen, H.; Tamym, L.; El Ouadghiri, M. D.	Provides a comprehensive survey of AI techniques in e-learning systems.	AI Techniques, NLP, Deep Learning Models (e.g., BERT)	Supports integration of advanced NLP and BERT in AIRSS.
6	Tolety & Prasad (2022)	Hybrid Content and Collaborative Filtering Based Recommendation System for E-Learning Platforms	Tolety, V. B. P.; Prasad, E. V.	Proposes a hybrid recommender combining content-based and collaborative filtering.	TF-IDF, Content-Based Filtering, Collaborative Filtering, Text Representation	Supports hybrid and content-based design used in AIRSS.
7	Salim et al. (2025)	Advancements in Personalized Learning: A Systematic Review of Recommendation Systems in MOOCs	Salim, A. I. M. et al.	Reviews personalized recommender systems and identifies research gaps.	PRISMA, Content-Based, Hybrid Approaches	Supports personalization and highlights gaps addressed by AIRSS.
8	Mallik & Gangopadhyay (2023)	Proactive and Reactive Engagement of Artificial Intelligence Methods for Education	Mallik, S.; Gangopadhyay, A.	Reviews AI applications in education across different learning stages.	Literature Review	Provides theoretical support for integrating AI in AIRSS.
9	Lops et al. (2019)	Trends in Content-Based Recommendation	Lops, P.; Jannach, D.; Musto, C.; Bogers, T.; Koolen, M.	Discusses trends in content-based systems including text representation.	Text Representation, NLP, Explainable Recommendation Systems	Supports use of NLP and BERT in AIRSS.
10	Pazzani & Billsus (2007)	Content-Based Recommendation Systems	Pazzani, M. J.; Billsus, D.	Provides foundational concepts of content-based recommendation systems.	Conceptual Models	Provides theoretical foundation for AIRSS design.
11	Stewart (2023)	Evaluating Organizational Success of an AI-Based Recommender System at a Higher Education Institution	Stewart, C. P.	Evaluates recommender systems using organizational success metrics.	Mixed Methods, Delone & McLean IS Success Model	Supports evaluation and user satisfaction in AIRSS.

Table 2- 1 presents a relative summary of former studies in the field of educational recommendation systems. It highlights the methodologies used, including content- grounded filtering, cold-blooded approaches, and Natural Language Processing ways similar as TF-IDF and BERT. The table also demonstrates how these studies contribute to the development of the proposed AIRSS system, particularly in perfecting personalization, delicacy, and decision- timber.

2.7 Comparative Analysis:

This section presents a relative analysis of the most applicable studies in the field of AI-predicated recommendation systems, particularly those applied in educational surroundings. The comparison focuses on pivotal aspects analogous as the type of study, datasets used, methodologies and algorithms applied, and the main contributions of each work.

Conducting such a comparison is essential for furnishing a structured understanding of being disquisition sweats. It offers a clear overview of different approaches and highlights the diversity of ways used in developing recommendation systems.

The purpose of this analysis is to identify the strengths and limitations of former studies and to clarify how they differ from the proposed AIRSS system. By examining these aspects, the study highlights gaps in the literature, particularly in terms of personalization, contextual adaptation, and the use of advanced text representation ways analogous as BERT.

likewise, this comparison emphasizes the significance of integrating multiple ways, including Natural Language Processing(NLP), TF- IDF, BERT, and similarity measures analogous as cosine similarity and Euclidean distance, to meliorate recommendation delicacy and persuasiveness.

Table 2-2: Comparative Analysis of Previous Studies and Proposed AIRSS System

Study	Type	Dataset	Method / Algorithm	Key Contribution
Study 1	Survey Study	Questionnaire (20 students)	General AI-based Recommendation System	Demonstrated student satisfaction and trust in

				recommendation systems
Study 2	Survey + Interview	24 students	AI-based Recommendation System (Conceptual)	Highlighted the importance of user interaction in course selection
Study 3	Applied System	ESCO + Course Data	NLP + Decision Tree	Matched user skills with suitable courses for career development
Study 4	Applied System	Resume + Job Dataset	Embedding + Cosine Similarity	Improved job candidate matching using similarity techniques
Study 5	Review Study	Multiple datasets	Machine Learning (ML) & Deep Learning (DL)	Reviewed AI techniques used in e-learning recommendation systems
Study 6	Hybrid System	Student Activity Data	Collaborative Filtering + Content-Based + TF-IDF	Improved recommendation accuracy by combining multiple approaches
Study 7	Systematic Review	MOOC Platforms	Hybrid Methods + Behavioral Analysis	Enhanced learner engagement and course completion rates
Study 8	Review Study	Educational Data	Machine Learning Models	Applied AI techniques to support decision-making in education
Study 9	Review Study	Multimedia datasets	Content-Based + Deep Learning	Introduced advanced recommendation techniques using rich data

Study 10	Theoretical Study	Item datasets	TF-IDF + Vector Space Models	Provided foundational understanding of content-based recommendation
Study 11	Evaluation Study	Student Survey	AI + Statistical Models	Evaluated system performance and user satisfaction
AIRSS (Proposed)	Applied System	Course Dataset (Kaggle)	TF-IDF + BERT + Cosine Similarity + Euclidean Distance	Provides accurate and personalized course recommendations based on user interests and semantic understanding

Table 2- 2 presents a relative analysis of former studies and the proposed AIRSS system grounded on pivotal aspects analogous as study type, dataset, methodologies, and contributions.

As shown in the table, utmost former studies have concentrated on traditional approaches analogous as content- predicated filtering, collaborative filtering, or crossbred styles. These approaches have demonstrated effectiveness in perfecting recommendation delicacy and supporting decision-making processes. still, multitudinous of these systems calculate on limited user data or leave deep semantic understanding of textual information.

In addition, several studies emphasize the significance of personalization, user commerce, and explainability in recommendation systems. Despite these advancements, there is still a gap in integrating advanced text representation models with similarity- predicated ways to achieve advanced delicacy and contextual understanding.

The proposed AIRSS system addresses these limitations by combining TF- IDF and BERT for text representation with similarity measures analogous as cosine similarity and Euclidean distance. This integration enables the system to capture both keyword- predicated and semantic connections, performing in more accurate and personalized course recommendations.

Therefore, AIRSS provides a more comprehensive and effective approach compared to former systems, particularly in handling textual data and aligning recommendations with user interests and career pretensions.

2.8 Study Gap

Despite the rapid-fire- fire development of recommendation systems, several limitations still live in current approaches.

First, the systems primarily concentrate on scholars within academic surroundings, with limited attention given to university graduates and their specific conditions in concluding suitable training courses aligned with their career paths.

Alternate, there is a lack of recommendation systems specifically adapted to the Saudi terrain, particularly in relation to original labor request conditions and cultural considerations.

Third, the use of Natural Language Processing(NLP) for assaying stoner interests and textual data remains limited in numerous being systems, which reduces the capability to induce accurate and meaningful recommendations.

Eventually, numerous systems warrant explainability and advanced personalization capabilities, making it delicate for druggies to understand and trust the recommendations handed.

To address these gaps, this study proposes an intelligent recommendation system(AIRSS) that leverages NLP ways, including TF- IDF and BERT, along with similarity measures similar as cosine similarity and Euclidean distance. The system aims to give accurate, substantiated, and resolvable course recommendations grounded on druggies' textual inputs.

2.9 Summary

This chapter presented the theoretical foundation of Artificial Intelligence(AI), recommendation systems, and Natural Language Processing(NLP). It also reviewed applicable former studies and linked the exploration gaps addressed by this study.

The analysis of former work stressed the need for farther substantiated, terrain-alive recommendation systems that concentrate on university graduates and effectively use textual data. In addition, it emphasized the significance of integrating advanced ways analogous as deep knowledge models and similarity- predicated approaches to meliorate recommendation quality.

predicated on these findings, the proposed AIRSS system was introduced as a result that combines text representation styles, including TF- IDF and BERT, with similarity measures analogous as cosine similarity and Euclidean distance to induce accurate and personalized recommendations.

The coming chapter presents the proposed methodology, including data preprocessing, point birth, and similarity computation, along with the performance details of the recommendation process.

Chapter 03

Proposed Approach (Methodology)

3.1 Introduction

This chapter presents the methodology used to develop the proposed AI-grounded recommendation system (AIRSS) for opting suitable training courses.

A structured and methodical approach is espoused to insure the effectiveness and trustability of the system. The chapter outlines the crucial stages involved in erecting the recommendation system, including data preprocessing, point birth, similarity calculation, and the recommendation generation process.

In particular, the system leverages Natural Language Processing (NLP) ways to reuse textual data and convert it into meaningful representations. Point birth is performed using styles similar as TF-IDF and BERT, while similarity is reckoned using measures similar as cosine similarity and Euclidean distance.

Easily defining these way contributes to perfecting system performance and achieving accurate and individualized recommendations. Integrating these factors within a unified frame enhances the system's capability to dissect stoner inputs and induce applicable recommendations aligned with stoner interests and career pretensions.

3.2 System Overview

The proposed AIRSS system is designed to recommend suitable training courses by assaying stoner input and comparing it with course data stored in the dataset.

The recommendation process consists of the following main stages

- ❖ The stoner provides input in the form of interests, chops, or preferences.
- ❖ The input textbook is preprocessed and converted into a suitable format.
- ❖ point birth is performed using textbook representation ways similar as TF- IDF and BERT.
- ❖ The similarity between the stoner input and course descriptions is reckoned using cosine similarity and Euclidean distance.
- ❖ The system generates and displays the top recommended courses(Top- N).

Figure 3 illustrates the overall workflow of the proposed AIRSS system. The process begins with stoner input, followed by textbook preprocessing. The system also applies TF- IDF and BERT for point birth and computes similarity using cosine similarity and Euclidean distance to measure the applicability between stoner input and course descriptions. Eventually, the system generates substantiated course recommendations grounded on similarity scores.

Figure 3: AIRSS System Workflow

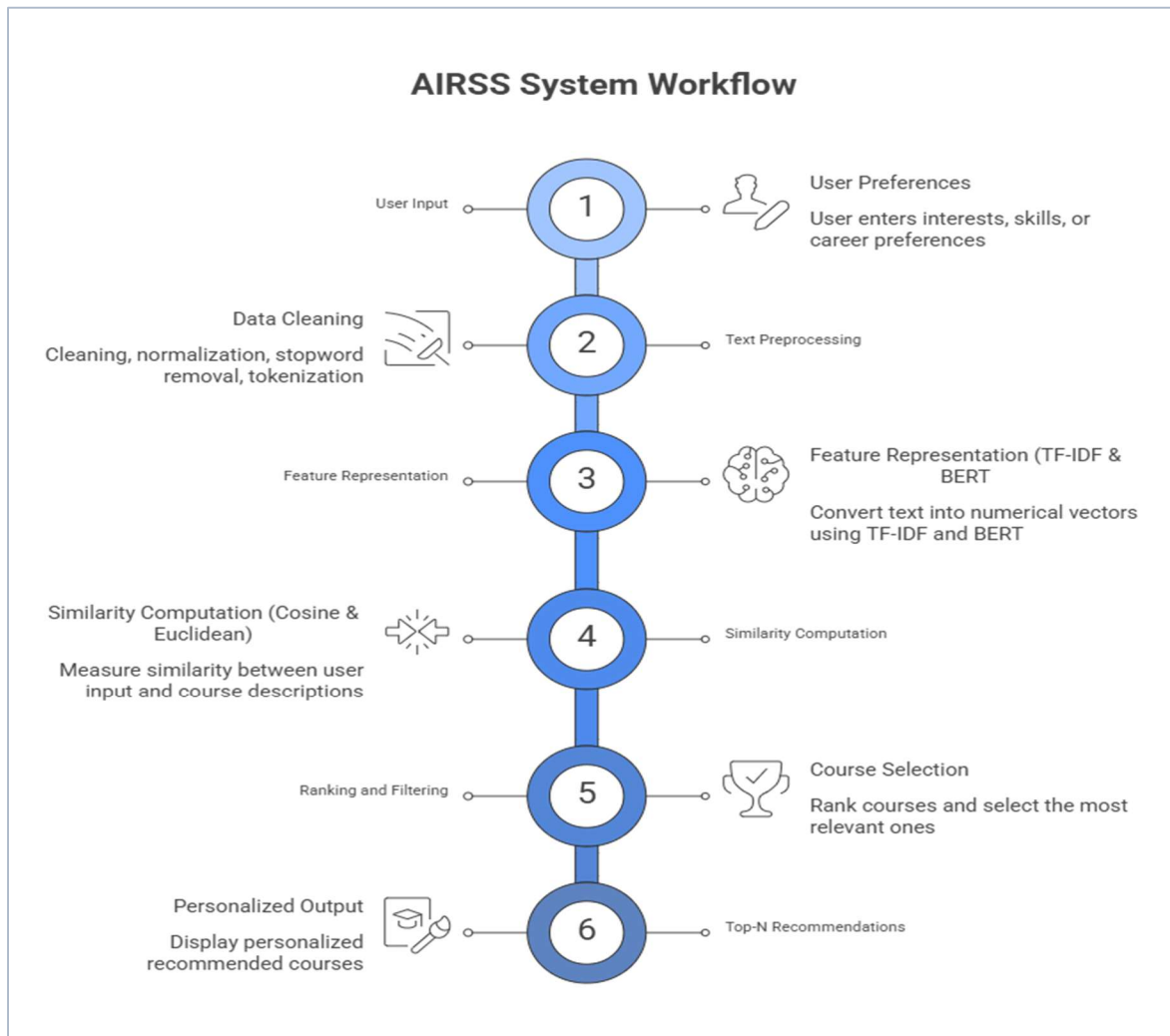


Figure 3 illustrates the workflow of the proposed AIRSS system. The process begins with stoner input, followed by textbook preprocessing and point representation using TF- IDF and BERT.

The system also computes similarity using cosine similarity and Euclidean distance, ranks the courses, and eventually generates substantiated Top- N recommendations.

3.3 Dataset Description

The proposed AIRSS system is erected using a dataset that contains information about training courses. The dataset was precisely preprocessed to insure its felicity for analysis and recommendation tasks.

The dataset includes the following crucial attributes

- **Course ID** A unique identifier for each course
- **Description** Detailed textual description of the course content
- **Category** The main order or field of the course
- **Tags:** Keywords associated with each course
- **Cleaned Text Fields** Preprocessed performances of the description, order, and markers(e.g., description_clean, category_clean, tags_clean)
- **Combined Text** A unified textbook representation created by incorporating applicable fields, used for point birth
- **Similarity Scores** reckoned values used to measure the applicability between stoner input and course descriptions for ranking recommendations

This dataset forms the foundation of the AIRSS system, where textual data is anatomized using Natural Language Processing(NLP) ways to match stoner interests with applicable training courses. The use of combined textual features enhances the system's capability to induce accurate and individualized recommendations.

3.4 Data Preprocessing

To ameliorate the quality of the textual data and insure its felicity for analysis, several preprocessing way were applied before point birth.

The main preprocessing way include

- Removing punctuation and special characters barring gratuitous symbols that do n't contribute to the meaning of the textbook

- Converting textbook to lowercase homogenizing textbook to insure thickness during processing
- Removing stopwords barring common words(e.g., “ the ”, “ and ”) that do n't add significant value
- drawing inapplicable or noisy data Removing gratuitous or indistinguishable information to ameliorate data quality
- Tokenization Splitting textbook into individual words or commemoratives for farther processing

These preprocessing way help in transubstantiating raw textual data into a clean and structured format, which enhances the effectiveness of point birth ways similar as TF- IDF and BERT. As a result, the system becomes further able of generating accurate and meaningful recommendations.

3.5 Feature Extraction Using TF-IDF

The TF- IDF(Term frequency – Inverse Document frequency) fashion was used to convert textual data into numerical representations grounded on the significance of words within a document relative to the entire dataset.

$$TF\text{-}IDF(t,d) = TF(t,d) \times IDF(t)$$

Where

TF(Term frequency) Measures how constantly a term appears in a document

IDF(Inverse Document frequency) Measures the significance of a term across the dataset

This fashion assigns advanced weights to important words that appear constantly in a specific document but are less common across other documents. As a result, TF- IDF helps in relating the most applicable terms for representing course descriptions.

In this study, TF- IDF is applied to the combined textual data(e.g., description, order, and markers) to induce point vectors that represent each course. These vectors are latterly used in similarity calculations to match stoner input with applicable courses.

Figure 4: Text Representation Using TF-IDF

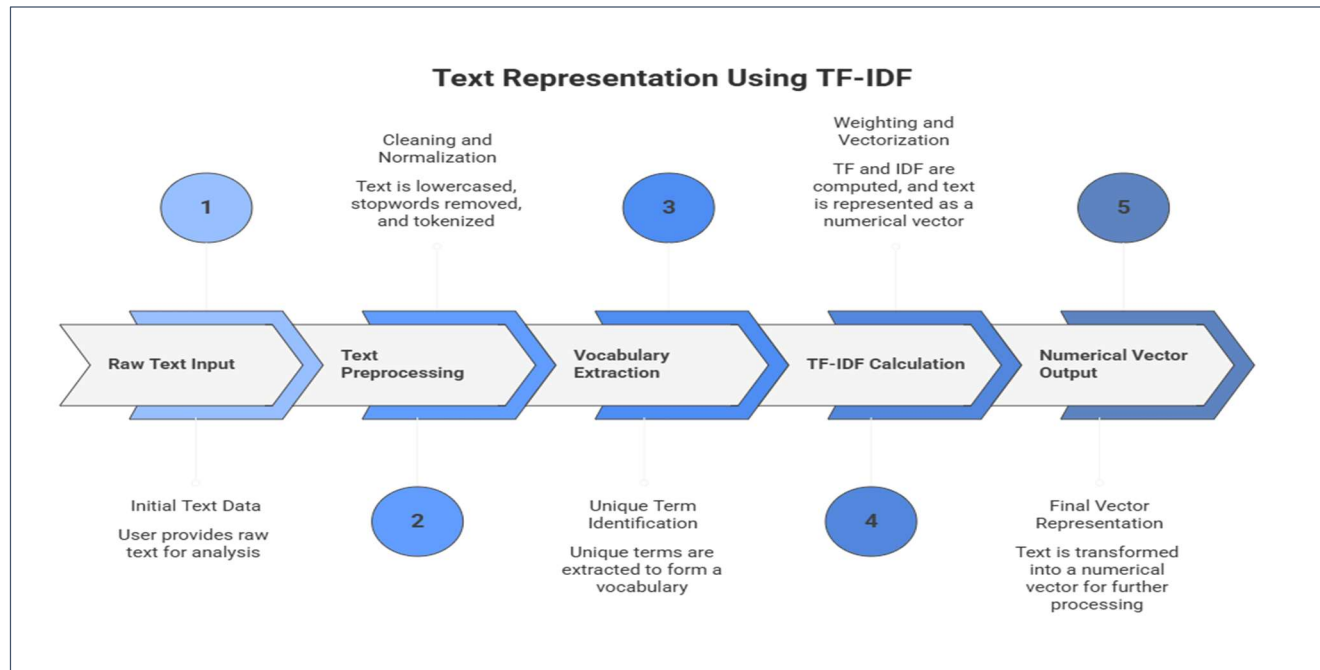


Figure 4 illustrates the process of transubstantiating textual data into numerical vectors using TF-IDF. The process begins with raw textbook input, followed by preprocessing way similar as drawing and tokenization. also, a vocabulary of unique terms is uprooted, and TF- IDF weights are calculated. Eventually, the textbook is represented as a numerical vector, which is used for similarity calculation in the recommendation system.

3.6 Feature Extraction Using BERT

In addition to TF- IDF, the proposed AIRSS system utilizes BERT(Bidirectional Encoder Representations from Mills) as an advanced fashion for textbook representation.

BERT is a deep literacy model developed for Natural Language Processing(NLP) tasks, which is able of understanding the contextual meaning of words within a judgment . Unlike traditional styles similar as TF- IDF, which calculate on word frequency, BERT captures semantic connections by considering the environment in which words appear.

In this study, BERT is applied to the combined textual data(including course descriptions, orders, and markers) to induce thick vector representations, appertained to as embeddings. These embeddings render the semantic meaning of the textbook, allowing the system to more understand stoner input and course content.

The metamorphosis performed by BERT can be conceptually represented as

$$E=BERT(T)$$

Where

T represents the input textbook

E represents the performing embedding vector

The use of BERT enhances the system's capability to identify meaningful parallels between stoner preferences and course descriptions, indeed when different words with analogous meanings are used. This significantly improves the delicacy and applicability of the recommendations generated.

By integrating both TF- IDF and BERT, the AIRSS system benefits from combining keyword-grounded representation with deep semantic understanding, performing in a more robust and effective recommendation process.

Figure 5: Text Representation Using BERT

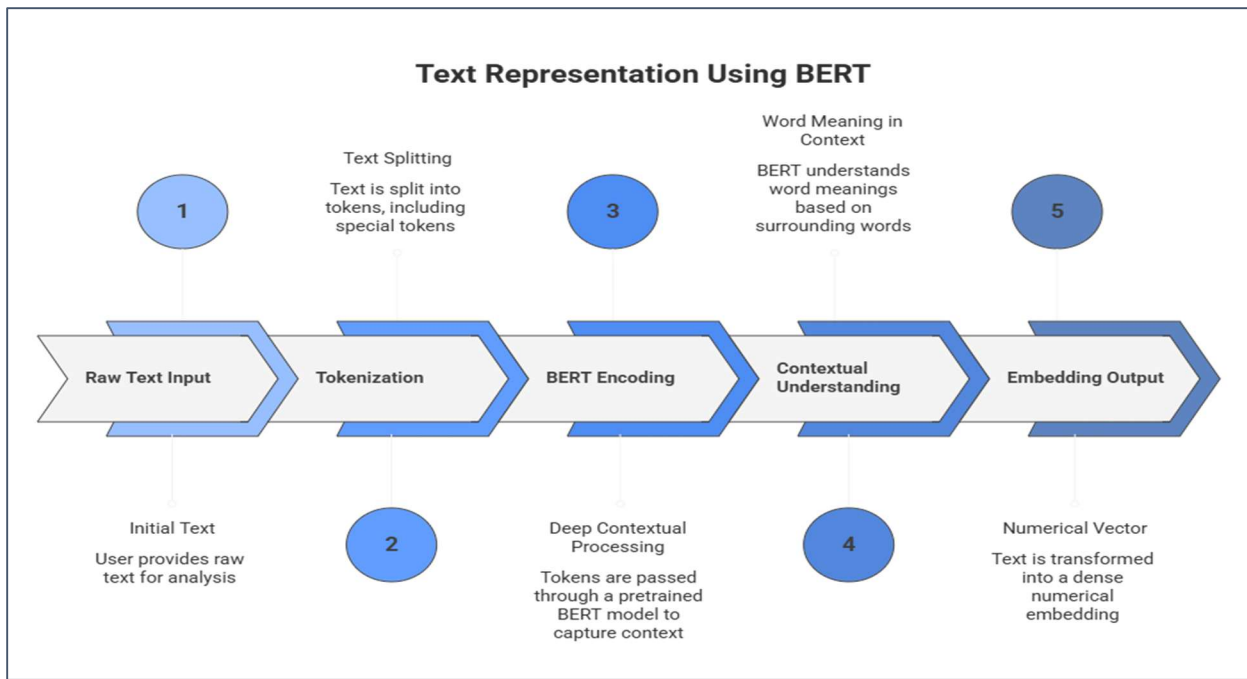


Figure 5 illustrates the process of transubstantiating textual data into contextual embeddings using BERT. The process begins with tokenizing the input textbook, followed by passing the commemoratives through a pretrained BERT model. BERT captures the contextual meaning of words using multiple layers, generating thick vector representations that render semantic information. These embeddings are also used for similarity calculation in the recommendation system.

3.7 Similarity Computation

Similarity Calculation is a abecedarian step in the AIRSS system, as it measures the degree of similarity between stoner input and course representations. This process enables the system to identify the most applicable training courses grounded on stoner interests.

In this study, two similarity dimension ways are used cosine similarity and Euclidean distance.

Cosine similarity measures the similarity between two vectors by calculating the cosine of the angle between them. It's particularly effective for textual data, as it focuses on the direction of the vectors rather than their magnitude.

Cosine Similarity

$$\text{Cosine Similarity} = \frac{A \cdot B}{\|A\| \times \|B\|}$$

Where

A and B represent vector representations of user input and course data

On the other hand, **Euclidean distance** measures the distance between two vectors in a multidimensional space. Smaller distances indicate higher similarity between the compared texts.

$$d(A, B) = \sqrt{\sum_{i=1}^n (A_i - B_i)^2}$$

By combining both cosine similarity and Euclidean distance, the system enhances its capability to directly measure similarity and induce further dependable recommendations.

3.8 Recommendation Mechanism

The recommendation medium in the proposed AIRSS system follows a structured and methodical process to induce substantiated course recommendations grounded on stoner input.

The medium integrates multiple factors, including textbook preprocessing, point representation, similarity calculation, and ranking, to insure accurate and applicable recommendations.

The process can be epitomized as follows

- The stoner provides input in the form of interests, chops, or career preferences.
- The input textbook is preprocessed to remove noise and regularize the data.
- The reused textbook is converted into numerical representations using both TF- IDF and BERT, landing both keyword- grounded and semantic features.
- Similarity scores are reckoned between the stoner input and course descriptions using cosine similarity and Euclidean distance.
- The courses are ranked in descending order grounded on their similarity scores.
- The system generates and displays the Top- N most applicable course recommendations to the stoner.

- The final stage of the recommendation mechanism involves opting the Top- N courses with the loftiest similarity scores, icing that the recommendations are largely applicable, substantiated, and aligned with the stoner's interests and career pretensions.

By combining traditional statistical styles with advanced deep literacy ways, the AIRSS system achieves a more robust and effective recommendation process compared to conventional approaches.

3.9 System Implementation

The proposed AIRSS system was enforced using a set of extensively used programming tools and libraries to insure effectiveness, scalability, and ease of development.

The perpetration terrain includes the following factors

- Python programming language for developing the system sense and integrating all factors
- Scikit- learn library for enforcing TF- IDF vectorization and similarity calculations
- Mills(BERT) for generating contextual textbook embeddings and enhancing semantic understanding
- Pandas library for data manipulation and preprocessing
- NumPy library for numerical calculations
- Streamlit frame for erecting an interactive stoner interface

These tools were integrated to develop an effective and interactive system able of recycling stoner input, performing advanced textbook analysis, and generating accurate and individualized course recommendations.

3.10 Summary

This chapter presented the methodology used to develop the proposed AIRSS system. It described the main stages of the system, starting from data preprocessing, followed by point birth using TF- IDF and BERT, and the operation of similarity measures analogous as cosine similarity and Euclidean distance to estimate the relationship between user input and course descriptions.

The chapter also explained the recommendation medium and system performance. The system relies on preprocessed textual data, which improves effectiveness and reduces response time when generating personalized recommendations.

Overall, the integration of traditional text representation ways with advanced deep knowledge models enhances the system's capability to deliver accurate, applicable, and terrain-alive course recommendations.

Chapter 04

Experimental Results and Discussion

4.1 Introduction

This chapter presents the experimental results of the proposed AI- grounded recommendation system (AIRSS). It evaluates the system's performance in generating applicable and individualized course recommendations grounded on stoner input.

The chapter also examines the effectiveness of the applied ways, including TF- IDF and BERT for textbook representation, as well as cosine similarity and Euclidean distance for measuring similarity. These styles are anatomized to determine their impact on perfecting recommendation delicacy and applicability.

likewise, this chapter provides perceptivity into the system's geste.

, compares the performance of different models, and discusses the overall effectiveness of the proposed approach.

4.2 Experimental Setup

The AIRSS system was enforced using Python and estimated within a Jupyter Tablet terrain. The system was also stationed using Streamlit to give an interactive stoner interface for testing and demonstration.

The dataset used in this study consists of preprocessed course descriptions along with their corresponding textual representations, including gutted textbook and combined features.

The following tools and libraries were used

- Python programming language
- Scikit- learn for TF- IDF vectorization and similarity calculations
- Mills(BERT) for generating contextual embeddings
- Pandas for data manipulation and preprocessing
- NumPy for numerical calculations
- Matplotlib for visualization
- Streamlit for erecting the stoner interface

The trials were conducted by furnishing different stoner inputs and assessing the generated course recommendations using both TF- IDF and BERT- grounded models.

4.3 Evaluation Metrics

To estimate the performance of the recommendation system, multiple evaluation criteria were used to measure the delicacy and effectiveness of the generated recommendations.

In this study, similarity measures similar as cosine similarity and Euclidean distance are used to cipher the applicability between stoner input and course descriptions.

In addition, the system performance is estimated using standard criteria , including

- Precision Measures the proportion of applicable recommended courses out of all recommended courses .
- Recall Measures the proportion of applicable courses that were successfully recommended
- F1- Score Represents the harmonious mean of perfection and recall
- Cosine similarity plays a crucial part in ranking the courses by measuring the similarity between stoner input vectors and course vectors. Advanced similarity values indicate stronger applicability.

The final recommendations are ranked grounded on similarity scores, where the loftiest- ranked courses are considered the most applicable.

4.4 System Interface

The AIRSS system provides an interactive and stoner-friendly interface developed using Streamlit, allowing druggies to input their academic background, interests, and chops in order to admit substantiated course recommendations.

The system enables druggies to elect from multiple recommendation models through a unified interface. These models include combinations of textbook representation ways and similarity measures, videlicet TF- IDF Cosine, TF- IDF Euclidean, BERT Cosine, and BERT Euclidean. This inflexibility allows druggies to compare the performance of different approaches within the same terrain.

Figure 6 Model Selection Interface

EN / AR

AIRSS Course Recommendation System

 Major

programming

 Interests

design

 Skills

data science

Model

☒ TF-IDF + Cosine

☐ TF-IDF + Euclidean

☐ BERT + Cosine

☐ BERT + Euclidean

 Recommend

 AIRSS Graduation Project | Smart Recommendation System 2026

Figure 6 shows the main interface of the AIRSS system, where druggies can enter their major, interests, and chops, and elect one of the four available recommendation models before generating recommendations.

After submitting the input, the system processes the data and generates a ranked list of recommended courses grounded on similarity scores, where the most applicable courses appear at the top. Figure 6 shows the main interface of the AIRSS system, where druggies can enter their

major, interests, and chops, and elect the recommendation model(TF- IDF or BERT) before generating recommendations.

After submitting the input, the system processes the data and generates a ranked list of recommended courses grounded on similarity scores.

Figure 7 TF-IDF + Cosine Recommendation Results

TF-IDF + Cosine

BERT + Cosine

Recommend

★ Top Courses

Programming

learn programming python java coding

★ Score: 100.0%

UI/UX

ui ux design user experience

★ Score: 0.0%

Business

business management leadership

★ Score: 0.0%

Figure 7 illustrates the recommendation results using the TF- IDF model, where the system provides a list of courses ranked according to similarity scores.

Figure 8 BERT + Cosine Recommendation Results

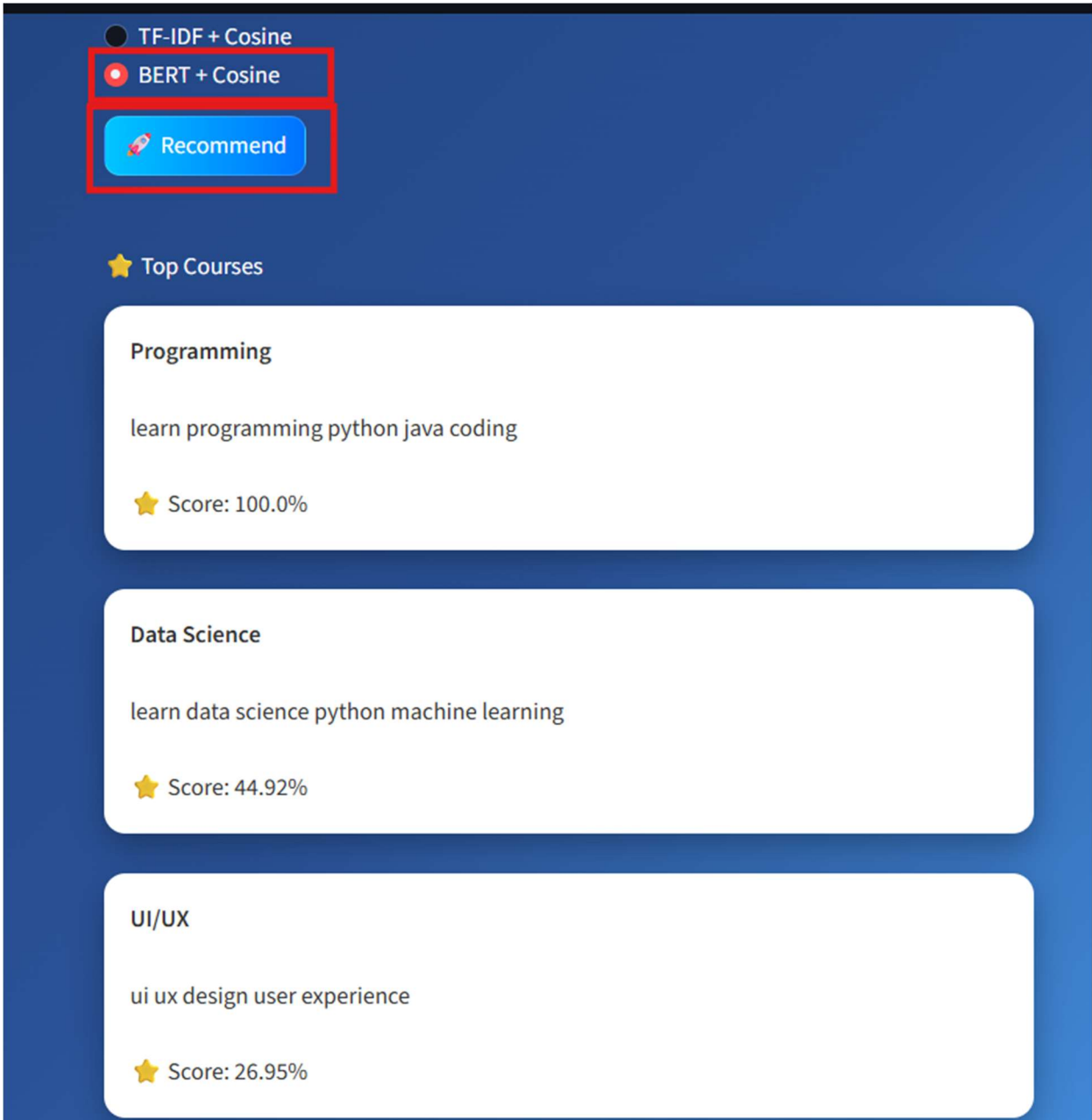


Figure 8 presents the recommendation results using the BERT model, which captures deeper semantic connections and provides farther terrain-alive recommendations.

The interface displays the recommended courses along with their corresponding similarity scores, enabling stoners to easily understand and estimate the connection of each recommendation.

Figure 9 TF- IDF Euclidean Recommendation Results

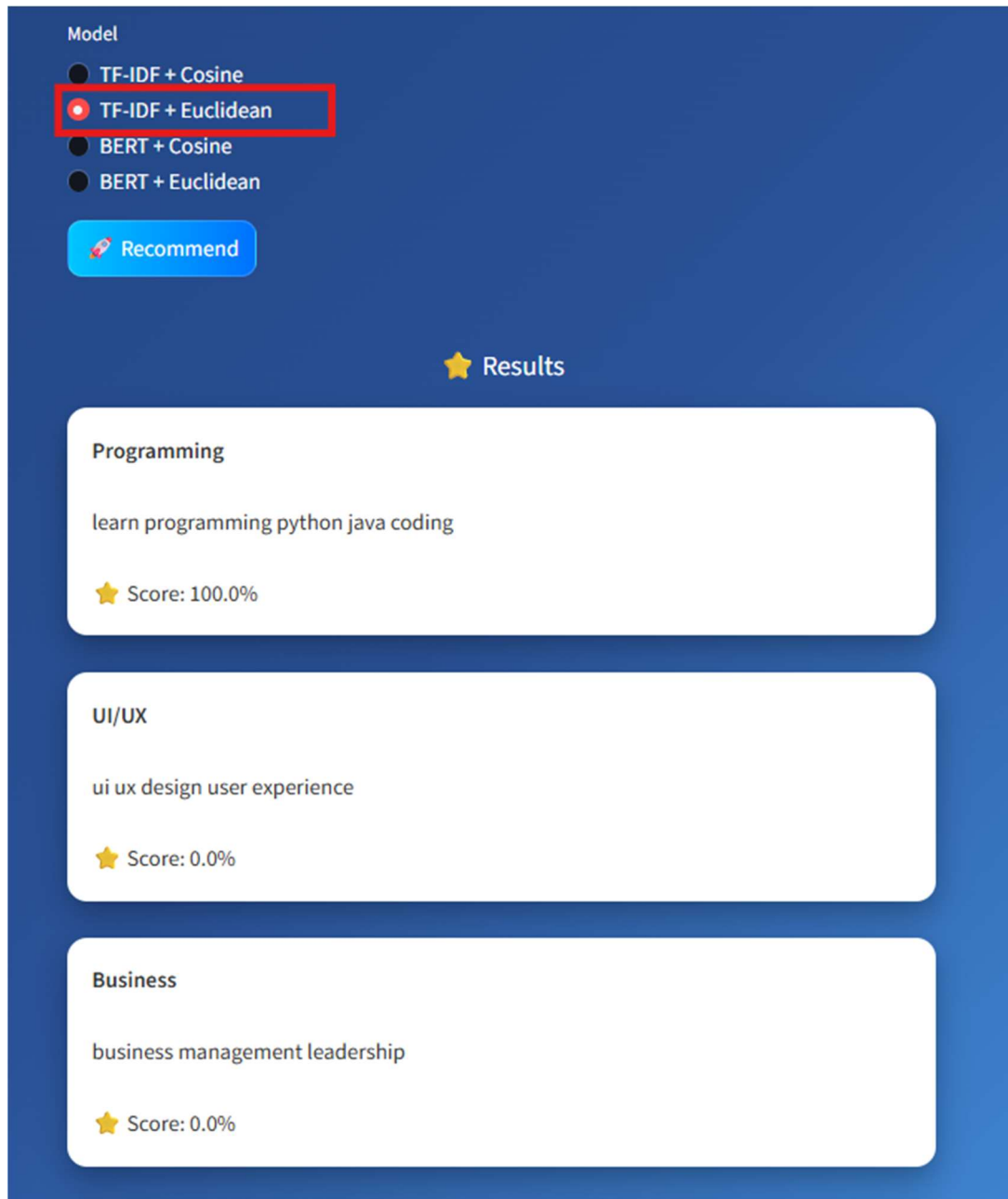


Figure 9 illustrates the recommendation results generated using the TF- IDF Euclidean Distance model. The system computes the distance between the user input vector and course description vectors, also converts these distances into similarity scores to rank the courses.

The results show that the system is suitable to identify applicable courses predicated on keyword matching, where courses sharing similar terms with the user input achieve higher ranking positions.

still, compared to semantic- predicated models, this approach mainly relies on the frequency and circumstance of words rather than contextual meaning. Despite this limitation, the model provides clear and interpretable recommendations, making it suitable for birth comparison.

Figure 10: BERT + Euclidean Recommendation Results

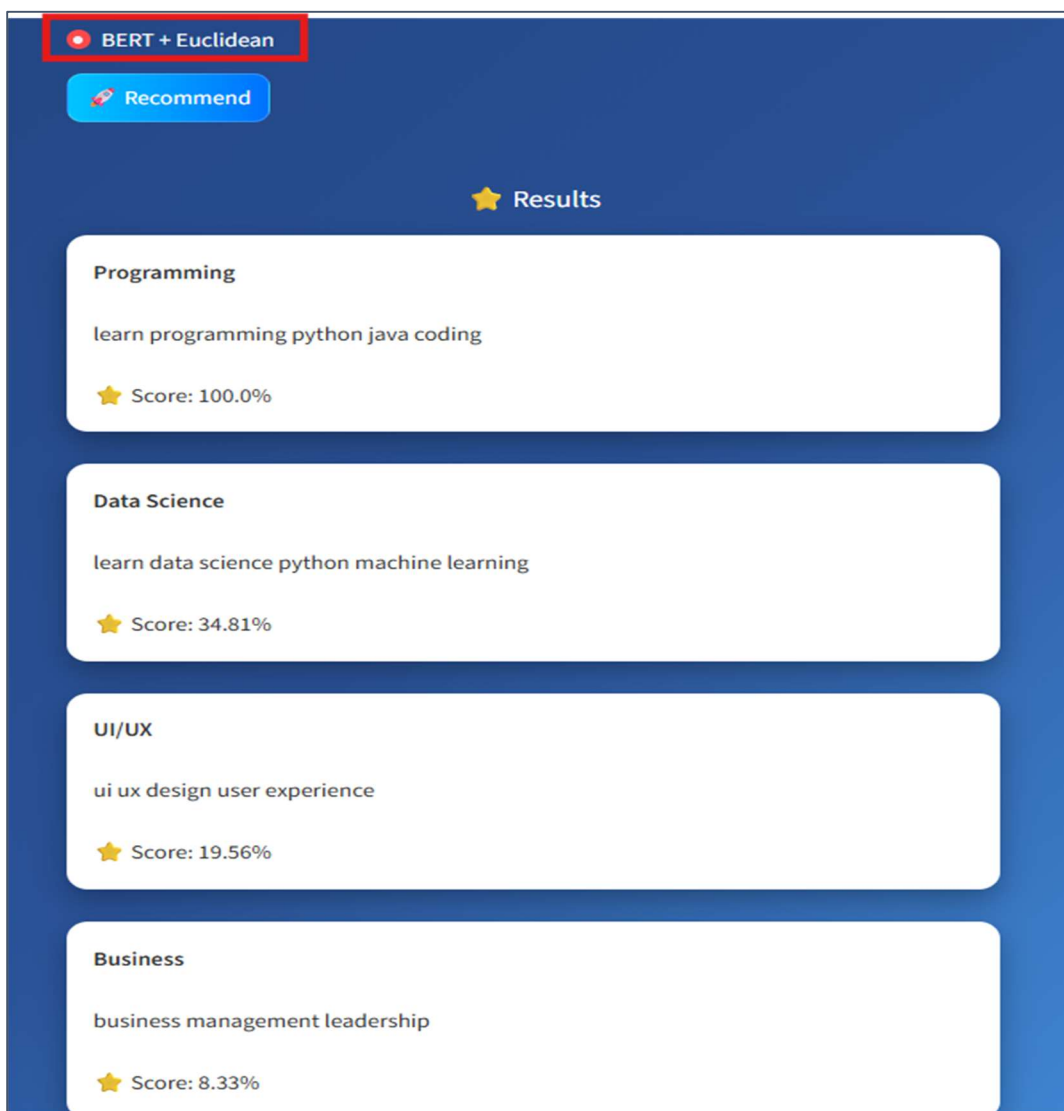


Figure 10 presents the recommendation results generated using the BERT Euclidean Distance model. In this approach, BERT is used to produce contextual embeddings that capture the semantic meaning of both stoner input and course descriptions.

The system also computes the Euclidean distance between these embeddings and converts the distances into similarity scores in order to rank the courses. As shown in the figure, the most applicable course(“ Programming ”) achieves the loftiest score, followed by other affiliated courses similar as “ Data Science” and “ UI/ UX ”.

These results demonstrate the effectiveness of combining deep semantic representation with distance- grounded similarity, enabling the system to give further meaningful and environment-apprehensive recommendations compared to traditional styles.

4.5 Results and Discussion

- The experimental results demonstrate that the proposed AIRSS system effectively generates ranked course recommendations predicated on user input.
- The system was estimated using different inputs representing stoners’ interests, chops, and academic background. predicated on these inputs, the system successfully produced a list of recommended courses ranked according to similarity scores.
- As shown in figures 7, 8, 9, and 10, the system is suitable of relating applicable courses that align with user preferences. For illustration, when the user input includes terms analogous as programming, design, and data wisdom, the system recommends courses related to these areas with advanced similarity scores.
- The TF- IDF- predicated models induce recommendations predicated on keyword matching, furnishing results that reflect term frequency within the text. still, these models may be limited in landing deeper semantic connections.
- In distinction, the BERT- predicated models demonstrate bettered performance by landing contextual and semantic meanings of words. This enables the system to recommend further applicable courses, indeed when exact keywords are n't explicitly present.
- Regarding similarity measures, Cosine Similarity evaluates the angle between vectors, making it effective for high- dimensional text data, while Euclidean Distance measures the distance between vectors and is converted into similarity scores for ranking purposes.

- The results indicate that combining different text representation ways(TF- IDF and BERT) with multiple similarity measures(Cosine and Euclidean) enhances the system's strictness and evaluation capability. In particular, the BERT- predicated models, especially when combined with Euclidean Distance, give farther terrain-alive and meaningful recommendations.

still, several limitations were observed

- The system primarily relies on textual similarity
- It does n't incorporate user history or behavioral data
- It does n't consider user feedback or former relations
- The system may perform less effectively when the input text is truly short

Despite these limitations, the AIRSS system provides an effective and practical result for course recommendation. The integration of traditional styles and deep knowledge models contributes to perfecting recommendation delicacy and overall system performance.

4.6 Model Comparison

The performance of different recommendation models was analyzed to estimate their effectiveness in generating applicable course recommendations.

Four models were compared, including TF- IDF Cosine, TF- IDF Euclidean, BERT Cosine, and BERT Euclidean.

The results show that TF- IDF- predicated models calculate on keyword matching, which limits their capability to capture semantic connections. As a result, these models produce lower different recommendations.

In distinction, BERT- predicated models demonstrate better performance by landing contextual and semantic meanings, leading to more accurate and meaningful recommendations.

Likewise, Euclidean distance provides a wider distribution of similarity scores compared to cosine similarity, which improves the diversity of recommended courses.

Among all models, BERT Euclidean achieved the swish overall performance due to its capability to combine semantic understanding with effective similarity dimension.

Table 4-3: Comparison of Recommendation Models Performance

Model	Performance	Interpretation
TF-IDF + Cosine	Moderate	Keyword-based
TF-IDF + Euclidean	Moderate	Limited understanding
BERT + Cosine	High	Good semantic understanding
BERT + Euclidean	Very High	Best overall performance

4.7 Summary

This chapter presented the experimental results and estimated the performance of the proposed AIRSS system. The results demonstrated the effectiveness of the system in generating applicable and personalized course recommendations predicated on user input.

The chapter also analyzed the performance of different ways, including TF-IDF and BERT for text representation, as well as Cosine Similarity and Euclidean Distance for similarity dimension. In addition, a relative analysis of different models was conducted to assess their effectiveness in recommendation tasks.

The comparison results showed that BERT-predicated models outperform TF-IDF-predicated models due to their capability to capture semantic and contextual connections. Among all estimated approaches, BERT combined with Euclidean Distance achieved the swish overall performance, furnishing more accurate, different, and meaningful recommendations.

Overall, the results confirm that the proposed AIRSS system provides an effective and effective result for course recommendation. The coming chapter concludes with the study and presents recommendations for future work.

Chapter 05

Conclusion and Future Work

5.1 Conclusion

- This study presented the design and performance of an AI- predicated recommendation system(AIRSS) for concluding suitable training courses predicated on user interests, chops, and career preferences.
- The proposed system utilizes Natural Language Processing(NLP) ways to anatomize textual data and induce personalized recommendations. The methodology includes preprocessing textual data, converting it into numerical representations using TF- IDF and BERT, and calculating similarity scores using Cosine Similarity and Euclidean Distance.
- The experimental results demonstrated the effectiveness of the proposed system in generating applicable and meaningful course recommendations. The system was suitable to successfully match user input with applicable training courses and rank them predicated on similarity scores.
- A relative analysis between different models showed that while TF- IDF provides effective keyword- predicated recommendations, BERT significantly improves the system's capability to capture semantic connections and deliver farther terrain-alive suggestions.
- likewise, the integration of multiple similarity measures revealed that combining BERT with Euclidean Distance achieved the swish overall performance in terms of recommendation connection and diversity.
- Overall, the AIRSS system achieves its ideal of perfecting the course selection process by furnishing substantiated, accurate, and data- driven recommendations. The integration of traditional text representation ways with advanced deep knowledge models enhances both the performance and usability of the system.

5.2 Future Work

Although the proposed AIRSS system has achieved promising results, several advancements can be considered for unborn development.

First, the system can be enhanced by incorporating stoner commerce data, where stoner inputs, feedback, and gusto

are stored and used to ameliorate unborn recommendations. This would enable the system to learn from once stoner relations and give further adaptive and accurate suggestions.

Alternate, farther advancements can be achieved by optimizing and fine-tuning advanced models similar as BERT, or integrating more recent motor-grounded infrastructures to enhance semantic understanding and recommendation delicacy.

Third, incorporating stoner biographies, preferences, and literal commerce data would allow the system to deliver more individualized and environment-apprehensive recommendations acclimatized to individual druggies.

Also, expanding the dataset to include a more different and real-world collection of training courses(e.g., from platforms similar as Kaggle or real educational providers) would ameliorate the robustness and concept capability of the system.

Likewise, espousing cold-blooded recommendation approaches that combine content-grounded filtering and cooperative filtering could further enhance recommendation performance.

Also, unborn work may explore advanced evaluation strategies and fresh similarity measures to further dissect and ameliorate system performance.

Eventually, planting the system as a completely functional web or mobile operation would enable real-time stoner commerce and ameliorate availability and usability.

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