

AI-Driven Personalized Learning Framework for Computing Fields Recommendations in Secondary and Pre-University Contexts

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Abstract—Students or learners, especially those at the secondary and pre-university levels, face challenges in identifying suitable computing fields for personalized educational resources towards their tertiary education specialization pathways. Traditional advising methods/approaches such as guidance from school counselors and teachers often lack personalization and practical relevance because their knowledge of the field is limited. This research aims to close this gap by proposing Computing Field Recommender (ComReF), an end-to-end Machine Learning framework that integrates student assessment and a profile built from demographic attributes and assessment performance, with semantic resource generation to deliver personalized, interpretable, and pedagogically grounded recommendations. A Random Forest-based multi-class classification strategy predicts suitable computing fields and corresponding proficiency levels, with empirical results showing improved performance over Decision Tree, Logistic Regression, and Naïve Bayes classifiers. NLP was also used for string cleaning and to automatically generate URLs for resources such as YouTube, Wikipedia, and Coursera. Consequently, all generated resources undergo a domain-informed validation protocol based on industry and academic checklists/benchmarks, ensuring their relevance and quality. The evaluation was conducted on a sample of 500 labeled instances using ChatGPT and available assessment data. The results show a strong classification accuracy (F1-score ≥ 0.8 for a well-represented field) in skill-level classification and field-level predictions across the computing fields/subfields that indicate moderate accuracy (with a weighted F1 = 0.59), reflecting real-world data imbalance, and producing relevant resource sets that are topically consistent with the predicted computing specializations and career goals. By bridging predictive modeling with semantic web navigation, ComReF offers a suitable solution for computing field recommendations and helps reduce gaps in traditional advising approaches.

Keywords—Artificial intelligence; machine learning models; pre-university level; personalized learning; computing fields; recommender systems

I. INTRODUCTION

The choice of specializations in Computing, particularly among secondary and pre-university students, depends on several factors. These factors include financial barriers, limited knowledge of the nature of various fields and their requirements, tuition fees for certain programs, the educational institutions offering the programs, and concerns about the ability to meet academic requirements [1]. Recommender

systems provide evidence-based information to help learners select courses by suggesting alternatives based on their interests and performance profiles and aligning with their academic goals and objectives [2]. In addition, these systems contribute to helping students meet curricular needs, expand their career opportunities, and engage in intellectual growth [3].

Advancements in artificial intelligence (AI) have allowed recommender systems to streamline individualized recommendations [4]. However, the extent to which AI-based systems can influence students' field choices remains under-researched. It is necessary to gain more understanding of how students perceive and expect such systems [5]. In addition, AI chatbots have become a topic of interest among scholars worldwide and have the potential to change educational systems in various ways. They can offer real-time support, answer questions, explain concepts, and provide individualized learning materials. Moreover, chatbots can serve as an additional tool of virtual teaching [6].

Over the years, students have often struggled to choose elective courses because of the growing number of choices available to them. As elective options expand, course recommender systems have become more relevant for accurate choices [7]. The significant increase in AI as a digital assistant is especially impressive, as it provides individualized learning by incorporating educational assets based on students' personal preferences and the requirements of their discipline [8]. They support teachers and learners across various dimensions of the educational process [9]. The potential to address the limitations of conventional career-support mechanisms is significant in the context of integrating AI-driven conversational frameworks into career guidance platforms [10]. Research suggests that AI-driven advising or career guidance can be effectively operationalized when supported by strong technological foundations, such as advanced natural language processing frameworks and secure, cloud-based machine learning services that provide effective, personalized guidance [11]. In addition, effective systems should be flexible enough to adapt to new work-market factors and institutional developments [12].

On the other hand, even with the rising demand for professionals holding bachelor's degrees in Computing-related fields, undergraduate enrollment in Computer science and Computer engineering programs has shown a marked decline in recent years [13]. An earlier alarm was also raised by Lent

[14], [15]. The continuing inadequate representation of women and minority groups in the computing sector, together with an associated downward trend in the number of students seeking computing courses, continues to raise a red flag despite the rising labor market demand [16].

The issue highlights the need to understand psychosocial and contextual factors that influence students' choices about whether to pursue or avoid computing disciplines, especially among underrepresented populations. In a larger sense, it reflects efforts to increase the number of students recruited and retained in STEM fields [17]. The dwindling interest in computer-related programs is a long-standing international issue with major long-term implications. This tendency underlines the dire need to come up with new methods of popularizing those fields and to reconsider the avenues through which they are marketed [18] Cohon et al. (2018). Student representatives of different groups still consider the interest in the career field as one of the most powerful factors in career decision-making [19].

Although there are attempts to democratize access to Computer Science, the field remains characterized by significant skewness beyond existing gender and socioeconomic imbalances. The level of computing interest and engagement is comparatively stronger and higher among male students, and undergraduates are prone to leaving school, especially among low-income earners [20], [16]. To this end, it is necessary to provide extensive, impartial exposure to computing, an indispensable requirement when increasing the level of involvement and broadening opportunities in these fields [21]. Computer Science is a crucial field in developing future technological leaders; however, the accessibility and inclusion problems are often ignored in existing curricula [22]. There is a growing need for practical guidance on accessible computing that equips learners with strategies to design more inclusive learning environments. This guidance must clarify the ethical, legal, and pedagogical requirements of accessibility and how inclusive practices can bring benefits to all learners, including learners with disabilities [23]. In addition, there is a need to differentiate teaching accessibility as a discipline on its own and the integration of accessibility principles into instructional practice as an educator [24].

Computing has been encompassed in a wide field of study known as Computer Science; it has since split into various specialized fields, including AI, cybersecurity, software engineering, network engineering, business intelligence, sustainable computing, and data science [25]. Each of these fields requires distinct competencies, offers unique career pathways, and follows differentiated learning trajectories [26]. The diversification can be seen as a sign of the maturation of the discipline and its embedding into almost all sectors of the world economy [18]; [27]. As a result, it poses a great cognitive and navigational dilemma to the students who, in most cases, must make high-stakes specialization choices without enough exposure, experience, or guidance [28].

Academic advising, mostly based on stagnant curricula or general career presentations, cannot even keep up with the fast-changing environment and does not fulfill the dynamic counseling requirements of the students [29], [30]. Conversely,

recommender systems are also used on online learning platforms like Coursera and edX, where they generally become active after enrolment and provide recommendations based on learners' previous interactions. Nonetheless, these systems rarely offer recommendations for choosing a field of study based on diagnostic data or assessment information [31]. Similarly, most educational data mining methods focus on predicting academic achievement or the risk of dropping out of school, rather than providing an all-inclusive, easy-to-use learning-to-career map for learners [32].

There is still a notable gap in recommender systems capable of linking diagnostic assessments with the automated generation of semantically relevant learning resources [33]. Most AI-driven tools provide only high-level labels, such as "AI," or numerical competency scores, leaving students to locate their own learning materials. This process is often time-consuming and susceptible to information overload [34]. Even when learning resources are recommended, they are seldom evaluated against established pedagogical standards or current industry benchmarks [35], [36]. In the context of our research, these three important terms are thus defined as below:

Semantic resource generation is the process of creating platform-specific URLs with full canonical field names (e.g., Business Intelligence) instead of short codes or initials ("BI" for Business Intelligence and "AI" for Artificial Intelligence), which overcomes problems of fields that may have the same initials as Cryptography and Cybersecurity. It also ensures lexical matching in search interfaces like Coursera and Wikipedia.

Interpretable: implies that it is possible to trace predictions to input features by using model-internal measures of feature importance and explicit, auditable code-to-name mapping, which removes the need to use black-box components like deep learning models or large language models (LLMs).

Actionable and coherent: refers to an output that consists of a non-redundant collection of screened links, each of which retrieves topic-aligned resources with explicit descriptors of skills, such as in React.js, Data Analysis, and Ethical Standards.

Existing studies have focused on course selection [2], [5], career guidance [10], learner profiling [37], and learning paths [38]. However, these functions are often addressed separately, with limited integration to guide secondary and pre-university learners toward suitable computing fields. To address this gap, ComReF integrates learner profiles and assessment data to recommend computing fields, identify skill levels, and provide relevant learning resources. Its main contribution is a lightweight and interpretable framework that supports early computing specialization and complements teacher and academic-adviser guidance.

To address the limitations mentioned earlier, ComReF is proposed as an end-to-end machine learning framework that transforms student assessments and profiles (including demographic and preference information) into personalized learning recommendations. It aims to guide and expose students to suitable computing fields from the secondary level based on their profiles and cognitive skills.

Hence, ComReF aims to reduce the gaps in the following aspects:

Learner Profiling: Learning unfolds differently for every individual. With the emergence of “Internet+” education, personalized learning has gained significant [39]. Digital learning materials have led to a significant rise in online learners in many aspects of activities [40]. As such, learners often face the problem of information overload and feel lost during the learning process [41]. These limitations may create a mismatch between a learner's actual competence and the difficulty of the suggested resources, increasing the risk of cognitive overload. Our approach aims to combine the ability to recognize and understand individual needs.

Field Mapping: The abundance of available learning resources has increased manifold, and the methods of resource selection have also changed in tandem with the learners. In that regard, learning materials have grown in significance [42]. Learning pathways are supposed to be adjusted to the educational field resources depending on learners' specific profiles [37]. We need to map resources by field, not randomly.

Resource Generator: A framework should allow searching by the entire field name to make the searches that are discovered pertinent and educational [43]. ComReF provides an organized learning path to help learners progress and optimize the entire learning experience.

Domain-Informed-Validation: This task is important as well as complicated, both in design, development, and evaluation of the learning environment in ways that support the distinct learner needs in a particular domain or field. A learning environment has several dimensions, such as physical, social, psychological, and pedagogical dimensions, that all constitute the environment where learning occurs [44]. In particular, the learning experiences refer to various interactions and different situations that stimulate the perceptions of learners [45]. ComReF screens suggested resources using a checklist based on compatibility with the requirements of the Malaysian education blueprints and industry standards.

Therefore, there is a need to develop accurate student profiles and models that analyze learners' affective, knowledge, personality, and skill levels. Thus, AI solutions offer considerable benefits, as they can incorporate reasoning into instructional decision-making and control potential sources of uncertainty. Therefore, they enable more efficient teaching and learning systems [46]. The following sections will elaborate on related works, the proposed framework, its implementation and prototyping, discussion, and conclusion.

II. RELATED WORKS

This section presents existing literature on educational recommender systems, career guidance in Computing education, semantic resource generation and validation, and validation pathways, which provide the foundation for this work and its relevance to targeted learners.

A. Educational Recommender Systems: From Courses to Careers

The evolution in educational recommender systems has shifted from primitive collaborative filtering methods such as

course recommendations based on peer activity [47] to advanced hybrid models that combine knowledge tracing, learner profiles, and contextual metadata [48]. For instance, Coursera, edX, and some similar platforms currently adopt deep learning models to personalize course sequences, with studies indicating improved click-through rates when recommendations align with learners' goals [2]. Regardless of such developments, these systems operate reactively, requiring prior engagement [49]. Massive Open Online Courses provide a rich range of learning materials; however, they often overwhelm students due to their enormous volume, which results in problems like data sparsity and cold-start problems [50].

To alleviate these hindrances, EGRec was proposed [49]. It is an innovative course recommendation model that augments recommendation accuracy, diversity, and relevance by combining knowledge graphs and heterogeneous graph attention networks. The model uses multimodal information and dynamically selected subgraphs to improve performance, but it does not focus on field diversification, as seen in the field of Computing. Most educational recommender systems consider a field as a label of a static unit, but not as a semantic unit [51]. Thus, a learner who is designated as fit for AI, such as Generative AI, Computer Vision, or AI Ethics, a field in which entirely different skills are required, is not provided with any additional guidance. A survey of major MOOC platforms shows that only a small number of studies distinguish sub-fields of computing from broad categories, such as Networking, Software Engineering, and Multimedia, and tend to include separate career paths in excessively general categories [52]. This reduced granularity limits practical usefulness, as computing job advertisements are becoming more demanding in more specific areas.

B. Career Guidance in Computing Education

Selecting a computing specialization is a significant challenge [53]. An in-depth examination of how Computer Science and Computational Thinking are taught at lower levels of education is essential to creating consistent, high-quality courses and implementing professional development programs [54]. Computing education has become a high-profile research area in major universities, and institutions, industries, and communities have launched initiatives; however, issues still hinder the widespread implementation of computing education at the K-12 level [55]. Computational Thinking and Problem-solving skills have become important in students' development. Digital and serious games are also entering education at an affordable cost and promise to enhance students' learning [56]. This is comparable to findings of the American National Academies, which warned that without proactive advice, students, especially underrepresented ones, would often gravitate towards familiar or oversaturated fields such as web development, which would overlook high-opportunity ones like DevOps and other emerging specialties [18]. The traditional advising interventions are not very scalable [57]. A randomized controlled trial showed that one-on-one career counseling can enhance field alignment, but it is time-consuming. Moreover, this resource-intensive approach is not feasible for large-scale enrollment within a limited timeframe [58].

C. Semantic Resource Generation and Validation

Recent studies have begun to integrate prediction with outcomes that can benefit learners. Anomalous state of knowledge theory suggests that learners require contextualized information pathways, rather than merely labels [59]. Building on this concept, systems like Path2Learn were realized [60]. The focus on personalized learning paths has become increasingly prominent in education. Tran and team [38] examine the performance evaluation of user-based Collaborative Filtering and Content-based recommendation techniques to develop innovative RSs specifically designed for Information Systems (IS) students. By integrating a primary dataset grounded in the students' knowledge-skill-attitude framework, the study addresses the challenge of navigating the extensive range of learning options in IS. Wan and Lei [61] outline the undisputed benefits of accessible online resources; however, the abundance of these resources often leads to confusion and decision paralysis, so individualized, well-designed guidance is also required. On the same note, LLM-based recommender systems can rank coherent resource lists, but they are vulnerable to hallucination, especially in technical fields [62]. This can result in suggestions for non-existent courses or outdated tools. Validation is often treated as an afterthought in educational AI systems. Though the research of Seo [63] incorporated an expert opinion in the AI sector, which is usually limited to scholars rather than industry practitioners. The advocates of human-in-the-loop AI insist on the necessity of introducing additional validation procedures, but few systems manage to adopt the strategy [64]. This mismatch is

alarming because industry expectations often differ from academic programs. For example, DevOps job descriptions often require cloud certifications, but many college programs do not include cloud platform training in their coursework. Therefore, the idea of generating and validating resources remains unexplored.

D. Validated Pathways

Uncovering meaningful hidden patterns in learner data is highly valuable within educational technology. Research on personalized, full-path learning recommendations is especially critical for advancing the development of more sophisticated adaptive learning systems [65]. The surge in online courses makes it harder for learners to select suitable learning paths. Recommender systems help by analyzing past interactions to predict interests and suggest relevant next steps [66]. In summary, none of the related studies focus on full-fledged computing field recommendations based on learners' profiles and assessment scores, using an ML approach to recommend a field alongside learning resources.

For better presentation, studies have explored educational recommendations from different perspectives, including course selection, career guidance, learner profiling, course advising, and personalized learning paths. However, their objectives and recommendation components differ from those integrated in ComReF. To clarify these differences and position the proposed framework's contribution, Table I compares representative related studies by focus and recommendation capabilities.

TABLE I. COMPARISON OF COMREF AND SOME EXISTING STUDIES

Study	Focus	Personalization	Field Guidance	Skill Level	Learning Resources
[5]	Course selection	✓	–	–	–
[10]	Career guidance	✓	–	–	–
[29]	Course advising	✓	–	–	–
[31]	Labor-market-driven education	✓	–	–	✓
[37]	Learner profiling/course recommendation	✓	–	–	✓
[38]	Personalized learning paths	✓	–	–	✓
ComReF	Computing-field guidance	✓	✓	✓	✓

Overall, ComReF differs from the reviewed approaches by integrating learner profiling, computing-field recommendation, skill-level identification, and learning resources for secondary and pre-university learners.

III. PROPOSED AI-DRIVEN RECOMMENDATION FRAMEWORK

The proposed ComReF is an end-to-end framework that converts a student's multidimensional aptitude profile (demographic, proficiency, and assessment data) into a personalized learning pathway. The system integrates machine learning models and prediction algorithms, semantic expansion, and cross-platform resource generation (see Fig. 1). It integrates three layers (Data/Interaction Layer, AI Process Layer, and Feedback/Resources/Validation Layer) to deliver personalized learning recommendations.

The Data/Interaction Layer first collects the student's basic information, learning preferences, and performance

assessments. These inputs are then used by the AI Process Layer to predict both the optimal field and the skill level of each student using a random forest classifier. It is particularly effective for multi-class prediction tasks, which are essential for recommending diverse computing fields such as Software Engineering, Data Science, and AI. In addition, NLP cleans and normalizes data and generates web search queries to retrieve relevant material. When it generates predictions, the recommender module uses field and skill predictions to deliver personalized resources, including YouTube tutorials, PDF documents, and other pages of interest. These resources are obtained by field, and content curation is adapted for semantic web search. More importantly, all resources are aligned with the industry skills and educational blueprints alignment checklist. ComReF tracks students' interactions with recommended resources and uses the data to make future recommendations.

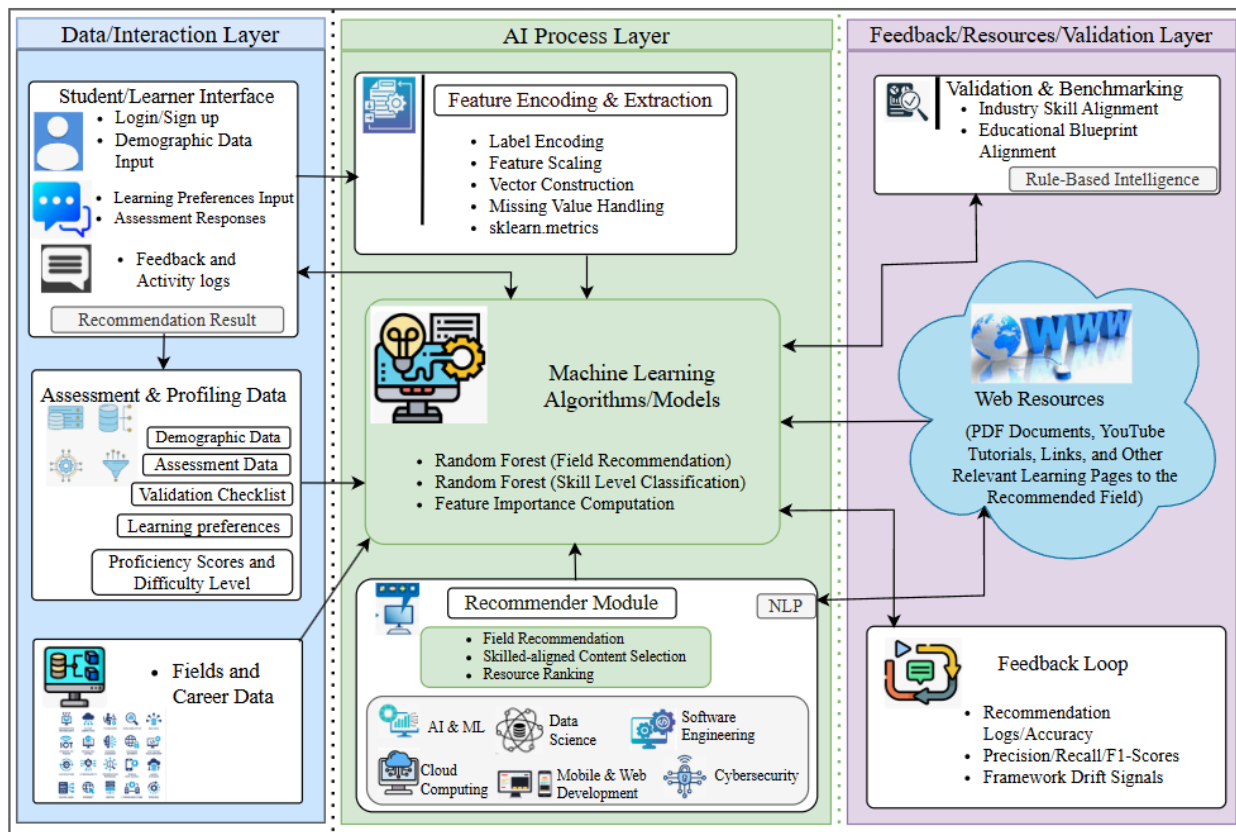


Fig. 1. Computing field recommendation framework (ComReF).

This continuous feedback loop improves accuracy and supports more personalized guidance as students navigate computing resources. The validation layer ensures that only the most relevant and up-to-date learning resources are recommended, ensuring all learners have access to appropriate materials. To improve ComReF's effectiveness, the feedback component incorporates precision, recall, and F1-scores, which are vital for evaluating performance. Drift signals monitor shifts in data patterns over time.

The remaining subsections detail how the framework operates and how the functional stages contribute to the overall recommendation process. Schematic flowcharts and mathematical formulations clarify the workflow, making the underlying reasoning, decision processes, and evaluation procedures clear.

A. Implementation Environment, Tools and Datasets

The implementation environment is a Jupyter Notebook interface for interactive prototyping and documentation, managed through Anaconda (Python version 3.9+). The main libraries deployed are scikit-learn for Random Forest classifiers, pipelines, and encoders; pandas and numpy for data loading, transformation, and analysis; urllib.parse for safe URL encoding across platforms; and re (regular expressions) for text cleaning and query sanitization. The framework does not require GPU support. However, accessing the generated links to external learning resources requires an Internet connection. The dataset requirements include:

Profiling data, consisting of demographic/contextual information, grade/level, learning attitude, motivation, goals, interests, and preferences, while cognitive attributes cover mathematical ability, logical and analytical reasoning, problem-solving, creativity, communication, teamwork, and self-learning readiness.

A field and career goals dataset, comprising identified Computing fields assessment scores mapped to the seven major computing fields: Computer Science, Software Engineering, Information Technology, Information Systems, Computer Engineering, Cybersecurity, and Data Science, and their associated subfields, which form the basis for field recommendations.

An assessment scores dataset that contains test scores to assess the learner's proficiency levels and to aid recommendations based on their overall scores and related attributes.

A validation and benchmarking checklist to ensure alignment with academic (Malaysia Education Blueprint: MEB alignment considers digital literacy, ICT integration, computational thinking, AI concepts, learning outcomes, student-centered learning, career relevance, and related educational requirements) and industrial requirements (digital and workplace skills, problem-solving, emerging technologies, practical application, career pathways, skill progression, professional standards, and Industry 4.0 relevance). These checklists are dynamic rather than fixed and can be updated

based on the target educational standard, industry demand, computing field, or recommendation goal.

B. Learner Profiling Process

The system captures students' demographic, behavioral, and other personalized learning attributes, and the ML label encoder transforms categorical data, such as gender and learning style, into numeric codes for use by all ML models. The encoded profiles then form feature vectors, which the ML models use. Fig. 2 illustrates the process, as shown in Eq. (1)

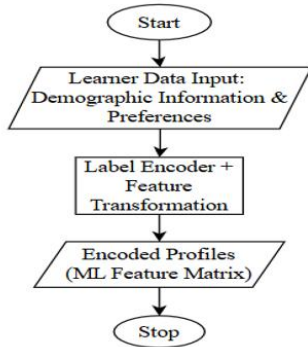


Fig. 2. Learner profiling process.

$$X_i = [x_{i1}, x_{i2}, \dots, x_{in}] \in \mathbb{R}^n \quad (1)$$

where, X_i represents the i^{th} learner across n attributes, $\mathbb{R}^n$ is the n -dimensional real space.

The process flows as follows: learner demographic and other personalized learning input data $\rightarrow$ encoding $\rightarrow$ ML feature matrix. The profiling stage transforms qualitative descriptors into quantitative representations. For instance, "Male/Female" is encoded as a binary variable (0/1), and settlement data such as "Urban/Rural" is similarly represented as (0/1). This preprocessing ensures compatibility with ML algorithms, which operate exclusively on numerical data spaces. The resulting feature vector X_i represents the i^{th} learner across n attributes and serves as input to the assessment and recommendation layers.

C. Assessment and Skill Level Evaluation

At this stage, each student takes predefined quizzes covering all the basic concepts of the identified Computing subfields and careers. The scores quantify proficiency and serve as learning features. Skill-level labels (beginner, intermediate, and advanced) are derived from performance thresholds. Fig. 3 shows the representation of the process, and Eq. (2) and (3).

$$Score_{ij} = \frac{CorrectAnswers}{TotalQuestions} \times 100 \quad (2)$$

where, $Score_{ij}$ represents the assessment score of the i^{th} learner in the j^{th} assessment, calculated as the percentage of correctly answered questions.

$$S_i = [S_{i1}, S_{i2}, \dots, S_{im}] \quad (3)$$

where, S_i denotes the assessment score vector of the i^{th} learner, consisting of m assessment scores.

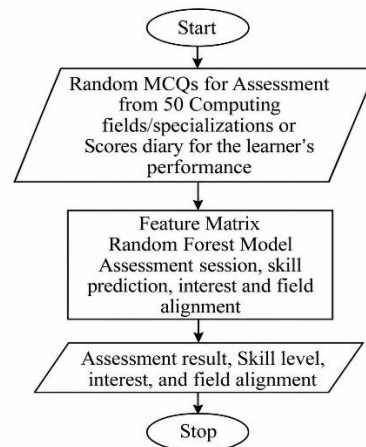


Fig. 3. Learners' assessment process.

The pipeline goes in this format:

Pipeline: Questions $\rightarrow$ Scores $\rightarrow$ Feature Matrix $\rightarrow$ Skill Prediction.

The skill evaluation process translates assessments into machine-readable performance metrics. Each dimension S_{ij} corresponds to the learner's score in one subfield. The dataset thus becomes a labeled multi-dimensional vector space where Random Forest classifiers can infer latent skill categories (Beginner, Intermediate, Advanced), and a supervised learning model is also incorporated.

D. Field Prediction Process

This stage predicts the optimal computing subfield for each student, models non-linear relationships between scores and fields or specializations, and handles multi-class classification through aggregated decision voting. Fig. 4 shows the process flow.

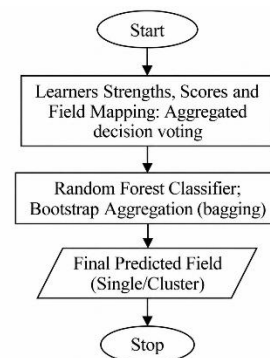


Fig. 4. Field prediction process.

This stage identifies the Computing field most aligned with a student's strengths. Each decision tree produces a class label such as Data Science, Cybersecurity, or Networking. The model aggregates these predictions through majority voting. Random Forest's bootstrap aggregation (bagging) strategy reduces variance, making predictions more stable across heterogeneous learners. The prediction process can be represented mathematically by Eq. (4)

$$y_{(pred)} = \arg \max_y \sum_{t=1}^T I(h_t(X) = y) \quad (4)$$

where, y_{pred} is the prediction label, y is the class, t is the individual tree, and T is the total number of trees; I is the indicator function, h is the hypothesis function, and X is the input vector.

E. Learner Proficiency Level and Framework Performance

This stage predicts the learner's overall proficiency level. The Standard-Scaler ensures uniform feature scaling. Thus, the framework performance is evaluated using accuracy, precision, recall, and F1-score, as shown in Eq. (5), (6), (7), and (8).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

$$F_1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (8)$$

where, Precision is the proportion of correct positive predictions, Recall is the proportion of actual positives that were correctly identified, F1 is the harmonic mean of Precision and Recall, TP denotes true positives, FP denotes false positives, TN denotes true negatives, and FN denotes false negatives. The process is presented as shown in Fig. 5.

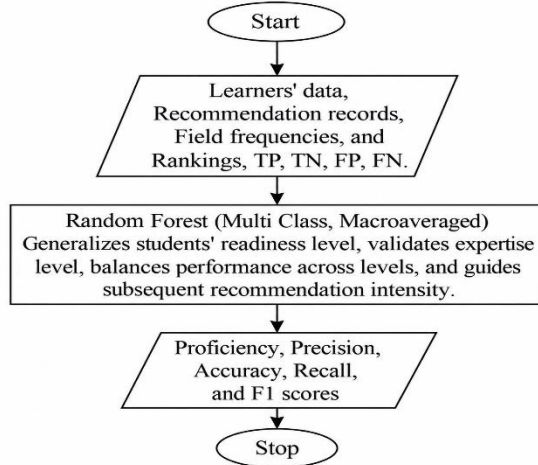


Fig. 5. Learner proficiency and framework performance.

Skill classification generalizes the student's readiness level. The macro-averaged F1 ensures balanced performance across all levels, even when classes are imbalanced. This stage ascertains how well the assessment vectors predict true expertise levels, guiding subsequent recommendation intensity for basic versus advanced materials.

F. Field Recommendations

The framework recommends fields and learning materials based on predicted outcomes, utilizing data-driven predictions with curated educational resource databases. The

recommendation combines ML-based inference with dynamic, rule-based content retrieval. The justification for choosing Random Forest is its interpretability, robustness with small datasets ($N \leq 500$), and resilience to feature correlations, which is important given the conceptual overlap between fields. Unlike deep learning alternatives, this approach requires no GPU infrastructure and yields clear feature importance rankings, supporting explainability in advising contexts [67]. Rule-based filtering is also utilized, as in Eq. (9) and Fig. 6.

$$Query = urllib.quote_plus(Field_Name) \quad (9)$$

where, *Query* is the URL-safe search string, *urllib.quote_plus* is a Python function that encodes spaces as '+' and special characters for use in web URLs, and *Field Name* is the full, human-readable name of the predicted computing field, such as Software Engineering, Data Science, and Cybersecurity.

In summary, this component converts framework predictions into educational pathways. Once the system identifies a field, for instance, "Cloud Computing," it queries multiple online repositories such as YouTube, Coursera, EdX, and Google Scholar to dynamically generate URL queries linking to relevant, high-quality materials that support the user's learning journey.

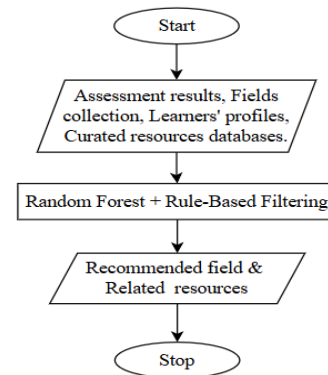


Fig. 6. Field recommendation process.

G. Resource Validation and Benchmarking

This stage is vital to ensure that the recommended materials align with both academic standards (the Malaysia Education Blueprint or MEB 2013-2025) and industry requirements specific to each computing-related career or field. Recommendations will be drawn from the top links on each specified platform, checking for keywords that match the criteria provided. The recommended material is considered suitable if it meets at least six criteria in the list. This process serves as a quality-control layer that ensures the recommended materials are relevant. This process is rule-based and deterministic, not reliant on a predictive ML algorithm, and aims to enhance the framework's performance. The mathematical process is expressed as in Eq. (10), as shown in Fig. 7.

$$Validated = (MEB_{yes} + Industry_{yes}) \geq 6 \quad (10)$$

NB. To validate each recommended resource effectively, we need access to defined learning sources such as Khan

Academy, Coursera, edX, MIT, etc. So this work relies on free, publicly available web resources as a proof of concept. Table I presents examples of dynamically generated resource-search links based on the recommended computing field. These links support resource discovery and should not be interpreted as individually validated learning resources.

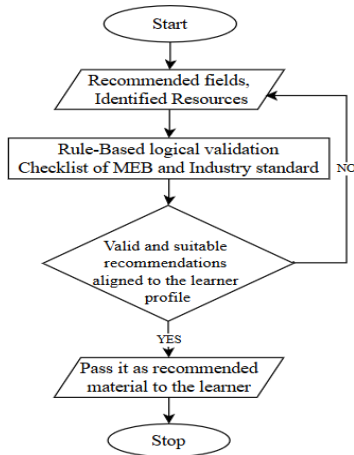


Fig. 7. Benchmarking and validation process flow.

H. Resource Generation and Retrieval

The system generates search queries using sanitized field names, then retrieves categorized resources such as videos, websites, and PDFs from multiple web sources. This action enhances the user experience by dynamically linking structured knowledge sources. Involves NLP-based string cleaning and automated URL generation for search queries. The flow is as in Fig. 8.

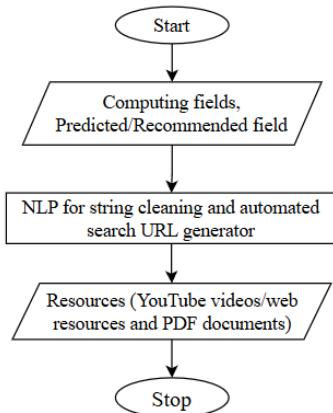


Fig. 8. Resource generation and retrieval.

NLP is used for dynamic query generation, including cleaning and encoding field names (e.g., removing parentheses and symbols), to ensure semantic accuracy in web search results. The objective is to maximize content relevance for each predicted field, as mathematically represented in Eq. (11).

$$URL = Base + urllib.parse.quote(Field) \quad (11)$$

where, URL denotes the generated link, Base represents the platform's search endpoint, *urllib.parse.quote* is a function that URL-encodes the field name, and Field refers to the full

subfield name (e.g., database engineering, multimedia technology, etc.).

I. Feedback and Logging

Collects user ratings and engagement metrics for post-recommendation. It also gathers log interaction data to retrain ML models for future recommendations. It adopts reinforcement learning principles for adaptive performance improvement and utilizes a feedback updater to achieve this, represented mathematically in Eq. (12).

$$Loss_{t+1} = \eta \frac{\partial Loss}{\partial \theta} \quad (12)$$

where, $Loss_{t+1}$ is the updated loss after iteration. $t + 1$, η is the learning rate, and $\frac{\partial Loss}{\partial \theta}$ represents the gradient of the loss with respect to the model parameters. The flow proceeds as follows: User Feedback $\rightarrow$ Model Update $\rightarrow$ New Recommendations. This looping flow is essential for continuous improvement. It treats user feedback as a reward signal, which optimizes the model's parameters through gradient-based updates. Conceptually, this forms a self-correcting intelligent tutor that adapts and evolves based on learner interactions. Fig. 9 illustrates the process.

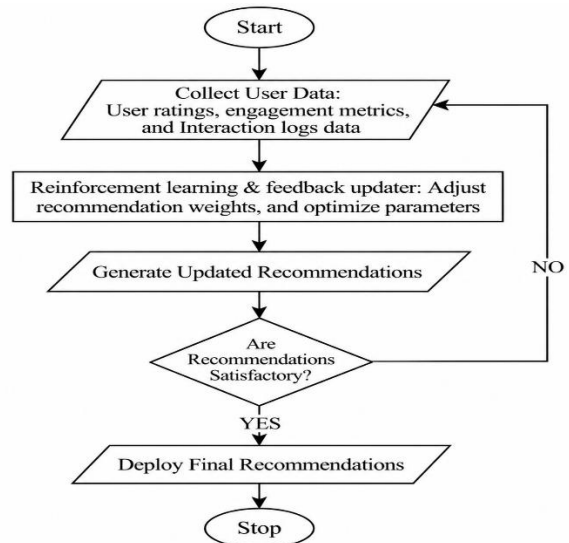


Fig. 9. Feedback loop and logging.

J. Overall Evaluation Accuracy of ComReF

At this stage, the framework is evaluated using the previously computed F1-score, Precision, and recall to determine overall accuracy and ensure balanced predictions across all identified computing fields. The evaluation process is conducted using *sklearn.metrics.classificationreport* with the overall accuracy represented in Eq. (13) and illustrated in Fig. 10, respectively.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (13)$$

where, Accuracy denotes the proportion of correct predictions, TP, TN, FP, and FN represent True Positives, True Negatives, False Positives, and False Negatives, respectively, measuring the overall correctness across all classes. This final

stage summarizes system performance. The F1-score provides a harmonic balance between Precision and Recall, which is critical for recommendation tasks. A high macro-average F1-score suggests that the framework is suitable for large-scale deployment, as it reflects consistent performance across all categories. Fig. 10 depicts the overall evaluation process.

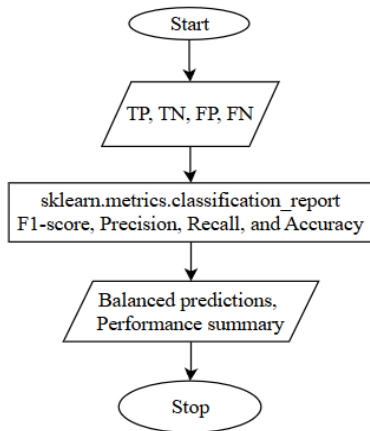


Fig. 10. Overall evaluation process.

IV. IMPLEMENTATION AND RESULTS

This section explains the implementation of the proposed ComReF, starting with the learner profiling process, followed by learning-resource recommendations, a report on classification performance, prototyping, and a comparison of the chosen Random Forest with three classification models. The dataset comprised 500 instances across 50 computing-field classes. The process used an 80:20 train-test split, resulting in 400 training and 100 testing instances; the same split was used across all evaluated classifiers to ensure a consistent comparison. No cross-validation was applied. Some computing fields/subfields were sparsely represented, with only 1 to 3 instances in the test set; therefore, interpreting the corresponding class-level performance metrics cautiously.

A. Learner Profiling

The framework's recommendations center on the learner profile, which drives the process. Thus, the profile includes demographic data and learner preferences that ChatGPT generates from prompts tailored to the expected diversity of learners in the Malaysian context.

S/No	Name	Gender	Grade	Race	Settlement	Skill Level \	
0	1.0	Lim G.	Female	12.0	Chinese	Urban	Advanced
1	2.0	Abdullah G.	Female	9.0	Malay	Rural	Beginner
2	3.0	Martin I.	Male	10.0	International	Urban	Beginner
3	4.0	Chan P.	Female	12.0	Chinese	Rural	Beginner
4	5.0	Naidu A.	Female	12.0	Indian	Urban	Intermediate
Learning Attitude							
0	Collaborative		Intrinsic		Innovation		Mobile Apps
1	Collaborative		Extrinsic		Innovation		Quantum Computing
2	Independent		Intrinsic		Innovation		AR/VR
3	Independent		Extrinsic		Skills		Cloud Computing
4	Independent		Intrinsic		Academic		AI & Machine Learning
Learning Preference				Career Goals			
0	Solitary			Computer Scientist, System Analyst, Researcher			
1	Visual			IT Specialist, Systems Analyst			
2	Kinesthetic			Computer Engineer, Embedded Systems Engineer			
3	Reading/Writing			IS Analyst, Systems Manager			
4	Kinesthetic			MIS Specialist, IT Manager			

Fig. 11. Basic learner profile information.

Fig. 11 illustrates the profiling information, which includes the students' IDs, names, races, residences, perceived skill

levels, learning attitudes, motivations, goals, interests, preferences, and career aspirations of the first five learners: Lim, Abdullah, Martin, Chan, and Naidu, and Fig. 12 then shows their respective recommendation report summaries: Lim for Cybersecurity, Abdullah for Data Science, Martin for Computer Engineering, Chan for Software Engineering, and Naidu for Computer Science. The full profile and recommendations are saved as a CSV file in a folder.

```
✓ Final Recommendation Report saved as Final_Recommendation_Report.csv
```

student_id	predicted_field	predicted_skill_level \
0	1 Cybersecurity	Intermediate
1	2 Data Science	Intermediate
2	3 Computer Engineering	Beginner
3	4 Software Engineering	Intermediate
4	5 Computer Science	Beginner

career_goals	resources_validated	validation_yes_total \
0 Cybersecurity Analyst	True	16
1 Data Scientist	True	16
2 Embedded Systems Engineer	True	16
3 Software Engineer	True	16
4 Computer Scientist	True	16

Fig. 12. Recommendation summary related to the student's profile.

B. Recommended Learning Resources

The recommended learning resources include YouTube video links, PDFs, and educational websites, all aligned with the learner's profile and assessment results in the suggested learning field. Based on the profiles in Fig. 11 and 12 and using Abdullah G. as an example for whom Data Science was recommended, Table II shows his recommended learning resources, including YouTube links, websites, and PDFs. The table was formatted for clarity, as the original display in the Anaconda environment looks complex/long, and links may not look well-formatted here.

TABLE II. RECOMMENDED RESOURCES FOR ABDULLAHI G., DATA SCIENCE

1. Abdullah G. ----- Data Science		
S/No.	Resource Type	Link
1	YouTube	https://www.youtube.com/results?search_query=Data+Science+tutorial
2	YouTube	https://www.youtube.com/results?search_query=Data+Science+course
3	YouTube	https://www.youtube.com/results?search_query=Data+Science+lecture
4	YouTube	https://www.youtube.com/results?search_query=Data+Science+advanced
5	Website	https://en.wikipedia.org/wiki/Data+Science
6	Website	https://www.coursera.org/search?query=Data+Science
7	Website	https://www.edx.org/search?q=Data+Science
8	Website	https://www.kaggle.com/search?q=Data+Science
9	Website	https://www.researchgate.net/search/publication?q=Data+Science
10	Website	https://www.ibm.com/search?lang=en&cc=us&q=Data+Science
11	PDF	https://scholar.google.com/scholar?q=Data+Science+filetype:pdf
12	PDF	https://www.google.com/search?q=filetype:pdf+Data+Science+course
13	PDF	https://www.google.com/search?q=filetype:pdf+Data+Science+lecture+notes
14	PDF	https://www.google.com/search?q=filetype:pdf+Data+Science+handbook

C. Classification Performance

This section presents the classification performance report of ComReF. The predictive performance was evaluated using standard metrics, including Precision, Recall, and F1-score, computed per class and aggregated using macro and weighted averages. For the best field prediction, ComReF achieved an overall accuracy of 64% with a weighted F1-score of 0.59, indicating moderate performance across the subfields/careers in Computing. Notably, several classes (1, 2, 3, 9, 13, 16, 18, . . . , 34, 36, and 49) achieved perfect or near-perfect F1-scores ($F1 \geq 0.80$), demonstrating strong generalization for well-represented fields. However, classes (4, 6, 7, 12, 17, 19, 21, 22, . . . , 40, 42, and 43) recorded comparatively lower performance metrics due to limited sample representation (support = 1–3). This outcome aligns with the known behavior of multi-class classifiers under imbalanced class distributions and does not undermine the overall performance trends. In contrast, the skill-level prediction model achieved 100% accuracy ($F1 \text{ score} = 1$); however, this reflects the uniformity of the test set, where all students exhibited similar/the same background skill levels. These results indicate that ComReF performs well when sufficient training data is available, highlighting the importance of data adequacy for future data collection and taxonomy refinement. Fig. 13 illustrates the classification results.

Best Field Prediction Report (Classes 0 – 30)					Best Field Prediction Report (Classes 31 – 49)				
Class	Precision	Recall	F1-score	Support	Class	Precision	Recall	F1-score	Support
0	0.50	1.00	0.67	2	31	0.75	1.00	0.86	3
1	1.00	1.00	1.00	2	32	1.00	1.00	1.00	1
2	0.75	1.00	0.86	3	33	0.00	0.00	0.00	1
3	1.00	1.00	1.00	1	34	1.00	1.00	1.00	2
4	0.00	0.00	0.00	1	35	1.00	0.50	0.67	2
5	0.67	0.67	0.67	3	36	0.75	1.00	0.86	3
6	0.00	0.00	0.00	2	37	0.50	1.00	0.67	3
7	0.00	0.00	0.00	3	38	0.50	0.67	0.57	3
8	0.25	0.50	0.33	2	39	0.50	1.00	0.67	2
9	1.00	1.00	1.00	2	40	0.00	0.00	0.00	1
10	0.33	1.00	0.50	1	41	0.50	0.50	0.50	2
11	0.50	0.33	0.40	2	42	0.00	0.00	0.00	2
12	0.00	0.00	0.00	2	43	0.00	0.00	0.00	1
13	1.00	1.00	1.00	2	44	0.67	0.67	0.67	3
14	0.50	0.50	0.50	2	45	0.50	0.50	0.50	2
15	0.67	1.00	0.80	4	46	1.00	0.50	0.67	2
16	1.00	1.00	1.00	2	47	1.00	0.50	0.67	2
17	0.00	0.00	0.00	2	48	1.00	0.50	0.67	2
18	0.00	1.00	0.00	4	49	1.00	1.00	1.00	1
19	0.00	0.00	0.00	1					
20	1.00	0.50	0.67	2	Accuracy			0.64	100
21	0.00	0.00	0.00	1	Macro avg	0.52	0.58	0.53	100
22	0.00	0.00	0.00	1	Weighted avg	0.58	0.64	0.59	100
23	0.00	0.00	0.00	1					
24	0.00	0.00	0.00	1	Skill Level Prediction Report				
25	0.00	1.00	0.00	1	Class	Precision	Recall	F1-score	Support
26	0.50	1.00	0.67	1	0	1.00	1.00	1.00	100
27	0.67	1.00	0.80	2	Accuracy				100
28	1.00	1.00	1.00	3	Macro avg	1.00	1.00	1.00	100
29	0.67	0.67	0.67	3	Weighted avg	1.00	1.00	1.00	100
30	0.50	0.33	0.40	3					

Fig. 13. The classification report.

Further implies that ComReF can accurately map student profiles to predicted or recommended fields and generate valid, skill-tagged learning resources across many platforms. Hence, the observed performance limitations, especially the low F1-scores for certain fields, come from data rather than design flaws. While the architecture is solid, rare or fragmented fields faced limited labeled representations. Possible enhancements of ComReF include merging similar niches, increasing data collection for underrepresented pathways, and implementing the pilot ComReF in live academic advising workflows to collect real-world labels and refine its calibration through iterative improvements.

D. Prototyping

This section elaborates on how the ComReF prototype is designed for recommendations in academic advising environments. It requires minimal infrastructure and offers

broad accessibility. It also provides two main inference interfaces: batch processing through CSV uploads and real-time prediction through webform integration.

CSV Upload (Batch Mode): Users can upload a CSV file containing one or more student profiles. Each row must include a student ID and scores (1–5) for all computing fields, for instance, Software Engineering, Data Science, Cybersecurity, and Network Engineering. The system processes the file within seconds, with a mean inference time of 0.38 seconds per student. It then generates a structured CSV output that includes the predicted field and skill level, career goals, and resource links from platforms such as YouTube, Wikipedia, Coursera, edX, Kaggle, ResearchGate, and Google Scholar (PDFs).

Web Form (Real-Time Mode): For integration purposes, ComReF provides a lightweight API endpoint. Both interfaces are implemented entirely in Python using pandas and scikit-learn, ensuring full cross-platform compatibility (Windows, macOS, Linux) and eliminating any dependence on large language models (LLMs) or cloud-based inference. Table III shows a representative input-output pair for a student with strong aptitude in Cryptography, Cybersecurity, Software Engineering, and AI. The prototype then generates the output in Table IV.

TABLE III. SAMPLE INPUT FOR INFERENCE LEARNER

Input Feature	Assessment Scores
Cryptography	8
Cybersecurity	6
Software Engineering	5
Artificial Intelligence	4
...List	...

TABLE IV. THE INFERENCE OUTPUT

Output Component	Value
Predicted Field	Cryptography
Skill Level	Advanced
Career Goal	System security expert
Resources	Four YouTube Videos, Six Learning sites, and four PDF documents

E. Baseline Comparison: Model Selection Justification

To justify selecting the Random Forest algorithm, we benchmarked three widely used classifiers: Decision Tree (DT), Logistic Regression (LR), and Naïve Bayes (NB). We evaluated each model under the same conditions: the same feature preprocessing pipeline and scaling techniques, with standard scaling applied to Random Forest, Decision Tree, and Logistic Regression, and Min-Max scaling applied to Naïve Bayes. All models were trained and tested using the same data splits and evaluated with consistent performance metrics. As demonstrated in Table IV, Random Forest consistently outperforms all baseline models in field-level prediction, achieving an accuracy of 0.640 and a weighted F1-score of 0.586. In comparison, Decision Tree (weighted F1 = 0.174), Naïve Bayes (weighted F1 = 0.321), and Logistic Regression

(weighted F1 = 0.086) exhibit significantly lower performance. This is especially evident given the task's high dimensionality and multi-class nature, which challenges Logistic Regression. Furthermore, as the macro F1-score indicates, the selected approach is robust to class imbalance (see Table V).

TABLE V. CLASSIFICATION PERFORMANCE ON THE FIELD PREDICTION FOR MODEL JUSTIFICATION

Model	Accuracy	Weighted F1	Macro F1
Random Forest	0.64	0.586	0.529
Decision Tree	0.20	0.174	0.118
Logistic Regression	0.09	0.086	0.074
Naïve Bayes	0.37	0.321	0.252

From Table V, Random Forest achieved the highest overall performance; the difference between its weighted F1 (0.586) and macro F1 (0.529) indicates uneven performance across computing fields, particularly those with fewer samples. This suggests that class imbalance may have affected minority-field predictions. Notwithstanding, Random Forest achieved the highest macro F1 among all evaluated models, indicating comparatively better performance across classes. The moderate performance should be considered in the context of the 50-class prediction setting and limited observations per class; unequal class representation may also contribute to the lower macro F1-score relative to the weighted F1-score. Future evaluation will therefore consider more balanced field representation to improve performance for underrepresented fields. Under controlled experimental conditions, Random Forest consistently outperformed the benchmark models in accuracy, weighted F1, and macro F1, supporting its selection as the primary classifier for ComReF.

V. DISCUSSION

ComReF is a learner-centered AI application for computing education that provides computing-field recommendations and related learning resources for secondary and pre-university learners. It is particularly intended to support learners who require early guidance on computing specializations before progressing to university-level studies. The prototype demonstrates the feasibility of combining learner profiles and assessment performance for personalized computing-field recommendations while remaining lightweight and interpretable. The following subsections discuss the findings in relation to previous research, feedback, and practical implications, and ComReF's strengths, limitations, and ethical considerations.

A. Findings, Feedback and Practical Implications

The findings agree with previous studies on AI-supported educational recommendations. Algarni and Sheldon [2] demonstrated the relevance of recommender systems for course selection, while Narimani and Barberà [37] emphasized learner profiling in personalized recommendations. Similarly, Wang *et al.* [43] showed the value of machine learning for personalized feedback. ComReF extends these approaches by integrating learner profiling, computing-field prediction, skill-level identification, and learning resources to support computing specialization at secondary and pre-university levels. ComReF

also incorporates a feedback loop in which learner performance and feedback can support reassessment and refinement of field and resource recommendations. In practice, it is intended to complement teacher and academic-adviser guidance, with periodic reassessment as learners' interests, skills, and performance change.

B. Strengths of the Proposed Work

Compared with other recommendation works, ComReF's major strength is its end-to-end integration of diagnostic assessment, career-path prediction, and learning-resource generation. ComReF's recommendations offer a complete learning itinerary that can reduce the major gap noted in prior studies, particularly the persistent disconnect between prediction and pedagogy. ComReF ensures that all recommendations are fully accessible to learners. In addition, ComReF aligns with the demand for explainable and trustworthy AI in education, strengthening confidence among students, advisors, and institutional stakeholders. ComReF is lightweight and suitable for computing educational platforms that require an advising module. In terms of adaptation, ComReF offers three major advantages due to its lightweight architecture:

- No GPU or cloud dependency: It runs efficiently on a standard CPU using less than 500 MB of RAM; thus, it is suitable even for local laptops and low-resource environments.
- Auditable: All processes rely on interpretable ML and rule-based logic; hence, it avoids the opacity of black-box LLMs.
- Preserve privacy: Student data is processed within the local environment without external API calls apart from accessing the generated resource URLs.

C. Limitations

However, ComReF is data-dependent as it relies on a labeled dataset containing students' profiles (demographic information and learning preferences), which is not always readily available. Thus, a primary challenge lies in acquiring sufficient labeled data. Future work could address this limitation by adopting semi-supervised or active learning strategies to boost the labeling process. Another limitation concerns the use of static resource templates, as the URL structures are hardcoded for major platforms. If a platform modifies its query syntax, for example, Coursera changing from: `?query=to?q=`, then the generated links may become invalid. An alternative approach would involve dynamic API integration or automated monitoring to increase dynamism in such cases.

D. Ethical Considerations

The first ethical issue involves the training data common in all supervised systems. Thus, ComReF inherits any biases present in its training data. If historical data has favored certain fields, such as Web Development over Bioinformatics, ComReF may spread these imbalances. Stratified sampling is necessary to mitigate this issue and evaluate performance across fields. However, fairness audits remain crucial to ensure balanced recommendations for learners' learning journey.

Another issue is the absence of equity across fields. Emerging fields such as Neurotechnology and Climate Informatics may have fewer learning resources available on mainstream platforms, potentially disadvantaging students who receive recommendations for these areas. To resolve this issue, ComReF provides a checklist protocol that flags recommendations with fewer than three available resources, indicating low-resource fields. Student agency versus algorithmic determinism is a concern. ComReF offers guidance; recommendations must not be perceived as prescriptive. In other words, all outputs clearly state that recommendations are suggestions, not mandates for learners. Future versions could consider counterfactual explanations like: "If you improved your score in Generative AI by 1 point, you would be recommended AI Ethics," to encourage exploration and give students more autonomy in their choices. Hence, ComReF demonstrates that lightweight, rule-based AI can deliver high-impact educational value when designed with pedagogical intent, in this case, for secondary or pre-university students in the Computing field. It offers a feasible alternative to learning via AI-driven recommendations, rather than the existing rigid approach.

VI. CONCLUSION AND FUTURE WORK

In conclusion, ComReF provides a personalized approach for guiding pre-university learners toward suitable computing fields using their profiles and assessment performance. It combines learner profiling, feature encoding, machine-learning prediction, skill-level estimation, and learning-resource recommendation. Among the evaluated classifiers, Random Forest performed best, with an accuracy of 0.64, weighted F1 of 0.586, and macro F1 of 0.529. The lower macro F1 reflects performance differences across computing fields, particularly those with limited representation. Skill-level prediction recorded an F1 of 1.00; however, only one skill-level class appeared in the test set, so this result does not represent discrimination across different skill levels.

ComReF contributes by integrating computing-field prediction, learner characteristics, skill level, and relevant learning resources into a single recommendation process for early computing specialization. Future work will extend recommendations to subfields within broad areas such as Software Engineering, AI, and Data Science and explore multi-label prediction for ranked field choices. Further evaluation will involve real learner profiles and integration with academic advising platforms to examine learner satisfaction, retention, career alignment, and industry relevance. LLMs may also be considered for resource summarization without replacing the framework's core prediction mechanism, while releasing ComReF as an open-source Python package could support reproducibility, improvement, and wider adoption.

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Appendix

1) *Data set sample and amount of data:* The experimental dataset contained 500 learner instances, 54 attributes, and 50 sub-field classes. The 54 attributes comprise 50 numerical assessment features, student_id, best_field, best_score, and skill level (Fig. 14).

[illegible]

Fig. 14. Profile dataset sample.

2) The 50 assessment attributes and best_score are numerical (integer), best_field and Skill Level are categorical, while student_id is an integer identifier excluded from model training.

3) *Processing flow*: Fig. 15 shows the processing timeline. The assessment attributes were already numerical; therefore, encoding was required only for the categorical prediction label. Fig. 16 shows the label encoding fragment.

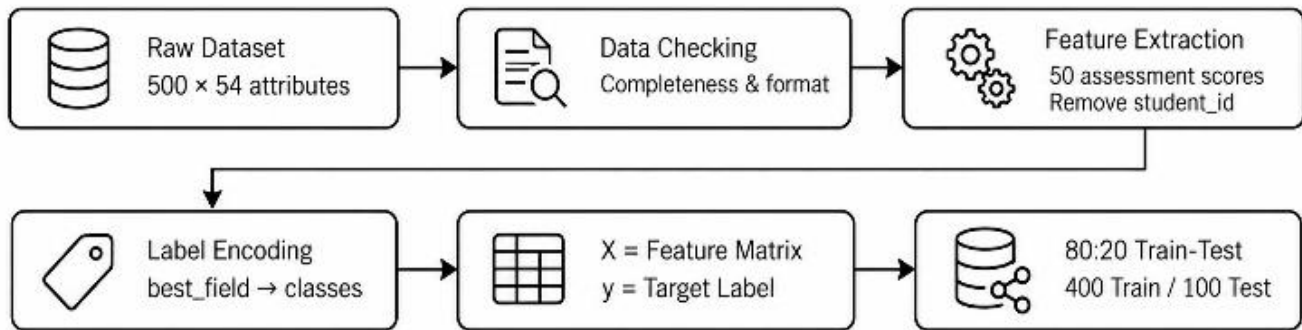


Fig. 15. The data processing flow.

The assessment attributes were already numerical; therefore, we needed to encode only the categorical prediction label.

```
X = df.drop(columns=['student_id', 'best_field',  
                    'best_score', 'Skill Level'])  
  
le = LabelEncoder()  
y = le.fit_transform(df['best_field'])
```

Fig. 16. The Feature extraction and target-label encoding code.

4) *Choice of models:* Random Forest, Decision trees, Logistic regression, and Naïve Bayes: We selected four classifiers to provide complementary classification approaches. We used Random Forest (RF) for its ensemble learning capability, robustness, and ability to model nonlinear relationships [68], [69] while Decision Tree (DT) provides interpretable, rule-based classification [70]. Logistic Regression (LR) was included as a linear probabilistic baseline [71] and Naïve Bayes (NB) as an efficient probabilistic classifier [72]. RF-based feature importance was further used to determine the relative contribution of assessment features to field prediction [73].

5) *Testing strategy:* The dataset was divided using an 80:20 train-test split, producing 400 training and 100 testing instances; the same split was used for all classifiers to ensure consistent comparison, and performance was evaluated using accuracy, precision, recall, and F1-score.