Unlocking Potential: Personality-Aware TVET Course Recommendations Revolutionize Skill Development

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Personality is a complex amalgamation of ideas, behaviors, and social constructs that shape our self-perception and influence our interactions with others. It tends to remain relatively stable over time. The development of personality-aware recommendation systems is driven by the understanding that human behavior and personality play a significant role in skill acquisition, career progression, and overall success. Technical and Vocational Education and Training (TVET) is crucial in building a skilled workforce, particularly in response to the demands of Industry 5.0. Unlike conventional recommendation systems, personality-aware systems effectively address persistent challenges such as the cold start problem and data sparsity. This paper introduces the Personality-aware TVET Course Recommender System (TCRS), which suggests the top three TVET courses by considering trainees' personality traits, demographic information, and the historical success patterns of previous trainees in similar courses. A standout feature of the TCRS is its Academic System Learner, which continuously incorporates insights from individual trainees' progress in TVET courses, thereby enhancing the accuracy of its machine learning model for predictive analysis. The effectiveness of the TCRS is assessed using seven classifiers, yielding notable prediction accuracies: 99% with Random Forest, 98% with Decision Tree, and 89% with k-Nearest Neighbors (kNN). In real-time testing, the TCRS demonstrated an accuracy rate of 84%.

Keywords: TVET Digitization; BFI Personality Traits; Personality-Aware Recommender Systems; Industry 5.0 and Digital Skills Development.

Introduction:

Personality encompasses a set of enduring patterns of cognition, affect, and behavior that define an individual, distinguishing them from others. It includes various aspects of identity such as habits, inclinations, beliefs, and emotional states. Although personality traits generally exhibit stability over time and across contexts, they are not immutable and can evolve throughout a person's life. The growing interest in personality-aware recommendation systems among researchers is driven by their improved accuracy and ability to address traditional challenges like the cold start problem and data sparsity [1]. Integrating user personality traits into computational frameworks has opened new research avenues, including automated personality recognition, and has enriched existing fields such as recommendation systems [2], [3], [4], [5], human-robot interaction, and more. The expansion of personality computing across diverse domains has led to a significant increase in scholarly output on this subject over the past decade [1], [6], [7], [8]. These systems have been successfully applied in various areas, including education [9], [10], tourism [11], image and music recommendations [12], [13], and social networking [14]. A deep understanding of human personality allows for better alignment between personality traits and learning objectives, skill acquisition, and career trajectories [15]. Personality-aware recommender systems have demonstrated significant advancements in several key areas, including enhanced accuracy, privacy protection, adaptability to cultural and contextual variability, and bias mitigation [16]. Recent studies [17], [18] not only underscore these improvements but also highlight practical applications and innovative methodologies that contribute to the ongoing evolution of personality-aware systems. Collectively, these developments offer a more nuanced and comprehensive understanding of current trends and solutions within the field.

In this study, we extend research on personality-aware recommendation models and apply them to the Technical and Vocational Education and Training sector. Within psychology, various tools like the Big Five, MBTI, HEXACO, and Eysenck models are used to extract personality traits. Among these, the Big Five Inventory (BFI), also known as the Five-Factor Inventory [19], is a widely used and well-established method for assessing personality traits through a specific set of questions. For our investigation, we collected personality trait data from these techechical trainees using the BFI's 50-item questionnaire, which is available through the International Personality Item Pool (IPP). The Big Five Personality Traits include Openness to Experience (O), Conscientiousness (C), Extraversion (E), Agreeableness (A), and Neuroticism (N), collectively referred to as the OCEAN traits.

TVET plays a critical role in Industry 5.0, which is characterized by the integration of human-centric approaches with advanced technologies to create intelligent and sustainable industrial ecosystems. Industry 5.0 represents a paradigm shift where human creativity [20] and cognitive abilities merge with the efficiency, precision, and Artificial Intelligence (AI) enabled capabilities of machines in industrial production [21]. AI is increasingly utilized in education and skills development through various means, including adaptive learning platforms, intelligent tutoring systems, AI-enhanced skills assessments, natural language processing, and Chabot's. The integration of AI with the principles of Industry 5.0 in education and skill development is fostering a more personalized, efficient, and human-centric learning environment. AI offers tools and platforms that tailor educational experiences to individual needs, while Industry 5.0 highlights the significance of human skills and collaborative approaches. Together, these advancements are transforming education by enhancing responsiveness to diverse learning styles, emphasizing comprehensive skill development, and aligning educational practices with the evolving demands of the modern workforce. This shift highlights the growing importance of human-computer interaction [22] in the manufacturing of industrial goods and the delivery of services. Research indicates that these technical and vocational institutions are essential in bridging the skills gap [23] inherent to Industry 5.0 by equipping learners with the necessary competencies to harness emerging technologies, including AI, robotics, and the Internet of Things (IoT). Additionally, aligning TVET initiatives with UNESCO's Sustainable Development Goals (SDGs) No. 4, 5, 8, and 17 [24] emphasizes its contribution to societal progress and sustainable development by 2030. However, the digital infrastructure within Pakistan's TVET sector remains underdeveloped [25], necessitating the adoption of digital methodologies, such as recommender systems [26], [27], to improve the effectiveness of technical and vocational education in the country. The proposed TCRS offers a versatile solution tailored to the needs of the technical education sector, enhancing its applicability in various developing contexts. Personalized TVET course delivery, aligned with individual learner attributes, not only improves return on investment but also strengthens the sector's ability to address the multifaceted challenges of Industry 5.0.

The motivation behind this research arises from the stark reality that, despite significant investments and the availability of free technical and vocational education for the youth, Pakistan faces alarmingly low employability rates among TVET graduates, hindering timely infrastructure development due to a lack of skilled labor. Notably, 63% of Pakistan's population consists of young individuals aged 15 to 30 years [26]. Over the past five years, the Government of Pakistan, along with provincial administrations and international development agencies like USAID, DFID, JICA, the British Council, and the World Bank, has implemented numerous skills development programs targeting the technical education sector. Despite these efforts, the employability rate in Pakistan's TVET sector remains at just 38% [28], exacerbating the persistent challenge of skill shortages. This shortage significantly contributes to delays in critical infrastructure projects, including those within the China-Pakistan Economic Corridor (CPEC) [29], [30]. To identify the root causes of this issue, a survey was conducted to explore how individuals gain admission to TVET courses. The findings revealed a concerning trend: 49% of respondents secured admission without prior knowledge of the field, 25% based on perceived course relevance, and 10% through informal referrals. Crucially, there is no provision for personality assessments, academic evaluations, career counseling, or guidance before enrollment, leading to a mismatch between individuals' skills and labor market demands.

Data collection for this study was conducted in collaboration with the Punjab Vocational Training Council (PVTC) [31], one of the largest technical education providers in Punjab. This extensive data collection and evaluation initiative spanned from July 2019 to September 2022 and involved 1356 trainees across 18 trades from eleven selected Vocational Training Institutes (VTIs). Formal authorization for data collection and publication was obtained from PVTC to ensure compliance with ethical standards. The data collection process included online portals and paper-based questionnaires, gathering information on trainee profiles, TVET course details, and BFI personality data. To protect privacy, each trainee was assigned a unique profile code, anonymizing personal identifiers like names, CNIC numbers, and contact details. After thorough data cleaning and preprocessing, involving 755 trainees, the dataset was deemed suitable for further analysis. A rigorous evaluation of seven classifier models was conducted to assess the TCRS model. Random Forest classifiers stood out, consistently achieving accuracy levels above 89% across key metrics like AUC, Classification Accuracy, F1 Score, Precision, Recall, and MCC. The decision tree classifier showed performance scores ranging from 69% to 98%, while the other classifiers scored below 55% across all evaluated metrics. In real-time testing, the TCRS achieved an accuracy rate of 84%.

A comprehensive systematic literature review [25] examined ICT enablement in TVET (education over a decade). The review revealed that the overall level of ICT adoption in the TVET sector remains very low. To our knowledge, the current study is pioneering in its approach, integrating personality traits into TVET course recommendations not only within Pakistan but also on a global scale in the TVET sector. This research introduces an innovation specific to the TVET sector, offering a new perspective compared to traditional, more generic, and less personalized methods. By adapting the BFI to the Pakistani TVET context, this study addresses the region's unique cultural and educational needs. It provides personalized course recommendations and career guidance based on personality assessments, thereby making a novel and impactful contribution to both personality psychology and vocational education. This localized approach ensures that the TCRS is both theoretically robust and practically relevant, with sensitivity to the cultural nuances of Pakistani students and professionals. The contribution of this research includes:

- Personality-aware TCRS for the TVET Sector
- First Personality dataset for the TVET sector of Pakistan

This research manuscript is organized as follows: The section State of the Art furnishes a comprehensive literature review; the Section Material and Methods delves into the discussion of materials employed in the study; the Result and Discussion Section delineates the presentation of results; the Conclusion Section encapsulates the conclusion drawn from the findings; and finally, Future Directions Section outlines the prospective avenues for future research endeavors.

State of the Art:

Our literature review begins with an exploration of traditional recommender systems before delving into the realm of personality-aware recommendation systems. Our focus is on advancing research in the TVET domain through the lens of personality-aware recommendation systems. Notably, this study appears to be a pioneering effort within the TVET sector. Nonetheless, we identified seven relevant academic studies on personality-aware recommendation systems, which are analyzed and discussed in this section.

Traditional Recommender Systems:

Recommender systems have long been integral to computing, offering various approaches to identify user preferences and generate recommendations. These systems can be broadly categorized into three types:

- **Content-based recommendations** [32]: These systems recommend items similar to those a user has liked in the past, relying on item features and user profiles.
- **Collaborative Filtering** [33]: This approach identifies patterns based on user interactions, recommending items that similar users have enjoyed.
- **Hybrid Recommendations** [34]: These systems combine content-based and collaborative filtering methods to leverage the strengths of both approaches.
- Recent research has explored the application of recommendation systems within educational settings, particularly in vocational and technical education. These studies highlight the potential of recommendation systems to revolutionize learning experiences:
- **Course Selection and Personalization:** A study by [35] demonstrates how recommendation systems can enhance course selection in educational contexts. By leveraging data analytics and machine learning, these systems offer personalized learning paths, course suggestions, and career guidance.
- **Student Engagement and Skill Development**: Similarly, [36] investigated how recommendation systems can improve student engagement, motivation, and self-directed learning in vocational education. By analyzing students' academic performance, interests, and career goals, these systems provide tailored recommendations for courses, training programs, and skill-building activities, optimizing educational outcomes and preparing students for the workforce.

These studies collectively underscore the transformative potential of recommendation systems in vocational and technical education, paving the way for personalized and effective learning experiences.

Personality-Aware Recommendation Systems:

The advent of personality computing in the early 2000s has led to significant advancements in personality-based recommendation systems. These systems often adapt their recommendation strategies based on the nature of the content and the user's personality traits. In our investigation into the existence of personality-aware Technical and Vocational Education and Training Course Recommender Systems (CRS), we conducted an exhaustive review. Unfortunately, we found no prior studies specifically addressing personality-aware TVET CRS. As a result, we expanded our literature review to include broader academic studies on personality-aware recommendation systems. A summary of the identified studies is provided in Table 1 for reference.

Table 1. Personality Aware RS Literature Summary

Study Title	Publication Year	Recommender System Approach
Personality-Aware Collaborative Learning: Models and Explanations [37]	2020	Collaborative personalized recommendations using KNN, Matrix Factorization, and iSplitting
Socially-Aware Conference Participant Recommendation with Personality Traits [38]	2017	Collaborative Hybrid approach using social network analysis
Improving Socially Aware Recommendation Accuracy Through Personality [39]	2017	Linear Hybrid Recommendation using social ties connections
Hybrid attribute and personality-based recommender system for book recommendation [40]	2018	Hybrid attribute-based methods using the most similar visited material and most similar learner
Recommender System Framework for Academic Choices [41]	2016	Stochastic probability distribution-based modeling using social media and academic features
Is Big Five better than MBTI? A personality computing challenge using Twitter data [42]	2018	NLP with Twitter Data
PCRS: Personalized Career-Path Recommender System for Engineering Students [43]	2020	Fuzzy logic-based intelligent system

As shown in Table 1, the literature reviewed utilizes a variety of data inputs, such as personality traits, social media content, student CGPA, and grades, to inform academic recommendations. A systematic review of course selection recommendation surveys [35] reveals that current course recommendations predominantly rely on content-based, collaborative, and hybrid methodologies. This review also highlights the urgent need for future development of AI-based recommender systems that are reliable, precise, and personalized to meet the unique needs of students. Additionally, a study by [44] emphasizes the importance of user-centric factors, such as autonomy, openness, and trust, in addressing the negative effects of usability issues in explainable recommendations.

Accurately measuring personality is a critical step in developing a personality-based recommender system, as errors in personality identification can significantly impact prediction accuracy. Generally, two primary methods are used for personality measurement [35]: Automatic Personality Recognition (APR) and Questionnaire-Based (QB) assessment. APR involves extracting personality insights from various sources, including text-based data such as social media posts and tweets, multimedia content like images, videos, and live streams, and behavioral patterns observed in preferences for social media and book recommendations. In contrast, QB assessment involves collecting personality data through self-reported responses to personality-related questions. QB-based personality measurement is widely regarded as more prevalent and accurate [45], [46], [47]. Multiple proximity functions are employed across various domains, including psychology, data analysis, and machine learning, to evaluate the similarity or closeness between multiple entities or variables. Commonly used functions include Euclidean distance, cosine similarity, and the Pearson correlation coefficient. We have chosen to utilize the Pearson correlation coefficient for personality neighborhood calculations due to its superior accuracy and widespread acceptance [38], [39], [48] in personality-aware recommendation systems.

In psychology, several tools are used to assess human personality, including the Big Five Inventory (BFI), the Myers-Briggs Type Indicator (MBTI), the HEXACO model (which includes Honesty-Humility, Emotionality, Extraversion, Agreeableness, Conscientiousness, and Openness to Experience), and the Eysenck Personality Questionnaire (EPQ). Among these, the BFI, also known as the Five-Factor Inventory [19], is particularly prominent due to its established reputation and widespread use [38], [35], [49]. The BFI is favored for its clear and structured approach to measuring personality traits through a series of well-defined questions. We chose the BFI for this study because of its user-friendly design and straightforward structure, which is easily understood by TVET trainees, who generally have a matriculation-level education. Additionally, we translated the questionnaire into the local language to enhance question clarity and ensure the quality of the responses. For this study, we specifically employed the BFI OCEAN personality assessment to achieve robust and reliable personality profiling.

Materials and Methods:

Our proposed TCRS is rooted in a personality-aware recommendation framework, with enhancements to the recommendation methodology. Traditionally, personality-aware recommendation systems utilize learning from text-based [50], [51], [52] APR, multimedia-based [53], [54], [55] APR, and behavior-based [56], [57], [58] APR approaches. However, in TCRS, the academic learner actively engages in learning and labeling processes facilitated by the Academic System Learner (ASL). In this section, we begin by outlining the architecture of TCRS, followed by a detailed explanation of the experimental dataset and the evaluation metrics employed in our study.

Problem Formulation:

Course recommender systems have become increasingly important in education, facilitating personalized learning experiences and helping students make informed decisions. However, in the technical education sector, prospective trainees are often admitted without undergoing academic testing, personality assessments, or career counseling. This study introduces a machine learning-based TCRS that leverages trainees' demographic information, academic performance, and personality traits to recommend three TVET courses that best align with their characteristics. Traditional recommender systems typically operate in three phases: rating, filtering, and recommendation. However, personality-aware recommendation systems incorporate two additional phases [59] within the rating process. Our proposed TCRS approach builds upon existing personality-aware methods, enhancing the system's ability to match trainees with suitable courses.

Table 2. Recommender System Phases

Conventional Recommender System	**Personality Aware Recommender System**	**TCRS**
• Rating Phase • Filtering Phase • Recommendation Phase	• Personality Measurement and Personality Matching • Rating Phase	• Personality Measurement • Personality Mapping • Personality Similarity, Age Similarity, Gender

	• Content Similarity, Personality Similarity, and Rating Similarity • Personality-Aware Recommendation	Similarity, and Course Progress • Personality Matching • Personality-Aware TVET Course Recommendation

Table 2 provides a comparative analysis of traditional recommendation systems, personality-aware recommendation systems, and the TCRS approach. In this new approach, the TCRS recommendation phase incorporates personality mapping after personality measurement. Following this addition, similarity, and personality matching are rearranged to occur after calculations involving personality, age, gender, and course progress similarities. The inclusion of personality mapping is essential to align TVET course progress with each student's personality traits in real time, facilitated by the Academic System Learner (ASL).

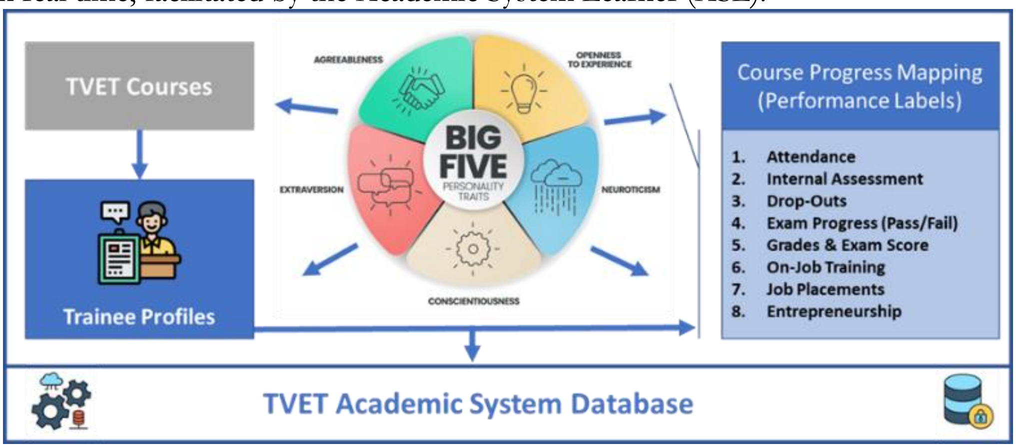

Figure 1. Academic System Learner (ASL)

The overarching goal of TCRS is to replicate the advisory process of TVET advisors by offering recommendations and guidance to incoming students based on a synthesis of their personality traits, demographic details, and academic performance. Figure 1 illustrates the ASL, which systematically tracks each trainee's academic progress in real-time. This dynamic process continues throughout the training cycle, with the model continually learning and annotating individual trainees' progress. Each trainee's journey is meticulously labeled, starting from admission and extending through attendance records, internal assessments, instances of dropout, examination progress, and eventual examination grades. Additionally, markers for on-the-job training, job placement, and entrepreneurship are also applied. For this study, we utilized labeled data related to exam progress and exam scores. Future research will explore the incorporation of data on on-the-job training, job placement, and entrepreneurship.

TCRS:

The TCRS architecture is outlined in Figure 2, beginning with Data Collection and advancing to Data Preparation. Data Collection involves gathering personal details, TVET-related information, VTI (Vocational Training Institute) specifics, and personality traits based on the Big Five Inventory (BFI). The personal details of trainees include their unique VTI identification number, name, parental information, enrolled TVET trade, date of birth (age), gender, educational qualification, residential address, contact number, and email address. To ensure privacy and data integrity, each trainee is assigned an additional profile code that is used within the dataset.

TVET trade details encompass the trade name, batch identification, admission session, type of TVET course, VTI designation, and the course's start and end dates. The Punjab Vocational Training Council (PVTC) conducts two admission sessions annually, in January and July. The distinction between course types is based on the evaluation methodology:

Competency-Based Training [60] (CBT) categorizes trainees as either "Competent" or "Not Competent," while the Regular Course awards examination scores and grades.

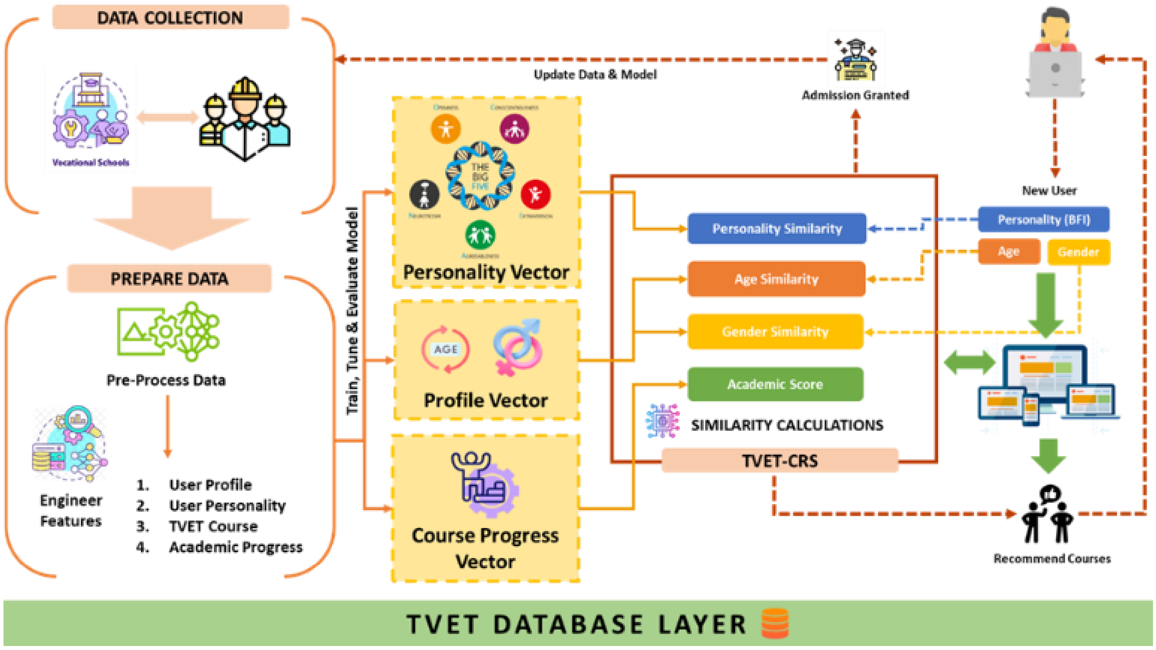

Figure 2. TCRS Architecture

Personality insights are obtained from the trainees' responses to the Big Five Inventory (BFI) questionnaire, a well-established psychological assessment tool [38], [35], [49] designed to measure personality traits. The BFI assesses personality across five dimensions: Openness to Experience (O), Conscientiousness (C), Extroversion (E), Agreeableness (A), and Neuroticism (N). During this phase, trainees complete a 50-item self-assessment questionnaire using Likert scales. The BFI analysis then provides scores for each of the five personality dimensions. Data preprocessing [61] involves cleaning, transforming, and integrating data to ensure it is suitable for analysis. During this phase, any inconsistent, missing, or unclear data was excluded. The data collection was carried out using an online web-based application integrated with Microsoft SQL Server. The necessary data were combined using SQL queries, and the final dataset for analysis was exported to Microsoft Excel.

The personality neighborhood technique is one of the most widely used methods in personality-aware recommendation systems [62]. This technique employs a proximity function to measure the similarity between two users' personalities and predict future behavior accordingly. Common proximity functions include the Pearson Correlation Coefficient, Euclidean Distance, Cosine Similarity, and Spearman's Correlation Coefficient. Among these, Pearson Correlation is the most frequently utilized [63], [64], [65] in personality-aware recommendation systems. It is particularly effective in calculating similarity scores between user profiles. After preprocessing and data labeling, the data is organized into three vectors: the personality vector, the profile vector, and the course progress vector. The personality vector calculates personality similarity, the profile vector assesses demographic similarity based on factors such as age and gender, and the course progress vector evaluates the Academic Score. Academic Score (AScore) will be calculated based on two mandatory conditions (i) the progress of the individual trainee must be completed successfully and (ii) the Trainee must be passed and his/her exam score is input to the Academic System. Equation 1 shows the AScore calculation:

$$AScore(TS, C) = \sum_{i}^{n}(CourseProgress = Completed)(MScore(TS, i) \qquad (1)$$

In equation 1:

- $AScore(TS, C)$ is Academic Score of TVET Student TS for Course C

- $(CourseProgress = Completed)$ TVET Course must be completed successfully by the TS
- $MScore(TS, i)$ Exam Score for TS will be calculated for i score weightage from 1.

Profile vector includes gender score and age score. In our dataset D, gender is an important variable because despite the gender data proportionate of F:36%, and M:64%), female trainees are 13.17% more correctly predicted than male trainees. Secondly, females normally get admission 2-3 years late into TVET courses as compared to male trainees. Gender Score means that if new trainees whose courses have to be recommended have the same gender then he/she will be assigned a score of one otherwise he/they will be assigned zero. Equation 2 shows the calculation of Profile Gender score ($PfGen$): -

$$PfGen(TS, G) = \sum_i^n (TS_G, G_i) \quad (2)$$

In equation 2:

- $PfGen$ is the profile score of new TVET Trainee TS for Gender G
- TS_G Matching TVET Trainee G and gender weightage G_i

The age vector score is input by the Profile Age (PfAge) variable. The age bracket of Dataset D is between 14 to 35 years of the trainees. The majority of 79.35% of trainees fall between 14 years to 21 years and 20.65% of trainees fall between 22 to 35 years. Keeping in view the dataset D age statistics, Table 3 weightage has been set for Age score calculation. As shown in Table 3, if the age difference between the new user and the existing dataset user is ±1 year, then a weightage of 1 will be assigned for age similarity. Similarly, Age difference and assigned weightage are shown in the Table. Greater than 10 years of age difference will be assigned zero weightage.

Table 3: Age Score Weightage Calculations Matrix

Age Difference	Weightage	Age Difference	Weightage
± 1 year	1	± 5 years	0.3
± 3 years	0.7	± 10 years	0
± 4 years	0.5	> 10 years	0

Profile Score Age $PfAge$ variable calculation is shown in Equation 3: -

$$PfAge(TS, A) = \sum_i^n (TS_A, A_i) \quad (3)$$

In equation 3:

- $PfAge$ is the profile score of new TVET Trainee TS for Age A
- TS_A Matching TVET Trainee A and weightage A_i

The personality score is calculated using the personality neighborhood filtering method. Personality neighborhood is similar to the Pearson Correlation coefficient but with a difference [3] it uses personality traits instead of items in personality-aware recommender systems. The personality of the user is based on the personality dimension score for the Big Five personality traits of OCEAN. The Personality descriptor of TVET user PT_a is shown in Equation 4. PT_a is an n-dimension vector of TVET User a in which each dimension is represented by one of the personality characteristics of the user.

$$PT_a = (P_{a,1,} P_{a,2,} \dots \dots \dots . P_{a,n,})^T \quad (4)$$

Personality matching Similarity (SIM) of new users Personality (P) with existing users is denoted in Equation 5.

$$Sim_P(a, b) \quad (5)$$

In equation 5:

Sim_P is Pearson Correlation personality neighborhood similarity of new user a for existing user b

Similarity calculation between a new user u_a and existing user u_b will be calculated using the Pearson Correlation Coefficient method, shown in equation 6.

$$SimTP(u_a, u_b) = \frac{\sum_i (pt_a^c - \overline{pt_a})\,(pt_b^c - \overline{pt_b})}{\sqrt{\sum_i (pt_a^c - \overline{pt_a})^2 (pt_b^c - \overline{pt_b})^2}} \quad (6)$$

In equation 6:

- $SimTP(u_a, u_b)$ User u_a and User u_b Similarity of TVET Personality,
- pt_a^c the personality trait of existing user a for TVET Course c
- $\overline{pt_a}$ and $\overline{pt_b}$ Average personality traits of the users u_a and u_b

In this research, we employed a linear scoring model technique based on a weighted sum. In contrast, the personality-aware recommender systems reviewed in the literature utilized matrix factorization, linear hybrid models, probability distributions, and collaborative hybrid approaches. These models have been built in school education, higher education, book recommendations, and conference participant recommendations. Along with personality data, the combination of other data like user profiles, academic features, and social networking data is used for hybrid recommendation. No personality-aware recommendation study for the TVET sector is found. Personality-aware recommendation system efficiently handles cold start and data sparsity problems therefore we have used the personality-aware recommendation system in technical and vocational education in this study. Secondly, the literature proves that the addition of personality along with academic and demographic features enhances the recommendation accuracy thus we have used BFI personality traits, user demographics like age, gender, and academic performance like exam scores in TCRS. Specifically, after collecting personality data, we labeled this data with the actual course progress for each user throughout their entire course journey. This meticulous approach to data labeling over multiple years represents a significant advancement over previous research.

TCRS recommendation generation process is shown in Figure 3. As shown, the recommendation engine will get three inputs from new users; (i) BFI Personality OCEAN data, (ii) Age, and (iii) Gender information. These three pieces of information will be input into the TCRS machine-learning model. The TCRS model will create a matrix for new users and existing users for similarities of BFI personality traits, age, gender, and academic score and add to the final score. Based on the final score, TVET's top three TVET matching courses will be recommended to the new user. The final score calculation is shown in Equation 7.

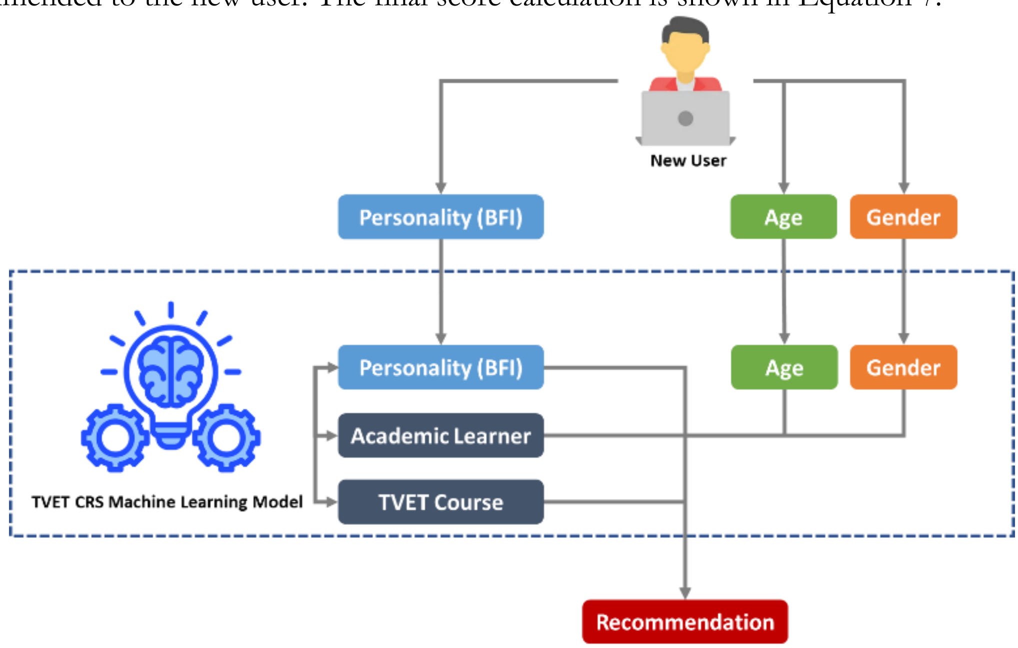

Figure 3. TCRS Recommendation Generation

TVET CRS Similarity calculations equation is shown in Equation 7.

$$\text{Score}\,(\text{TS}, \text{C}) = \overline{\text{pt}_a} + k\sum_{u\in\Omega_u} \text{Sim}_P(a,b) + (\,\text{SimTP}) + (\text{PfAge}) + (\text{PfGen}) + (\text{AScore})\,(\text{pt}_b, \text{C} - \overline{\text{pt}_b}) \quad (7)$$

In equation 7:

- $\text{Score}\,(\text{TS}, \text{C})$ The score of TVET Students for the Course
- $\overline{\text{pt}_a}$ the personality trait of existing user a for TVET Course c
- $\sum_{u\in\Omega_u} \text{Sim}_P(a,b)$ denotes neighbor for the user TS that has the previous similarity for C
- SimTP Similarity score of BFI personality matching user TS
- PfScore Profile score of matching user TS
- AScore Academic score of matching user TS
- $\text{pt}_b, \text{C} - \overline{\text{pt}_b}$ is a score given to the user pt_b for Course and $\overline{\text{pt}_b}$ is the average score of the user

Recommendation generation in personality-aware recommender systems has evolved significantly with recent advancements in machine learning and data analytics. The latest trends emphasize the integration of deep learning techniques and sophisticated natural language processing to enhance the accuracy and personalization of recommendations. Modern systems leverage neural collaborative filtering and autoencoders to model complex user-item interactions, incorporating not just personality traits but also nuanced behavioral patterns and contextual data. Considering our target audience of youth, who are generally less educated and technology-oriented compared to those in higher education, we have adopted a recommendation generation process that emphasizes personality traits, age, and gender demographics. This filtering approach enables a more nuanced understanding of user preferences and dynamic needs. Additionally, the ASL system continuously updates its data, which enhances the model's accuracy and relevance. These innovations collectively contribute to more precise, relevant, and personalized recommendations, aligning with the latest trends in improving user experience and engagement. Future research could explore the integration of additional contextual factors, such as real-time engagement metrics and evolving learning preferences, to further enhance recommendation accuracy. Additionally, investigating the impact of incorporating diverse data sources, such as interactive learning platforms and external feedback, may provide deeper insights into user behavior and improve model performance.

Here is the deployment pseudo code for the TCRS algorithm.

ALGORITHM 1: Pseudocode for TVET CRS

```
// Declear and initialize variables
i, j and n; // Integer variables
PersonVector[n], AgeScore[n], GenScore[n] CourseProgVector[n], FinalRSScore[n]; // Floating Variables
Participants[UserID, Course, O_Score, C_Score, E_Score, A_Score, NScore, Gender, Age, CourseProgress, ExamScore] // Array of Participants of size n
Register [NewUser] with Personal Information (Including Input Age and Input Gender) and Get the BFI Personality Assessment Test
NewUser[Calculate Personality, Get Age, Get Gender]; // Input Variables
for i=0 to i<n; i++ do
for j=0 to j<n; j++ do
Calculate [NewUser] Personality Score from [Participants] and Store into PersonVector using PT_a [Equation 4]
Calculate [NewUser] Age Score from [Participants] and Store into AgeScore using PfAge [Equation 3]
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Calculate [NewUser] GenScore from [Participants] and Store into GenScore using PfGen [Equation 2]
Calculate Course Progress Score where [NewUer] Personality = [Participants] and Store into CourseProgVector using AScore [Equation 1]
Add PersonVector, AgeScore, GenScore, CourseProgVector score into FinalRSScore using SimTP [Equation 6] and Score (TS, C) [Equation 7] into matrix "A"
end for
end for
// TVET Course Recommendation
For i=0 to i <=3; i++ do
Sort on FinalRSScore in Descending Order
Print Output: Recommended TVET Course[i] = [Course]
end for
```

TCRS application deployment logic is shown in Algorithm 1 in pseudocode. As shown, after the declaration of initial variables, the participant's (existing TVET trainees) data will be loaded into the array. Then new user personal information including Age and Gender will be stored in the database. The new users will be suggested to go for the BFI Personality Assessment Test and his/her personality scores will be calculated. New User Personality, Age, and Gender will be stored into variables. Then a for loop will be executed till the end of dataset D Records for new user's personality, age, and gender similarities will be calculated and added into the matrix "A". Matching personalities for Participants (existing users) Academic Score weightage will also be added into the matrix "A". Based on the final score, in descending order, existing users corresponding top three TVET courses will be recommended to the new users. The entire data will be stored in the database.

Dataset:

Data collection, labeling, and analysis for this research were carried out between 2019 and 2022, resulting in a comprehensive dataset from 1,356 trainees. Of these, data from 1,075 trainees were initially used as input data, while the remaining 281 trainees' data were set aside for testing the TCRS. During the data preparation process, information from 320 trainees was found to be unsuitable for analysis and was subsequently excluded. This left a total of 755 thoroughly cleaned and validated data entries for use in the research. The stages of input data collection are depicted in Figure 4.

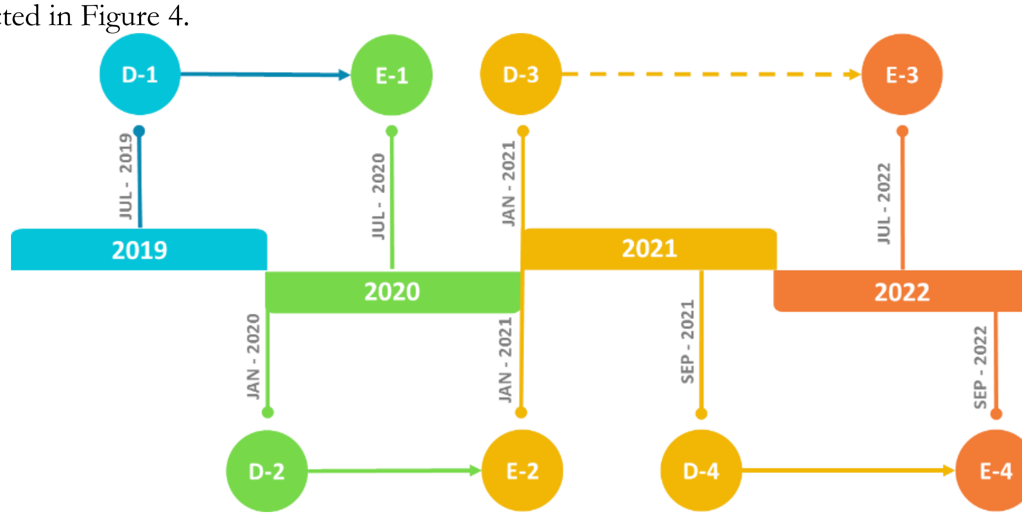

Figure 4. Research Input Data Collection

Following data collection, the process moved on to data analysis, where correlations between machine learning models [66] and predictions [26] were assessed, leading to the development of the final model. In January 2024, a live testing phase was conducted with the

281 reserved trainees, and the results of this testing are presented in the results section. In data 755 preprocessing data, all trainees will be updated with their course progress, and all those trainees who have successfully passed and secured 75+ marks data for dataset D were used to train the TCRS model. Dataset D used in the model training data dictionary is shown in Table 4.

Table 4. Dataset Dictionary

S #	Field Name	Value	Description
01	Profile Code	Numeric Values	Trainee unique identification code
02	Trade	Trade Name	Name of the Trade in which the Trainee is studying
03	Gender	Male / Female	Gender of the Trainee
04	Age	Numeric Value	Age of the Trainee
05	Score_O	BFI Openness	Trainee BFI personality Openness to Experience Score
06	Score_C	BFI Conscientiousness	Trainee BFI personality Conscientiousness Score
07	Score_E	BFI Extroversion	Trainee BFI personality Extroversion Score
08	Score_A	BFI Agreeableness	Trainee BFI personality Agreeableness Score
09	Score_N	BFI Neuroticism	Trainee BFI personality Neuroticism Score

Evaluation Metrics:

To evaluate the accuracy of the TCRS model, seven widely recognized classifier models were utilized to measure prediction accuracy, as documented in the literature [5], [67], [39], [68]. The Confusion Matrix of the TCRS model is presented in the results section. Typically, a Confusion Matrix is a table that illustrates the performance of a classifier on a set of test data with known true values. A visual representation of the Confusion Matrix is shown in Figure 4.

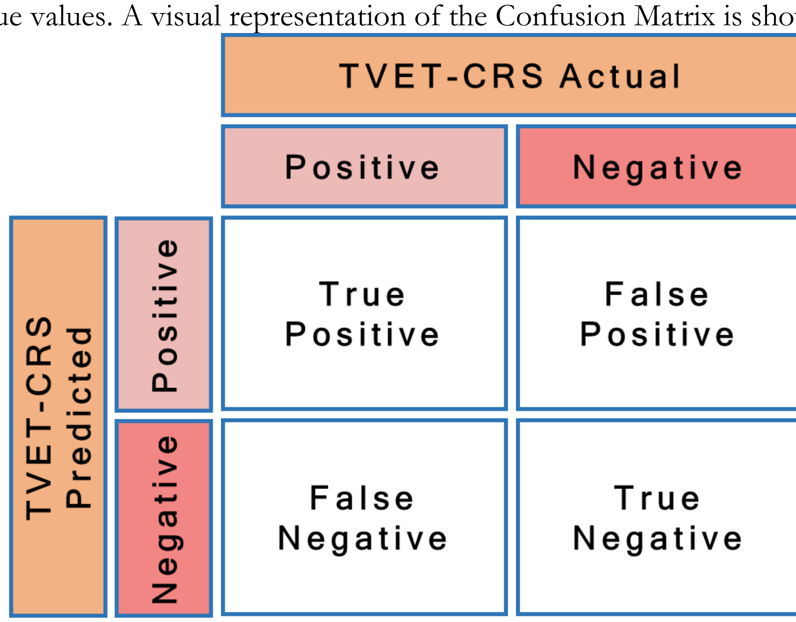

Figure 5. TCRS Confusion Matrix

This matrix includes actual and predicted values, consisting of True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN) generated by the TVET CRS model. The accuracy of the TCRS model was assessed using various metrics, including the Area Under the ROC Curve (AUC), Classification Accuracy (CA), F-Score (F1), Precision, Recall, and Matthews Correlation Coefficient (MCC) [69]. These metrics are commonly employed in evaluating the performance of recommender systems, as supported by the literature [1], [70],

[71]. The calculations for AUC (Equation 8), CA (Equation 9), F1 (Equation 10), Precision (Equation 11), Recall (Equation 12), and MCC (Equation 13) are outlined below:

$$AUC = \int_0^1 \Pr[TP]\,(v)\,dv \tag{8}$$

Where $\Pr[TP]$ is a function of $v = \Pr[FP]$

$$CA = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

$$F1 = \frac{2TP}{2TP + FP + FN} \tag{10}$$

$$Precision = \frac{\sum TP}{\sum TP + FP} \tag{11}$$

$$Recall = \frac{\sum TP}{\sum TP + FN} \tag{12}$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{13}$$

Result and Discussion:

The results of this study serve as a critical benchmark for assessing the efficacy of the TCRS in personalized learning environments. They offer valuable insights into the system's accuracy and performance, which can inform future enhancements and optimizations. Moreover, these findings highlight the importance of leveraging machine learning techniques to improve educational experiences and decision-making processes within the TVET sector. Table 5 shows the classifier model and accuracy metrics results: -

Table 5. TCRS Accuracy Result

S #	Model	AUC	CA	F1	Precision	Recall	MCC
1	Decision Tree	0.983	0.725	0.720	0.736	0.725	0.695
2	Support Vector Machine (SVM)	0.867	0.379	0.313	0.415	0.379	0.288
3	Stochastic Gradient Descent (SGD)	0.548	0.200	0.153	0.207	0.200	0.101
4	Random Forest	0.994	0.902	0.901	0.906	0.902	0.891
5	Naïve Bays	0.804	0.282	0.263	0.293	0.282	0.225
6	Logistic Regression	0.788	0.289	0.243	0.286	0.289	0.186
7	K-Nearest Neighbor (kNN)	0.892	0.407	0.388	0.418	0.407	0.330

As detailed in Table 5, the TCRS model demonstrates its highest accuracy with an impressive AUC score of 99% when using Random Forest classifiers. Decision Tree classifiers achieve a notable accuracy of 98%, while kNN scores 89%. Conversely, the SGD classifiers show the lowest AUC accuracy at 54%. Classification Accuracy (CA), which represents the proportion of correctly predicted outcomes relative to the total predictions, reveals that Random Forest leads with a CA score of 90%, followed by Decision Tree at 72%. The remaining classifiers fall below 40% in CA.

The F1 score, which combines precision and recall into a single metric, is highest for Random Forest at 90%, with Decision Tree at 72%. All other classifiers have F1 scores below 40%. In terms of Precision, which measures the proportion of positive identifications that are actually correct, Random Forest again excels with 90%, while Decision Tree follows with 73%. Other classifiers have precision scores below 45%. For Recall, which measures the proportion of actual positives that are correctly identified, Random Forest achieves 90%, with Decision Tree close behind at 73%. The other classifiers score below 40%. The Matthews Correlation Coefficient (MCC), which evaluates the correlation between observed and predicted classifications, shows Random Forest with the highest MCC of 89%, and Decision Tree with a commendable 69%. All other classifiers have MCC scores below 35%.

In summary, Random Forest classifiers consistently outperform others across all confusion metrics — AUC, CA, F1, Precision, Recall, and MCC— achieving above 89% accuracy in each. The random forest has performed with exceptional accuracy of 99.4%. By combining predictions from multiple decision trees, Random Forest reduces variance and improves overall prediction accuracy. This ensemble approach ensures that the model is less sensitive to fluctuations in the training data and more stable in its predictions. This is the reason for the exceptional accuracy performance of the Random Forest classifier. The Decision Tree classifier also performs well, with scores ranging between 69% and 98%. The wide performance range of the Decision Tree classifier, spanning from 69% to 98%, highlights its sensitivity to factors such as data quality, tree depth, and feature relevance. Recognizing and addressing these factors is essential for improving the model's accuracy and reliability. Enhancing Decision Tree performance involves tackling issues related to data preparation, implementing pruning techniques, and exploring ensemble methods. By focusing on these areas, the stability and reliability of the Decision Tree classifier can be improved, resulting in more consistent and accurate outcomes for the TCRS. kNN performs well in AUC with 89%, while SGD shows a lower AUC accuracy of 54%, and both kNN and SGD score below 41% in the remaining metrics. SVM, Naïve Bayes, and Logistic Regression classifiers underperform, scoring below 45% in all metrics.

Table 4 compares the accuracy of our model (OMA) with that of other models (OTH-MA) using similar datasets and classifiers. The results indicate that TCRS demonstrates superior accuracy across Decision Tree, SVM, Random Forest, Naïve Bayes, and KNN classifiers. However, no comparison is available for the SGD classifier. In the case of Logistic Regression, TCRS exhibits an accuracy that is 6.2 percentage points lower compared to similar studies. Overall, TCRS has shown improved accuracy results relative to comparable studies.

Table 6. Accuracy Measure and Comparison

S #	Model Name	OMA	OTH-MA
1	Decision Tree	98.3	84.1 [72]
2	SVM	86.7	84.9 [72]
3	SGD	54.8	--
4	Random Forest	99.4	83.0 [73]
5	Naïve Bays	80.4	74.7 [74]
6	Logistic Regression	78.8	85.0 [75]
7	KNN	89.2	83.6 [72]

Following the evaluation of classifiers, the TCRS underwent scrutiny to assess the concordance between the recommendations generated by the system and the actual TVET trainees, based on a dataset of 281 instances. Cohen's Kappa statistic was employed for this purpose, aiming to quantify the level of agreement. Cohen's Kappa ("k") is a statistical measure widely utilized in analogous academic contexts [43] particularly in personality-aware recommendation systems, to gauge the agreement between two raters who categorize items into distinct groups. This metric proves particularly valuable in situations where judgments are subjective and categories lack a natural hierarchy. The findings revealed a moderate level of agreement between the recommendations and the actual trainees ($k = 0.44$, 84% CI, $p < 0.05$). A similar Personalized Career Recommender System (PCRS) for engineering students [43] achieved a Cohen's Kappa of $k = 0.23$, indicating a slight agreement between the recommendations generated by the PCRS and the actual choices of engineering students. In contrast, TCRS demonstrates a moderate level of agreement in comparison with the literature. Although the dataset has been cleaned to address missing values, noisy data, inconsistencies, imbalances, and irrelevant features, further improvements to TCRS performance can be achieved through enhanced feature engineering, regularization techniques, model tuning, continuous monitoring, and incorporating additional data.

Conclusion:

Personality-aware recommendation systems are based on the idea that human behavior and personality traits profoundly impact skills acquisition, career advancement, and overall success. With the advent of Industry 5.0, marked by collaboration between individuals and advanced technologies such as AI-driven robots—the importance of personality computing in skill development is increasingly clear. This research seeks to bridge the gap between human personality traits and learning outcomes in the TVET sector through the development of a personality-aware recommendation system.

This study represents a notable advancement in the field of personality-aware recommendation systems, particularly within the context of TVET. By proposing, implementing, and evaluating the TCRS model in Pakistan, we have established a framework that holds potential for application in various developing countries. The evaluation of the TCRS model reveals exceptional performance, with Random Forest classifiers achieving accuracy rates above 89%, and Decision Tree classifiers ranging between 69% and 98% across all confusion matrix parameters.

The final testing of the TCRS model on real trainee data demonstrates an accuracy rate of 84%, validating the strong correlation between personality traits and skills acquisition outcomes. An accuracy rate of 84% in real-time testing represents a significant achievement for personality-aware TVET course recommendations. This level of accuracy has several positive implications for the TVET sector, including enhanced decision-making, increased confidence in recommendations, improved returns on investments, and optimized resource allocation. While an 84% accuracy rate for the TCRS is commendable, there remains potential for further improvement. Enhancing the model could be achieved through the incorporation of additional data, more refined feature engineering, and the application of deep learning techniques. By continually advancing the model, the TCRS can better meet the needs of trainees and educational institutions, leading to more successful career outcomes and a more efficient TVET system. These findings suggest that personality-aware systems can effectively predict and recommend suitable TVET courses for new trainees, thereby optimizing their educational experiences and improving workforce readiness.

Future Directions:

The future trajectory of TCRS research offers several avenues for enhancement and refinement:

- Investigation into factors contributing to dropouts from TVET courses, aiming to develop proactive strategies for retention and success.
- Implementation of measures to enhance the effectiveness and outcomes of On Job Trainings (OJT) within the TVET framework.
- Development of interventions to bolster the employability rates of TVET graduates, aligning their skills with market demands and industry requirements.
- Integration of career guidance initiatives tailored to the unique needs and aspirations of TVET graduates, facilitating informed decision-making and career progression.

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