information

MDPI

Article

Personality-Aware Course Recommender System Using Deep Learning for Technical and Vocational Education and Training

Rana Hammad Hassan [1], Malik Tahir Hassan [1], Muhammad Shujah Islam Sameem [2] and Muhammad Aasim Rafique [3,*]

[1] School of Systems and Technology, University of Management and Technology, Lahore 54770, Pakistan; s2017288002@umt.edu.pk (R.H.H.); tahir.hassan@umt.edu.pk (M.T.H.)
[2] Department of Computer Science, College of Computer Science and Information Technology, King Faisal University, Al Hofuf 31982, Saudi Arabia; msameem@kfu.edu.sa
[3] Department of Information Systems, College of Computer Science and Information Technology, King Faisal University, Al Hofuf 31982, Saudi Arabia
* Correspondence: mrafique@kfu.edu.sa

Abstract: Personality represents enduring patterns, providing insights into an individual's aptitude and behavior. Integrating these insights with learning tendencies shows promise in enhancing learning outcomes, optimizing returns on investment, and reducing dropout rates. This interdisciplinary study integrates techniques in advanced artificial intelligence (AI) with human psychology by analyzing data from the trades of Technical and Vocational Education and Training (TVET) education, by combining them with individual personality traits. This research aims to address dropout rates by providing personalized trade recommendations for TVET, with the goal of optimizing outcome-based personalized learning. The study leverages advanced AI techniques and data from a nationwide TVET program, including information on trades, trainees' records, and the Big Five personality traits, to develop a Personality-Aware TVET Course Recommendation System (TVET-CRS). The proposed framework demonstrates an accuracy rate of 91%, and a Cohen's Kappa score of 0.84, with an NMAE at 0.04 and an NDCG at 0.96. TVET-CRS can be effectively integrated into various aspects of the TVET cycle, including dropout prediction, career guidance, on-the-job training assessments, exam evaluations, and personalized course recommendations.

Keywords: deep learning; personality-aware recommender system; big five-personality model; TVET systems

check for updates

Citation: Hassan, R.H.; Hassan, M.T.; Sameem, M.S.I.; Rafique, M.A. Personality-Aware Course Recommender System Using Deep Learning for Technical and Vocational Education and Training. *Information* **2024**, *15*, 803. https://doi.org/10.3390/info15120803

Academic Editor: Vincenzo Moscato

Received: 11 November 2024
Revised: 28 November 2024
Accepted: 5 December 2024
Published: 12 December 2024

1. Introduction

Recommender systems, sophisticated algorithms meticulously crafted to propose items to users, operate on the bedrock of user preferences, behaviors, or shared characteristics with other users. Their pivotal role spans diverse domains, underpinned by their remarkable capacity to individualize experiences, amplify user involvement, and catalyze commercial success. Personality-aware recommendation systems have garnered mounting attention among researchers, owing to their heightened precision and their promise to tackle longstanding issues in recommendation systems, such as data sparsity and cold start [1]. The amalgamation of individual user personality traits into computing frameworks has not only opened up novel avenues of inquiry, notably in automatic personality recognition, but has also accelerated ongoing research trajectories, including recommendation systems [2–4] and investigations into human–robot interaction. Deep learning techniques have become pivotal in advancing recommender systems, fundamentally reshaping the landscape of personalized recommendations [5]. By harnessing sophisticated neural network architectures, deep learning empowers recommender systems to glean intricate patterns and representations from vast datasets, facilitating more nuanced and accurate predictions [6]. The integration of deep learning with recommender systems has ushered in unprecedented levels of performance, effectively mitigating challenges, such as cold starts, sparsity, non-linear interactions, scalability, and the integration of contextual and multimodal data for improved personalization and recommendation quality [7]. Understanding human personality enables us to establish correlations between personality traits, learning objectives, skills, and career paths [8]. Incorporating personality traits into deep learning recommender systems represents a compelling avenue [9] for augmenting the personalization and efficacy of recommendations.

TVET encompasses technical skills training programs designed to prepare individuals with practical skills, knowledge, and competencies tailored to specific occupations or industries. Recognized by various names globally, such as Vocational Education and Training (VET), Career and Technical Education (CTE), apprenticeship programs, and polytechnic education, TVET programs primarily aim to prepare individuals for careers across diverse technical, vocational, and skilled trades sectors. These sectors span disciplines such as engineering, information technology, healthcare, construction, hospitality, and agriculture. Undoubtedly, TVET assumes a critical role in bridging skills gaps, catalyzing economic development, and enhancing workforce productivity across numerous nations. In the context of Industry 5.0, which emphasizes the integration of human-centric approaches with advanced technologies to promote smart and sustainable industrial systems, the importance of TVET is further highlighted. This industrial paradigm [10] seamlessly integrates human prejudice and acumen with the efficiency, artificial intelligence (AI), and precision of machines in manufacturing environments. Consequently, the demand for human–computer interaction (HCI) within industrial products and services has surged, driven by the rapid technological advancements characterizing Industry 5.0. As industries increasingly rely on technologies, such as artificial intelligence (AI), robotics, and the Internet of Things (IoT), the need for skilled professionals who can effectively interact with these innovations has never been more urgent. Research [11] underscores the critical role of TVET institutions in bridging the skills gap by equipping learners with the competencies required to leverage these transformative technologies. This aligns directly with several of the UNESCO Sustainable Development Goals (SDGs), namely, No. 4 (Quality Education), No. 5 (Gender Equality), No. 8 (Decent Work and Economic Growth), and No. 17 (Partnerships for the Goals) [12] all of which highlight TVET's central role in fostering global development and sustainable growth by 2030. However, despite its pivotal role, the TVET sector in Pakistan is facing significant digital infrastructure challenges [13]. As global trends accelerate the shift toward digital and tech-driven economies, Pakistan's TVET educational framework lags in adopting the tools necessary to meet these demands. The adoption of digital methodologies, such as recommender systems, becomes not only a solution but also an imperative for enhancing the accessibility, relevance, and quality of TVET education in Pakistan. With the rapid pace of technological change, failing to address these infrastructure gaps could leave Pakistan at a disadvantage in preparing its workforce for the challenges and opportunities of Industry 5.0, underscoring the immediate need for strategic investment in digital education platforms [14].

The motivation behind this research stems from the persistent challenge faced by Pakistan despite substantial investments and the provision of free technical and vocational education for its youth. Despite these initiatives, Pakistan continues to grapple with low employability rates among graduates of TVET programs, leading to delays in critical infrastructure projects due to a dearth of skilled labor. Notably, Pakistan boasts a youthful population, with approximately 63% comprising individuals aged between 15 and 30 years [15]. Over the past five years, the Government of Pakistan, alongside provincial governments and international funding agencies, such as USAID, DFID, JICA, the British Council, and the World Bank, has implemented numerous skills development programs aimed at enhancing the TVET sector. However, despite these concerted efforts, the employability rate within Pakistan's TVET sector remains at a mere 38% [16], exacerbating the nation's ongoing skill shortage predicament. This scarcity of skilled labor is a significant contributor to the delayed implementation of infrastructural projects, including those under the China-Pakistan Economic Corridor (CPEC) [17]. To ascertain the underlying causes of this issue, a survey [18] was conducted to investigate the mechanisms through which trainees gain admission to TVET courses. The findings of this survey reveal a concerning trend, with 49% of trainees gaining admission without any prior knowledge, 25% based on perceived relevance, and 10% through informal channels such as word of mouth. Notably, no provision for personality tests, academic assessments, career counseling, or guidance exists before admission, underscoring the need for a comprehensive examination of the admission processes within the TVET sector. This research endeavors to uncover the systemic deficiencies in the current admission procedures of TVET courses, aiming to propose evidence-based strategies for enhancing the alignment between training programs and industry demands. By elucidating the root causes of the employability crisis in the TVET sector, this study seeks to catalyze transformative reforms that will not only bolster workforce readiness but also accelerate socio-economic development initiatives nationwide.

This study proposes a TVET Course Recommender System (TVET-CRS) using personality-aware traits as an additional input to a deep learning algorithm. Prior to proposing TVET-CRS, we analyzed the correlation and predictive accuracy between BFI personality traits and TVET trades. Utilizing an ensemble approach that incorporated BFI personality traits, age, and gender, we achieved a prediction accuracy of 83.95% for TVET trades [9]. Additionally, our Chi-Square (χ^2) analysis revealed a positive correlation between the BFI personality traits of Openness and Extraversion and TVET trades [19]. Subsequently, we developed a deep learning-based, personality-aware recommender system model for TVET trade predictions based on BFI personality traits, age, and gender. This sequential model featured multiple hidden layers with a high number of neurons, embeddings for categorical variables to enhance the understanding of relationships, and dropout layers to prevent overfitting. This model achieved an accuracy of 58%. To further enhance the accuracy of the recommender system model, we customized the deep learning-based recommender system using a hyperparameter tuner with Bayesian optimization, along with batch normalization, early stopping, learning rate reduction, L2 regularization, callback functions, and an attention mechanism. Hyperparameter tuning is essential for optimizing the performance and generalization of machine learning models [20]. To stabilize training and prevent overfitting, we employed batch normalization and L2 regularization. Additionally, we implemented callback functions to halt training when the validation loss stops improving and learning rate reduction to fine-tune the learning rate dynamically. These techniques collectively enhance deep learning models by improving training stability and preventing overfitting [21–23]. We also incorporated early stopping to monitor validation loss, terminating training when the loss ceases to improve and applying the attention mechanism to enable the model to focus on the most relevant parts of the input. Early stopping prevents overfitting by halting training when validation performance degrades [24], while attention mechanisms enhance model performance by allowing focus on key input features [25]. These customizations to the TVET recommender system model not only enhance the accuracy of TVET course predictions to 91% but also introduce a novel approach to improving the effectiveness of personality mapping with learning skills.

The subsequent sections of this article are structured as follows: Section 2 discusses an in-depth review of related work. Section 3 details the methodology for data collection and preprocessing. Section 4 elucidates the experimental setup used to validate the proposed approach. Section 5 presents the results and subsequent discussion. Section 6 offers a comprehensive evaluation summary and comparative analysis. Section 7 explores global applications of TVET-CRS. Finally, Section 8 encapsulates the conclusions and future work of the study.

2. Related Work

Initially, we examined various aspects of personality theories, assessment tools, measurement techniques, and matching studies pertinent to our research objectives. Then, we discussed the personality-aware recommender system and the existing personality-aware recommender system. We identified and analyzed several relevant case studies on personality-aware course recommendation systems, which provided valuable insights into effective methodologies and frameworks. By synthesizing these diverse strands of literature, we compiled a comprehensive assessment of the current state of knowledge in this field. In summary, our literature review clarifies the existing research landscape, identifies gaps in knowledge, and lays the groundwork for advancing personality-aware recommendation systems within the TVET sector.

Personality computing represents a burgeoning field that amalgamates personality psychology with computing systems. The surge in its usage across multiple domains can be attributed to its capacity to address commonly encountered inquiries [26]. Within this realm, personality computing facilitates the extraction of personality data from diverse sources, including gaming behaviors, written texts, speech patterns, and smartphone usage patterns. By harnessing the power of personality computing, recommendation systems can discern user preferences from novel perspectives [27]. A comprehensive understanding of personality traits necessitates the utilization of major personality theories to obtain insights from human behavior and individual differences. These theories include the Big Five Inventory (BFI), the Myers-Briggs Type Indicator (MBTI), NEO Personality Inventory-Revised (NEO-PI-R) and HEXACO (honesty-humility (H), emotionality (E), extraversion (X), agreeableness (A), conscientiousness (C), and openness to experience (O)). Among these theories, the Big Five model stands out for its holistic approach to personality assessment, delineating traits across five dimensions: openness, conscientiousness, extraversion, agreeableness, and neuroticism [28–30]. Personality measurement constitutes a crucial phase in the development of personality-based recommender systems, as misidentification of user personality can significantly affect predictive accuracy. Generally, two types of personality measurement methods are distinguished: Automatic Personality Recognition (APR) and Questionnaire-Based (QB) methods [30]. APR entails the extraction of personality insights from text-based data such as social media posts, multimedia content like images and videos, and behavioral cues related to personality traits [31]. Conversely, QB methods involve the collection of personality data through self-report questionnaires. QB personality measurement is generally regarded as more popular and accurate [32,33]. Therefore, we have used the BFI personality trait 50-item questionnaire in this research for the TVET trainee's personality assessment.

Personality-aware recommendation systems have demonstrated superiority over traditional recommender systems, particularly in addressing issues such as cold start and data sparsity [1]. Through an examination of data amalgamated from various studies [33], it becomes evident that personality traits wield significant influence over personalized learning. The efficacy of personality-aware recommender systems extends to aiding engineering students in career counseling [34], guiding academic choices [35], and offering book recommendations [36]. Similarly, the utilization of personality-aware recommendation systems leveraging NLP and Twitter (now X) data has been documented [37]. In the hospitality domain, the development of adaptive recommendation systems in tourism [38] utilizes deep learning techniques to provide personalized services. By processing vast amounts of big data, these systems tailor services based on user information and usage patterns. The proposed system incorporates three layers to categorize and recommend tourism options based on user personality traits, thereby enhancing efficiency and scalability.

The literature review also examines personality-aware recommender systems within the context of TVET. In our preliminary study [39], we investigated a matrix-factorization-based personality-aware recommendation system, which achieved over 80% accuracy in predicting TVET courses using various classifiers, including Random Forest, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Naïve Bayes. In addition to our initial findings, we expanded our literature review upon discovering a lack of existing personality-aware TVET recommender systems. Consequently, we incorporated a broader range of deep learning-based personality-aware academic course recommender systems in the literature review. Identifying systems such as Personalized Career-Path Recommender

System for Engineering Students (PCRS) [34], Improving Socially Aware Recommendation Accuracy Through Personality (PerSAR) [40], Hybrid Attribute and Personality-based Recommender System for Book Recommendation (MSV-MSL) [36], Socially-Aware Conference Participant Recommendation with Personality Traits (SPARP) [41], and Recommender System Framework for Academic Choices Personality Based Recommendation Engine (PERFECT) [35]. Upon reviewing the PCRS, PerSAR, MSV-MSL, SPARP, and PERFECT recommender systems, it is evident that these models have been developed primarily for applications in school education, higher education, book recommendations, and conference participant recommendations. These systems utilize not only personality data but also a combination of other data types, including user profiles, academic features, and social networking information. The models employ fuzzy logic and hybrid recommendation techniques. In contrast, TVET differs significantly from traditional school and higher education. TVET programs typically integrate theoretical instruction with practical curriculum, focusing on skill development tailored to specific roles such as plumbing, mechanics, dressmaking, machining, electrical work, auto mechanics, and computer operations. Upon review of PCRS, PerSAR, MSV-MSL, SPARP, and PERFECT recommender systems models it is found that 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 are used. These models have employed fuzzy logic and hybrid recommendation techniques for recommendation. Comparatively TVET education is different from school education and higher education. In TVET education, one subject is taught with a combination of theory and practical curriculum. The main objectives are to provide skills that are required by a specific role like Plumbing, Mechanic, Dress Making, Machinist, Electrician, Auto Electrician, Motorcycle Mechanic Computer Operator, etc. TVET programs have distinct challenges such as aligning training with industry needs, addressing diverse learner backgrounds, and improving engagement and retention. Our research addresses these specific challenges by leveraging personality traits to enhance the relevance and effectiveness of recommendations using deep learning.

In conclusion, it is evident from the literature review that existing personality-aware recommender systems leverage user personality traits across various domains such as higher education academic choices, career counseling, conference participation recommendations, and social media analysis. Similarly, deep learning-based recommender systems utilize personality traits for tasks such as personality detection from textual documents, user-based recommendations in tourism, and personality identification from short videos and images. The effectiveness, widespread usage, and acceptance of the Big Five personality traits underscore their application in this research. Notably, this study represents the inaugural endeavor in applying deep learning to personality-aware recommendation systems within the TVET sector.

3. Materials and Methods

3.1. Data Collection and Preprocessing

Data collection for this research was conducted at a Vocational Training Council (VTC) [42] which oversees the implementation of more than a hundred vocational courses across its training institutes across culturally diverse regions. This study encompassed the collection, annotation, and examination of data spanning more than four years from eleven Vocational Training Institutes (VTIs), encompassing eighteen distinct trades. Figure 1 presents the TVET Trade Wise number of trainee's data collection synopsis of dataset "D", encapsulating the study's scope and findings.

A total of 1356 trainee records were collected, of which 1075 TVET trainees were utilized for the development of the TVET-CRS model, while 281 trainees were used to evaluate the proof of concept.

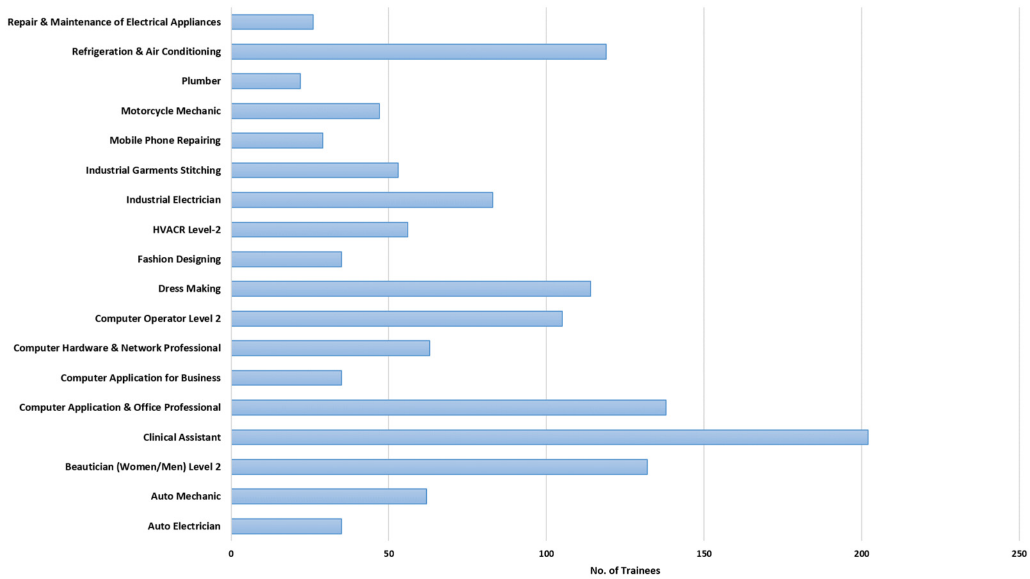

Figure 1. Trade Wise data collection.

The initial data collection included trainee profiles, institute profiles, trade information, and BFI personality traits. A web-based application was employed for data collection from participants. This application was developed using VB.NET and hosted on a Windows Server 2018 cloud-based server, with Microsoft SQL Server 2016 serving as the backend database. For data analysis, we utilized an Intel® Core i7 processor (HP brand equipment was sources in Lahore, Pakistan) at 1.8 GHz, 32 GB of RAM, and a 1 TB SSD, operating on Windows 10. Figure 2 presents data collection VTI's. In the data preprocessing phase of the dataset "D", several key steps were undertaken, including data cleaning, integration, transformation, and reduction. During the data cleaning process, unclear, ambiguous, and inconsistent records, as well as those with missing information, were removed. Consequently, out of a total of 1075 records, 111 were discarded to enhance data quality. This resulted in 964 cleaned entries that were utilized for developing the deep learning-based personality-aware TVET-CRS model. In the stages of data transformation and reduction, all personal information of the trainees was anonymized, and a unique profile code was assigned to each trainee to ensure the privacy and security of personal data. The transformed data were then compiled into a Microsoft Excel file for subsequent analysis using Python 3.11.4. We employed Jupyter Notebook 6.5.4 for both data analysis and model development. Table 1 presents a data dictionary of the final processed dataset, detailing the field names, value explanations, and comprehensive descriptions corresponding to each field.

Table 1. Preprocess data 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	Marks	Numeric Value	Trainees Exam Marks
06	Score_O	BFI Openness	Trainee BFI personality Openness to Experience Score
07	Score_C	BFI Conscientiousness	Trainee BFI personality Conscientiousness Score
08	Score_E	BFI Extroversion	Trainee BFI personality Extroversion Score
09	Score_A	BFI Agreeableness	Trainee BFI personality Agreeableness Score
10	Score_N	BFI Neuroticism	Trainee BFI personality Neuroticism Score

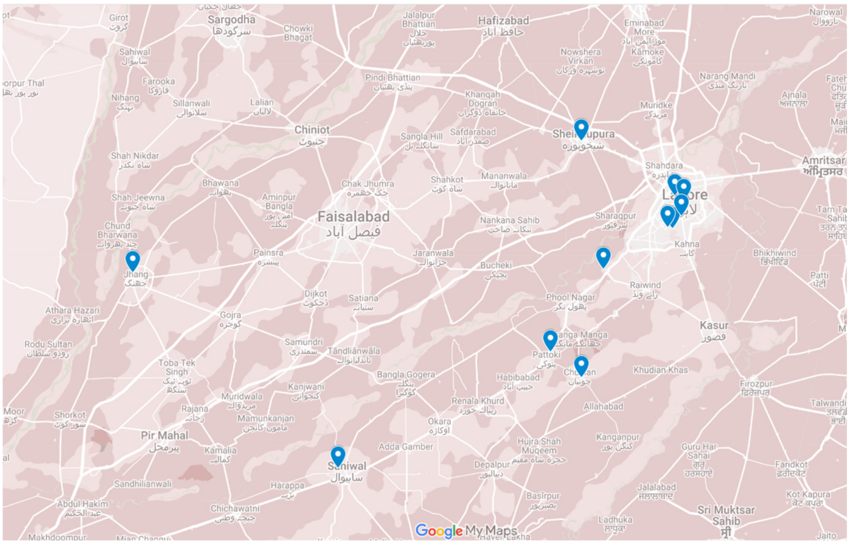

Figure 2. Data collection of VTI's locations.

We visualized the BFI OCEAN scores in Figure 3, depicting boxplot results for each personality dimension among trainees in dataset "D". Each OCEAN score ranges from 0 to 40. Figure 3 presents the boxplot results for the BFI personality Openness quartile score, ranging from 23 to 25, with a median of 27.02. The Conscientiousness score ranges from 28 to 36, with a median of 31.65. Extroversion ranges from 18 to 25, with a median of 21.47. Similarly, Agreeableness falls between 26 and 33, with a median of 29.53, and Neuroticism ranges from 13 to 24, with a median of 18.81. Outliers for all BFI dimensions are also highlighted. Overall, a noticeable disparity exists across all five BFI personality dimensions in terms of quartile scores (Q1 and Q3), median values, and the range between minimum and maximum scores. Notably, the majority of trainees score between seven to eleven on most BFI OCEAN dimensions. This visualization underscores the distribution and variability of OCEAN personality scores among the trainees in dataset "D".

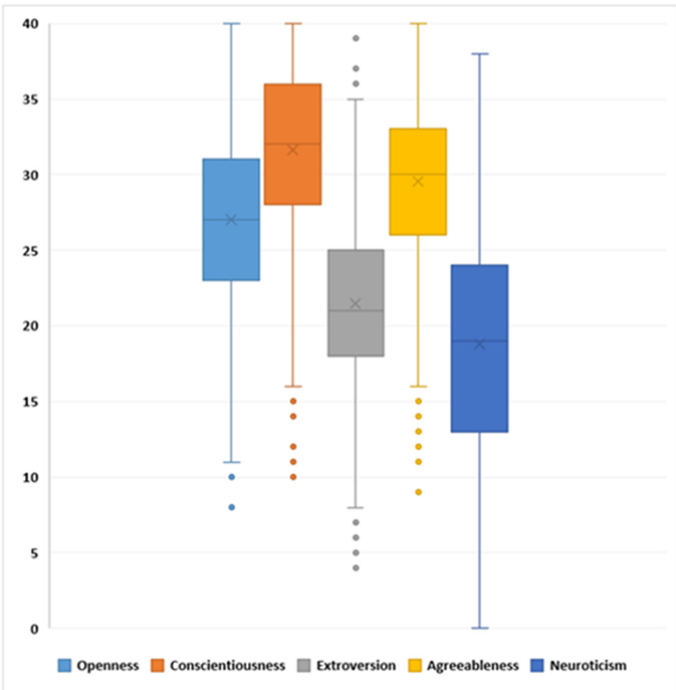

Figure 3. BFI OCEAN score boxplot.

3.2. Model Architecture

Figure 4 illustrates the architecture of the TVET-CRS, which employs advanced neural networks and incorporates several key techniques: hyperparameter tuning, Bayesian optimization, L2 regularization, callback features, and an attention mechanism. Hyperparameter tuning is essential for optimizing model performance and convergence speed [43]. Bayesian optimization provides a more efficient method for identifying optimal hyperparameters compared to traditional approaches [44]. L2 regularization mitigates overfitting by penalizing large weights, and promoting generalization [45]. Callback features enhance training efficiency by enabling adaptive strategies like early stopping [46]. The attention mechanism improves interpretability and performance by allowing the model to focus on relevant input data [47]. The model comprises multiple hidden layers with varying neuron configurations to capture intricate data patterns. The TVET-CRS model initiates with a function definition, build_model(hp), tailored to construct a neural network using customizable hyperparameters through the Keras Tuner framework. This function takes hp as its parameter, encapsulating the hyperparameters for optimization. The model construction begins by specifying input, hidden, and output layers. The input layer serves as the entry point for raw or preprocessed dataset features, receiving and distributing initial information to subsequent layers. Hidden layers, positioned between input and output layers, perform the bulk of computation. The output layer synthesizes processed representations to generate final predictions.

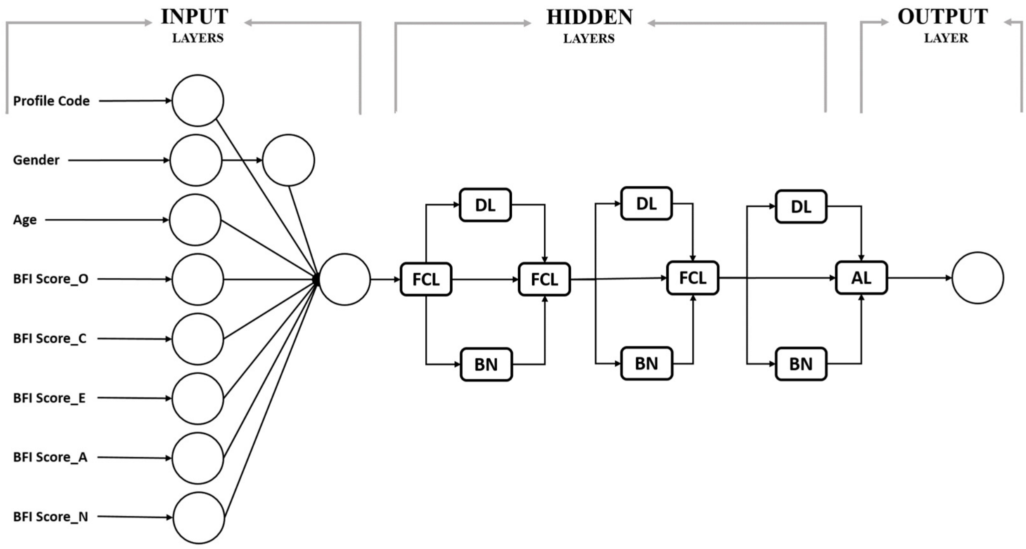

Figure 4. TVET-CRS Model.

As shown in Figure 4 of the TVET-CRS architecture, the input layer includes eight features: 'ProfileCode', 'Gender', 'Age', and psychological trait scores ('Score_E', 'Score_A', 'Score_C', 'Score_N', 'Score_O'). The categorical feature 'Gender' undergoes embedding via Embedding Layers (EL) to enhance the model's ability to extract meaningful insights. Subsequently, the embedding layer and seven other feature layers connect to a Connection Layer (CL). This connection layer is further linked to Fully Connected Layers (FCL) within hidden input layers. FCL integrates Batch Normalization (BN) and Dropout Layers (DL) to stabilize training and prevent overfitting. After several iterative adjustments, a final Fully Connected Layer (FCL) is connected to an Attention Layer (AL). AL incorporates an attention mechanism, allowing the model to focus on pertinent aspects of the input data. Finally, AL connects to the output layer, which recommends courses to TVET trainees based on the model's predictions. Figure 4 displays the utility of advanced neural network techniques in enhancing the TVET-CRS model's predictive capabilities. By integrating features such as hyperparameter optimization and an attention mechanism, the architecture not only improves accuracy but also ensures relevance in recommending courses to TVET trainees. This approach underscores the model's ability to adapt to diverse datasets and complex patterns, making it a valuable tool in educational and vocational training settings.

The recommendation process for TVET-CRS model is shown in Figure 5. As shown, the new trainee will provide his/her demographic information of age and gender and then go through the BFI personality test. The BFI personality test is a 50-item questionnaire. After capturing all 50 questions, the BFI OCEAN score will be calculated. Both age and gender and BFI OCEAN score will be stored in the database with a unique ID. Data are captured using web-based applications and is also captured through mobile applications. An interface of mobile applications for reference is shown in Figure 5. These three parameters will be stored in a database and passed on to the TVET-CRS recommendation engine. Based on matching BFI personality, age, and gender similarities calculations, three TVET courses will be recommended to the new user.

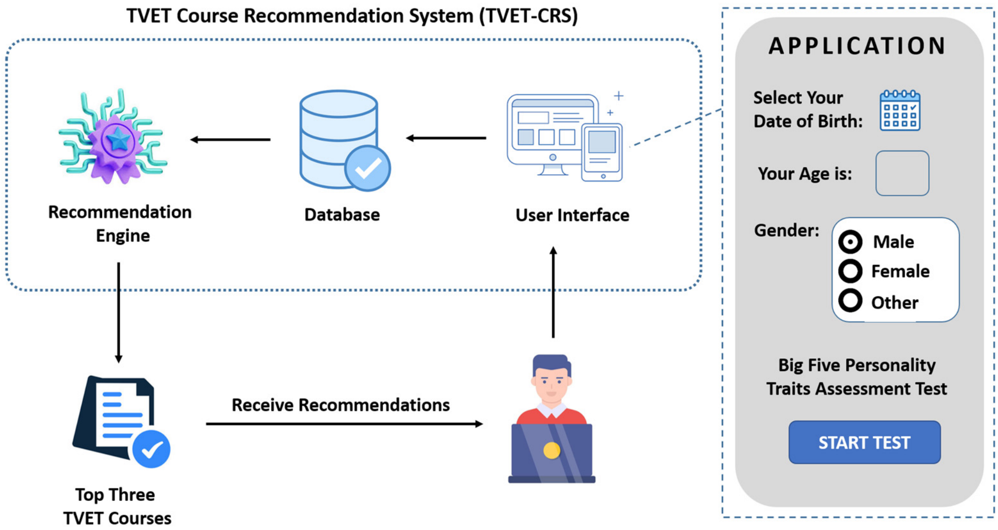

Figure 5. TVET-CRS recommendation generation process.

Evaluating deep learning models is a critical aspect of building robust and effective machine learning systems. Deep learning model evaluation entails measuring the performance of the trained model on new, unseen data. This process typically includes various metrics and techniques tailored to the specific task and dataset. We evaluated four dimensions: predictions and accuracy evaluation, error reduction evaluation, inter-rater reliability evaluation, and ranking evaluation through twelve metrics to thoroughly examine the accuracy and performance of the TVET-CRS model.

4. Experimental Setup

The experimental workflow of TVET-CRS is shown in Figure 6. Initially, Python libraries and functions are imported, followed by the removal of the existing Tuner directory project to facilitate the saving of the new model. Subsequently, the process proceeds through feature engineering, data transformation, normalization, and data splitting. The training data are then passed to the TVET-CRS model. Central to this workflow is the function build_model(hp), crucial for constructing a versatile neural network model optimized for hyperparameter tuning using Keras Tuner. The function initiates by defining input layers for various features such as 'ProfileCode', 'Gender', 'Age', and psychological trait scores ('Score_E', 'Score_A', 'Score_C', 'Score_N', 'Score_O'). Notably, an embedding layer is specifically applied to the categorical feature 'Gender' to extract meaningful insights. The function consolidates all input layers into a unified tensor for subsequent processing. The model architecture integrates fully connected layers enhanced with dropout regularization and batch normalization to bolster robustness and mitigate overfitting. An attention mechanism is incorporated using dense layers and softmax activation to dynamically weigh feature importance across layers. For multi-class classification tasks, the output layer employs softmax activation, and the model is compiled using the Adam optimizer and categorical cross-entropy loss function. This comprehensive setup facilitates efficient hyperparameter tuning, ensuring that the model's adaptability and performance optimization is tailored to specific dataset characteristics and task requirements.

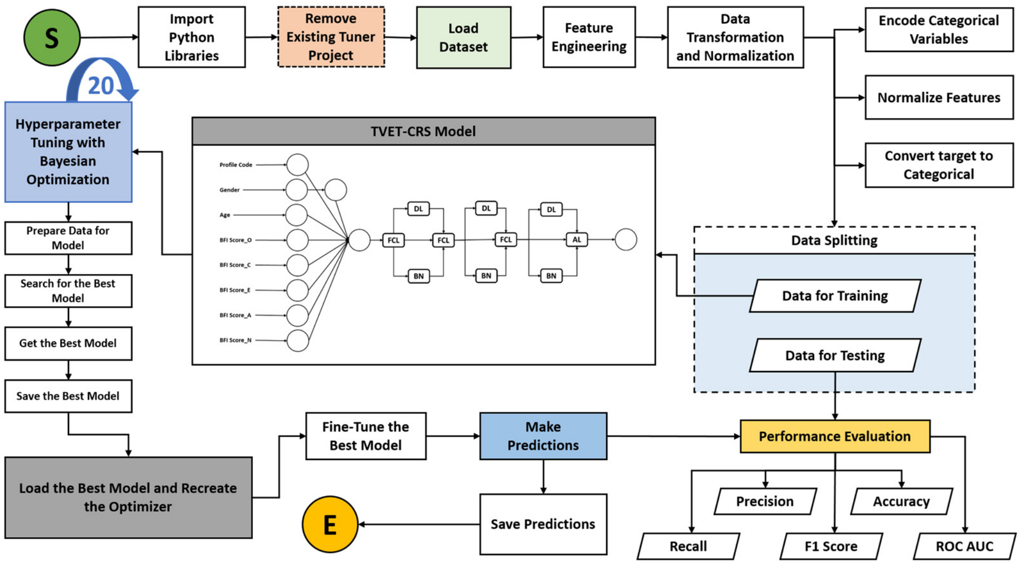

Figure 6. TVET-CRS's flow of activities.

Next, Bayesian optimization is employed for hyperparameter tuning. The tuner is setup using build_model to optimize validation accuracy across 20 trials, each with three executions. Logs and outcomes from each trial are saved in the 'keras_tuner_dir' directory under the project name 'tvet_course_recommender'. By setting overwrite = True, existing project records can be updated as needed, ensuring a streamlined optimization process without redundancies. This structured approach enables methodical exploration and the enhancement of model performance, utilizing Bayesian optimization to effectively refine hyperparameters for the TVET course recommender system. Then, the data preparation step is carried out, which organizes the training and test datasets into dictionaries suitable for feeding into the neural network model. In the next step, there is a search for the best model with 100 epochs, and a 20% validation split is carried out. Additionally, an EarlyStopping callback is employed to monitor validation loss (monitor = 'val_loss'), halting training if no improvement is observed after 10 epochs (patience = 10) and restoring the best weights (restore_best_weights = True). This systematic approach facilitates the identification of hyperparameter settings that optimize model performance, enhancing the neural network's effectiveness in predicting outcomes for the TVET course recommender system. This model is then assigned to the variable best_model, enabling further evaluation, prediction, or deployment in applications requiring optimal performance from the TVET course recommender system. This step consolidates the iterative tuning process, ensuring that the final model configuration maximizes predictive accuracy based on the dataset and evaluation criteria established earlier. The best model is saved as 'best_model.h5'.

In the next step of loading the best model, the best-saved model is loaded and the optimizer is recreated with the 'adam' optimizer, loss of 'categorical_crossentropy', and accuracy metrics. Then, the model is fine-tuned via early stopping and a learning rate reduction to optimize model training. Utilizing EarlyStopping with a monitoring criterion of validation loss, patience of 10 epochs, and restore_best_weights = True, ensures training halts if validation loss does not improve beyond 10 epochs, reverting to the best weights observed. Meanwhile, learning rate reduction via ReduceLROnPlateau dynamically adjusts the learning rate if validation loss plateaus, with a reduction factor of 0.2 after 5 epochs and a minimum learning rate of 0.001. These strategies collectively refine the model's performance and generalization capabilities during training. Finally, predictions are made on the unseen test data, and the predicted labels are decoded for result interpretation and evaluation against the actual labels and saved in a Microsoft Excel file.

5. Results and Discussion

The evaluation of TVET-CRS performance is evaluated in different educational contexts and underscores their applicability in enhancing predictive accuracy within TVET programs. The results of TVET-CRS are presented across four dimensions: predictions and accuracy evaluation, error reduction evaluation, inter-rater reliability evaluation, and ranking evaluation. The Predictions and Accuracy Evaluation dimension assesses the model's predictive capabilities and accuracy using metrics such as Accuracy, F1 Score, Precision, Recall, Receiver Operating Characteristic Area Under the Curve (ROC AUC), and Matthews Correlation Coefficient (MCC) [48–50]. Accuracy measures the proportion of correct predictions among all instances, serving as an indicator of the model's overall performance. The F1 Score combines precision and recall into a single metric, offering a balanced perspective, particularly useful when dealing with imbalanced classes. Precision focuses on the correctness of positive predictions, while Recall assesses the model's effectiveness in capturing actual positives. The Receiver Operating Characteristic Area Under the Curve (ROC AUC) evaluates how well the model can differentiate between classes, with values ranging from 0 to 1. Finally, the Matthews Correlation Coefficient (MCC) provides a comprehensive assessment of binary classification quality by factoring in true and false positives and negatives, delivering a balanced evaluation even when class distributions are uneven.

TVET-CRS Error Reduction Evaluation measures the model's ability to reduce prediction errors using metrics including Mean Absolute Error (MAE), Normalized Mean Absolute Error (NMAE), and Root Mean Squared Error (RMSE) [51–53]. Mean Absolute Error (MAE) quantifies prediction accuracy by averaging the absolute differences between predicted and actual values, offering a clear and interpretable measure. Normalized Mean Absolute Error (NMAE) enhances MAE by scaling it relative to the range or mean of the actual values, facilitating comparisons across different datasets and scales. Root Mean Squared Error (RMSE) provides a measure of model performance by taking the square root of the average of squared differences, which emphasizes larger errors more than smaller ones, making it particularly sensitive to outliers. Together, these metrics offer a comprehensive view of prediction accuracy and model performance. TVET-CRS Inter-Rate Reliability Evaluation gauges the consistency and agreement among different raters using Cohen's Kappa coefficient [54,55]. Cohen's Kappa is a valuable metric in recommender systems for assessing the agreement between model predictions and user preferences or expert annotations. It quantifies how closely the recommendations correspond to actual user ratings while accounting for the likelihood of random agreement, providing a clearer picture of the model's effectiveness in reflecting user sentiment.

Finally, the Ranking Evaluation assesses the effectiveness of the model in ranking predictions using metrics such as Mean Reciprocal Rank (MRR) and Normalized Discounted Cumulative Gain (NDCG) [56]. Mean Reciprocal Rank (MRR) is a performance metric for information retrieval systems that calculates the average of the reciprocal ranks of the first relevant result for a series of queries, highlighting how efficiently users can find pertinent information. Normalized Discounted Cumulative Gain (NDCG) evaluates the quality of ranked lists by taking into account both the relevance of items and their positions, placing greater emphasis on relevant items that appear earlier. Together, these metrics provide valuable insights into the effectiveness of search and recommendation systems, aiding in their optimization. By examining TVET-CRS results through these four dimensions and associated metrics, a comprehensive evaluation of its performance and effectiveness can be achieved.

Table 2 shows TVET-CRS performance and accuracy results. As demonstrated in Table 2, the TVET-CRS has achieved an accuracy of 91%. Accuracy, or Classification Accuracy, serves as a comprehensive measure of the correctness of recommendations. In terms of precision performance, TVET-CRS has exhibited an impressive 93% precision accuracy. Precision, also referred to as positive predictive value, signifies the proportion of true positive cases identified correctly among the total cases identified. In terms of ROC-AUC, the TVET-CRS has achieved a remarkable ROC-AUC score of 98%. ROC AUC serves as a common performance metric used to assess the predictive capability of binary classification models, quantifying their ability to distinguish between positive and negative classes across various threshold settings. The F1 Score offers an alternative approach to evaluating machine learning models, emphasizing their predictive performance across different classes rather than solely focusing on overall accuracy. This score amalgamates two contrasting measures—Precision and Recall—to provide a holistic assessment of a model's performance. In the case of the F1 Score, the TVET-CRS achieved 90% in the F1 evaluation. A Recall score of 91% was observed for TVET-CRS evaluation. Recall assesses the frequency with which a machine learning algorithm accurately identifies positive instances (true positives) among all the genuine positive examples in the dataset. In the MCC performance metrics of TVET-CRS, a score of 85% was observed. MCC, or Matthews Correlation Coefficient, is a widely used performance metric for evaluating the quality of binary classification models, especially in scenarios involving imbalanced datasets. It takes into consideration true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) to offer a balanced assessment of classification performance.

Table 2. TVET-CRS performance and accuracy Results.

Evaluation Metrics	Result	Evaluation Metrics	Result
Accuracy	0.91	F1 Score	0.90
Precision	0.93	Recall	0.91
ROC AUC	0.98	MCC	0.85
MAE	0.08	Cohen's Kappa	0.84
RMSE	0.29	MRR	0.34
NMAE	0.04	NDCG	0.96

A performance evaluation of error reduction metrics, namely MAE, NMAE, and RMSE, has been conducted for TVET-CRS. Generally, a value closer to zero indicates higher accuracy of the model. In terms of MAE, TVET-CRS was 0.08. MAE serves as a metric utilized to gauge the average magnitude of errors between predicted values and actual values. In the assessment of NMAE, the performance metrics of TVET-CRS was 0.04. NMAE is a variant of MAE that scales the MAE by dividing it by the range of the target variable, providing a normalized measure of error that facilitates interpretation and comparison across different datasets. In the evaluation of RMSE metrics for TVET-CRS, a 0.29 score was achieved. MAE, NMAE, RMSE, and RMSE are crucial metrics in evaluating the accuracy of predictive models. They provide quantitative measures of how well a model's predictions align with actual observations, offering insights into the model's performance across different scales and helping to identify areas for improvement in predictive accuracy and reliability.

The Inter-Rater Reliability metric proves especially valuable in scenarios involving the assessment of more than two categories and where chance agreement between raters is a possibility. Cohen's Kappa, an evaluation metric commonly utilized in the field of psychology [57], serves to gauge the inter-rater reliability or agreement between two annotators or raters when categorizing items into multiple predefined categories. Before delving into Cohen's Kappa result for TVET-CRS, let us first examine its interpretation [58] as outlined in Table 3. Cohen's Kappa values range from 0 to 1, where a value of 0 signifies no agreement between the two variables, and a value of 1 represents perfect agreement. The performance of TVET-CRS Cohen's Kappa was 0.84. Comparing this score with Cohen's Kappa interpretation presented in Table 3, it can be inferred that a "Near Perfect Agreement" exists between the predictions and actual values of TVET trade courses. Furthermore, we conducted an evaluation involving 281 trainees to test the TVET-CRS model's predictions against the actual trainee enrollment data. The findings revealed that TVET-CRS accurately predicted enrollment for 84% of the trainees.

Table 3. Cohen's Kappa interpretation table.

Cohen's Kappa	Interoperation
0	No Agreement
0.10–0.20	Slight Agreement
0.21–0.40	Fair Agreement
0.41–0.60	Moderate Agreement
0.61–0.80	Substantial Agreement
0.81–0.99	Near Perfect Agreement
1	Perfect Agreement

Ranking metrics offer valuable insights into the performance of recommender systems by assessing their capability to prioritize relevant items higher for users. TVET-CRS underwent evaluation for MRR and NDCG ranking metrics, with the results presented in Table 4. Generally, a ranking metric score approaching one signifies perfect effectiveness in ranking, while a score near zero indicates average effectiveness. MRR measures the average rank of the first relevant recommendation. In the case of MRR, TVET-CRS achieved a 0.34 score. Regarding NDCG, the TVET-CRS attained a 0.96 score. In conclusion, the ranking metrics of TVET-CRS NDCG outperformed MRR metrics.

Table 4. TVET-CRS summary and comparison with the literature.

Evaluation Metrics	TVET-CRS	Literature Comparison
Accuracy	0.91	0.86 [59], 0.73 [60], 0.75 [61], 0.75 [62]
F1 Score	0.90	0.75 [59], 0.60 [62]
Precision	0.93	0.72 [59], 0.79 [63], 0.84 [64]
Recall	0.91	0.74 [59], 0.76 [63], 0.81 [64]
ROC AUC	0.98	0.96 [65], 0.81 [66]
MCC	0.85	--
Cohen's Kappa	0.84	0.23 [34]
MAE	0.08	0.95 [41], 0.24 [40], 0.30 [64]
NMAE	0.04	0.24 [41], 0.94 [40]
RMSE	0.29	0.32 [64]
MRR	0.34	2.52 [63]
NDCG	0.96	0.64 [67], 0.82 [64]

6. Evaluation Summary and Comparison with Literature

The comprehensive evaluation of TVET-CRS offers valuable insights into its performance across various metrics, illuminating its effectiveness in recommending pertinent educational pathways to users. These findings highlight TVET-CRS's proficiency in aiding users to navigate the intricate landscape of vocational education, directing them towards personalized and impactful learning experiences through personality-aware recommendations. A summary of TVET-CRS evaluation metrics, along with comparisons with the existing literature, is presented in Table 4. Some metric comparisons were unable to find similar literature for comparison; hence, they were left blank. The literature available for personality-aware recommendation systems was dated between 2016 and 2020, which is old for a literature comparison for this study. Therefore, we broadened the canvas of the comparison and selected the Course Recommender System published during the year 2023 until June 2024.

According to Table 4, TVET-CRS demonstrates outstanding accuracy, achieving a notable score of 0.91, which is 19.78% higher than the maximum observed in other studies. In terms of other performance metrics, TVET-CRS excels with a 16.67% higher F1 Score compared to the literature. In Precision, TVET-CRS consistently outperforms existing studies by margins ranging from 9% to 22%, while in Recall, it achieves superior performance with improvements ranging from 11% to 18%. Regarding ROC AUC performance, TVET-CRS shows a slight edge, being 2% higher than the literature study. Notably, there is no available evaluation for MCC comparison in the literature for Course Recommender Systems. TVET-CRS also demonstrates substantial Inter-Rater Reliability, measured by Cohen's Kappa, achieving a score of 0.84, which is notably higher than the 0.23 observed in comparable studies an improvement of 72% in performance. Additionally, TVET-CRS exhibits lower errors in MAE, RMSE, and NMSE compared to similar literature. In NDCG, TVET-CRS shows superior performance, ranging from 14% to 33% higher than the literature.

TVET-CRS was evaluated alongside similar deep learning-based course recommendation systems to assess its performance. Following a detailed analysis, three studies with available datasets on GitHub were selected for comparison. While previous models have demonstrated commendable accuracies and predictive abilities, our model consistently exhibits superior outcomes. In a deep learning-based recommender system [66], which predicts student success from 817 records, the model achieved an AUC score of 81.10%. When evaluated with the same dataset, TVET-CRS excelled with an impressive AUC of 98.1%, marking a significant 17.33% performance improvement over the baseline model. Another study focused on Recurrent Neural Network (RNN)-based personalized course recommendations [62] achieved 75.23% accuracy and a 60.24% F1 score. This model's evaluation utilized AUC and F1 Score metrics. Comparatively, TVET-CRS achieved 89% accuracy and an 87% F1 Score using the same dataset. Overall, TVET-CRS improved accuracy by 15.47% and F1 score by 30.76%. Lastly, in the evaluation of the online recommender system BrightFit [68], which suggests courses based on a user's job profile and desired skills, ranking metrics such as NDCG were used. BrightFit achieved an NDCG score of 0.844. Applying TVET-CRS to the same dataset, TVET-CRS achieved an NDCG ranking score of 0.92, demonstrating an 8.26% improvement over BrightFit.

In conclusion, TVET-CRS demonstrates notable strengths in accuracy and performance metrics compared to existing studies on Course Recommender Systems (CRS). With an impressive accuracy score of 0.91, TVET-CRS outperforms comparable studies which range between 0.73 and 0.86. Moreover, TVET-CRS shows significant advancements in F1 Score, Precision, and Recall, surpassing literature benchmarks by substantial margins. The ROC AUC performance indicates a slight advantage over existing studies, and the Inter-Rater Reliability, measured by Cohen's Kappa, reveals Near Perfect Agreement, marking a 72% improvement over comparable studies. Despite higher RMSE and lower MRR scores, TVET-CRS demonstrates superior performance in MAE. RMSE and NMSE, highlighting its effectiveness in reducing prediction errors. Additionally, its performance in NDCG surpasses literature benchmarks by 14% to 33%. Overall, these findings underscore TVET-CRS as a robust and effective model in the field of TVET Course Recommender Systems, achieving significant advancements in accuracy, reliability, and error reduction compared to current literature.

7. Global Application of TVET-CRS

In the future, the adoption of a deep learning personality-aware recommendation system in TVET skills learning will have several practical implications for various stakeholders. TVET-CRS can be integrated with platforms for personalization, improved user experience, and seamless personalized recommendations. This customization can enhance user satisfaction and retention rates. Developers can enhance platforms with advanced AI capabilities, content creators can produce more relevant and effective learning materials, marketers can optimize outreach strategies, and end-users can enjoy a more personalized and effective learning journey. This integration not only improves educational outcomes but also boosts user satisfaction and engagement across the board. This study can assist content creators in targeted content creation; with insights from personality-aware recommendations, creators can tailor content to specific learning styles and preferences, thereby increasing content relevance and engagement. The study can further explore how users interact with content and provide guidance for creators in refining their materials. This feedback loop ensures continuous improvement in content quality and effectiveness. Human resource departments can leverage personality data to segment their resources more accurately. This targeted approach can optimize the continuous growth of resources. Most importantly, it can enhance the learning experience, as learners benefit from personalized recommendations that match their learning styles and preferences, thereby improving their overall learning experience by providing more relevant and engaging content. In summary, stakeholders in TVET skills learning stand to gain significantly from the implementation of a deep learning personality-aware recommendation system. While the TVET-CRS model is rooted in psychological traits, trainee demographics, and examination performance, applying the same data across different regions enhances its generality and global adaptability.

The TVET-CRS system, originally developed using data from institutes in Pakistan, offers significant potential for global expansion. By adapting the system to different cultural, educational, and economic contexts, its effectiveness can be greatly enhanced worldwide. Culturally, TVET-CRS can be customized to align with regional norms, skill demands, language preferences, and career pathways. Collaborating with local TVET institutions will ensure that recommendations are tailored to the specific needs of each workforce. Additionally, the system can be aligned with local industries by emphasizing skills needed in emerging sectors like technology, healthcare, and renewable energy, while continuously updating course content based on evolving labor market trends. Multi-language support is essential for broad accessibility, particularly in non-English-speaking regions, and online platforms will help ensure global reach. To address diverse educational infrastructures, the system must be scalable and flexible, offering offline functionality in areas with limited digital resources and seamless integration with existing Learning Management Systems (LMS) in more advanced settings. The long-term advantages of deploying TVET-CRS internationally include improved global employability by equipping learners with the skills most in demand by employers, thereby bridging the gap between education and the job market. By tailoring vocational training programs to the specific needs of various industries, TVET-CRS can help cultivate a skilled, adaptable workforce, enhancing learners' prospects for securing relevant employment both locally and internationally.

The long-term implementation of TVET-CRS across diverse settings offers significant benefits for global employability, career advancement, and economic development. By tailoring vocational training to meet the specific needs of various industries, TVET-CRS effectively bridges the gap between education and the job market, fostering a skilled and adaptable workforce essential for navigating the demands of the rapidly evolving global economy. Through personalized recommendations, the system guides learners in selecting courses aligned with career aspirations and industry requirements, enhancing their prospects for relevant employment both locally and internationally. Additionally, TVET-CRS supports continuous professional development by offering pathways for advanced training and upskilling, ensuring workers remain competitive in response to changing industry demands. The system also addresses critical skill shortages by aligning training with the evolving needs of global industries, contributing to sustainable economic growth. Furthermore, TVET-CRS promotes social mobility and inclusivity by providing marginalized groups, such as women and economically disadvantaged individuals, with tailored learning opportunities that improve employability and support poverty alleviation. From an economic standpoint, the system offers a strong return on investment for governments and educational institutions by cultivating a qualified workforce that meets market demands, while employers benefit from access to skilled labor that drives productivity and innovation. Finally, the global expansion of TVET-CRS fosters international collaboration, facilitating the exchange of best practices, curriculum standards, and technological advancements, thus enhancing the quality and accessibility of vocational education worldwide and contributing to the development of a dynamic, skilled global workforce.

8. Conclusions and Future Work

Personality-aware deep learning recommender systems effectively address traditional challenges in recommender systems, including cold starts, data sparsity, non-linear interactions, and scalability, while also enhancing personalized recommendation quality through the integration of personality traits. By establishing a clear correlation between personality traits, learning objectives, and career paths, these systems significantly improve the effectiveness of TVET programs. Furthermore, personalized TVET course recommendations can boost the employability of graduates, alleviate the skills shortage, and optimize returns on investment. This study proposes a deep learning-based recommendation system that recommends courses for personalized technical and vocational training programs. The personality data integrated with other historical preferences and performance records data improves the efficacy of the recommender system in TVET. The proposed recommender system TVET-CRS based on deep learning achieves a notable 91% accuracy, surpassing benchmarks established in existing literature, giving a Cohen's Kappa score of 0.84, indicating substantial agreement between predicted and actual trades. Its lowest error rate of NMAE is 0.04, and the highest ranking of NDCG is 0.96. This personalized approach boosts engagement while accelerating the comprehension and retention of essential technical skills. Through adaptive learning pathways and real-time feedback, deep learning algorithms adjust recommendations based on performance, ensuring content is both relevant and tailored to learners' cognitive strengths and weaknesses.

This research and its findings are based on data collected from young boys and girls attending vocational training institutes in Punjab, Pakistan. Although the TVET-CRS model is grounded in psychological traits, trainee demographics, and examination performance, incorporating the same data from any region makes the model both generic and adaptable globally. Incorporating additional factors, such as cultural implications, social norms, values, educational systems, access to technology, economic conditions, and institutional infrastructure across countries, could further enhance its effectiveness. We emphasize the need for further research in diverse settings to validate, refine, and adapt the approach for broader applications across various cultural and socio-economic contexts. Additionally, integrating dynamic factors, such as real-time learner data and environmental changes, could help personalize and optimize recommendations, improving the system's overall effectiveness. Future research should focus on monitoring the real-world outcomes of the system, particularly its impact on learners' career progression and employability. This would provide a more comprehensive evaluation of the model's effectiveness, offering valuable insights into its practical applicability and long-term benefits for trainees in diverse contexts.

Finally, this study harnesses data-driven insights, and empowers various stakeholders, including TVET providers, policymakers, trainees, funding agencies, government authorities, and international employers, enabling them to make informed decisions. Beyond mere improvements in dropout rates, internal assessments, and course success, the findings have the potential to enhance employability and human resource development.

Author Contributions: R.H.H. conceptualized the study, developed the methodology, conducted the research, and wrote the initial draft of the manuscript. M.T.H. supervised the first author's activities and provided guidance throughout the research process. M.S.I.S. contributed to funding acquisition. M.A.R. edited and enhanced the manuscript. All authors participated in the research and contributed to the final manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This work is supported by the Deputyship of Research and Innovation, Ministry of Education in Saudi Arabia work through project number KFU241465.

Institutional Review Board Statement: The data collection process, the collected data, and the preprocessed data were presented to the Research Ethics Committee of the University of Management and Technology, Lahore, Pakistan, for approval. The committee formally approved the research for publication.

Informed Consent Statement: Written consent for data collection and publication was obtained from the Punjab Vocational Training Council. Prior to data collection, participants were verbally informed about the research objectives, the data collection process, and the anonymous publication of the findings. Additionally, a formal statement was included in the data collection survey form, which participants were required to agree to before completing the questionnaire.

Data Availability Statement: The dataset, algorithm code, and README file are available at the repository link: https://github.com/RanaHammadHassan/TVET_CRS, accessed on 24 October 2024.

Acknowledgments: The authors extend their appreciation to the Deputyship for Research and Innovation, Ministry of Education in Saudi Arabia for funding this research work through project number KFU241465.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Dhelim, S.; Aung, N.; Bouras, M.A.; Ning, H.; Cambria, E. A survey on personality-aware recommendation systems. *Artif. Intell. Rev.* **2022**, *55*, 2409–2454. [CrossRef]
2. Jena, K.K.; Bhoi, S.K.; Malik, T.K.; Sahoo, K.S.; Jhanjhi, N.Z.; Bhatia, S.; Amsaad, F. E-Learning Course Recommender System Using Collaborative Filtering Models. *Electronics* **2023**, *12*, 157. [CrossRef]
3. Fernández-García, A.J.; Rodríguez-Echeverría, R.; Preciado, J.C.; Manzano, J.M.C.; Sánchez-Figueroa, F. Creating a recommender system to support higher education students in the subject enrollment decision. *IEEE Access* **2020**, *8*, 189069–189088. [CrossRef]
4. PersoNet: Friend Recommendation System Based on Big-Five Personality Traits and Hybrid Filtering. Available online: https://ieeexplore.ieee.org/document/8675299/ (accessed on 24 September 2023).
5. Zheng, R.; Qu, L.; Cui, B.; Shi, Y.; Yin, H. AutoML for Deep Recommender Systems: A Survey. *ACM Trans. Inf. Syst.* **2023**, *41*, 101. [CrossRef]
6. Bakariya, B.; Singh, A.; Singh, H.; Raju, P.; Rajpoot, R.; Mohbey, K.K. Facial emotion recognition and music recommendation system using CNN-based deep learning techniques. *Evol. Syst.* **2024**, *15*, 641–658. [CrossRef]
7. Bhatti, U.A.; Tang, H.; Wu, G.; Marjan, S.; Hussain, A. Deep Learning with Graph Convolutional Networks: An Overview and Latest Applications in Computational Intelligence. *Int. J. Intell. Syst.* **2023**, *2023*, 8342104. [CrossRef]
8. Corr, P.J.; Matthews, G. *The Cambridge Handbook of Personality Psychology*; Cambridge University Press: Cambridge, UK, 2020.
9. Hassan, R.H.; Hassan, M.T. An Ensemble Classifier for TVET Course prediction using Big Five Personality Traits. In Proceedings of the 2023 25th International Multitopic Conference (INMIC), Lahore, Pakistan, 17–18 November 2023; pp. 1–6. [CrossRef]
10. Leng, J.; Sha, W.; Wang, B.; Zheng, P.; Zhuang, C.; Liu, Q.; Wuest, T.; Mourtzis, D.; Wang, L. Industry 5.0: Prospect and retrospect. *J. Manuf. Syst.* **2022**, *65*, 279–295. [CrossRef]
11. Rodzalan, S.A.; Noor, N.N.M.; Abdullah, N.H.; Saat, M.M. TVET Skills Gap Analysis in Electrical and Electronic Industry: Perspectives from Academicians and Industry Players. *J. Tech. Educ. Train.* **2022**, *14*, 158–177. [CrossRef]
12. Stephanidis, C. Paradigm shifts towards an inclusive society: From the Desktop to Human-Centered Artificial Intelligence. In Proceedings of the 2nd International Conference of the ACM Greek SIGCHI Chapter (CHIGREECE '23), Athens, Greece, 27–28 September 2023; Association for Computing Machinery: New York, NY, USA, 2023; pp. 1–4. [CrossRef]
13. Tvet, R. Sustainable Development Goals-Pakistan TVET REFORM Support Programme. 2018. Available online: https://tvetreform.org.pk/sustainable-development-goals/ (accessed on 20 October 2024).
14. Hassan, R.H.; Hassan, M.T.; Naseer, S.; Khan, Z.; Jeon, M. ICT enabled TVET education: A systematic literature review. *IEEE Access* **2021**, *2021*, 3085910. [CrossRef]
15. Hassan, R.H.; Hassan, M.T. A Meta-Analysis of Correlation Between Big Five Personality Traits and TVET Skills Acquisition. *J. Xi'an Shiyou Univ. Nat. Sci. Ed.* **2024**, *20*, 168–174.
16. A Ilemobayo, J.; Durodola, O.; Alade, O.; J Awotunde, O.; T Olanrewaju, A.; Falana, O.; Ogungbire, A.; Osinuga, A.; Ogunbiyi, D.; Ifeanyi, A. Hyperparameter Tuning in Machine Learning: A Comprehensive Review. *J. Eng. Res. Rep.* **2024**, *26*, 388–395. [CrossRef]
17. Burkholz, R. Batch Normalization is Sufficient for Universal Function Approximation in CNNs. 2024. Available online: https://publications.cispa.de/articles/conference_contribution/Batch_normalization_is_sufficient_for_universal_function_approximation_in_CNNs_/26892709 (accessed on 25 October 2024).
18. Hou, Z.; Yu, L.; Liang, Y.; Xu, B.; Lei, Y. Integrating L1 and weighted L2 regularization for moving force identification from combined response measurements. *Measurement* **2024**, *228*, 114337. [CrossRef]
19. Radhakrishnan, A.; Beaglehole, D.; Pandit, P.; Belkin, M. Mechanism for feature learning in neural networks and backpropagation-free machine learning models. *Science* **2024**, *383*, 1461–1467. [CrossRef] [PubMed]
20. Mahesh, T.R.; Thakur, A.; Gupta, M.; Sinha, D.K.; Mishra, K.K.; Venkatesan, V.K.; Guluwadi, S. Transformative Breast Cancer Diagnosis using CNNs with Optimized ReduceLROnPlateau and Early Stopping Enhancements. *Int. J. Comput. Intell. Syst.* **2024**, *17*, 14. [CrossRef]

21. Djenouri, Y.; Belhadi, A.; Yazidi, A.; Srivastava, G.; Lin, J.C. Artificial intelligence of medical things for disease detection using ensemble deep learning and attention mechanism. *Expert Syst.* **2024**, *41*, e13093. [CrossRef]
22. Hassan, R.H.; Awan, S.M. Identification of Trainees Enrollment Behavior and Course Selection Variables in Technical and Vocational Education Training (TVET) Program Using Education Data Mining. *Int. J. Mod. Educ. Comput. Sci.* **2019**, *11*, 14–24. [CrossRef]
23. ADB. 2022 Asian Development Bank. Available online: https://www.adb.org/sites/default/files/linked-documents/52069-001-ssa.pdf (accessed on 15 October 2023).
24. Ojha, A.; Habibnezhad, M.; Jebelli, H.; Leicht, R. Barrier Analysis of Effective Implementation of Robotics in the Construction Industry. In Proceedings of the Construction Research Congress 2022, Arlington, VI, USA, 9–12 March 2022; American Society of Civil Engineers: Arlington, VI, USA, 2022; pp. 661–669. [CrossRef]
25. Hassan, R.H.; Hassan, M.T. Identification of Technical and Vocational Education and Training (TVET) trainee's personality attributes which impact skills learning. In Proceedings of the 2024 5th International Conference on Advancements in Computational Sciences (ICACS), Lahore, Pakistan, 19–20 February 2024; pp. 1–7. [CrossRef]
26. PVTC. PVTC Official Website. Punjab Vocational Training Council Official Website. Available online: http://www.pvtc.gop.pk/ (accessed on 11 July 2024).
27. Abdurahman, S.; Vu, H.; Zou, W.; Ungar, L.; Bhatia, S. A deep learning approach to personality assessment: Generalizing across items and expanding the reach of survey-based research. *J. Pers. Soc. Psychol.* **2024**, *126*, 312. [CrossRef]
28. Akbari, M.; Seydavi, M.; Jamshidi, S.; Marino, C.; Spada, M.M. The Big-five personality traits and their link to problematic and compensatory Facebook use: A systematic review and meta-analysis. *Addict. Behav.* **2023**, *139*, 107603. [CrossRef]
29. Luo, X.; Ge, Y.; Qu, W. The association between the Big Five personality traits and driving behaviors: A systematic review and meta-analysis. *Accid. Anal. Prev.* **2023**, *183*, 106968. [CrossRef]
30. Meyer, J.; Jansen, T.; Hübner, N.; Lüdtke, O. Disentangling the Association Between the Big Five Personality Traits and Student Achievement: Meta-Analytic Evidence on the Role of Domain Specificity and Achievement Measures. *Educ. Psychol. Rev.* **2023**, *35*, 12. [CrossRef]
31. Algarni, S.; Sheldon, F. Systematic Review of Recommendation Systems for Course Selection. *Mach. Learn. Knowl. Extr.* **2023**, *5*, 560–596. [CrossRef]
32. Topolewska, E.; Skimina, E.; Strus, W.; Cieciuch, J.; Rowiński, T. The short IPIP-BFM-20 questionnaire for measuring the Big Five. *Rocz. Psychol.* **2019**, *17*, 385–402.
33. Haehner, P.; Rakhshani, A.; Fassbender, I.; Lucas, R.E.; Donnellan, M.B.; Luhmann, M. Perception of major life events and personality trait change. *Eur. J. Pers.* **2023**, *37*, 524–542. [CrossRef]
34. Zheng, Y.; Subramaniyan, A. Personality-Aware Collaborative Learning: Models and Explanations. In *Advanced Information Networking and Applications*; Barolli, L., Takizawa, M., Xhafa, F., Enokido, T., Eds.; Springer International Publishing: Cham, Germany, 2020; pp. 631–642. [CrossRef]
35. Qamhieh, M.; Sammaneh, H.; Demaidi, M.N. PCRS: Personalized career-path recommender system for engineering students. *IEEE Access* **2020**, *8*, 214039–214049. [CrossRef]
36. Uddin, M.F.; Banerjee, S.; Lee, J. Recommender system framework for academic choices: Personality based recommendation engine (PBRE). In Proceedings of the 2016 IEEE 17th International Conference on Information Reuse and Integration (IRI), Pittsburgh, PA, USA, 28–30 July 2016; pp. 476–483.
37. Hariadi, A.I.; Nurjanah, D. Hybrid attribute and personality based recommender system for book recommendation. In Proceedings of the 2017 International Conference on Data and Software Engineering (ICoDSE), Palembang, Indonesia, 1–2 November 2017; pp. 1–5.
38. Celli, F.; Lepri, B. Is big five better than MBTI? A personality computing challenge using Twitter data. In Proceedings of the Proceedings of the Fifth Italian Conference on Computational Linguistics CLiC-it, Torino, Italy, 10–12 December 2018; pp. 93–98.
39. Jeong, C.-S.; Lee, J.-Y.; Jung, K.-D. Adaptive Recommendation System for Tourism by Personality Type Using Deep Learning. *Int. J. Internet Broadcast. Commun. IJIBC* **2020**, *12*, 55–60.
40. Hassan, R.H.; Hassan, M.T. Unlocking Potential: Personality-Aware TVET Course Recommendations Revolutionize Skill Development. *Int. J. Innov. Sci. Technol.* **2024**, *6*, 1228–1248.
41. Asabere, N.Y.; Acakpovi, A.; Michael, M.B. Improving socially-aware recommendation accuracy through personality. *IEEE Trans. Affect. Comput.* **2017**, *9*, 351–361. [CrossRef]
42. Xia, F.; Asabere, N.Y.; Liu, H.; Chen, Z.; Wang, W. Socially-Aware Conference Participant Recommendation with Personality Traits. *IEEE Syst. J.* **2017**, *11*, 2255–2266. [CrossRef]
43. Garrido-Merchán, E.C.; Fernández-Sánchez, D.; Hernández-Lobato, D. Parallel predictive entropy search for multi-objective Bayesian optimization with constraints applied to the tuning of machine learning algorithms. *Expert Syst. Appl.* **2023**, *215*, 119328. [CrossRef]
44. Wang, X.; Jin, Y.; Schmitt, S.; Olhofer, M. Recent Advances in Bayesian Optimization. *ACM Comput. Surv.* **2023**, *55*, 287. [CrossRef]
45. Yang, L.; Zhu, D.; Liu, X.; Cui, P. Robust feature selection method based on joint L2, 1 norm minimization for sparse regression. *Electronics* **2023**, *12*, 4450. [CrossRef]
46. Zollanvari, A. Deep Learning with Keras-TensorFlow. In *Machine Learning with Python*; Springer International Publishing: Cham, Germany, 2023; pp. 351–391, ISBN 978-3-031-33341-5.

47. Li, X.; Li, M.; Yan, P.; Li, G.; Jiang, Y.; Luo, H.; Yin, S. Deep learning attention mechanism in medical image analysis: Basics and beyonds. *Int. J. Netw. Dyn. Intell.* **2023**, *2*, 93–116. [CrossRef]
48. Ko, H.; Lee, S.; Park, Y.; Choi, A. A survey of recommendation systems: Recommendation models, techniques, and application fields. *Electronics* **2022**, *11*, 141. [CrossRef]
49. Chen, J.; Dong, H.; Wang, X.; Feng, F.; Wang, M.; He, X. Bias and Debias in Recommender System: A Survey and Future Directions. *ACM Trans. Inf. Syst.* **2023**, *41*, 67. [CrossRef]
50. Wang, S.; Zhang, X.; Wang, Y.; Ricci, F. Trustworthy Recommender Systems. *ACM Trans. Intell. Syst. Technol.* **2024**, *15*, 84. [CrossRef]
51. El Youbi El Idrissi, L.; Akharraz, I.; Ahaitouf, A. Personalized e-learning recommender system based on autoencoders. *Appl. Syst. Innov.* **2023**, *6*, 102. [CrossRef]
52. Krishna, C.V.M.; Rao, G.A.; Anuradha, S. Analysing the impact of contextual segments on the overall rating in multi-criteria recommender systems. *J. Big Data* **2023**, *10*, 16. [CrossRef]
53. Kirubahari, R.; Amali, S.M.J. An improved restricted Boltzmann Machine using Bayesian Optimization for Recommender Systems. *Evol. Syst.* **2024**, *15*, 1099–1111. [CrossRef]
54. Dudekula, K.V.; Syed, H.; Basha, M.I.M.; Swamykan, S.I.; Kasaraneni, P.P.; Kumar, Y.V.P.; Flah, A.; Azar, A.T. Convolutional neural network-based personalized program recommendation system for smart television users. *Sustainability* **2023**, *15*, 2206. [CrossRef]
55. Etemadi, M.; Abkenar, S.B.; Ahmadzadeh, A.; Kashani, M.H.; Asghari, P.; Akbari, M.; Mahdipour, E. A systematic review of healthcare recommender systems: Open issues, challenges, and techniques. *Expert Syst. Appl.* **2023**, *213*, 118823. [CrossRef]
56. Acharya, A.; Singh, B.; Onoe, N. LLM Based Generation of Item-Description for Recommendation System. In Proceedings of the 17th ACM Conference on Recommender Systems, Singapore, 18–22 September 2023; ACM: Singapore, 2023; pp. 1204–1207.
57. Chang, C.-H. Cohen's kappa for capturing discrimination. *Int. Health* **2014**, *6*, 125–129. [CrossRef] [PubMed]
58. Derksen, B.M.; Bruinsma, W.; Goslings, J.C.; Schep, N.W.L. The Kappa Paradox Explained. *J. Hand Surg.* **2024**, *49*, 482–485. [CrossRef] [PubMed]
59. Atalla, S.; Daradkeh, M.; Gawanmeh, A.; Khalil, H.; Mansoor, W.; Miniaoui, S.; Himeur, Y. An Intelligent Recommendation System for Automating Academic Advising Based on Curriculum Analysis and Performance Modeling. *Mathematics* **2023**, *11*, 1098. [CrossRef]
60. Tan, M.; Li, S. A Course Recommendation System Based on Collaborative Filtering Algorithm. In Proceedings of the 2023 International Conference on the Cognitive Computing and Complex Data (ICCD), Huaian, China, 21–22 October 2023; pp. 213–217. [CrossRef]
61. Gulzar, Z.; Leema, A.A.; Deepak, G. PCRS: Personalized Course Recommender System Based on Hybrid Approach. *Procedia Comput. Sci.* **2018**, *125*, 518–524. [CrossRef]
62. Jiang, W.; Pardos, Z.A.; Wei, Q. Goal-based Course Recommendation. In Proceedings of the 9th International Conference on Learning Analytics & Knowledge, Tempe, AZ, USA, 4–8 March 2019; ACM: Tempe, AZ, USA, 2019; pp. 36–45. [CrossRef]
63. Ahmad, H.K.; Qi, C.; Wu, Z.; Muhammad, B.A. ABiNE-CRS: Course recommender system in online education using attributed bipartite network embedding. *Appl. Intell.* **2023**, *53*, 4665–4684. [CrossRef]
64. Amin, S.; Uddin, M.I.; Mashwani, W.K.; Alarood, A.A.; Alzahrani, A.; Alzahrani, A.O. Developing a Personalized E-Learning and MOOC Recommender System in IoT-Enabled Smart Education. Available online: https://ieeexplore.ieee.org/document/10328772 (accessed on 22 June 2024).
65. Ma, Y.; Ouyang, R.; Long, X.; Gao, Z.; Lai, T.; Fan, C. DORIS: Personalized Course Recommendation System Based on Deep Learning. *PLoS ONE* **2023**, *18*, e0284687. [CrossRef]
66. Volk, N.A.; Rojas, G.; Vitali, M.V. UniNet: Next term course recommendation using deep learning. In Proceedings of the 2020 International Conference on Advanced Computer Science and Information Systems (ICACSIS), Depok, Indonesia, 17–18 October 2020; pp. 377–380.
67. Amin, S.; Uddin, M.I.; Alarood, A.A.; Mashwani, W.K.; Alzahrani, A.O.; Alzahrani, H.A. An adaptable and personalized framework for top-N course recommendations in online learning. *Sci. Rep.* **2024**, *14*, 10382. [CrossRef]
68. Bijl, T.; van Weeren, N.; Verberne, S. Efficient course recommendations with T5-based ranking and summarization. *arXiv* **2024**, arXiv:2406.19018. [CrossRef]