Improving Online Learning via VARK Learning Styles and Machine Learning-Driven Personalisation

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Abstract: Understanding student engagement and academic performance is crucial in online learning environments. However, many learning management systems (LMS) lack mechanisms to adapt to diverse learning styles and support meaningful collaboration. This study addresses these challenges by proposing a Personalised and Collaborative Learning Experience (PCLE) framework that integrates the Visual, Auditory, Reading/Writing, and Kinaesthetic (VARK) learning style model with collaborative filtering techniques. Unlike existing approaches that rely only on rating data, PCLE incorporates personalised learning styles into the recommendation process to create learner-centred outcomes. To overcome the lack of publicly available datasets containing personalised learning style data, a self-collected dataset was developed to reflect authentic learner preferences. Benchmark datasets from Coursera and Udemy were also used to validate baseline collaborative filtering performance. Three machine learning models—K-Nearest Neighbours (KNN), Singular Value Decomposition (SVD), and Neural Collaborative Filtering (NCF)—were applied and evaluated using Mean Absolute Error (MAE), Hit Rate (HR), and Average Reciprocal Hit Ranking (ARHR). Results from the benchmark datasets confirmed earlier findings that KNN performs well on structured review data, while the self-collected dataset demonstrated the added value of integrating learning styles. The self-collected dataset was evaluated separately, incorporating personalised learning styles into the recommendation process. This dataset represents the main contribution of the study, as VARK preferences were embedded alongside course interactions to extend recommendations beyond standard rating-based methods. This study highlights how personalisation and collaboration can be integrated into one framework to enhance learner engagement. While the same models were applied, embedding learning preferences into the self-collected dataset represents a methodological enhancement rather than a direct comparison with existing datasets. Findings highlight the role of dataset characteristics in shaping both accuracy and ranking quality and show how the PCLE framework balances personalisation with collaboration to support learner-centred outcomes. Future research should expand dataset diversity, include additional learner attributes, and explore advanced recommendation models to further optimise adaptability and performance.

Keywords: Personalised learning, Collaborative filtering, KNN model, SVD model, NCF model

1. Introduction

Online learning systems have become increasingly essential, especially after the COVID-19 pandemic (Khalaf, et al., 2022), driving demand for effective learning management systems (LMS) that offer adaptive and personalised learning to improve student engagement and academic success. Artificial Intelligence (AI) driven approaches (Ayouni, et al., 2021; Kanchon, et al., 2024) and personalised learning technologies (Essa, et al., 2023) improve engagement by tailoring content to learning preferences. Integration of AI-driven tools, such as mobile interactive systems (Lai, et al., 2021) and freehand writing applications (Lai, et al., 2022), improved outcomes in virtual classrooms, while collaborative learning strategies (Herrera-Pavo, 2021) support knowledge sharing and peer interactions.

Many existing systems still lack effective ways to predict and adapt to learning styles. This study aims to address this gap by developing a Personalised and Collaborative Learning Experience (PCLE) framework that integrates learning styles with collaborative filtering and machine learning. Learning style frameworks are particularly relevant in health science education (Childs-Kean, et al., 2020), and structured frameworks like Information Technology Capability (ITC) (Lew & Krishnasamy, 2023) and Technological Pedagogical and Content Knowledge (TPACK) (Lai, et al., 2021) enhance engagement and performance. Integrating learning styles into the framework (Taheri, et al., 2021) enhances tailored learning, and advanced collaborative filtering techniques, such as Adaptive KNN and SVD (Rahman, 2023) significantly improve recommendation accuracy.

This study lies in the potential to contribute to Malaysia's post-COVID-19 educational landscape by integrating personalised learning and collaboration to support future-ready talent development. Literature review and machine learning applications (William Fernandes, et al., 2023) identify factors influencing student performance and engagement. The study by Moubayed, et al (2018) highlighted links between engagement patterns and academic outcomes. Building on this foundation, this study evaluates benchmark collaborative filtering methods, including K-Nearest Neighbours (KNN), Singular Value Decomposition (SVD), and Neural Collaborative Filtering (NCF) to analyse recommendation performance in personalised learning environments.

Existing LMS often fail to integrate personalised learning styles with collaborative methods effectively (Jena, et al., 2023; Sanjabi & Ali Montazer, 2020), limiting support for diverse learning needs. Understanding Generation Z healthcare students' preferences (Shorey, et al., 2021), is crucial for adaptive education. Collaborative filtering improves recommendation accuracy (Joorabloo, et al., 2020), but structured methods to combine learning styles with collaboration remain limited. This study bridges these gaps by introducing a PCLE framework to address these challenges and enhance student engagement outcomes.

This study develops and evaluates a PCLE framework to enhance student engagement and performance in AI-driven environments. The specific objectives are: (1) To determine factors contributing to students' academic performance in AI-driven digital transformation. (2) To investigate effects of a learning style, academic records and intelligence agent assistance on personalised collaborative learning experience (PCLE). (3) To develop a PCLE framework for predicting and improving students' engagement and academic performance. (4) To evaluate student's engagement and academic performance with the proposed PCLE framework. This study is divided into five sections: introduction, literature review, methodology, results and discussion, and conclusion. The methodology in this study builds on prior work involving model evaluation and comparative analysis of machine learning techniques in education (Ling & Weiling, 2025), as demonstrated in a previously published study in IEEE Access.

2. Literature Review

2.1 Introduction to Learning Styles

Waladi, et al. (2023) highlighted various learning style models, including VARK, Honey and Mumford, Kolb's Experiential Learning, Gregorc Style Delineator, and Dunn and Dunn, in adaptive educational environments. AI technology has advanced e-learning by enabling adaptive learning based on individual styles, though this approach requires large datasets and real-time adaptation. This study aims to overcome these challenges by evaluating AI-driven methods within the Personalised and Collaborative Learning Experience (PCLE) framework to adapt and predict preferences.

The study by Mpwanya & Dockrat (2020) emphasised the importance of understanding students' learning styles for effective instruction. Most undergraduate logistics students displayed an accommodator style, preferring hands-on learning, though the study was limited by small sample size and single institution focus. The findings provide valuable insights into the relationship between learning styles and demographics, guiding tailored instructional methods. Similarly**,** Subagja & Rubini (2023) showed aligning materials with preferred learning styles enhances knowledge acquisition among science students, with 35% kinaesthetic, 30% visual, 21% auditory, and 14% reading or writing preferences. Despite being limited to one institution, these findings highlight style diversity. This study will also build on such findings by exploring different learning styles in the PCLE framework to ensure inclusivity and adaptability.

2.2 Kolb, Felder-Silverman, VARK and Other Learning Models

Key learning style models include Kolb, Felder-Silverman, VARK, Gregorc's Mind Styles, Riding's Cognitive Styles, and Myers-Briggs Type Indicator, providing insights to support adaptive education environments. This study applies KNN, SVD and NCF models for collaborative filtering-based course recommendations, evaluated using MAE, HR, and ARHR, creating data-driven learning experience. The study by Mwangi and Muchiri (2019) assessed physiotherapy students' learning preferences at Kenya Medical Training College using Honey and Mumford (1982) and Neil Fleming (1987) questionnaires. Results showed Reflector was most prevalent style, with Kinaesthetic also common. The VARK questionnaire effectively identifies learning preferences to enhance teaching, though the study was limited to one college, with a small sample size and not considering confounding factors. The findings provide insights into how learning preferences impact student performance in medical education. Furthermore, the study by Zine, et al. (2019) investigates the effectiveness of various learning style models in adaptive educational environments. The author evaluated Gregorc, Riding, Myers-Briggs, Felder-Silverman, and Kolb models in adaptive environments, finding Felder-Silverman model is the most suitable for adaptive e-learning due to the comprehensive approach to learning styles. However, the finding's applicability is limited to adaptive systems. Zine's study provides valuable insights for designing adaptive educational environments by emphasising popular learning styles like VARK and Kolb models. Building on these insights, this study uses VARK within the PCLE framework with KNN, SVD, and NCF to enhance personalised learning through data-driven adaptation, addressing gaps in traditional LMS approaches.

2.3 Integrating Learning Styles in e-Learning

With the rapid advancement in technology, the application of learning styles in e-learning has demonstrated significant value, particularly in personalising learning paths (Seghroucheni & Chekour, 2023). The Felder-Silverman model has proven effective but functions optimally only under specific technical conditions, limiting adaptability to mobile platforms. Similarly, Glazunova, et al (2020) adapted educational content based on learning styles, customising materials to individual preferences. Limitations include restricted testing of scalability and real-time adaptation. These studies highlight the potential of data-driven learning style identification to improve adaptive learning platforms and inform tailored educational strategies.

Many current personalised educational platforms often struggle to address diverse student abilities, learning paces, and preferences (William Fernandes, et al., 2023). To address this issue, the study by William employs supervised machine learning techniques to dynamically schedule assignments based on student characteristics, evaluating Logistic Regression (LR), K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF). Random Forest achieved the highest effectiveness with 94% F1-score and accuracy rate, successfully classifying students into appropriate learning modes. Building on these findings, this study incorporates machine learning methods like KNN and SVD within the PCLE framework to dynamically adapt learning paths for diverse students.

2.4 Impact of Learning Styles on Academic Performance and Engagement

The study by Subramaniam, et al (2023) investigated Kolb's learning styles among 80 students and the effect on learning outcomes. Diverger was the most common learning style among participants, followed by Assimilator, Accommodator, and Converger. Divergers engage in concrete experience and reflective observation, often brainstorming before making decisions. Assimilators focus on theoretical understanding rather than practical application. Convergers excel in problem solving and applying theories to real-world tasks, while Accommodators learn best through hands-on activities and direct engagement. Despite the small sample, the findings provide useful insights for educators to design instructional methods that accommodate different learning preferences. In a related study, Kamal, et al (2021) found healthcare students preferred unimodal styles, emphasising the need for personalised strategies. Besides that, the study by Yean, et al (2024) reported Reflector as the most popular style among third-language learners, highlighting tailored strategies for multilingual education despite not assessing learning outcomes.

The study by Taheri, et al (2021) examined Kolb and VARK styles with emotional creativity among 250 dental students, finding Accommodator as dominant. The limitations include focus on one field and uncontrolled variables, yet the study illustrates interactions between learning styles, creativity, and performance. Furthermore, Rastovski & Tomić (2023) examined VARK's recognition across 40 studies but noted limited empirical testing across contexts, highlighting the importance of individual differences in material design. AI-based personalised e-learning systems demonstrate effectiveness in providing tailored learning experiences (Murtaza, et al., 2022). While limited diverse user personas restrict understanding of varied behaviours, the framework successfully delivers individualised learning solutions.

2.5 Collaborative Learning Styles

The study by Khalaf, et al (2022) examined the effectiveness of e-learning management systems, Moodle and Blackboard, highlighting tools for personalised and collaborative learning. Moodle offers greater cost-effectiveness and flexibility, supporting external APIs and older systems better than Blackboard. However, limitations include management challenges, technical issues, and financial constraints. Despite this, the findings emphasise e-learning systems' potential to enhance engagement and optimise learning technologies, particularly during crises like COVID-19. The integration of analytics in collaborative learning platforms (Lai, et al., 2024) can further improve engagement and outcomes. Another study by Alanya-Beltran (2024) introduced a personalised learning recommendation system using collaborative filtering and machine learning. User-based and item-based filtering identified similarity patterns, while machine learning models, such as decision trees, generated tailored recommendations based on preferences, historical behaviour, and performance. The autoencoder model outperformed other methods in predicting course ratings.

Additionally, Jena, et al (2023) presented an e-learning course recommender using KNN, SVD, and NCF on one lakh Coursera reviews from Kaggle. The results show that KNN outperforms other models by achieving higher hit rates (HR), average reciprocal hit ranking (ARHR), and lower mean absolute error (MAE), supporting informed course selection based on learner preferences. A LMS is a digital platform designed to manage, deliver, and track educational content and learning activities (Saleh, et al., 2024), facilitating online learning through content creation, communication, assessment, and progress monitoring.

2.6 Personalisation of Learning Styles

Sanjabi & Ali Montazer (2020) explored personalisation of e-learning using Kolb's learning style model, finding that tailoring strategies improved academic outcomes and satisfaction. Further real-world testing and scalability analysis are needed. The study by Sihombing, et al (2020) aimed to enhance e-learning by personalising content with the Felder-Silverman Learning Style Model (FSLSM), digitising the Index of Learning Styles (ILS) questionnaire to customise learning, which improved engagement and performance. However, the finding's limitation was the small sample size, with only 30 students participating. Furthermore, Rekha's study (Rekha, et al., 2024) investigated AI-powered personalised learning, showing adaptive paths, gamification, and predictive analytics enhance engagement and performance. Rekha's study showed that personalised learning systems cannot perfectly fit every student, but AI shows potential to address individual learning needs effectively.

3. Methodology

3.1 Dataset

This study uses both publicly available datasets and a self-collected dataset to implement and evaluate the proposed Personalised and Collaborative Learning Experience (PCLE) framework in an AI-driven Learning Management System (LMS). Initially, two education-related datasets from Kaggle were explored. The first dataset contains 100k scraped course reviews from the Coursera website as of May 2017 (Jena, et al., 2023). The second dataset is about the 209k courses detailed information and comments from the Udemy Courses website in Oct 2022. Figure 1 shows the proposed PCLE framework, from data collection and preprocessing to the integration of VARK learning styles, collaborative filtering, model evaluation, and results analysis.

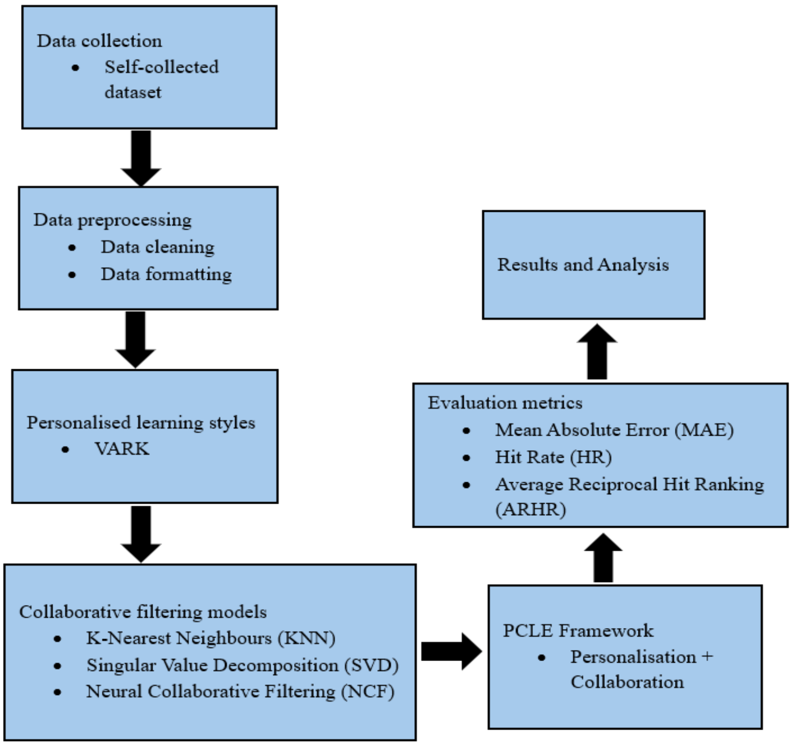

Figure 1: Proposed Framework

The first dataset (Adona, 2018) downloaded from Kaggle in the CSV file consists of 140,321 data and 4 columns. The second dataset (Hossain, 2022) that downloaded consists of 209,735 data and 25 columns. Figure 2 presents the features of dataset 1 and dataset 2. These two datasets provide benchmarks for evaluating baseline recommendation performance without personalised learning style attributes.

#	Dataset 1 Features	Description	Dataset 2 Features	Description
1	Id	The unique identifier for a review.	Comment Id	The unique identifier assigned to each comment row.
2	Course Id	The course tag found in the URL of the course on the Coursera website.	Course Id	The unique identifier or tag for each course.
3	Review	The actual text of the course review.	Rate	The numerical rating given by users for the course.
4	Label	The rating of the course review, categorised by score.	Date	The date associated with the comment.

Figure 2: Features in Datasets 1 and 2 (only the first 4 rows are shown to conserve space)

To address the limitation of existing datasets that lack personalised learning style attributes, a self-collected dataset was developed. This dataset includes participant responses from Multimedia University students and incorporates VARK learning style preferences. Figure 3 presents the features in self-collected dataset. The inclusion of this self-collected dataset enables a more accurate implementation of the PCLE framework by incorporating real learner preferences and personalised learning style data, which is an area often overlooked in existing datasets.

#	Features	Description
1	Response Number	A unique identifier assigned to each survey response.
2	Submitted Date and Time	The exact date and time when the response was submitted.
3	Course	The name of the course.
4	Full Name	The complete name of the respondent.
5	Username	The username or ID used by the participant in the system.
6	Complete	Indicates whether the survey was fully completed by the respondent.
7	Email Address	The participant's email address.
8	Question 1	Questions related to the preferred learning styles in the VARK model.
9	Question 2	Questions related to the preferred learning styles in the VARK model.
10	Question 3	Questions related to the preferred learning styles in the VARK model.
11	Question 4	Questions related to the preferred learning styles in the VARK model.
12	Question 5	Questions related to the preferred learning styles in the VARK model.
13	Personalised Learning Styles	Indicates the respondent's preferred learning style, categorised by models like VARK.
14	Module	The specific module of the course.
15	Rating	The overall rating given by the participant to the module.
16	Comment	Additional open-ended feedback provided by the participant.

Figure 3: Features in the Self-Collected Dataset

3.2 Data Preprocessing

After loading the dataset into Jupiter Notebook, the two CSV files were merged to combine relevant information. Duplicate entries were removed to maintain a clean and unique dataset. Next, missing values were checked, and rows containing “NaN” were dropped. Additionally, text preprocessing was performed on the “Review” column, including removing special characters, extra whitespace, and converting text to lowercase for consistency. For the self-collected dataset, VARK questionnaire responses were encoded into categorical features and merged with course-rating data. The resulting sparse matrix was stored in Compressed Sparse Row (CSR) format for efficiency. Finally, all datasets were split into training and testing subsets.

3.3 Personalised Learning Styles

The VARK (Visual, Auditory, Reading/Writing, and Kinaesthetic) model was applied to assess learning preferences. Responses determined the dominant learning style for each participant, and these attributes were integrated into learner profiles. This model is commonly used in education to tailor content delivery to different learning styles, enhancing engagement and effectiveness. In the PCLE framework, this enabled personalisation by grouping learners with similar VARK profiles and combining this with course interaction patterns, allowing recommendations to reflect both personal preferences and collaborative filtering. By incorporating this model into the study, the aim is to create a more personalised learning experience based on the identified preferences.

3.4 K-Nearest Neighbours (KNN) Model

Next, this study implemented a K-Nearest Neighbours (KNN) algorithm to recommend courses based on user preferences (Jena, et al., 2023). The KNN model was chosen due to simplicity and effectiveness in collaborative filtering. Secondly, using the scikit-learn library, the KNN model was initialised with cosine similarity as the distance metric. After training on the sparse course-user interaction matrix, a recommendation function retrieved the most similar courses, with lower cosine distance indicating higher similarity. Finally, the recommendations reveal course similarity patterns within the dataset. For the self-collected dataset, similarity was calculated using both course interactions and VARK attributes, ensuring that recommendations reflected collaborative patterns enriched by personalised preferences.

3.5 Singular Value Decomposition (SVD) Model

Besides that, the Singular Value Decomposition (SVD) model was used to recommend courses based on user preferences (Jena, et al., 2023). SVD is a technique that breaks down the user-item interaction matrix into smaller parts, which helps identify hidden factors influencing user choices. This allows the model to predict missing ratings or interactions, which is useful for recommending courses that users may be interested in. For the benchmark datasets, this process was based on course ratings alone. For the self-collected dataset, VARK attributes were embedded into the interaction matrix, aligning predictions with learner preferences.

3.6 Neural Collaborative Filtering (NCF) Model

Neural Collaborative Filtering (NCF) is a deep learning-based approach to collaborative filtering that uses neural networks to model user-item interactions (Jena, et al., 2023). Unlike traditional methods like KNN or SVD, which rely on linear relationships, NCF learns complex, non-linear interactions between users and items. This approach is better suited for large and complex datasets. For the self-collected dataset, VARK features were added as additional embeddings, allowing the model to generate recommendations based on both rating behaviour and learning style profiles.

3.7 Train-Test Split and Model Evaluation

To evaluate the performance of the recommendation model, the dataset was split into training and testing subsets using a 60-40 ratio, 70-30 ratio and 80-20 ratio (Jena, et al., 2023). The training data was used to train the KNN model, SVD model and NCF model. On the other hand, the test set contains unseen user-course interactions that the model has not encountered before. The model is trained on the training data and evaluated using the test data. The purpose of using test data is to simulate how well the model would perform in a real-world scenario, where predictions would need to be made based on unseen interactions. This helps in assessing the accuracy and effectiveness of the model in recommending courses that match user preferences.

3.8 Performance Metrics Calculation

The performance of the model was analysed by calculating Mean Absolute Error (MAE), Hit Rate (HR), and Average Reciprocal Hit Ranking (ARHR) (Jena, et al., 2023). The "calculate_metrics" function compared the model's recommendations with actual ratings in the test dataset. The Mean Absolute Error (MAE) assessed overall accuracy, where lower values indicate predictions closer to actual ratings. The Hit Rate (HR) measured how often relevant courses were recommended, with higher values indicating better performance. The Average Reciprocal Hit Ranking (ARHR) evaluated ranking quality, with higher values showing relevant courses appearing near the top of the recommendation list. The benchmark datasets reflected baseline collaborative filtering performance, while the self-collected dataset highlighted the PCLE contribution by balancing prediction accuracy with learner-centred personalisation.

4. Results and Discussion

4.1 Performance Results of KNN, SVD, and NCF Models

The KNN model was evaluated using three training-test splits for Datasets 1 and 2, and the self-collected dataset. In Dataset 1, results improved as training size increased, with MAE decreasing, HR increasing, and ARHR stable for 70-30 and 80-20 splits, confirming the findings of Jena et al. (2023) and validating the reliability of the benchmark dataset in testing collaborative filtering methods. In Dataset 2, performance declined as the training size increased, highlighting the influence of dataset structure and sparsity on algorithm effectiveness. In the self-collected dataset, performance remained stable for smaller splits, while the largest split showed slightly reduced accuracy but improved ranking, indicating that incorporating personalised learning styles may reduce accuracy (MAE) while improving ranking quality (ARHR), aligning more closely with learner relevance.

The SVD model showed consistent performance across splits in Dataset 1, while Dataset 2 showed less accurate predictions but stable ranking quality. In the self-collected dataset, smaller splits maintained stable performance, while the largest split improved ranking despite some reduction in accuracy.

The NCF model performed steadily on Dataset 1 with Dataset 2 maintaining stable rankings despite decreased prediction accuracy. In the self-collected dataset, smaller splits were stable, and the largest split showed reduced prediction accuracy but enhanced ranking quality. Figure 4 summarises MAE, HR, and ARHR for all three models across datasets and splits.

Model	Ratio	Dataset	MAE	HR	ARHR
KNN	60-40	Dataset 1	0.0152	0.9000	0.1267
		Dataset 2	2.8332	0.8000	0.1783
		Self-collected dataset	0.7507	0.6667	0.4167
	70-30	Dataset 1	0.0131	0.9200	0.1500
		Dataset 2	2.6253	0.6000	0.2044
		Self-collected dataset	0.7507	0.6667	0.4167
	80-20	Dataset 1	0.0080	0.9600	0.1500
		Dataset 2	2.3101	0.4000	0.1067
		Self-collected dataset	0.7937	0.3333	0.5000
SVD	60-40	Dataset 1	0.0103	0.7000	0.1370
		Dataset 2	1.4842	0.7000	0.1370
		Self-collected dataset	0.7507	0.6667	0.6667
	70-30	Dataset 1	0.0100	0.7000	0.1370
		Dataset 2	1.4556	0.7000	0.1370
		Self-collected dataset	0.7507	0.6667	0.6667
	80-20	Dataset 1	0.0105	0.7000	0.1370
		Dataset 2	1.4511	0.7000	0.1370
		Self-collected dataset	0.7937	0.3333	1.0000
NCF	60-40	Dataset 1	0.0115	0.9000	0.1370
		Dataset 2	1.6667	0.9000	0.1370
		Self-collected dataset	0.7507	0.6667	0.4167
	70-30	Dataset 1	0.0121	0.9000	0.1370
		Dataset 2	1.6667	0.9000	0.1370
		Self-collected dataset	0.7507	0.6667	0.4167
	80-20	Dataset 1	0.0085	0.9000	0.1370
		Dataset 2	1.6667	0.9000	0.1370
		Self-collected dataset	0.7937	0.3333	0.5000

Figure 4: KNN, SVD and NCF Model Results for Three Ratios across Three Datasets

4.2 Comparative Analysis Of KNN, SVD, and NCF Models

A comparison of KNN, SVD, and NCF models on Dataset 1 and Dataset 2 revealed several key observations. KNN performed best on Dataset 1, showing the lowest MAE, highest HR, and stable ARHR, confirming earlier findings by Jena et al. (2023) that KNN performs well in collaborative filtering with well-structured review data. SVD also performed well in Dataset 1, but minimal variation across training-test splits suggested limited responsiveness to data size. Dataset 2 posed more challenges as SVD and NCF maintained stable HR and ARHR values, but with much higher MAE, while KNN's performance dropped sharply as data sparsity increased. These results underline how strongly dataset characteristics influence algorithm behaviour.

The self-collected dataset was evaluated separately because personalised learning style attributes were included, unlike in the other two datasets. This dataset represents the key contribution of the PCLE framework, as user preferences based on VARK were integrated into the recommendation process. Although the same models were applied, the inclusion of learning styles represents a methodological difference, so results were not directly compared with Dataset 1 and 2. Predictive accuracy (MAE) was lower compared to Dataset 1, but ranking quality (ARHR) improved, showing that personalisation enhanced recommendation relevance for learners even when overall error rates were higher. Results from the self-collected dataset provide additional insight into how personalised features can enhance AI-driven recommendations. This reflects a different priority where, instead of maximising accuracy alone, the PCLE framework aims to support learner-centred outcomes through a balance of prediction and relevance. Unlike traditional approaches that focus on a single dataset, this study compares model performance across datasets with different characteristics, emphasising data structure's impact on recommendation effectiveness.

5. Conclusions

In summary, this study explored the development and evaluation of a Personalised and Collaborative Learning Experience (PCLE) framework in AI-driven learning environments. Findings highlight the importance of AI-driven collaborative learning strategies, particularly in the post-COVID-19 era. A comparative analysis of KNN, SVD, and NCF models showed KNN performed best for Dataset 1, while SVD and NCF showed stable predictive accuracy, indicating that dataset characteristics significantly influence recommendation effectiveness. A key limitation was the lack of publicly available datasets with learning style data, addressed by using a self-collected dataset incorporating personalised learning styles. This contribution extends evaluation beyond standard rating-based datasets and demonstrates how personalisation can improve relevance for learners, even with some reduction in accuracy. By combining personalisation with collaboration, the PCLE framework offers insights into how adaptive learning systems can better align recommendations with learner needs. Future work could involve larger, more diverse datasets, additional learner attributes, and advanced recommendation models to enhance adaptability and performance. The findings of this study contribute to research on adaptive learning, emphasising the importance of dataset structure and personalised features in optimising recommendation effectiveness.

Ethics Declaration: This manuscript is an original work, has not been submitted elsewhere, and all authors approve its submission.

AI Declaration: No generative Artificial Intelligence (AI) tools were used in the preparation of this manuscript.

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