applied sciences

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Developing an Intelligent Recommendation System for Non-Information and Communications Technology Major University Students

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Abstract: Various services and applications based on information and communications technology (ICT) are converging with cultural aspects of historical implementations. At the same time, developing a convergence course for non-ICT majors is becoming increasingly popular in universities. In this paper, we develop an AI application course for non-ICT major university students toward convergence with recommendation systems and Silk Road studies. Based on our five-year research on the martial arts, dance, and play of seven Silk Road countries, we have created and categorized an accessible database for 177 items in those countries. For our convergence course, we measure the similarity between the items for summary and perform collaborative filtering based on alternating least squares (ALS) matrix factorization so that our prototyped intelligent recommendation engine can predict the items in which a user might be interested. The course is designed to teach non-ICT major university students not only historical aspects of the Silk Road but also implementation aspects of recommendation systems with web services.

Keywords: AI application course; convergence course; recommendation system; Silk Road

Citation: Kim, T.; Lim, J. Developing an Intelligent Recommendation System for Non-Information and Communications Technology Major University Students. *Appl. Sci.* **2023**, *13*, 12774. https://doi.org/10.3390/app132312774

Academic Editors: Yu Liang, Wenjun Wu and Ying Li

Received: 18 November 2023
Revised: 23 November 2023
Accepted: 24 November 2023
Published: 28 November 2023

1. Introduction

Convergence education refers to an interdisciplinary approach that combines diverse fields of study, such as technology, the arts, the sciences, and the humanities [1,2]. It aims to foster a well-rounded understanding of complex issues by integrating different perspectives, knowledge, and skills. This approach encourages students to think critically, solve problems creatively, and make connections between seemingly unrelated subjects.

In a world where technology is rapidly changing and becoming more integrated into various fields, a basic understanding of ICT is essential [3,4]. In this regard, convergence education is important for non-ICT major students because it allows them to develop a broader set of skills that are relevant in today's technology-driven world. Convergence education provides students with an interdisciplinary approach that combines different fields of study, such as computer science, engineering, design, and business [5,6]. This allows students to develop a deeper understanding of how technology can be used to solve real-world problems and create new opportunities.

Developing a convergence course for non-ICT major students contributes to the interdisciplinary field by fostering a diverse workforce, addressing skills gaps, broadening perspectives, and future-proofing careers in an increasingly interconnected world [7]. Specifically, non-ICT major students may not have a strong background in technology, but by exposing them to convergence education, they can acquire a basic understanding of ICT-related concepts. This helps create a diverse workforce that possesses a broader range of skills, fostering innovation and adaptability within different industries.

At the same time, as artificial intelligence is growing to a great extent, recommendation systems have also received much attention in various areas, such as e-commerce, media, banking, telecom, and more [8,9]. The recommendation systems market is anticipated to reach 54 billion dollars by 2030, growing at a compound annual growth rate of 37% from 2022 [10,11]. While artificial intelligence and recommendation systems do not likely fall into the same research area, they share something in common in some dimensions in that both leverage predictive analytics based on machine learning techniques in a user-centric approach [12–15].

There are three major approaches to recommendation systems: (1) content-based filtering [16,17], (2) collaborative filtering [18,19], and (3) hybrid approaches [20–22]. Literally, content-based filtering methods use items' contents, such as summary, description, and profile information. The content-based methods are suitable for applications that use well-known data sets, including identifiers, descriptions, GPS locations, or metadata [23]. Occasionally, content-based methods utilize data from users. For example, a movie recommendation system utilizes the reviews of moviegoers. A recommender engine then provides suggestions and recommends options to those who have similar tastes based on some type of similarity measurement.

The basic assumptions of the collaborative filtering methods are that a particular user group is likely to use similar items in the future [24,25]. Therefore, it elaborates on making well-classified user groups based on complex criteria. Occasionally, collaborative methods use other user profile information that contains a past rating history. Hybrid recommendation approaches combine two or more filtering methods. In this paper, we consider hybrid recommendation systems that use both content-based filtering and collaborative filtering methods. The benefits of using hybrid recommendation systems are apparent. They provide better user experiences while achieving business goals. The target for our recommendation system is the martial arts, dance, and play of seven of the Silk Road countries (Korea, Japan, China, Mongolia, Kazakhstan, Uzbekistan, and Iran).

In this paper, we develop a convergence course for students not majoring in ICT toward convergence with intelligent recommendation systems and Silk Road studies. We expect that our convergence course can help them develop skills that are highly valued in the job market, such as problem-solving, critical thinking, creativity, and collaboration.

The Silk Road played an essential role in the embracement and development of cultures, in addition to being the main route of trade. Based on the accumulated resources, we provide a convergence course for the martial arts, dances, and plays of the Silk Road countries. The expected outcome is to highlight the importance of the cultural heritage (martial arts, dances, and plays) of the Silk Road. It is important to pay attention to and raise awareness about the intangible heritage of the Silk Road, as the potential gains are significant for countries regardless of their level of international integration. In this regard, understanding the martial arts, dances, and plays of the Silk Road can be a vital tool to dissolve the barriers between countries through physical and emotional communication.

The long-term outlook for developing the convergence course of martial arts, dances, and plays on the Silk Road is promising. We can establish a firm foothold in martial arts, dance, and play on the Silk Road, which can act as a stepping stone into the world of integration. This implies that our research will support the transmission of traditional cultures from generation to generation and lay the foundation to produce a brave new world in harmony with modern cultures.

The rest of the paper is organized as follows: Section 2 discusses our research motivation and related work. Section 3 provides implementation details for our intelligent hybrid recommendation system. Next, we present the proposed convergence course for non-ICT major university students in Section 4. Finally, Section 5 gives the conclusions and future research directions.

2. Research Motivation and Related Work

In this section, we provide the research motivation to develop a hybrid recommendation system for the martial arts, dance, and play of seven Silk Road countries for our convergence course. Then, we review previous work related to our study.

2.1. Research Motivation

The research motivation for developing a convergence course for non-ICT major students that involves developing a hybrid recommendation system for the martial arts, dance, and play of Silk Road countries could be to promote cultural exchange and understanding among countries along the Silk Road while also fostering technological innovation. By developing a hybrid recommendation system, students can learn both the cultural elements and the technical skills necessary for designing and implementing such a system. Additionally, the course would encourage students to engage in interdisciplinary learning, which could lead to creative problem-solving and innovation.

After five years of research and development, we would build datasets and databases for the martial arts, dance, and play of seven Silk Road countries. In addition to the database, we are also planning to make our database useful. To this end, we are making a convergence course (a mixture of cultures and information and communications technology) for non-ICT major university students. As a part of the course development, we built an intelligent hybrid recommendation system for the martial arts, dance, and play of seven Silk Road countries. Since the convergence course is for non-ICT major university students, we make it understandable and straightforward rather than complex and complicated. In the next subsection, we review the existing methods for recommendation systems.

2.2. Content-Based Filtering

The content-based filtering method often uses users' profile information in the system. There are two general methods to construct users' profile information. One is the preference model, and the other involves users' data history [26,27]. Technically, the profile information can be converted to a discrete score or number rating. The well-known representation for user profile information is the term frequency-inverse document frequency (tf-idf) or vector space representation [28,29]. The tf-idf method converts user profile information to a vector space based on item features.

In this paper, we use the tf-idf method to develop content-based filtering. While there are more sophisticated methods, such as support vector machines [30,31], Bayesian classifiers [32,33], and deep learning [8,34,35], we leave those for future work since these methods often require a deeper level of technical expertise and are more appropriate for advanced students who have already acquired a foundational understanding of the subject matter. Additionally, introducing these methods too early may overwhelm students and discourage them from continuing with the course. By leaving these methods as future research work, students can build on their existing knowledge and skills and gradually work toward more advanced topics as they become more confident and proficient.

The important thing when implementing the content-based filtering method is whether the recommendation system can learn and use the profile information in an effective manner. To solve the issue, we build summaries for 177 items related to martial arts, dance, and play in seven Silk Road countries and use them for item similarities. The details and descriptions of the tf-idf and the similarity measure are provided in Section 3.2.

2.3. Collaborative Filtering

The collaborative filtering method provides recommended items for a specific page (web page or application panel). The collaborative filtering method uses rating history information from all the users in the recommendation system. Explicit or implicit data collection methods can be used to achieve this [36,37]. The explicit data collection method allows users to respond to the score or rating for items (e.g., movie review and rating system).

On the other hand, the implicit data collection method uses various data, including item view history, online cart or purchase information, and likes and dislikes in social network services. There is a key issue in implementing the implicit data collection method: privacy. The operator of the recommendation system must obtain the users' agreement and specify the usage in the Terms and Conditions. To avoid this issue, we use the explicit data collection method in our recommendation system.

The basic method to implement collaborative filtering is matrix factorization [38–40]. Mathematically, matrix factorization is able to represent information about users and items in a latent feature space or embedding space, which is similar to dimensionality reduction methods such as principal component analysis (PCA). This method is called latent-factor collaborative filtering. One potential problem with matrix factorization is selecting the proper number of columns in factor matrices. To deal with the issue, the authors of [41] proposed an automatic hyper-parameter learning method based on the Bayesian model.

The authors of [42] introduced matrix factorization techniques for recommender systems, aiming to capture latent factors in user–item interactions and provide accurate predictions for personalized recommendations. The authors of [43] proposed neural collaborative filtering, a hybrid recommendation approach that combines matrix factorization and deep learning techniques to capture both user–item interactions and item–item correlations for enhanced recommendation performance. Although these state-of-the-art studies involve sophisticated techniques and methods, we focus on basic and straightforward methods for non-ICT major students.

2.4. Hybrid Recommendation Systems

Hybrid recommendation systems combine content-based and collaborative filtering approaches to leverage the strengths of both methods to provide more accurate, diverse, and adaptable recommendations while addressing the limitations of each individual approach. Hybrid recommendation systems offer certain advantages: (1) more accurate recommendations, (2) overcome data sparsity, (3) more diverse recommendations, (4) mitigate the cold-start problem, and (5) flexibility and adaptability [44,45].

In this paper, we implement a hybrid recommendation system by combining content-based filtering and collaborative filtering methods. There are seven approaches to building a hybrid recommendation system [46,47]: (1) weighted, (2) switching, (3) mixed, (4) feature combination, (5) feature augmentation, (6) cascade, and (7) meta-level. From them, we chose a mixed approach that combines different techniques or sources of information to enhance the recommendation process. Each recommendation technique has strengths and weaknesses. By combining them, a mixed approach can leverage the complementary aspects of different methods, which leads to a synergistic effect and potentially improves the overall quality of the recommendations.

2.5. Silk Road and Convergence Education

The Silk Road played a crucial role in the exchange of cultures, including martial arts, dance, and play, among the countries along its route. Martial arts like Kung Fu, Karate, and Taekwondo have historical roots in the Silk Road region, spreading through trade and cultural interactions [48]. Similarly, various forms of traditional dance and play originated from the diverse cultures along the Silk Road [49,50]. Traditional games and sports were also exchanged, fostering cultural understanding and unity among the Silk Road countries [51,52]. These artistic and recreational practices not only enriched the cultural heritage of the Silk Road but also contributed to the mutual influence and appreciation between nations.

As far as convergence education is concerned, which combines technical and non-technical subjects, it is increasingly important in today's world. It offers students a well-rounded education that integrates different disciplines and helps them develop a broader skill set. By merging technical and non-technical contents, convergence education promotes critical thinking, creativity, problem-solving abilities, and interdisciplinary understanding.

It prepares students to navigate complex real-world challenges that often require a combination of technical expertise and a deep understanding of social, cultural, and ethical implications [53].

Convergence education in this study also cultivates innovation by encouraging students to explore connections between seemingly unrelated fields. In a rapidly evolving global society, convergence education equips students with the versatility and adaptability needed to thrive in various professional domains. It bridges the gap between different areas of knowledge and promotes lifelong and sustainable learning [54].

3. The Proposed Recommendation System

In this section, we provide our hybrid recommendation system for non-ICT major university students. After reviewing the overall architecture and its implementation details, we provide detailed procedures and examples with a working example.

3.1. Overall Architecture and Implementations

The overall architecture for our hybrid recommendation system is depicted in Figure 1. We use both Silk-road datasets and user data, including profiles, view history, and rating information. For content-based filtering, similarity measures (tf-idf and cosine similarity) are used. For collaborative filtering, the k-nearest neighbors (KNN) classifier and ALS factorization are used. In the collaborative filtering procedure, the user similarity is also calculated. As our recommendation system uses a hybrid approach, both methods (content-based filtering and collaborative filtering) are combined with additional online data. That is, users' item rating information and users' view history data are stored in the database, and the stored data are also intelligently used for calculating top-N recommendations.

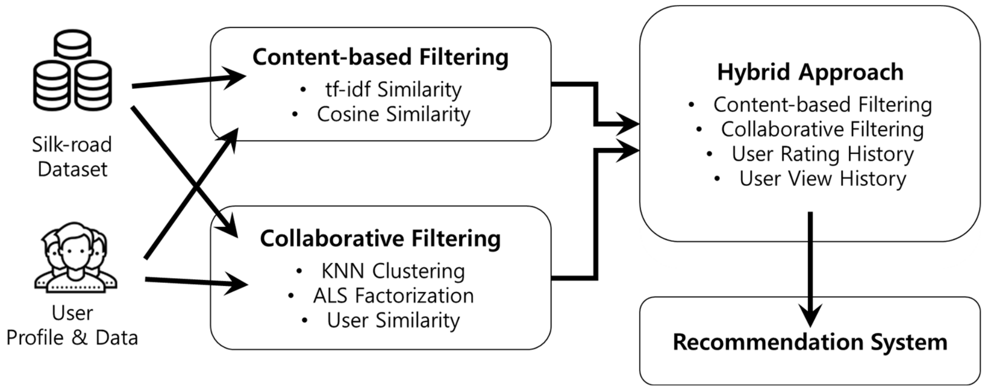


Figure 1. The overall architecture of the recommendation system.

Implementing a hybrid recommendation system requires careful consideration of data preprocessing, feature selection, similarity calculation, and weighting strategies. The high-level algorithmic procedures for implementing a hybrid recommendation system based on content-based filtering and collaborative filtering are described as follows:

1. Data collection
   - Gather user–item interaction data (ratings, reviews, etc.) for collaborative filtering.
   - Collect item features (types, keywords, etc.) for content-based filtering.
2. User profiling
   - Create user profiles based on their historical interactions using collaborative filtering techniques.
   - Analyze user preferences, behaviors, and similarities with other users.
3. Item profiling
   - Extract relevant features from items using content-based filtering techniques.
   - Represent items in a feature space based on their attributes.

4. Hybrid score calculation
    - Calculate a similarity score between the target user and other users using collaborative filtering.
    - Compute a similarity score between the target item and other items using content-based filtering.
5. Weighted combination
    - Assign weights to the similarity scores from collaborative filtering and content-based filtering based on their importance.
    - Combine the scores using a weighted sum or other fusion techniques.
6. Top-N recommendations
    - Rank the items based on the combined scores from the previous step.
    - Select the top-N items with the highest scores as recommendations for the target user.

3.2. Preprocessing

To effectively process content-based and/or collaborative filtering, stop words should be removed. Since the data sets for the recommendation system are written in Korean, libraries such as Natural Language Toolkit (NLTK) [55,56], which provides natural language processing only for English in the Python programming language, cannot be used. Thus, we included the most-used Korean stop words in addition to special characters (e.g., '{', '}', '[', ']', '.', '?', etc.). The number of stop words in Korean is about 700. With the collected stop words ready, we perform the iteration process to remove stop words for the data sets and the tokenizing process.

3.3. Content-Based Filtering

To examine the similarity between items, we use tf-idf, which is defined as Equation (1) [28,29].

$$tf - idf(t,\ d) = tf(t,\ d) \times idf(t,d), \tag{1}$$

where t is a term, d is a document, $tf(t, d)$ is the number of occurrences of t in d, and $idf(t, d)$ is the inverse document frequency. Simply put, tf-idf is the product of the term frequency and the inverse document frequency. The idf(t, d) is defined as Equation (2).

$$idf(t,d) = log\frac{n_d}{1 + df(d,t)}, \tag{2}$$

where n_d is the number of documents in the data set, and $df(d, t)$ is the number of documents that contain t.

For example, we assume that there are three simple documents:

1. Kevin likes drinking.
2. Jack likes drinking warm juice.
3. Kevin and Jack like drinking cold water.

The total word frequency can be summarized in Table 1.

Table 1. An example of tf.

	And	Cold	Drinking	Jack	Juice	Kevin	Like	Warm	Water
Document 1	0	0	1	0	0	1	1	0	0
Document 2	0	0	1	1	1	0	1	1	0
Document 3	1	1	1	1	0	1	1	0	1

However, instead of using raw term frequencies, it is typical to normalize data, such as L2-normalization, to get a vector of length 1. The L2-normalization can be calculated as Equation (3) [57].

$$v_{norm} = \frac{v}{||v||_2} = \frac{v}{\sqrt{v_1^2 + v_1^2 + \cdots + v_n^2}} = \frac{v}{(\sum_{i=1}^{n} v_i)^{1/2}} \tag{3}$$

Next, we measure similarities between items. In the context of tf-idf, an item can be considered a document for our data sets as shown in Table 2. There are numerous similarity measures in the data science field. Among them, we use the cosine similarity measure, which is calculated as Equation (4) [58,59].

$$cosine\ similarity = \cos(\theta) = \frac{A \cdot B}{||A||||B||} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}, \tag{4}$$

where A and B are two separate documents. The result of cosine similarity for our example is listed in Table 3. Note that, unlike the Euclidean similarity measure, the cosine similarity measure is scale-insensitive, and thus, it can be used for general use cases.

Table 2. An example of tf-idf.

	And	Cold	Drinking	Jack	Juice	Kevin	Like	Warm	Water
Document 1	0	0	1	0	0	1.41	1	0	0
Document 2	0	0	1	1.41	2.10	0	1	2.10	0
Document 3	2.10	2.10	1	1.41	0	1.41	1	0	2.10

Table 3. An example of document similarity using $\cos(\theta)$.

	Document 1	Document 2	Document 3
Document 1	1	0.28	0.46
Document 2	0.28	1	0.25
Document 3	0.46	0.25	1

3.4. Collaborative Filtering

In addition to content-based filtering, we also use collaborative filtering. The advantage of using collaborative filtering is that it is able to recommend things based on the patterns of others without requiring personal or item information. Collaborative filtering has become popular because of the Netflix Prize, an open competition for the best collaborative filtering algorithm.

We use two notable algorithms for collaborative filtering. The first algorithm for collaborative filtering is the KNN classifier [60–62]. The KNN algorithm is one example of lazy learning since it memorizes the data sets instead of learning a discriminative function from the data sets. As the name implies, the KNN algorithm is straightforward.

1. Get the system parameters, such as k (the number of neighbors) and a metric for measuring the distance.
2. Locate reference points for data sets in a feature space.
3. Find the k-nearest neighbors based on the distance metric.
4. Calculate the majority and assign a label to a class.

Simply put, the KNN algorithm uses the following formula for the expected similarity to weigh the score based on the k-nearest neighbors in a feature space:

$$Expected(r_{u,i}) = \frac{\sum_v Similarity(u,v) \times r_{v,i}}{\sum_v Similarity(u,v)} \tag{5}$$

In Equation (5), the expected rating ($r_{u,i}$) for user u for item i can be calculated with the average of the neighbors' rating scores for $r_{v,i}$. Note that it can use various similarity measures, such as cosine similarity and the Pearson correlation. One requirement of using the KNN classifier is that the data sets must contain the score or rating information of the items for users. To this end, we allow users to rate items on the user page, as shown in Figure 2.

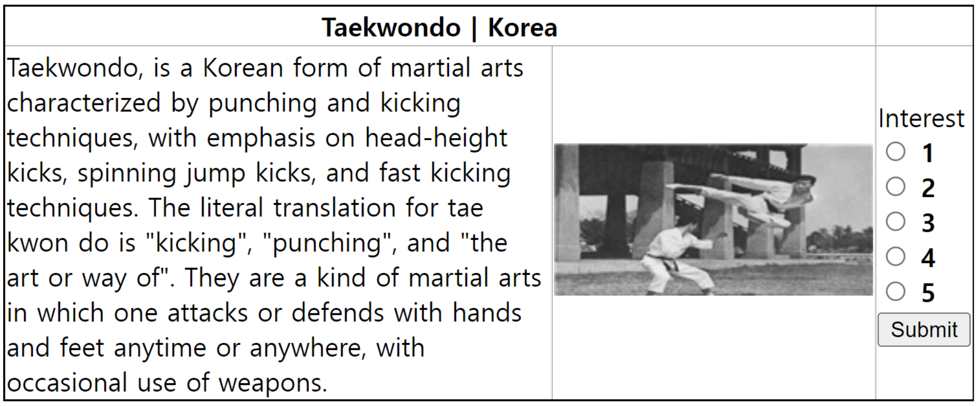


Figure 2. User page example with interest ratings. Users' interest rating scale is 1–5 (1 is the lowest and 5 is the highest value).

The second algorithm for collaborative filtering is the latent factor model [63,64]. The basic concept of latent factor collaborative filtering is to find a latent factor that represents users and items to fill empty slots in the rating matrix. The core principle of latent factor collaborative filtering is matrix factorization, which is also used in the Netflix Prize.

The well-known methods for latent factor collaborative filtering are singular value decomposition (SVD) [65], stochastic gradient descent (SGD) [66,67], and alternating least squares (ALS) [68,69]. The downside of SVD is that it neither captures biases for users and items nor allows missing values. Note that SVD can be defined for complete matrices; thus, zeroing missing values is used instead of removing entire rows. The SGD method performs matrix diagonalization, like eigenvalue decomposition. In fact, the SGD method optimizes two matrices (user latent and item latent) simultaneously.

Meanwhile, the ALS method fixes one of the two matrixes and optimizes the other matrix. Hence, the optimization problem can be converted to a convex type, which makes convergence faster than SGD. Thus, we use the ALS method for our collaborative filtering. The procedures for ALS are as follows:

1. Initialize both the user latent and the item latent.
2. Optimize the user latent while fixing the item latent.
3. Optimize the item latent while fixing the user latent.
4. Iterate steps 2 and 3.

For example, we consider four users and three items (4 × 3 matrix), as shown in Table 4. It initializes the user latent and the item latent. Then it optimizes the user latent while fixing the item latent and vice versa with Equations (6) and (7), respectively.

$$u_i = \left(V^T \times V \times \lambda I\right)^{-1} \times V^T \times R_i \tag{6}$$

$$v_i = \left(U^T \times U \times \lambda I\right)^{-1} \times U^T \times R_j \tag{7}$$

Table 4. An example of rating scores for four users.

	Item 1	**Item 2**	**Item 3**
User 1	1	0	5
User 2	0	0	3
User 3	3	2	4
User 4	2	1	5

After 10 iterations of steps 2 and 3, the user latent and the item latent are equivalent in Tables 5 and 6, respectively. The result of ALS can be calculated with the dot product of the item latent and the user latent, as shown in Table 7.

Table 5. The user latent matrix after 10 iterations.

	Item 1	**Item 2**	**Item 3**
User 1	1	0	5
User 2	0	0	3
User 3	3	2	4
User 4	2	1	5

Table 6. The item latent matrix after 10 iterations.

	Item 1	**Item 2**	**Item 3**
User 1	1	0	5
User 2	0	0	3
User 3	3	2	4
User 4	2	1	5

Table 7. The result of the dot product (item latent · item latent).

	Item 1	**Item 2**	**Item 3**
User 1	0.57	0.29	1.02
User 2	0.22	−0.16	0.97
User 3	1.03	0.95	0.99
User 4	1.02	0.94	0.99

3.5. Working Example

In this subsection, we provide a working example of our hybrid recommendation system for martial arts, dance, and play in seven Silk Road countries. For our prototype and convergence course for non-ICT major university students, we built a synthetic user history data set for 177 items. We assume that 2000 users are using the recommendation system for martial arts, dance, and play from seven Silk Road countries with a Poisson distribution where $\lambda = 1$, as shown in Figure 3. The x-axis is the number of unique items, and the y-axis is the number of users.

For KNN clustering, choosing the proper k is essential. To figure out the effect of k in KNN, we calculate the cluster sum of squares (WCSS), and the result is defined as Equation (8).

$$WCSS = \sum_{x \in C} (x - \mu_C)^2, \tag{8}$$

where x is a sample, C is a cluster, and μ_C is the center of the cluster.

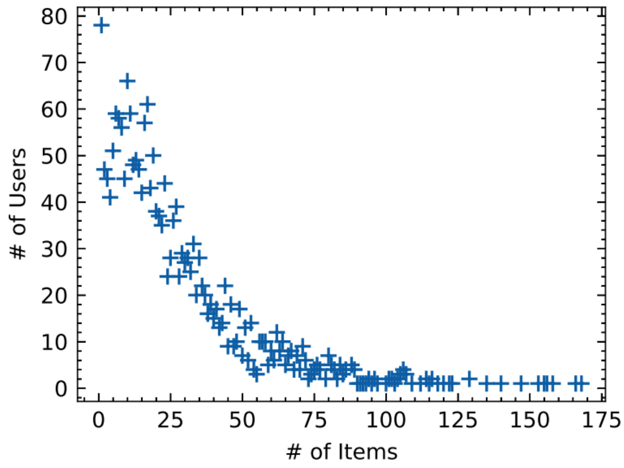


Figure 3. The distribution of users' item view history. Data points are marked as blue cross.

Figure 4 shows WCSS with the number of k increasing. The WCSS is inversely proportional to the number of k. The slope is steepest between k = 1 and k = 2, and the slopes decrease as the number of k increases. In this case, the proper value of k can be 2 or 3.

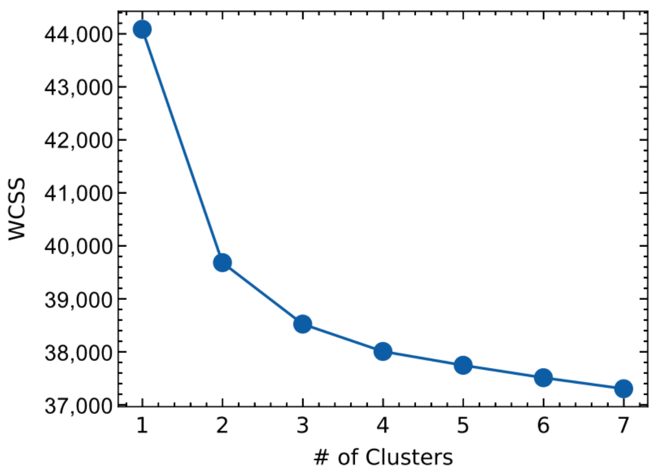


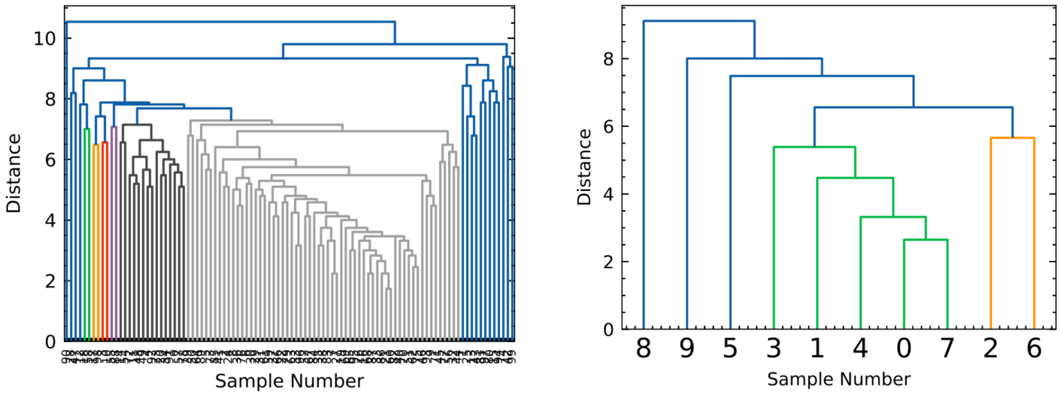
Figure 4. WCSS with the number of clusters. Data points are marked as blue dots.

In addition to WCSS, we use agglomerative and divisive hierarchical clustering to figure out the properties of the synthetic data set. To visualize the hierarchical clustering, we show the dendrogram for sample data. In order to calculate the distance between two clusters, we use Equation (9).

$$d(u,v) = \sqrt{\frac{|v|+|s|}{T}d(v,s)^2 + \frac{|v|+|t|}{T}d(v,t)^2 - \frac{|v|}{T}d(s,t)^2}, \tag{9}$$

where u (the union of s and t), v, s, and t are clusters, and T is $|v| + |s| + |t|$.

Figure 5 shows the dendrogram for hierarchical clustering with the Euclidean distance. Note that we only show a limited number of samples for visibility (100 in Figure 5a and 10 in Figure 5b). Note that the dendrogram does not indicate whether the clustering result is good or bad. Rather, it demonstrates the process of clustering to determine proper clustering.



(**a**) # of sample: 100 (**b**) # of sample: 10

Figure 5. Dendrogram for hierarchical clustering. Different colors indicate different subtrees.

Figure 6 shows the prototype example of our hybrid recommendation system for martial arts, dance, and play in seven Silk Road countries. The figure shows the item for Taekwondo (a Korean form of martial arts) with its title, summary, representative figure, interest rating form, and four recommended items (at the bottom of the page). Note that the first two recommended items are from content-based filtering, and the last two items are from collaborative filtering.

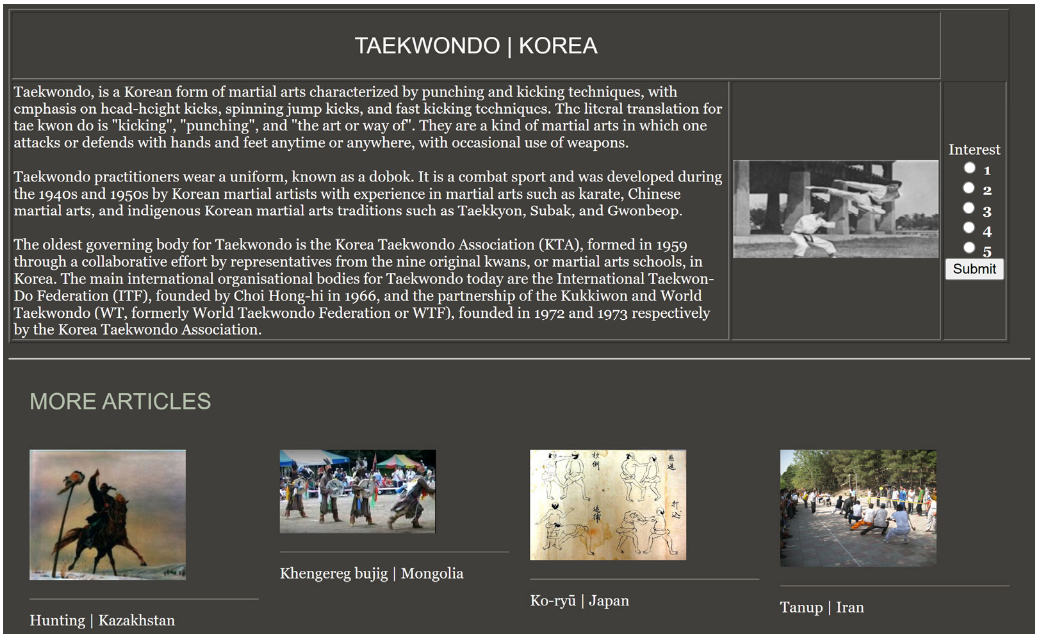


Figure 6. A prototype example of the recommendation system.

4. Curriculum and Discussion

In this section, we discuss the result of the proposed hybrid recommendation system for martial arts, dance, and play in seven Silk Road countries and its usefulness by proposing the convergence course for non-ICT major university students. Table 8 shows the outline of the convergence course for non-ICT university students. As a one-semester course for three credits, the course consists of many topics that should be covered for non-ICT major university students.

Table 8. Outline of the convergence course for non-ICT university students.

Week	Contents	Note
1	Programming environment setup - Installing Anaconda (Python, JupyterLab, etc.) - Construct virtual environments in Anaconda	Including a course introduction Homework Assignment #1 (Programming Environment Setup)
2–4	Python programming basics - Variables, assignment statements, and arithmetic operations - Input and output statements - Control statements	Use IDE, IPython, and Jupyter
5–7	Functions - Built-in functions and defining functions Classes - Defining user-defined classes, controlling access to attributes, and case studies Libraries - NumPy, Matplotlib, Pandas, etc.	Homework Assignment #2
8	Mid-term examination	Practical-based
9–11	Introduction to recommendation systems - Content-based filtering - Collaborative filtering	Homework Assignment #3
12–14	Implementing a hybrid recommendation system - Implementing content-based filtering in Python - Implementing collaborative filtering in Python	Homework Assignment #4
15	Build a website for the recommendation system	Presentation
16	Final examination	Practical-based

Hence, no advanced topics are covered in detail. Rather, it reviews essential topics and programming basics in Python. The students are expected to have studied web programming skills (e.g., HTML, Javascript, and Cascading Style Sheets) because the web programming course is set as a prerequisite. Therefore, the convergence course can be composed of the essential topics to implement the hybrid recommendation system for martial arts, dance, and play in seven Silk Road countries.

While the proposed convergence course for non-ICT university students is based on ICT technologies and programming languages (e.g., Python, HTML, and PHP), the main contents and data sets are about martial arts, dance, and play in seven Silk Road countries. Hence, it promotes learning both the cultural aspects of martial arts, dance, and play in the seven Silk Road countries and the programming concepts needed to develop the hybrid recommendation system.

The core concept of the recommendation system stems from mathematics. However, the students are non-ICT majors; some students may have no mathematical background. With consideration of that, the convergence course does not dive deep into mathematical topics. Rather, it focuses on the concept and guidance of using mathematical libraries in Python. Furthermore, the convergence course utilizes JupyterLab to provide a connection between the offline course and independent studying. With JupyterLab installed in university classrooms and on students' laptops or PCs (Homework Assignment #1), students can learn and study in an efficient way.

Unlike the previous studies [70,71], the learning of historical aspects of martial arts, dance, and play in Silk Road countries can contribute to the interdisciplinary field in different ways. First, martial arts and dance were often used as means of self-defense and physical exercise by people who traveled along the Silk Road. By learning about these practices, we can understand how people adapted to the challenges of their environment, developed resilience, and maintained their physical and mental well-being. This knowledge can help us promote healthy lifestyles and eco-friendly practices.

Second, play and entertainment were essential components of cultural exchange along the Silk Road. People from different cultures and backgrounds would come together to share their traditions, skills, and values through music, games, and performances. By learning about these practices, we can appreciate the diversity of human expression, foster cross-cultural understanding and respect, and promote cultural preservation and inclusivity.

Lastly, the historical aspects of martial arts, dance, and play in Silk Road countries can also inspire innovation and creativity in modern-day practices. By learning about the historical aspects of Silk Road countries, we can understand how different cultures and civilizations interacted with each other and how they adapted to the challenges of their environment. This knowledge can help us promote ethical practices in industry culture.

As far as non-ICT major students are concerned, there are learning challenges faced by non-ICT major students [72–74]. That is, (1) technical terminology (Non-ICT students may find it difficult to understand and grasp the technical jargon and terminology used in ICT subjects.), (2) lack of foundation (Non-ICT students may not have a strong foundation in computer science concepts, programming languages, and other fundamental ICT knowledge, making it harder for them to grasp advanced ICT topics.), and (3) rapid technological changes (ICT is a rapidly evolving field, and keeping up with the latest technologies and trends can be challenging for non-ICT students, especially if they do not have regular exposure to ICT-related subjects.).

Hence, we consider the following teaching principles for non-ICT major university students for the course:

- Fundamentals first: start with foundational concepts and ensure that non-ICT students have a solid understanding of basic ICT principles before moving on to more advanced topics.
- Practical application: emphasize hands-on projects and real-world applications of ICT concepts to help non-ICT students understand the practical relevance of what they are learning.
- Contextualization: relate ICT concepts to other disciplines and fields of study to help non-ICT students see the interdisciplinary nature of ICT and how it can be applied in various domains.

Developing a convergence course that balances technical and cultural/historical aspects can be challenging. Therefore, we suggest guidance on teaching instructions and assessments.

- Define learning objectives for both technical and cultural/historical aspects and communicate them clearly to students.
- Use project-based learning or case studies to contextualize technical skills within cultural and historical contexts.
- Incorporate diverse perspectives and voices in course materials and discussions to broaden students' cultural understanding.
- Provide opportunities for students to reflect on their learning and engage in critical thinking about the intersections between technology and culture/historical contexts.
- Use a variety of assessments, such as coding assignments, research papers, and presentations, to evaluate both technical skills and cultural/historical knowledge.

Regarding the guidance, our proposed curriculum meets the basic requirements of a convergence course and the needs of the era of the ICT convergence industry. In the context of convergence education, which encompasses both technical and non-technical aspects, Bloom's Taxonomy [75] is important. Bloom's Taxonomy provides a framework for categorizing educational objectives and learning outcomes into different levels of cognitive complexity. It can be applied to various fields, including the convergence of technical and non-technical subjects, to promote critical thinking, problem-solving, creativity, and holistic learning experiences. In the context of Bloom's Taxonomy, we suggest and recommend the following structures for our proposed convergence course:

1. **Remembering**
   - Encourage students to create mind maps or concept maps that connect technical and non-technical concepts.
   - Use multimedia resources, such as videos or interactive websites, to reinforce understanding and retention of information.
2. **Understanding**
   - Engage students in discussions that explore the connections between technical concepts and their real-life applications or societal impacts.
   - Assign case studies or project-based tasks that require students to analyze and explain the interplay between technical and non-technical factors.
3. **Applying**
   - Design hands-on activities or simulations that integrate technical skills with problem-solving in real-world contexts.
   - Encourage students to develop innovative solutions by combining technical knowledge with insights from non-technical fields.
4. **Analyzing**
   - Assign tasks where students evaluate the ethical, social, or environmental implications of technical decisions or advancements.
   - Provide opportunities for students to analyze and compare different approaches to solving a problem, considering both technical and non-technical factors.
5. **Evaluating**
   - Encourage students to critically assess the effectiveness and limitations of technical solutions for addressing complex societal challenges.
   - Foster debates or presentations where students evaluate the impact of emerging technologies on various aspects of society.
6. **Creating**
   - Assign open-ended projects that require students to design and develop innovative solutions by integrating technical and non-technical elements.
   - Encourage interdisciplinary collaboration, where students from different backgrounds contribute their expertise to create something new.

5. Conclusions

Developing an intelligent recommendation system for non-ICT major university students is not a trivial task since it requires ICT skills (data science and programming skills). In this paper, we present a convergence course for non-ICT major university students toward convergence with recommendation systems and Silk Road studies. Simultaneously, we try to integrate cultural aspects of martial arts, dance, and play from seven Silk Road countries into the proposed intelligent recommendation system. To achieve the two discrete goals, we built our database for martial arts, dance, and play from seven Silk Road countries, and the database is used in the recommendation system as the main content.

By bridging the gap between non-ICT disciplines and technology, this course has enabled students to acquire valuable skills in both domains. Through the course, students have gained a deeper understanding of the cultural heritage of Silk Road countries, particularly in the realms of martial arts, dance, and play. They have also learned various ICT techniques and tools necessary for developing a hybrid recommendation system. This hands-on experience has not only enhanced their technical proficiency but also fostered their appreciation for the rich diversity of cultural expressions.

When teaching the convergence course for non-ICT major students, there are a few limitations to consider. Since the convergence course aims to cover a wide range of topics within a limited time, it can be difficult to strike a balance between covering topics and providing sufficient depth in each subject area. In addition, students in the course may have varying skill levels and learning abilities. Hence, teaching methods to accommodate this diversity can be a challenge.

In this case, the convergence course can be a co-taught class that includes both technical and non-technical experts, which greatly enhances the effectiveness of learning in convergence education. The reasons for recommending a co-taught class are: (1) the combination of technical and non-technical experts brings a wide range of knowledge and skills to the classroom. Technical experts can provide an in-depth understanding of technology-related concepts, tools, and applications, while non-technical experts can contribute their expertise in other subject areas and pedagogical approaches; this comprehensive expertise allows for a more holistic and well-rounded learning experience. (2) Having both technical and non-technical experts in the classroom enables a seamless integration of different subject areas, fostering interdisciplinary learning and connections between various fields. (3) Students can engage in meaningful teamwork, bringing together diverse perspectives and skills to tackle complex challenges with both technical and non-technical experts since convergence education emphasizes collaborative problem-solving and real-world application of knowledge. (4) In a co-taught class, technical and non-technical experts can provide individualized support to students based on their unique needs; thus, students can receive guidance and assistance in both technical and non-technical aspects of the curriculum, ensuring a more personalized and tailored learning experience.

Author Contributions: Methodology and writing-original draft preparation, T.K.; conceptualization and writing-review, J.L. as the corresponding author. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2017-S1A5B4055939 and NRF-2021R1F1A1063307) and by Hankuk University of Foreign Studies Research Fund of 2023.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data available on request. The data are not publicly available due to privacy.

Acknowledgments: We thank the anonymous reviewers for their careful reading and insightful suggestions to help improve the manuscript.

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

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