An Online Course Recommender System in e-Learning Using Learners' Profile and Learning Behavior-Based Mechanism

Winyu Niranatlamphong[1], Wicha Charoensuk[2,*], and Worasit Choochaiwattana[3]

[1]College of Creative Design and Entertainment Technology, Dhurakij Pundit University, Bangkok, Thailand
[2]Department of Interactive Design and Game Development, College of Creative Design and Entertainment Technology, Dhurakij Pundit University, Bangkok, Thailand
[3]Department of Statistics, Chulalongkorn Business School, Chulalongkorn University, Bangkok, Thailand
Email: winyu.nir@dpu.ac.th (W.N.); wicha.cha@dpu.ac.th (W.C.); worasit@cbs.chula.ac.th (W.C.)
*Corresponding author

Manuscript received May 9, 2023; revised June 5, 2023; accepted July 19, 2023; published January 29, 2024

***Abstract*—The advent of online learning platforms, such as Coursera and Udemy, has facilitated global access to diverse educational opportunities. However, integrating recommender algorithms into these online learning systems presents a notable challenge. To address this challenge, this research paper proposes an architecture for online course recommender systems that leverages learners' profiles and learning behavior. The proposed architecture comprises six core components: 1) User Management Engine, 2) Online Course Content Management Engine, 3) Learning Behavior Observer and Recorder, 4) Profile and Learning Behavior Builder Engine, 5) Course Recommendation and Filtering Engine, and 6) Feedback Engine. These components collectively form the foundation of the online course recommender system. In order to facilitate practical implementation, a prototype of the online course recommender system has been developed. To evaluate the system's performance, a comparative analysis was conducted, to compare the personalized recommended list with the non-personalized recommended list. The analysis revealed an average precision of 77.60% for the personalized recommended list, while the non-personalized recommended list achieved an average precision of 65.60%. These findings highlight the superiority of the personalized approach in generating more accurate and relevant online course recommendations.**

***Keywords*—course recommendation, e-learning, personalization, recommender mechanism, recommender system**

I. Introduction

The Internet and World Wide Web (WWW) have served as a convenient platform for information storage and dissemination for over a decade. However, the exponential growth of information available on the Internet and WWW has led to a considerable challenge for users in locating relevant and engaging content. The pervasive issue of information overload necessitates the utilization of technologies that facilitate the discovery of information aligned with users' specific consumption needs. Considering this predicament, recommender systems have emerged as an intriguing approach to address this challenge.

The recommender systems are tools that provide suggestions for their users according to the users' need [1, 2]. The recommender systems can help facilitate people's lives in terms of many aspects, e.g., product recommendation [3–6], movie recommendation [7–9], travel recommendation [10, 11], knowledge recommendation [12, 13], and research paper recommendation [14, 15].

Recently, web-based learning systems such as Coursera, Udemy, and edX, have become increasingly popular with people all around the world. Among of these well-known systems, they are designed to support many learners with different backgrounds and interests. In addition, they offer numerous courses and cover wide variety of subject categories. The content diversification and enormity in the web-based learning systems can lead to the inconvenience of content exploration and discovery for learners. It is challenging to integrate recommender mechanisms into the web-based learning systems. The recommender mechanisms can help the learners to discover relevant learning content. The online course recommender systems have emerged as indispensable tools for facilitating effective and efficient course exploration among learners. Nevertheless, upon reviewing existing research papers in the field of recommender systems within the education domain [16–18], it is evident that the majority of scholars have focused their efforts on the application of recommendation techniques, namely collaborative filtering and content-based filtering. Furthermore, researchers have also explored the integration of compelling technologies like augmented reality [19], machine leaning [20], and data mining technique [21]. with their recommender systems.

The existing literature reveals a limited number of research papers that propose an architecture of e-learning systems that integrate recommendation mechanism, specifically focusing on the exploration of strategies to effectively exploit user information and behavior for recommendation tasks.

The primary objective of this research paper is to present a novel architecture for online course recommender systems that leverage learners' profiles and learning behavior. Additionally, the study aims to investigate the extent to which learners' profiles and learning behavior contribute to the effectiveness of course recommendation.

This paper is structured as follows. The second section provides an in-depth description of the proposed architecture, including the underlying recommendation mechanism employed by the online course recommender. Furthermore, it discusses the development of a prototype online course recommender and outlines the experimental setup and evaluation methodology. The preliminary findings and subsequent discussion are presented in the third section. Finally, the fourth section offers conclusive remarks, while the fifth section acknowledges the contributions made by individuals and organizations that have supported this research endeavor.

doi: 10.18178/ijiet.2024.14.1.2036

II. MATERIALS AND METHODS

A. The Proposed Architecture of Recommender System

According to recommendation techniques used in e-learning [22], there are four major techniques used in the recommender systems, which are content-based recommendation techniques, collaborative filtering-based recommendation techniques, knowledge-based recommendation techniques, and hybrid recommendation techniques. Typically, the recommender systems in different domains share similar core components, which are 1) Content/Item Information Management, 2) User Information Management, and 3) Recommendation Component. Many researchers have introduced more components to increase an effectiveness and efficiency of their recommender systems [2, 5, 23, 24]. Under different circumstances, it is sometime difficult to apply the same core components to develop the recommender systems especially in the education domain. The recommender systems in the education domain requires different components depending on the recommendation techniques used.

Fig. 1 shows the proposed architecture of online course recommender systems using learner's profile and learning behavior. The core components in the proposed architecture are 1) User Management Engine, 2) Online Course Content Management Engine, 3) Learning Behavior Observer and Recorder, 4) Profile and Learning Behavior Builder Engine, 5) Course Recommendation and Filtering Engine, and 6) Feedback Engine. Each component is responsible for different tasks in the recommender systems.

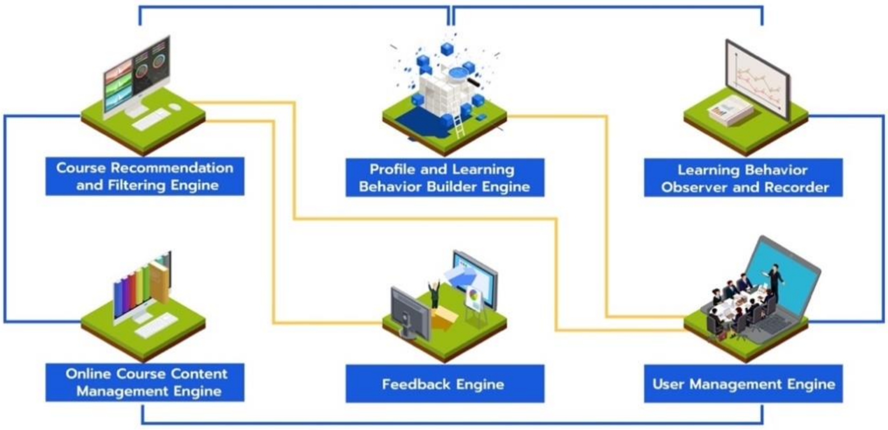

Fig. 1. The proposed architecture of online course recommender system in E-learning using learner's profile and learning behavior-based mechanism.

The User Management Engine has a responsibility for managing all aspects of user information including user profile and user interaction logging. The Online Course Content Management Engine has a responsibility for managing all aspects of online course information including quizzes and examinations as well as learning outcome evaluation. The first two components are the common components that appear in the recommender systems. While the Learning Behavior Observer and Recorder and the Profile and Learning Behavior Builder Engine are special components proposed by the proposed architecture. The Learning Behavior Observer and Recorder works closely with the User Management Engine to keep tracks of learners' interaction with the online classes. The Profile and Learning Behavior Engine help create learning profile and convert learners' interaction to a set of data structure that represents learners' topic interest. In addition, the Course Recommendation and Filtering Engine has a responsibility for creating a list of recommended courses by comparing the learners' topic interest with the set of data structure that represent the course content. Last but not least, the Feedback Engine has a responsibility for keeping track of how well a list of recommended courses is and recording the learners' interaction with the list of recommended courses.

B. The Proposed Recommendation Mechanism

The proposed recommendation mechanism, as illustrated in the Fig. 2, exploits the usage of course content tag to recommend learning courses. The recommendation mechanism, proposed in this paper, is adapted from the Tag-Based Recommendation Mechanism proposed in [13]. To implement the recommendation mechanism, there are six main components—*set of learners, set of learners' profile tags, set of interaction with courses, set of learners' topic interest, set of tags from new/unenrolled courses, and set of new/unenrolled courses.*

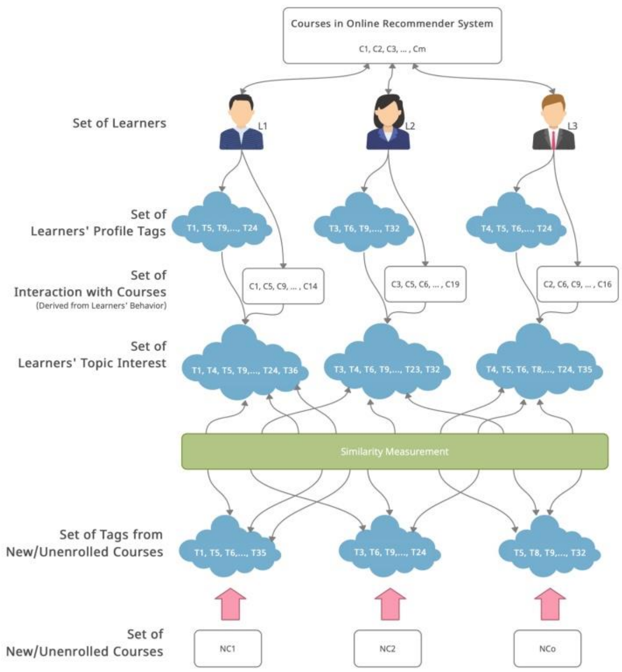

Fig. 2. A concept of recommendation mechanism.

Assume that there is N_u learners and N_c courses in the online course recommender system. Let L be a set of learners and contains all learners in the online course recommender system; $L = \{l_1, l_2, l_3, \ldots, l_n\}$, C be a set of courses and contains all courses in course corpus; $C = \{c_1, c_2, c_3, \ldots, c_m\}$, T be a set of content tag and contains all content tag associated with courses; $T = \{t_1, t_2, t_3, \ldots, t_p\}$ and LT_x be a set of learners' profile tags of a learner l_x and contains all profile tags representing initial interesting contents; $LT_x = \{lt_1, lt_2, lt_3, \ldots, lt_p\}$ and $LT_x \subseteq T$. Let M_{LC} be the $N_L \times N_C$ association matrix between learners and courses. $M_{LC}(l_x,c_y)$ will be equal to 1 when the learner l_x enrolls and completes learning the course c_y with 85% passing score. Thus, each row, or LC_i in M_{LC} represents a learner's interaction with courses.

In addition, for each learner l_x, let LTC_x be a set of learners' topic interest that derived from M_{LC} and combined with LT_x; $LTC_x = \{< l_x, t_p > | l_x \in L \wedge t_p \in T \wedge M_{LC}(l_x, c_y) = 1\} \cup LT_x$ and $NTC_y(l_x)$ be a set of tags form new or unenrolled courses that derived from M_{LC}; $NTC_y(l_x) = \{< c_y, t_p > | c_y \in C \wedge t_p \in T \wedge M_{LC}(l_x, c_y) = 0\}$.

To recommend courses to each learner in the online course recommender system, cosine similarity scores between LTC_x, representing topic interest of learner x, and $NTC_y(l_x)$, representing content of new or unenrolled courses of learner x, will be calculated as illustrated in (1).

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

For this study, when the similarity score is greater or equal to a predefined threshold ($\alpha = 0.65$), the recommendation mechanism will then recommend the course to that learner.

C. A Prototype of an Online Course Recommender System

To make the process of prototype development easier, the learner's journey is designed to explain how all components in the proposed architecture work together as illustrated in the Fig. 3.

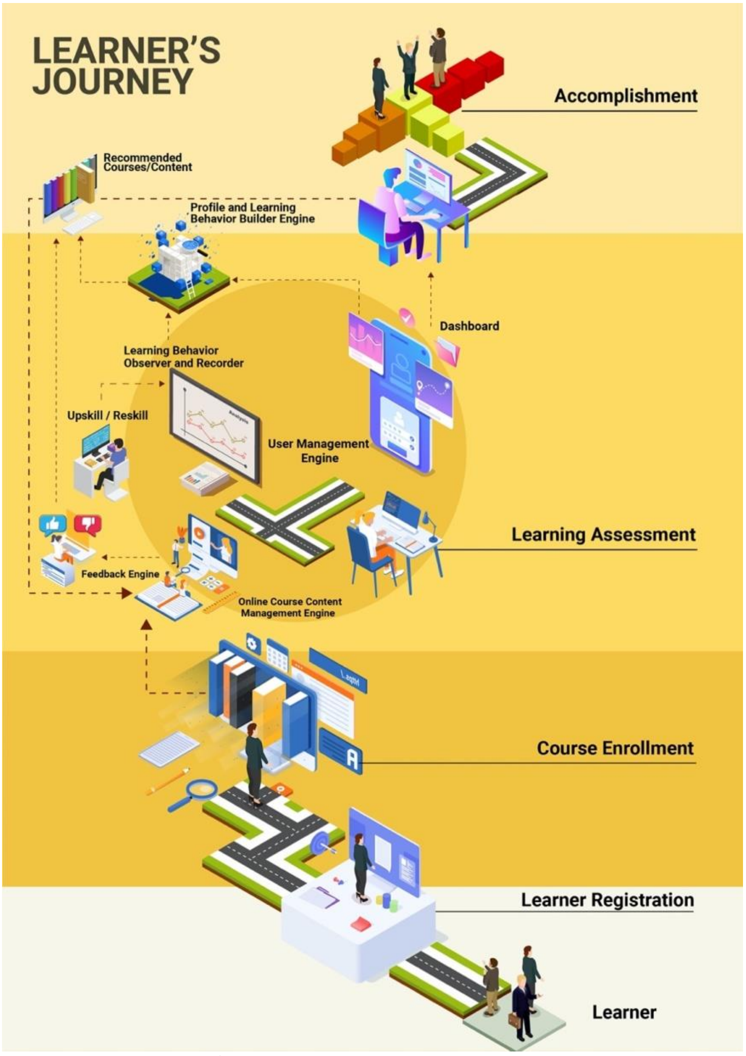

Fig. 3. A learner's journey in the proposed architecture.

Next, a prototype of an online course recommender system, called "AntX$_{rs}$", is developed. The proposed architecture mentioned in the previous is used as a blueprint for the development. The Fig. 4 shows a screenshot of a learner's learning dashboard, which is the main interface of the online course recommender system. It provides learner's information, completed courses, courses in progress, and recommended courses. While the Fig. 5 shows a screenshot an online learning, which can be viewed as an online classroom. It provides learning content, quizzes and examinations, and learning outcome evaluation. It should be noted that the prototype is developed for the purpose of the architecture evaluation only. Thus, the prototype still has limited functionalities.

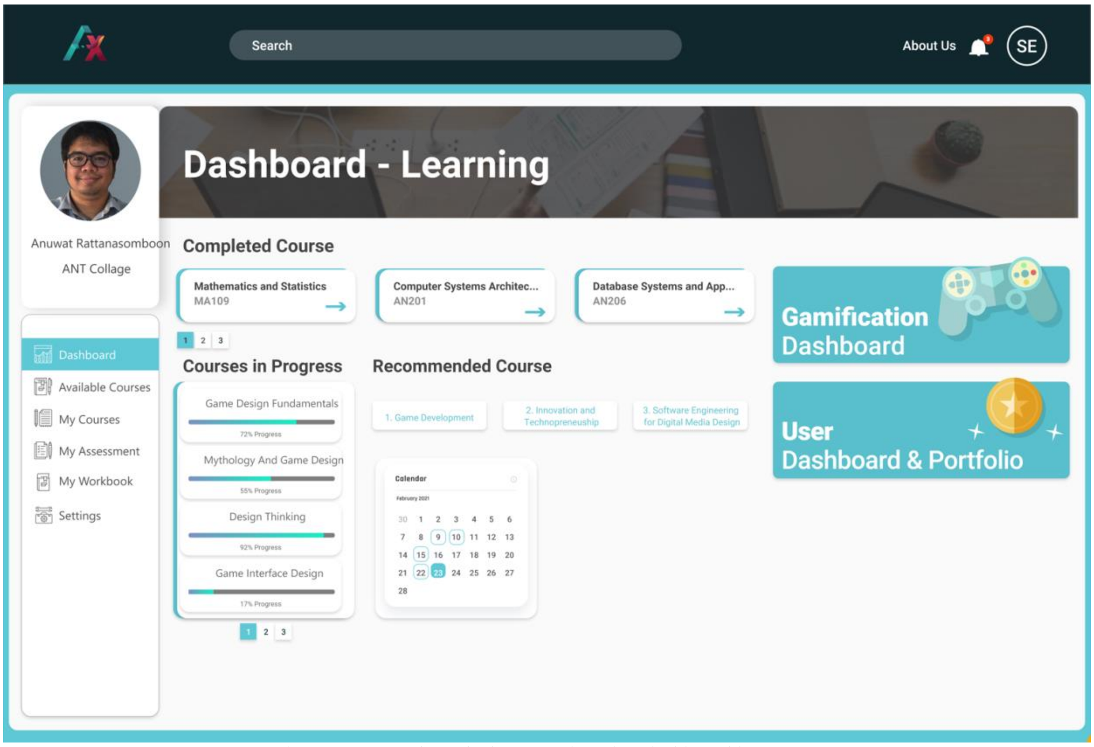

Fig. 4. A screenshot of a learner's learning dashboard in AntX$_{rs}$.

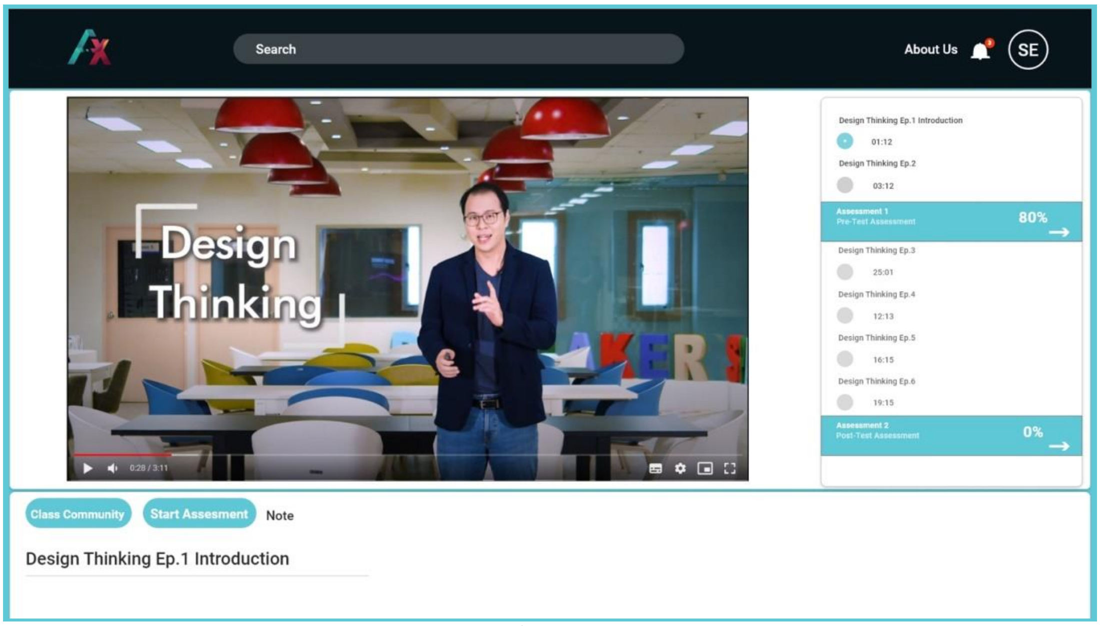

Fig. 5. A screenshot of an online learning in AntX$_{rs}$.

III. Experiment and Evaluation

To evaluate the performance of the proposed recommender system, thirty-two online short courses and video content created by professors and instructors from Dhurakij Pundit University are uploaded into the AntX$_{rs}$. The precision or positive predictive value in online course recommendation is used as an evaluation metric as illustrated in Eq. (2). The precision is defined as the percentage of relevant results. Thus, 100% precision means the learner satisfies with all courses in the recommendation list.

$$Precision = \frac{No.\ of\ Relevant\ Recommendation\ Courses}{No\ of\ Recommendation\ Courses} \times 100\% \qquad (2)$$

A total of 25 graduate students were selected to participate in this research investigation. A prerequisite for their inclusion as participants was their familiarity with online learning systems. The participants were assigned the task of utilizing the prototype system to register for courses aligning with their individual interests. In order to ensure comprehensive data collection for the recommender system, each participant was required to dedicate a minimum of thirty hours of engagement with the prototype prior to the evaluation phase. This time commitment was essential to capture and utilize each participant's behavioral patterns and interactions with the online courses.

Upon completion of the course recommender mechanism's task of generating a personalized list of recommended courses, the five personalized recommendation courses with the highest similarity score will be merged with the top 5 courses that have garnered the highest user registration rates, referred to as the non-personalized recommended courses. The resultant amalgamation will constitute the final recommended course list. Subsequently, this list will be presented in a randomized order to the learners on their learning dashboard, as depicted in the Fig. 4. It is important to note that the participants will remain unaware of whether the recommended courses originate from the personalized list or the non-personalized list. Consequently, their decision to register for a course from the recommended list will serve as an indicator of satisfaction with the respective recommendation. Conversely, the decision not to register for a recommended course indicates dissatisfaction. The precision of the recommendations from both the personalized and non-personalized lists is then calculated and compared.

IV. Results and Discussion

As mentioned at the beginning of this paper, the aim of this research paper is to introduce a novel architecture for online course recommender systems that capitalizes on the integration of learners' profiles and learning behavior. In order to assess the effectiveness of incorporating these factors into the course recommendation process, a preliminary evaluation was undertaken. The precision metric was employed to quantify the accuracy and efficacy of the recommendation mechanism, with higher precision values indicating a more effective system. The personalized list, which considers learners' profiles and learning behavior, was compared to the non-personalized list, which considers only the popularity of the course. The precision values for each participant are documented in Table 1 and 2, providing a comprehensive overview of the recommendation system's performance.

Table 1. Precision of the personalized recommendation for each participant

Participant	Personalized Recommendation Mechanism	
	No. of Relevant Recommended Courses	Precision (%)
A	3	60.00
B	5	100.00
C	4	80.00
D	4	80.00
E	4	80.00
F	3	60.00
G	4	80.00
H	4	80.00
I	4	80.00
J	4	80.00
K	3	60.00
L	4	80.00
M	4	80.00
N	3	60.00
O	5	100.00
P	3	60.00
Q	5	100.00
R	4	80.00
S	3	60.00
T	4	80.00
U	4	80.00
V	4	80.00
W	3	60.00
X	4	80.00
Y	5	100.00
Average		77.60

Table 2. Precision of the non-personalized recommendation for each participant

Participant	Non-personalized Recommendation Mechanism	
	No. of Relevant Recommended Courses	Precision (%)
A	2	40.00
B	3	60.00
C	3	60.00
D	3	60.00
E	4	80.00
F	4	80.00
G	3	60.00
H	3	60.00
I	4	80.00
J	5	100.00
K	4	80.00
L	3	60.00
M	3	60.00
N	3	60.00
O	3	60.00
P	3	60.00
Q	3	60.00
R	3	60.00
S	4	80.00
T	3	60.00
U	4	80.00
V	4	80.00
W	2	40.00
X	3	60.00
Y	3	60.00
Average		65.60

A comparative analysis was conducted to assess the performance of the personalized recommended list and the non-personalized recommended list. The results revealed an average precision of 77.60% for the personalized recommended list, while the non-personalized recommended list achieved an average precision of 65.60%. These findings highlight the varying levels of precision achieved by the two recommendation approaches. These precision values serve as indicators of the accuracy and effectiveness of the respective recommendation approaches. The results highlight the superior performance of the personalized recommended list in providing more precise course recommendations compared to the non-personalized approach.

To further investigate the significance of these differences, a t-Test dependent sample analysis was employed. The results demonstrate a statistically significant difference between the average precision of the personalized recommended list and the average precision of the non-personalized recommended list as illustrated in the Table 3.

Table 3. Comparing precision values of the personalized recommended list and the non-personalized recommended list

Precision Value	n	mean	S.D.	t	df	sig
Personalized Recommended List	25	65.60	13.56	−3.13	24	0.00
Non-personalized Recommended List	25	77.60	13.32			

The findings of this study indicate that the recommendation mechanism effectively fulfills its objective of course recommendation. The learners' profile tags emerge as a valuable representation of their interests in specific learning topics. Furthermore, the analysis of learning behavior data facilitates the identification of associations between learners' interactions and courses. However, upon conducting additional investigation, it was observed that challenges arise when learners exhibit a wide-ranging interest in various topics. In such cases, the similarity scores between the learners' profile tags and the course content tags tend to be relatively lower.

V. Conclusion

This research study centers around presenting an architecture for online course recommender systems that leverages learners' profiles and learning behavior, while simultaneously examining the extent to which these factors contribute to the course recommendation task.

The preliminary evaluation yielded promising results, indicating that both learners' profiles and learning behavior significantly contribute to the effectiveness of online course recommendations. However, to further enhance the efficacy and efficiency of the online course recommendation system, it is imperative to conduct a more comprehensive investigation into learners' profiles and learning behavior. Additionally, the development of more robust recommendation mechanisms and techniques is crucial to optimize the overall performance of the system. These endeavors will facilitate the creation of an advanced and refined online course recommendation system capable of providing highly accurate and personalized recommendations to learners.

Acknowledgment

We would like to thank all staff members and graduate students from the Department of Web Engineering and Mobile Application Development, College of Creative Design and Entertainment Technology, Dhurakij Pundit University for being participants in our experiment. They also provide us comments and suggestions to make the system better. In addition, we would like to extend our gratitude to all professors and instructors to allow us to upload their digital content from their classes to our development server in order to conduct the evaluation of our proposed architecture. Without their help and support, this research project could not be completed.

Conflict of Interest

The authors declare no conflict of interest

Author Contributions

All authors made significant contributions to this research. Winyu Niranatlamphong was responsible for conceptualizing and designing the proposed recommender system architecture, conducting an extensive literature review, and formulating ideas for the recommendation mechanism. Wicha Charoensuk played a critical role in designing the prototype of the online course recommender system, conducting experiments, assisting in data collection and analysis, and providing valuable input during the critical review of the manuscript. Worasit Choochaiwattana brought his expertise to the design of the recommendation mechanism and the development of the online course recommender system prototype. Additionally, he drafted, reviewed, and edited the manuscript to enhance its overall clarity and coherence. The successful completion of this research was the result of the collaborative efforts of all authors, who collectively approved the final version of the manuscript.

References

[1] F. Ricci, L. Rokach and B. Shapira, "Introduction to Recommender Systems Handbook," in F. Ricci, L. Rokach, B. Shapira, P. Kantor (Eds.) *Recommender System Handbook*, Springer, Boston, Massachusetts, 2011, pp. 1–35.

[2] F. Alyari and N. J. Navimipour, "Recommender systems: A systematic review of the state of the art literature and suggestion for future research," vol. 47, no. 5, 2018, pp. 985–1017.

[3] D. J. Dudhia, S. R. Dave, and S. Yagnik, "Self attentive product recommender—a hybrid approach with machine learning and neural network," *International Conference for Emerging Technology 2020*, Karnataka, India, June 5–7, 2020, pp. 1–4.

[4] R. Dong, M. P. O'Mahony, M. Schaal, K. McCarthy, and V. Smyth, "Sentimental product recommendation," *7th ACM Conference on Recommender Systems 2013*, Hong Kong, October 12–16, 2013, pp. 411–414.

[5] V. Sembium, R. Rastogi, A. Saroop, and S. Merugu, "Recommending product sizes to customers," *11th ACM Conference on Recommender Systems 2017*, Como, Italy, August 27–31, 2017, pp. 243–250.

[6] P. Kouki, I. Fountalis, N. Vasiloglou, N. Yan, U. Ahsan, K. A. Jadda, and H. Qu, "Product collection recommendation in online retail," *13th ACM Conference on Recommender Systems 2019*, Copenhagen, Denmark, September 16–20, 2019, pp. 486–490.

[7] M. Gupta, A. Thakkar, Ashish, V. Gupta, and D. P. S. Rathore, "Recommender system using collaborative filtering," *International Conference on Electronics and Sustainable Communication Systems 2020*, Coimbatore, India, July 2–4, 2020, pp. 415–420.

[8] R. E. Nakhil, H. Moradi, and M. A. Sadeghi, "Movie recommender system based on percentage of view," *5th International Conference on Knowledge Based Engineering and Innovation 2019*, Tehran, Iran, February 28–March 1, 2019, pp. 656–660.

[9] A. Chauhan, D. Nagar, and P. Chaudhary, "Movie recommender system using sentiment analysis," *International Conference on Innovative Practices in Technology and Management 2021*, Gautam Buddh Nagar, India, February 17–19, 2021, pp. 190–193.

[10] P. Jomsri and W. Choochaiwattana, "Machine learning mechanism for adaptive tourist recommendation using bayesian algorithm," *International Journal of Artificial Intelligence*, vol. 19, no. 1, pp.109–122, 2021.

[11] M. Figueredo, J. Ribeiro, N. Cacho, A. Thome, A. Cacho, F. Lopes, and V. Araujo, "From photos to travel itinerary: A tourism recommender system for smart tourism destination," *4th IEEE International Conference on Big Data Computing Service and Applications 2018*, Bamberg, Germany, March 26–29, 2018, pp. 85–92.

[12] W. Niranatlamphong and W. Choochaiwattana, "Hybrid approach for a knowledge recommender service: A combination of item-based and tag-based recommendation," *Walailak Journal of Science and Technology*, vol. 14, no. 10, pp. 161–165, 2017.

[13] W. Choochaiwattana, "A comparison between item-based and tag-based recommendation on a knowledge management system: A preliminary investigation," *International Journal of Information and Education Technology*, vol. 5, no. 10, pp. 754–757, 2015.

[14] P. Jomsri, S. Sanguansintukul, and W. Choochaiwattana, "A framework for tag-based research paper recommender system: An IR approach," *IEEE 24th International Conference on Advanced Information Networking and Applications Workshops 2010*, Perth, Australia, April 20–23, 2010, pp. 103–108.

[15] M. B. Magara, S. O. Ojo, and T. Zuva, "A comparative analysis of text similarity measures and algorithms in research paper recommender systems," *Conference on Information Communications Technology and Society 2018*, Durban, South Africa, March 8–9, 2018, pp. 1–5.

[16] K. Bhumichitr, S. Channarukul, N. Saejiem, R. Jiamthapthaksin, and K. Nongpong, "Recommender systems for university elective course recommendation," *14th International Joint Conference on Computer Science and Software Engineering 2017*, Nakhon Si Thammarat, Thailand, July 12–14, 2017, pp. 1–5.

[17] Z. Khoja and S. Shetty, "Hybrid recommender system for college courses," *International Conference on Computational Science and*

Computational Intelligence 2017, Las Vegas, NV, USA, December 14–16, 2017, pp. 1167–1171.
[18] A. A. Neamah and A. S. El-Ameer, "Design and evaluation of a course recommender system using content-based approach," *International Conference on Advanced Science and Engineering 2018*, Iraq, October 9–11, 2018, pp. 1–6.
[19] S. Anuvareepong, S. Phooim, N. Charoenprasoplarp, and S. Vimonratana, "Course recommender system for student enrollment using augmented reality," *6th IIAI International Congress on Advanced Applied Informatics 2017*, Hamamatsu, Japan, July 9–13, 2017, pp. 212–217.
[20] M. Isma'il, U. Haruna, G. Aliyu, I. Abdulmumin, and S. Adamu, "An autonomous courses recommender system for undergraduate using machine learning techniques," *International Conference in Mathematics, Computer Engineering and Computer Science 2020*, Lagos, Nigeria, March 18–21, 2020, pp. 1–6.
[21] F. Pesántez-Avilés, D. Calle-López, V. Robles-Bykbaev, M. Rodas-Tobar, and C. Vásquez-Vásquez, "A recommender system based on data mining techniques to support the automatic assignment of courses to teachers in higher education," *International Conference on Information Systems and Computer Science 2017*, Quito, Ecuador, November 23–25, 2017, pp. 231–236.
[22] Q. Zhang, J. Lu, and G. Zhang, "Recommender systems in e-learning," *Journal of Smart Environments and Green Computing*, vol. 1, pp. 76–89, 2021.
[23] K. Dahdouh, L. Oughdir, A. Dakkak, and A. Ibriz, "Smart courses recommender system for online learning platform," *IEEE 5th International Congress on Information Science and Technology 2018*, Marrakech, Morocco, October 22–24, 2018, pp. 328–333 .
[24] A. Koene, E. Perez, C. J. Carter, R. Statache, S. Adolphs, C. O'Malley, T. Rodden, and D. McAuley, "Ethics of personalized information filtering," in: T. Tiropanis, A. Vakali, L. Sartori, and P. Burnap (Eds.) *Internet Science*, *INSCI 2015*, *Lecture Notes in Computer Science*, vol. 9089, Springer, Cham, 2015, pp.123–132.