Hwang, W. et al. (Eds.) (2022). Proceedings of the 30th International Conference on Computers in Education. Asia-Pacific Society for Computers in Education

Designing a Recommender System for Mobile Applications Focusing on Relative Importance Weights of Learner-related Variables

Woorin HWANG[a], Hyo-Jeong SO[a*], Chiyoung SONG[b], & Hyeji JANG[a]
[a]*Ewha Womans University, Republic of Korea,* [b]*MOTOV, Republic of Korea*
*hyojeongso@ewha.ac.kr

Abstract: To embrace why and how people learn and how to combine learner characteristics for recommending foreign language learning mobile applications (apps), this research presents a recommender system based on the relative importance weights of learner-related variables. In developing the system, 100 adult learners used 4-6 foreign language learning apps, resulting in 557 user-satisfaction data to calculate the relative importance of 14 learner-related variables in four categories: (a) demographic information, (b) motivational orientation for language learning (instrumental/integrative), (c) learning style, and (d) learning experience. The result showed that the model considering the relative importance weights of learner-related variables outperforms the dummy model in predicting users' satisfaction with the apps.

Keywords: Recommender System, Mobile Applications, Feature Importance, Learner Variables

1. Introduction

In the flood of information and the expansion of informal learning spaces, the learners face up with the difficulty in selecting appropriate learning resources since they cannot judge what kind of learning information is meaningful to them. Also, as most of the app recommendations have been developed in the commercial area, it is uneasy for them to adopt the recommendations directly for educational or learning purposes. While these commercial algorithms are grounded on general factors such as demographic information, installed apps, age groups, user device information, and preference (Cheng et al., 2016), Garcia-Martinez and Hamou-Lhadj (2013) emphasized that educational recommender systems should be distinguished from those developed in the business area in terms of goal, context, the influence of pedagogical factors, and classification of users. Essalmi et al.(2015) also mentioned that, in education, personalized recommendation needs to focus on the combination of learners' characteristics coupling with learning objects. With this backdrop, this research proposes a method to design an educational recommender system of apps for foreign language learning. First, the newly-developed system reflects the fundamental factors for learning — why and how people learn. Moreover, to harmonize learner-related variables considering that not all variables are equally important, it is based on the relative importance of learner-related variables in model estimation.

2. Method

2.1 Participants

The participants were recruited from online bulletin boards and included 100 adult learners (33 males and 67 females) in Korea, aged 19 to 39. At the time of the study, 53 participants were students, followed by 32 working as office or professional workers, and 9 unemployed. In terms of their educational background, they include 38 undergraduates, 41 graduates, and 21 with master's or higher degrees.

2.2 Constructing a Recommender System

2.2.1 Data Collection

First, the participants self-reported their characteristics in four categories: (i) demographic information (age, gender, education level, job-related factors), (ii) language learning experience, (iii) learning style by Felder-Solomon's Index of Learning Style (ILS), and (iv) motivational orientation for language learning (instrumental/integrative). Second, four to six apps among 18 foreign language learning apps were randomly assigned to each participant. The 18 were selected from App Store (iOS) and Google as they rated three points or higher (out of five). As the result, 557 satisfaction data (1= "not satisfied at all" to 5= "very satisfied") were collected. All procedure was conducted after the approval by the IRB committee of the researchers' institution.

2.2.2 Relative Importance and Algorithm

RandomForestRegressor (Scikit-Learn 1.0.2., 2022) was used in the data analysis process to calculate the relationship between user satisfaction with 18 apps and 14 sub-variables. Table 1 presents the relative importance weights of each variable according to the rank of importance.

Table 1. *Description of Learner-related Variables and Relative Importance Weights*

Category	Code ID	Description	Importance Weight(Rank)
Demographic Information	AgeR	*Age group* (1: 19-24, 2:25-29, 3:30-34, 4: 35-39)	0.0657(6)
	Gen	*Gender*: Whether the learner is male (0) or female (1)	0.0569(7)
	Schooling	*Education*: The learner's highest education completed (1: high school level or under, 2: college/university level, 3: graduate school or above)	0.0514(8)
	N-yn	*Job*: Whether the learner has a job (1) or not (0)	0.0247(13)
	S-yn	*Job*: Whether the learner is a student (1) or not (0)	0.0263(12)
Learning Style	LS1	*Information Processing*: active (1) or reflective (-1)	0.0658(5)
	LS2	*Information Perception*: intuitive (1) or sensory (-1)	0.0399(9)
	LS3	*Information Reception*: visual (1) or verbal (-1)	0.0245(14)
	LS4	*Information Understanding Progression*: global (1) or sequential (-1)	0.0337(10)
Language Learning Motivation	MIT	*Motivation in total:* The extent to which the learner is motivated for learning a language	0.1674(2)
	MI1	*Integrative Motivation:* The extent to which the learner is oriented toward integrative motivation (e.g., understanding the target culture)	0.1520(3)
	MI2	*Instrumental Motivation*: The extent to which the learner is oriented toward instrumental motivation (e.g., reaching practical goals such as getting a job)	0.1808(1)
Language Learning Experience	LE	*Whether the learner has ever used any mobile apps* for language learning (1) or not (0)	0.0283(11)
	LLPW	*The frequency of language learning per year*	0.0826(4)
		Sum of Importance Weights	1.0

The top five variables with high importance weights are all three variables in language learning motivation (MI2=.1808, MIT=.1674, MI1=.1520), usage frequency in the learning experience (LLPW=.0826), and perception in learning style (LS1=.0658).

2.2.3 System Interface and Evaluation

The proposed system can be described in Figure 1. In calculating the similarity between learners, the weighted cosine similarity was employed by reflecting the importance weights of the variables. The interpolation in the learners' satisfaction scores that they did not rate was made with Inverse Distance Weighting(IDW) — giving greater weight to the value of the former learner with the closest similarity.

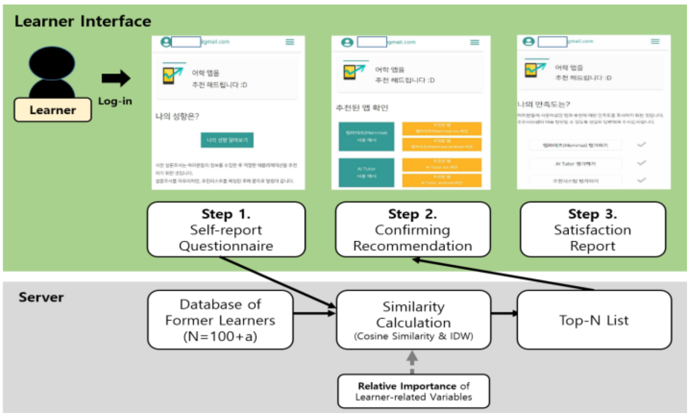

Figure 1. Recommender System Architecture

The performance of the developed system was compared with the dummy model which postulated recommending every 18 apps to everyone. As the result, the former (Precision=.647, Recall=.403, F1-score=.494) outperformed the latter (Precision=.564, Recall=.388, F1-score=.459).

3. Conclusion and Future Work

This research presents how the relative importance weights among learner-related variables can affect a recommender system of language learning apps. Overall, we confirmed that learner characteristics in the affective domain, such as language learning motivation, learning style (Information Processing), and app usage frequency carry higher importance weights than the general demographic information such as gender and job. This led to the result that the proposed system reflecting the relative importance of the variables was better in predicting learner satisfaction than the random recommendation. Some limitations of this study should also be noted. First, since the importance weights were calculated with a limited number of variables, we need to expand the model with more diverse variables to develop more meaningful recommender systems. Second, this study used self-reported questionnaires to determine learning style and motivation, requiring learners of extended time and effort. Thus, future research on educational recommender systems should take into account utilizing proxy indicators or automatic detectors to capture learning motivations and styles. Third, the complex interaction among learner variables can be detected by adopting more advanced ways for analysis, such as Support Vector Machine, Gradient Boosting, or Deep Neural Network Model.

Acknowledgements

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT)(No. 2020R1F1A1073469).

References

Cheng, H. T., Koc, L., Harmsen, J., Shaked, T., Chandra, T., Aradhye, H., ... & Shah, H. (2016, September). Wide & deep learning for recommender systems. *Proceedings of the 1st workshop on deep learning for recommender systems* (pp. 7-10).

Essalmi, F., Ayed, L. J. B., Jemni, M., & Graf, S. (2015). Generalized metrics for the analysis of E-learning personalization strategies. *Computers in Human Behavior*, *48*, 310-322.

Garcia-Martinez, & S., Hamou-Lhadj, A. (2013). Educational recommender systems: A pedagogical-focused perspective. In *Multimedia services in intelligent environments* (pp. 113-124). Heidelberg: Springer