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Learner Perception of an Educational Recommender System based on Relative Importance of Learner Variables*

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This study suggests that educational recommender systems should be explainable and extend beyond the commercially driven algorithms that primarily rely on user preferences and purchase behaviors. Instead, we propose a recommendation method that considers how and why people learn by employing the relative importance of various learner variables. To develop a recommendation algorithm, 100 adult participants used 4 to 6 foreign language learning mobile applications(apps), generating a dataset of 557 user perception reports. Using this data, we designed and developed a recommender system based on the importance weights of 14 learner variables, categorized into four groups: (a) demographic information, (b) motivational orientation for language learning (instrumental vs. integrative), (c) learning styles, and (d) learning experience. The results based on RandomForestRegressor model revealed that language learning motivation, learning styles (specifically information processing), and usage frequency were significantly more influential than general demographic factors in predicting learners' evaluation of the apps. Furthermore, learners' perception of the recommender system revealed that the recommender system was relevant and engaging, effectively meeting their needs and assisting them in selecting appropriate language learning apps. Overall, this study demonstrates the potential of educational recommender systems that consider learners' motivation, experience, and learning styles.

Keywords : Recommender System, Mobile applications, Mobile learning, Learner variables, Individual Difference

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Introduction

In recent years, education has rapidly expanded from formal face-to-face interactions to informal online environments. Learning experiences, in particular, have been enhanced by the development of the Internet and mobile devices, which support seamless learning across different locations and timescales. Among these technological advancements, an increasing number of mobile learning applications (apps) integrated with artificial intelligence (AI) highlight the growing popularity of informal learning (Holmes et al., 2019). For instance, 49% of AI-integrated educational apps in the app market are related to foreign language learning (Lee et al., 2020). This trend is corroborated by the fact that over 80% of college students report studying English online in informal settings (Jung, 2019). The widespread use of mobile apps for foreign language learning is likely due to the immediate, personalized, and widely accessible learning opportunities they offer (Yuen & Schlote, 2024).

Despite these advantages, learners with limited expertise often struggle to choose appropriate resources and apps for learning, as they may not know what type of content is most valuable to them (Han & Lim, 2017). This challenge is compounded by the overwhelming amount of available information and resources. Because of this lack of information and the number of available apps, learners need guidance in informal learning settings. This guidance often comes in the form of recommender systems to reduce the information overload of learners, helping them find relevant applications quickly and efficiently (Davidsson & Moritz, 2011; Pimenidis et al., 2018).

However, most recommender systems for applications are made for commercial purposes. These commercial recommender systems are known to rely on general variables such as demographic data, installed apps, age groups, device information, usage patterns, and user preferences (Cheng et al., 2016). Moreover, these systems are often considered “black boxes,” which use various machine learning techniques without revealing how and why a certain item is recommended, making it difficult to do backtracking (Pesovski et al., 2022). The lack of transparency and explainability in recommender systems makes it challenging for developers, educators and learners to understand the logic behind the recommendations (Vultureanu-Albişi & Bădică, 2021; Zhang & Chen, 2020). Additionally, depending on general variables can be inadequate for educational purposes since educational recommender systems are required to consider various educational variables and contexts for their effectiveness. Researchers have emphasized that educational recommendations must account for learning goals and contexts, as well as the influence of pedagogical factors in classifying learners (Essalmi et al., 2015; Tarus et al., 2017). Developing educational recommender systems also entails other challenges, such as limited data on understanding learning variables or learning processes and balancing short-term engagement with long-term learning goals (Santos & Boticario, 2012).

While there are several challenges and research gaps in the field of educational recommender systems, this study focuses on understanding the relative importance of learner variables in developing an educational recommender system and identifying learners' perceptions of this new type of recommender system that considers why and how people use foreign language learning applications. The following questions guide the present study:

1) Which factors among the learner variables (demographic information, learning styles, motivation, and learning experience) are relatively more important than others for predicting learners' evaluation of foreign language learning apps?
2) What are learners' overall perceptions of the new recommender system proposed in this study?

Literature Review

Educational Recommender Systems

As observed in popular digital platforms such as Netflix and Amazon, recommender systems play a role as "tools and techniques that suggest items that are most likely of interest to a particular user" (Ricci et al., 2015, p. 1). In the context of education, recommender systems can assist learners by suggesting potential activities, content, courses, and communities (Santos & Boticario, 2012). Further, educational recommender systems can enhance learners' academic performance and motivation by providing personalized learning content (Garcia-Martinez & Hamou-Lhadj, 2013).

While educational and commercial recommender systems share some similarities, they differ in significant ways. First, the primary goal of commercial recommender systems is to drive purchases, whereas educational recommender systems are designed to enhance learning experiences and support the development of specific skills and knowledge. This means that educational recommendations should prioritize learner's interests and goals, focusing on educational values rather than being solely motivated by commercial metrics. Second, educational recommender systems need to consider educational factors such as learning objectives, pedagogical needs, and learner engagement in the learning process (Cheng et al., 2016; Essalmi et al., 2015). In contrast, commercial systems typically base recommendations on purchase history, browsing behaviors, demographics, and product popularity, which are factors that do not necessarily align with effective and meaningful learning experiences.

Given these distinctions, the following sections will examine learner-specific variables such as learning goals and contexts highlighted in prior studies on educational recommender systems and foreign language learning. We will also explore how learners were classified in previous educational recommender systems to better understand their specific needs and learning trajectories.

Learner Variables for Educational Recommender Systems

In general recommender systems, factors influencing recommendations are diverse, ranging from users' demographic data to system factors such as accessibility, device types and graphical interface (da Silva et al., 2023; Garcia-Martinez & Hamou-Lhadj, 2013). Essalmi et al. (2015) suggest that recommendation methods for personalized learning need to focus on the combination of learners' characteristics coupled with learning goals. Regarding the combination of variables, many recommendation algorithms require variable selections from numerous parameters. As not all variables are equally important, these algorithms consider relative variable importance in terms of their ranking and model estimation (Genuer et al., 2010).

da Silva et al. (2023) analyzed articles published in scientific journals from 2015 to 2020 to investigate the approaches used in developing educational recommender systems. As shown in Table 1, the study found that educational recommender systems are generally based on various factors such as learners' past ratings, learning styles, motivation, objectives, learner behaviors, and learning experiences as well as other factors like item attributes, academic and social relations, or available time.

The most frequently included factor in educational recommender systems was the learning experience, which encompasses academic information or learning level/score. Yanes et al. (2020) collected students' academic learning information such as the number of students in the course or course credit hours to assist academic staff in improving the quality of teaching. Similarly, Fernádez-García et al. (2020) examined subjects taken by learners to collect academic information.

Other factors frequently included in educational recommendations are learning styles and learners' past ratings about the recommended items. For instance, Tarus et al. (2017) used Felder and Silverman's (1988) theory on learning styles to provide online learning materials along with learning level and item attributes. While mentioned less frequently, learning motivation, learning objectives, and learner behaviors were also addressed as important factors for recommendations. Wan and Niu (2020), for example, collected data on learning objectives through the questionnaire along with learning styles, tags, and learning experiences (academic information and social relations) to develop educational recommender systems in an e-learning environment.

Table 1
Learner Variables Used in Educational Recommender Systems

	Past Rating	Learning Styles	Motivation /Objective	Learner Behaviors	Learning Experience	Item –related /Others
Wu et al. (2015)	O		O	O	O	
Zapata et al. (2015)	O					
Sergis & Sampson (2016)	O				O	
Wan & Niu (2016)		O				O
Tarus et al. (2017)	O	O			O	O
Klašnja- Miliéević et al. (2018)				O		O
Rahman & Abdullah (2018)				O	O	O
Wan & Niu (2018)		O	O	O		O
Huang et al. (2019)					O	
Ismail et al. (2019)						O
Nafea et al. (2019)	O	O				O
Fernandez- Garcia et al. (2020)					O	
Nabizadeh et al. (2020)					O	O
Wan & Niu (2020)		O	O		O	O
Wu et al. (2020)						O
Yanes et al. (2020)					O	

Note: The table was adapted from "Summary of ERS (Educational Recommender System) techniques and input parameters used in the selected papers," by da Silva et al., (2023, p. 3304-3306).

While prior research has acknowledged the importance of considering learner characteristics such as prior learning experiences, learning styles, motivations, and objectives in educational recommender systems, there is limited research on why these characteristics are crucial in specific contexts where the recommender system is applied. Furthermore, previous studies have rarely identified which learner variables hold more significance than others under specific learning contexts.

Learner Variables in Foreign Language Learning

Given that this study aims to recommend applications for foreign language learning, we investigated key factors in this domain. Previous research has identified several learner variables that significantly influence the process and outcomes of language acquisition. These variables can be mainly grouped into cognitive, affective, and social domains, each uniquely contributing to the learner's experience and success in acquiring a new language.

First, cognitive variables mean a variety of learning preferences and progress at different rates due to inherent biological and psychological differences, which encompass learning styles, language aptitudes, and language learning strategies (Lightbown & Spada, 2021; Qiao, 2024). Also, learners have distinctive learning styles, so researchers have developed various tools to evaluate and measure these diverse learner preferences. Aligning students' learning preferences and styles with suitable teaching methods can greatly enhance their motivation, performance, and achievements. Second, affective variables are related to motivation or personality traits. The motivation for learning a foreign language is a complex phenomenon influenced by two major factors: integrative and instrumental motivations (Lightbown & Spada, 2021). The former is specifically the desire to become part of the target language speech community while the latter is the practical and utilitarian reasons related to second language learning. Personality traits such as grit are also associated with language learning. Lastly, social variables are external factors such as the geological location of learners, race, or cultural context. These factors are related to the learners' interaction with their class group or social position (Dörnyei & Kormos, 2000). Learners' interactions with others impact their progress, as social support and exposure provide opportunities for practical application and reinforcement of language skills.

Given the importance of learner variables in foreign language learning and the existing gaps in the literature, this study focuses on the relative importance of factors to determine the optimal composition of data and variables that should be considered in educational recommender algorithms to better address foreign language learners' needs. Specifically, our proposed model centers on learner-related variables such as learning styles (how learners learn), language learning motivation (why learners learn), along with demographic information (e.g., age, gender, occupation, educational level) and learning experience (e.g., frequency of language learning, experience with language learning apps).

Research Methods

The research process described in Figure 1 includes two main parts: 1) developing learner profiles for the recommender system and 2) evaluating learner perceptions about the proposed recommender system. The entire research process was conducted after the approval by the IRB committee of the researchers' institution.

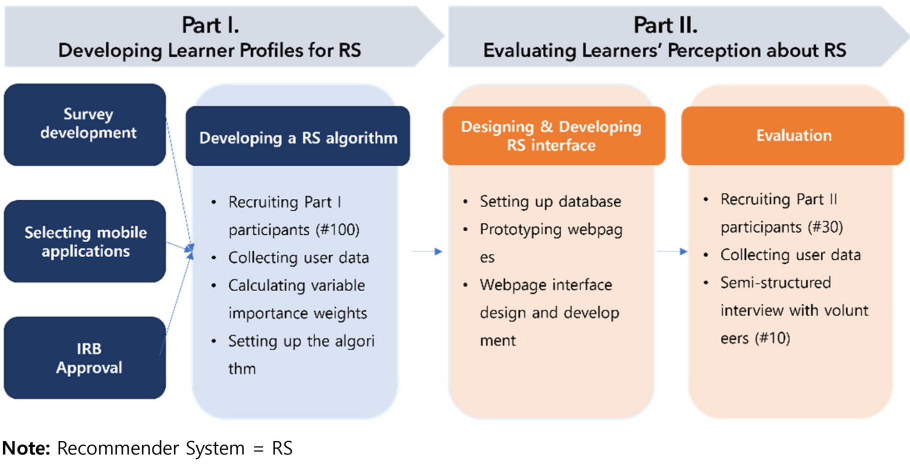

Figure 1. Research Process

Part I. Developing Learner Profiles for the Recommender System

Survey Instrument

Based on the factors frequently addressed in the prior research (e.g., da Silva et al, 2023), we used an instrument with 70 items to collect learner variables in four categories: 1) learners' demographic information, 2) language learning experience and habit, 3) learning styles, and 4) motivational orientation for language learning. Table 2 shows the variables in each category and their codes used in the recommendation algorithm.

Table 2
Learner Variables for Recommendation Algorithms

Category	No. of items	Code ID	Description
Demographic Information	4	AgeR	*Age group* (1: 19-24, 2:25-29, 3:30-34, 4: 35-39)
		Gen	*Gender*: Whether the learner is male (0) or female (1)
		Schooling	*Education*: The learner's highest education completed (1: high school level or under, 2: college/university level, 3: graduate school or above)
		Job	*N-yn*: Whether the learner has a job (1) or not (0)
			S-yn: Whether the learner is a student (1) or not (0)
Learning styles	44	LS1	*Information Processing*: active (1) or reflective (-1)
		LS2	*Information Perception*: intuitive (1) or sensory (-1)
		LS3	*Information Reception*: visual (1) or verbal (-1)
		LS4	*Information Understanding Progression*: global (1) or sequential (-1)
Language Learning Motivation	20	MIT	*Motivation in total:* The extent to which the learner is motivated to learn a language
		MI1	*Integrative Motivation:* The extent to which the learner is oriented toward integrative motivation (e.g., understanding the target culture)
		MI2	*Instrumental Motivation*: The extent to which the learner is oriented toward instrumental motivation (e.g., reaching practical goals such as getting a job)
Language Learning Experience	2	LE	*Whether the learner has ever used any mobile apps* for language learning (1) or not (0)
		LLPW	*The frequency of language learning per year*

First, for demographic information (4 items), we asked about learners' age range, gender, education level, and job status. Second, to identify learners' learning experiences and habits, we asked whether the learner has ever used any mobile apps for language learning and the frequency of language learning per year (2 items).

Third, to understand learners' learning styles, we used Felder and Solomon's (1996) Index of Learning Style (ILS, 44 items), which is one of the most frequently used instruments with proven validity and reliability in the existing literature. The ILS instrument identifies learning styles with the propensity in four subcategories: information processing (LS1), information perception (LS2), information reception (LS3), and information understanding (LS4). Information processing (LS1) indicates whether the learner prefers to process information actively or reflectively. Information perception (LS2) distinguishes whether the learner prefers a sensing approach or an intuitive approach when perceiving information. Information reception (LS3) differentiates whether the learner prefers visual stimuli or verbal stimuli. Information understanding (LS4) indicates whether the learner prefers a global (integrative) approach or a sequential approach to understanding information. According to Felder and Solomon (1996), individual learners have one strong propensity in each category. So, a learner can fall into one of 16 learning styles, which combines ones from the four categories.

Lastly, for learners' motivational orientation for language learning, we asked 20 items on a 5-point scale regarding the extent to which the learner is oriented toward instrumental motivation (MI1) or integrative motivation (MI2), adapted from Al-Taani's (2018) study. Instrumental motivation indicates the extent to which the learner is motivated to learn a language for practical purposes (e.g., finding a job). On the other hand, integrative motivation reflects the degree to which the learner is motivated for language learning by integrative purposes (e.g., assimilation into the target culture). The average motivation score (MIT) between the two types represents the learner's overall motivation to learn a language.

Participants & Data Collection

To collect data for developing the recommender system of foreign language learning applications, we recruited participants from several online bulletin boards. Table 3 shows the demographic information about the participants. They include 100 adult learners (33 males and 67 females), aged 19 to 39. Among them, 53 were university students, followed by 32 working professionals, and 9 unemployed. In terms of their educational background, the participants included 38 undergraduate students, 41 university graduates, and 21 with master's or higher degrees.

Table 3
Part I Participants Information (N=100)

Age	• 19-29 years old: n=73 • 30-39 years old: n=27
Gender	• Female: n= 67 • Male: n= 33
Education Level	• Undergraduate: n= 38 • University: n= 41 • Master's or higher degree: n= 21

To collect application usage and evaluation data, four to six apps from the list (Table 4) were randomly assigned to each participant. Learners used these assigned apps in their places for one week. We selected the list of AI-integrated applications based on the following criteria: (a) apps for foreign language learning, (b) apps clearly integrated with AI technology (e.g., speech recognition, adaptive learning, learner data analysis, and recommendation features), (c) availability to download in Google Play Store or iOS App Store in South Korea, (d) average user rating of 3.0 or higher (out of 5.0), and (e) free for easy access for learners. Through this process, we collected 557 app evaluation data (1= "not satisfied at all" to 5= "very satisfied") with 100 learner profiles.

Table 4
List of AI-integrated applications in Language Learning

ID	App	ID	App Name	ID	App Name
app 1	Riid Tutor	app 7	Say Voca	app 13	Bigple
app 2	Super Chinese	app 8	Youbot Chinese	app 14	Memrise
app 3	Plang	app 9	Duolingo	app 15	Mondly
app 4	Opic up	app 10	Cake	app 16	AI Tutor
app 5	Lingo Champ	app 11	Youbot English Speaking	app 17	Rosetta Stone
app 6	Easy Voca	app 12	ELSA Speak	app 18	Busuu

Data Analysis

Variable importance weight means the extent to which the features contribute to the predictive power, which can be used in the process of selecting specific variables (Williamson et al., 2023). Quantifying the variable importance is essential to rank the variables prior to a stepwise estimation in regression, to interpret data, and to figure out the underlying phenomenon in numerous applied problems (Genuer et al., 2010).

While there are several options to measure the variable importance, this study employed RandomForestRegressor. Compared to decision tree and traditional linear regression methods, regression with Random Forest algorithm has several advantages such as improving the accuracy of classification and regression, resolving the overfitting problem by unexpected variables, and facilitating the measurement of the relative importance of variables (Géron, 2019; Grömping, 2009). Additionally, in this study, the similarity between learners was estimated by reflecting the learner variable importance weights. The interpolation in the learners' rating scores that learners did not rate was made with Inverse Distance Weighting (IDW) — giving greater weight to the value of the former learner with the closest similarity.

Recommendation Method

Regarding the filtering method for recommending applications, this study employed knowledge-based (ontology) filtering with an emphasis on learner-related variables, as illustrated in Figure 2. Knowledge-based filtering leverages domain knowledge about the user or product to make recommendations. This technique typically involves explicitly soliciting the user's requirements for the desired product. Since users may struggle to clearly articulate their preferences, expert knowledge helps them explore and assess the usability or substitutability of various features within the product domain.

Our recommender system begins with a predefined set of learner variables and their relative importance weights. The algorithm of the recommender system takes into account the relative importance weights of learner variables to enhance system performance and reduce processing load. Adjusting these importance weights has been shown to improve the accuracy of predictions in recommender systems (Bobadilla et al., 2012) and to minimize processing load by reducing the number of variables the system needs to analyze (Scholz et al., 2017). Following that, the algorithm also incorporated ratings from similar users who have already used the apps to suggest those most suitable for a specific user.

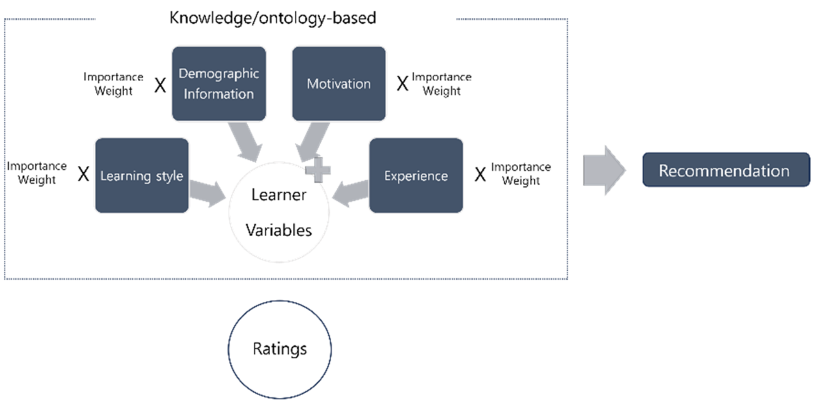

Figure 2. Recommendation Approach

Part II. Evaluating Learners' Perception of the Recommender System

Interface Design & Development

The recommender system interface has two main components: 1) the data server and 2) the user interface. The data server was constructed in Airtable (airtable.com) to store learner login information entered during the registration phase and to save recommendation information according to the final algorithm. The user interface was developed to help participants follow the three steps of the online evaluation as shown in Figure 3. The user interface had three main pages: 1) self-questionnaire page to administer the learner characteristics survey, 2) recommendation confirmation page to display the links to recommended apps, and 3) perception report page to collect data on learners' overall evaluation with the recommender system and recommended items.

Table 5
Part II Participant Information (N= 30)

Age	• 19-29 years old: n= 15 • 30-39 years old: n= 15
Gender	• Female: n= 15 • Male: n= 15
Education Level	• Undergraduate: n= 4 • Graduate: n= 19 • Master's or higher degree: n= 7

Participants & Data Collection

To evaluate learners' perception of the developed recommender system, an additional 30 evaluators aged between 19 and 39 were recruited from online bulletin boards (Table 5). The evaluators include 15 males and 15 females, aged 19 to 39. Most of the evaluators were graduate students (n=19), followed by seven with master's or higher degrees and four undergraduate students. The evaluators followed three steps as shown in Figure 3.

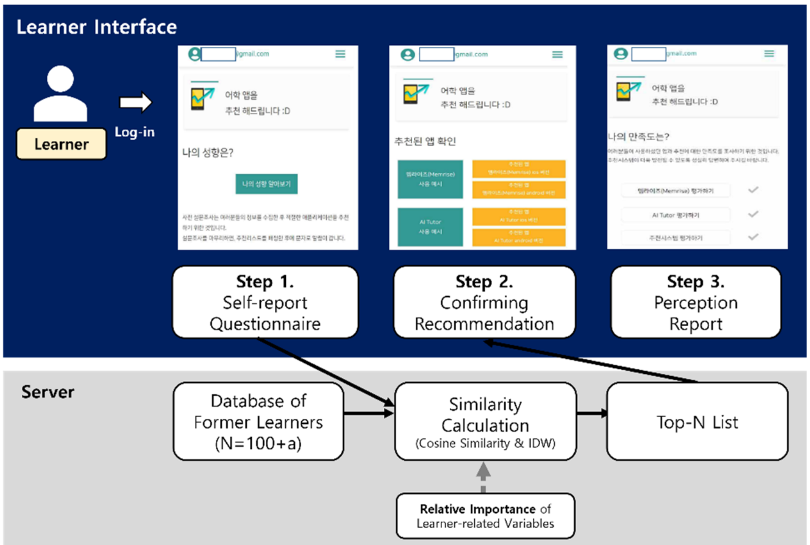

Figure 3. Recommender System Evaluation Process

In Step 1, the *Self-report stage*, learners completed the same survey as in Part I to provide learner profile information for the recommendation. The survey included 70 items for learner variables (demographic information, learning styles, motivation, and learning experience) as presented earlier in Table 2.

In Step 2, *confirming recommendation,* each learner was recommended with two apps based on the algorithm developed in this study. Learners were asked to use recommended apps for a week in their place.

In Step 3, the *perception report*, each participant completed the evaluations of the recommender system and the recommended apps through the online survey. As shown in Table 6, the survey included 12 items about accuracy, novelty, satisfaction, and self-reference on a 5-point Likert scale adapted from Han and Lim's (2017) study. Accuracy included three items, asking whether the recommendation is relevant or helpful to choose the relevant app. Novelty has three items concerning whether the recommended apps meet their curiosity for learning. Satisfaction has three items related to whether the learner feels satisfied with the recommended apps and the recommender system. Self-reference has three items asking whether the personalization in the recommendation meets their individual needs.

Semi-structured interviews were conducted with 10 volunteers via Zoom. These interviews aimed to confirm the survey data and gather additional feedback and suggestions regarding the recommender system proposed in this study. Ten volunteers were selected from the 30 participants, with in-depth questions posed to those who expressed interest in the interview. Each interview lasted approximately 30 minutes to 1 hour. One researcher (first author) conducted all interviews, which were recorded and transcribed for analysis. The questions focused on participants' perception with the recommender system, key factors they considered when evaluating it, reasons for giving low or high scores in the survey, and suggestions for improvement. The questions were semi-structured to explore the reasoning behind participants' narratives.

Table 6

Perception Survey Questions

Constructs	Item
Accuracy (3 items)	• This system provides the recommendations I need. • This system helps in choosing a learning app. • This system provides a learning app that is appropriate for me.
Novelty (3 items)	• The recommendations pique my curiosity. • The recommendation is not familiar to me. • The recommendation provides me with a new app of my interest.
Satisfaction (3 items)	• I am very satisfied with the recommender system. • I am satisfied with the recommender system I used. • My choice to follow the recommendation was wise.
Self-reference (3 items)	• The recommendations are relevant to me. • The recommendation page explains it well to me. • I believe the recommender system provided a learning app considering my interest.

Data Analysis

To understand learners' perception of both the recommended apps and the recommender system, we analyzed descriptive statistics of the perception survey. We calculated the average scores for each construct-accuracy, novelty, satisfaction, and self-reference along with the overall perception score for the recommender system. Two themes emerged from the perception survey analysis were further examined in the interview data: what made the learners satisfied with the system, and why the novelty score shows high variances. The qualitative data from the recorded interviews were transcribed and analyzed thematically to identify common themes and issues focusing on the questions of what factors they considered the most important when evaluating the recommender system, the reason for giving the lowest score or high score in the survey item. In the first step of qualitative data analysis, the keywords in the transcription were highlighted. In the second step, the keywords are categorized into similar topics for each question.

Results

Relative Importance Weight in Learning Variables

The app evaluation data from the first 100 participants were analyzed using Random Forest Regression to address the first research question regarding the relative importance of learner variables in recommending language learning apps. This analysis estimated the relationship between individual learners' evaluation of the apps and the learner variables. Table 7 displays the relative importance weights of each variable, ranked by their significance.

The top five variables with the highest importance weights are: three variables related to language learning motivation (MI2 = 0.1808, MIT = 0.1674, MI1 = 0.1520), usage frequency in the learning experience (LLPW = 0.0826), and perception in learning styles (LS1 = 0.0658). These results confirm that learner variables in the affective domain, such as language learning motivation, as well as learning styles (Information Processing) in the cognitive domain and app usage frequency, hold

Table 7
Relative Importance Weights of Learner Variables

Rank	Code ID	Importance weight	Rank	Code ID	Importance weight
1	MI2	0.1808	8	Schooling	0.0514
2	MIT	0.1674	9	LS2	0.0399
3	MI1	0.1520	10	LS4	0.0337
4	LLPW	0.0826	11	LE	0.0283
5	LS1	0.0658	12	S-yn	0.0263
6	AgeR	0.0657	13	N-yn	0.0247
7	Gen	0.0569	14	LS3	0.0245

Sum of Importance Weights: 1.0

greater importance than general demographic information such as gender and occupation.

Additionally, we assessed the accuracy of the recommender system by evaluating the importance of learner variables using Precision, Recall, and F1-score metrics. These scores range from 0 to 1, with higher values indicating better performance. If the Precision, Recall, and F1-score of the developed system exceed those of its counterpart, it can be concluded that the developed system outperforms the alternative. We compared the performance of our developed system with that of a dummy model, which recommended all 18 apps to every user. As shown in Table 8, our recommender system achieved a Precision of 0.647, Recall of 0.403, and F1-score of 0.494, whereas the dummy model yielded a Precision of 0.564, Recall of 0.388, and F1-score of 0.459. These results demonstrate that our recommendation method,

Table 8
Performance of the New Model Compared with the Dummy Model

	Dummy Model	New Model
Precision	.564	.647
Recall	.388	.403
F1-score	.459	.494

which is based on the relative importance of learner variables, outperformed the dummy model.

Learner Perceptions

To address the second research question concerning learners' perceptions of the recommender system for AI-integrated language learning apps, participants completed an online survey, and 10 selected learners took part in semi-structured interviews.

In the perception survey results (Table 9), the mean scores for accuracy and self-reference were 4.38 and 4.25 respectively, indicating that learners were generally satisfied with the system across all areas. The learners felt that the recommender system effectively met their needs and assisted them in selecting appropriate learning apps. The high score for self-reference suggests that the recommendations were perceived as relevant and engaging, increasing learners' interest. The average satisfaction score was 4.29, reflecting overall high satisfaction with both the recommender system and the recommended apps. A notable observation from the survey was the novelty score, where the mean was 3.86 (SD=0.64). Some learners reported familiarity with certain apps (e.g., Duolingo and Cake), leading them to perceive the recommendations as low novelty.

Table 9
Perception Survey Mean Scores

Factors	n	Mean	SD	Min	Max
Accuracy	30	4.38	0.50	3.33	5.00
Novelty	30	3.86	0.64	2.33	5.00
Satisfaction	30	4.29	0.56	3.33	5.00
Self-reference	30	4.25	0.53	3.67	5.00

Using the interview data, we wanted to confirm two points: first, what made the learners satisfied or unsatisfied with the system, and second, why the novelty score shows high variances. To identify the satisfaction or dissatisfaction factors of the recommender system, we categorized the responses into two main types-satisfaction factors and dissatisfaction (or improvement) factors. The respondents' feedback was thematically categorized into the following areas: self-relevance, design and interface of the apps, ease of use, and continuous management, all of which were consistent with the survey results. The factors identified for system improvement included transparency, partial satisfaction, and the payment model of the apps. First, regarding information transparency, learners expressed a desire for more insight into the recommendation process, specifically which aspects of their characteristics were utilized in the app recommendations. Second, learners reported partial satisfaction with the recommendation results. That is, when multiple apps are suggested, not all recommended apps fully meet the learner's needs, which should be taken into account when assessing recommendation satisfaction. Third, the payment model of the mobile apps whether paid, free, or partially free-was found to be closely associated with learner satisfaction. Although this study initially selected apps that were free or offered some free features, the majority were partially free, limiting learners' access to only a few features, which contributed to dissatisfaction.

Through the interviews, we also discovered that the novelty factor in the survey was influenced by the intensity of each learner's previous experience with specific language learning apps. This was reflected in one interviewee's response: "I have extensive experience using apps, so the apps themselves didn't feel particularly new. However, the method of receiving recommendations through a series of steps was novel." This suggests that learners who have extensively used language learning apps tend to find the recommendations less novel, whereas those with limited experience may perceive them as more innovative and unfamiliar.

Discussions

This research aimed to explore effective methods for recommending language learning apps within educational recommender systems. Based on the results from this study, we discuss several key insights into the effectiveness and user perceptions of language learning app recommendations.

First, our recommender system provides explanations about why educational recommendations should account for the complexity of various learner variables, alongside the relative importance. This study reveals that learner variables, particularly those related to language learning motivation and learning styles, along with app usage frequency, hold significant importance to learners' positive perceptions. In designing educational recommender systems, greater emphasis should be placed on learner variables, such as language learning motivation (affective domain), learning styles (Information Processing in the cognitive domain), and app usage frequency, rather than on general demographic information like gender and occupation.

As an innovative approach to designing recommender systems, this study shows the possibility of enhancing both the accuracy of recommendations and learners' positive perceptions of recommender systems based on various learner variables. The current study confirmed that incorporating the relative importance of each learner variable into the design of recommender systems improves both system accuracy and learners' positive perception of recommended items. Specifically, the effectiveness of this developed recommender system was confirmed in terms of accuracy and self-relevance. This is evidenced in the evaluators' report that the app recommendations provided by the system accurately reflected their needs and goals in language learning, with clear relevance to their characteristics. This alignment is assumed to stimulate learner interest and motivation to use the system, resulting in positive perceptions of the recommendation method.

This promising result closely aligns with and supports the current trend on the transparency and explainability of AI or machine-learning-based recommender systems. As Zhang and Chen (2020) discussed, algorithm accuracy is not the only factor to be considered in the recommender system. Instead, learners' satisfaction with the recommender system can increase when the system caters to learner-related factors such as motivation and styles with more persuasiveness and transparency. Therefore, future recommender systems for learning should aim to enhance algorithmic accuracy and learner satisfaction by incorporating the importance of various learner variables.

Limitations and Areas for Future Research

This study has some limitations to be acknowledged. First, we had a limited set of learner variables. To develop more meaningful educational recommender systems, future research should expand the model to include a broader range of variables. Additionally, this study could not fully consider the dynamic characteristics of learners, focusing on rather static learner characteristics at a specific point in time. Since learner variables encompass both static and dynamic characteristics (Premlatha et al., 2016), future research should aim to incorporate dynamic features, such as changes in learning levels over time with the system, reflecting a variety of learner variables.

Second, considering that educational level is relevant to the use of mobile apps as well as foreign language learning, the skewed composition of study participants might have affected the results concerning learners' perceptions. For more balanced perceptions from learners, the educational level of participants should be equally distributed in future research.

Third, this study is based on a knowledge-based recommender system, which cannot address the cold start problem. Future research should consider employing a hybrid approach to filtering. User profiles in the current study were based on self-reported questionnaires, which may limit the depth of understanding learners. Future studies should consider using proxy indicators or automatic detection methods to capture learning profiles.

Fourth, while this study focused on AI-integrated mobile apps as recommended items, the characteristics of AI in the selected apps were not reflected in the recommendation process due to limited accessibility to the information on the AI functions in the apps. As Garcia-Martinez and Hamou-Lhadj (2013) noted, the factors influencing recommendations include not only learner-related aspects but also resource- and system-related elements. Future studies can develop more compelling recommender systems by incorporating item-related features in the filtering process. Additionally, algorithmic performance, which was compared to a dummy model in this study, could be assessed against more sophisticated models as further research on application recommender systems progresses.

Fifth, the usability testing in our study could have been improved through the experts' heuristic evaluations of system usability and objective usage, such as the time spent on the apps. We suggest that future studies include expert validation of both the system's algorithm and interface usability, along with practical usage data during system development for a more comprehensive analysis.

Conclusions

With the increasing trend of using mobile apps in language learning, this research aimed to identify key factors, along with their relative importance, for recommending language learning apps to better assist learners in selecting relevant educational resources through a novel recommendation approach with non-standard machine learning method. Additionally, we explored learners' perceptions of this recommender system and the recommended apps.

Our findings indicate that, in the development of educational recommender systems, motivation factors and the cognitive learning styles of individual learners should take precedence over simple demographic information. Although many variables beyond learner-related factors exist, prioritizing learners' motivation, learning styles, and experience may enhance their positive perception with AI-integrated language learning apps and recommender systems. We hope these findings offer practical implications for the development of better recommendation methods for learners, thereby fostering more meaningful learning experiences.

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