Mandailing Journal of Education and Sciences (MJOES)
https://jurnal.mandailingpublisher.com/index.php/mjoes
Doi: https://doi.org/10.66698/mjoes.v1i2.9

E-ISSN: 3124-8861
Vol. 1 No. 2, Juli 2026
Halaman. 62-67

AI-DRIVEN VOCABULARY PERSONALIZATION: FILLING THE GAP IN TRANSPARENCY AND LEARNER TRUST IN ADAPTIVE RECOMMENDER SYSTEMS FOR LANGUAGE LEARNING

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Dikirim: 23 April 2026, **Revisi**: 16 Mei 2026, **Diterima**: 7 Juni 2026, **Diterbitkan**: 1 Juli 2026

Abstract

AI-driven vocabulary recommender systems can personalize vocabulary practice by using learner data such as prior performance, error patterns, goals, and review schedules. However, many systems remain opaque because they recommend words without explaining why the items are selected or how learners can adjust the recommendation process. This conceptual article examines transparency as a key design issue in technology-enhanced language learning and synthesizes literature on explainable AI, trust in automation, technology acceptance, and self-regulated learning. The results of the synthesis show that transparent vocabulary personalization is most likely to support learning when it strengthens three mechanisms: perceived control, calibrated trust, and sustained adoption. The analysis also indicates that the most appropriate design is not excessive technical disclosure, but concise explanations, on-demand details, and learner controls that allow users to correct or adjust recommendations. These findings suggest that trustworthy vocabulary recommenders should combine pedagogically meaningful explanations with learner agency so that adaptive systems support, rather than replace, self-regulated learning.
Keywords: *Explainable AI, Adaptive Learning, Vocabulary Learning, Recommender Systems, Learner Trust.*

INTRODUCTION

Vocabulary knowledge is a central foundation for second and foreign language development because it supports reading, listening, speaking, and writing. Vocabulary growth requires repeated exposure, retrieval practice, and review over time, which are difficult to maintain through classroom instruction alone (Nation, 2013; Cepeda et al., 2006). Technology-enhanced language learning (TELL) can help address this challenge by providing flexible and individualized practice opportunities.

AI-driven recommender systems are increasingly used to select target words, schedule reviews, and suggest materials based on learner performance, goals, and interests. In vocabulary learning, such systems may improve efficiency by directing learners to words that are useful, difficult, or likely to be forgotten. Nevertheless, many systems still function as black boxes: learners are told what to study, but not why a recommendation appears or how their data influence it.

This lack of transparency is important because language learning depends not only on efficient scheduling, but also on learner motivation, agency, and sustained engagement. When recommendations seem arbitrary, learners may ignore them, over-rely on them, or abandon the system. Prior research on educational recommender systems has often emphasized accuracy and short-term outcomes, while giving less attention to explanation, trust calibration, and learner control (Drachsler et al., 2015; Santos & Boticario, 2015).

This paper addresses the gap by developing a conceptual account of how explanation transparency can influence perceived control, trust, adoption, and vocabulary outcomes. The contribution of the paper is threefold: it clarifies the role of transparency in AI-driven vocabulary recommendation, proposes a learner-centered framework, and offers design implications for future empirical testing and classroom implementation.

METHOD

This study uses a conceptual literature review and integrative synthesis method. It does not report a completed classroom experiment; instead, it analyzes relevant theoretical and empirical literature to build a framework for future research on transparent vocabulary recommender systems. This approach is appropriate because the main purpose of the paper is to clarify constructs, identify relationships among them, and generate design implications.

The literature was organized around four domains: vocabulary learning and TELL, educational recommender systems, explainable AI and recommender explanations, and learner trust, technology acceptance, and self-regulated learning. Core sources were selected because they explain major concepts relevant to the topic, including spaced practice and vocabulary acquisition (Nation, 2013; Cepeda et al., 2006), educational recommendation (Drachsler et al., 2015; Santos & Boticario, 2015), explanation in recommender systems (Tintarev & Masthoff, 2007; Miller, 2019), trust in automation (Lee & See, 2004; Hoff & Bashir, 2015), technology acceptance (Davis, 1989; Venkatesh et al., 2003), and self-regulated learning (Zimmerman, 2002; Pintrich, 2004).

The analysis was conducted in three stages. First, key problems in vocabulary personalization were identified, especially opacity, limited learner control, and weak evidence about trust. Second, concepts from the selected literature were compared and grouped into explanatory categories: transparency, perceived control, trust, adoption, and vocabulary outcomes. Third, the relationships among these categories were synthesized into a conceptual framework and translated into practical design principles.

To make the framework applicable for future empirical work, the paper also outlines a possible three-condition design: personalization without explanations, personalization with basic explanations, and personalization with interactive explanations and learner controls. This proposed design is presented as a methodological implication of the synthesis rather than as data already collected in the present paper.

LITERATURE REVIEW

Vocabulary Learning and Personalization in TELL

Vocabulary learning requires repeated exposure, retrieval practice, and meaningful engagement with lexical items. Research has consistently shown that spaced repetition and distributed practice support long-term vocabulary retention, particularly for EFL learners with limited opportunities to encounter English outside the classroom (Cepeda et al., 2006; Nation, 2013). In Technology-Enhanced Language Learning (TELL), adaptive systems are increasingly used to personalize vocabulary learning by determining which words should be studied, when learners should review them, and which contextual materials should be presented.

Educational recommender systems are designed to support learners by providing personalized recommendations based on learner needs, preferences, and performance (Drachsler et al., 2015). In vocabulary learning applications, personalization commonly uses learner data such as previous performance, review history, and learning goals to recommend vocabulary items and review schedules. Previous studies have highlighted the benefits of mobile-assisted and adaptive vocabulary learning for improving engagement and learning efficiency (Stockwell, 2010). However, many recommender systems still emphasize predictive accuracy and short-term learning gains rather than transparency and learner trust. As a result, learners may receive recommendations without understanding why particular vocabulary items are selected or how their learning data are being used.

Explainable AI and Learner Trust

Explainable Artificial Intelligence (XAI) aims to make AI-driven decisions understandable to users (Doshi-Velez & Kim, 2017). In recommender systems, explanations are considered important because they can improve transparency, trust, satisfaction, and acceptance (Tintarev & Masthoff, 2007). Explanations may appear in different forms, such as simple textual rationales, example-based explanations, or interactive explanations that allow users to modify preferences and learning goals.

In educational contexts, explanations should not only clarify system recommendations but also support learning processes. Research on trust in automation suggests that users are more likely to rely on automated systems when they understand how the system works and perceive it as reliable (Lee & See, 2004; Hoff & Bashir, 2015). Similarly, studies on algorithmic transparency indicate that explanations can reduce perceived arbitrariness and improve users' confidence in recommendations (Kizilcec, 2016). Nevertheless, excessive or overly technical explanations may increase cognitive load and reduce usability (Miller, 2019). Therefore, explanations in vocabulary recommender systems should remain concise, understandable, and relevant to learners' needs.

Self-Regulated Learning and Learner Agency

Self-regulated learning (SRL) emphasizes learners' active role in planning, monitoring, and evaluating their learning processes (Zimmerman, 2002; Pintrich, 2004). In adaptive learning environments, recommender systems can support SRL by reducing planning burden and helping learners focus on vocabulary items that require further practice. However, excessive automation may weaken learner agency if learners follow recommendations without understanding or reflecting on them.

For vocabulary learning, learner agency is important because learners often prioritize vocabulary based on academic needs, interests, and perceived usefulness. Transparent recommender systems may strengthen learner agency by allowing learners to understand why recommendations are provided and by giving them opportunities to adjust learning preferences or goals. Integrating explainability with SRL perspectives therefore provides an important basis for understanding how transparency may influence learner trust, engagement, and sustained use of adaptive vocabulary learning systems.

This study proposes a conceptual framework that connects explanation transparency, learner trust, perceived control, and vocabulary learning outcomes in AI-driven recommender systems. The framework integrates three perspectives: explainable AI (XAI), trust and technology acceptance, and self-regulated learning (SRL). Explanation transparency refers to the extent to which the system provides understandable and relevant reasons for vocabulary recommendations. Transparent explanations are expected to increase learners' perceived control because learners can better understand how recommendations are generated and how personalization aligns with their learning goals. Increased perceived control may then strengthen trust in the recommender system and encourage continued use and engagement.

This framework is also informed by the Technology Acceptance Model (TAM), which highlights the importance of perceived usefulness and perceived ease of use in influencing technology adoption (Davis, 1989; Venkatesh et al., 2003). In vocabulary learning contexts, trust and perceived usefulness may affect learners' willingness to follow recommendations and complete scheduled reviews. Consistent engagement is particularly important because vocabulary retention depends on repeated practice over time (Cepeda et al., 2006).

At the same time, transparency may not always produce positive effects. Overly detailed explanations may create cognitive overload or reduce usability, especially for learners with limited AI literacy or lower language proficiency (Miller, 2019). Therefore, this study positions transparency not only as a technical feature but also as a pedagogical factor that shapes learner agency, trust, and long-term vocabulary learning outcomes.

RESULTS AND DISCUSSION

Transparency as a central gap in vocabulary personalization

The first result of the synthesis is that transparency is a central but underdeveloped issue in AI-driven vocabulary personalization. Vocabulary recommenders often use relevant signals such as accuracy, response time, errors, review interval, proficiency level, and learner goals. However, when these signals are hidden, learners may not understand why a word is repeated, why a difficult item appears, or why the system prioritizes one topic over another. This opacity can reduce perceived usefulness and weaken learner trust.

In educational contexts, explanation should not merely persuade learners to accept recommendations. It should help them understand the learning purpose behind a recommendation. For example, a useful explanation may state that a word is recommended because the learner missed it recently, because it is due for review, or because it is relevant to the current course unit. This type of explanation connects system behavior with pedagogical logic.

Perceived control as a link between transparency and trust

The second result is that perceived control is the key mechanism connecting transparency with trust. Trust in automation should be calibrated rather than maximized (Lee & See, 2004). Learners need enough information to decide when to follow a recommendation and when to question it. When explanations are paired with controls, learners can adjust difficulty, topic focus, review intensity, or goal settings. These actions make personalization more visible and allow learners to correct recommendations that do not fit their needs.

This finding is consistent with self-regulated learning theory, which views learners as active agents who set goals, monitor progress, and adjust strategies (Zimmerman, 2002; Pintrich, 2004). Opaque personalization may reduce these processes by shifting too much control to the system. In contrast, transparent and adjustable personalization can function as a metacognitive scaffold because learners can reflect on why certain words are selected and how those selections relate to their own learning goals.

Adoption and retention as expected learning pathways

The third result is that transparency is expected to influence vocabulary learning mainly through adoption and adherence. Explanations alone do not automatically improve vocabulary knowledge. Their value lies in helping learners interpret recommendations, accept useful ones, adjust inappropriate ones, and continue reviewing over time. Because vocabulary retention depends strongly on repeated and distributed practice, consistent engagement is likely to be the pathway through which transparent recommendation supports delayed retention.

A future empirical study could test this pathway by comparing three conditions: no explanation, basic explanation, and interactive explanation. The basic condition would provide short reasons for recommendations, while the interactive condition would also allow learners to adjust goals, difficulty, topic focus, or review intensity. Vocabulary pretests, immediate posttests, delayed posttests, trust scales, perceived-control scales, system logs, and learner interviews could be used to examine whether transparency improves adoption and retention.

Explanation design implications

The synthesis suggests that explanations should be brief, pedagogically meaningful, and actionable. A basic explanation might say, "Recommended because you missed this word recently and it is due for review." An example-based explanation might show that the learner confused affect and effect, so similar academic words are included for contrast. A counterfactual explanation might state that if the learner lowers the difficulty setting, the next session will include more everyday words and fewer academic items.

These examples show that the best explanation is not necessarily the most detailed one. Excessive technical information can increase cognitive load, especially for learners who are already focused on difficult language tasks. A practical solution is progressive disclosure: the system provides a short default explanation and allows learners to open more details or controls only when needed.

Pedagogical and ethical implications

For teachers, transparent vocabulary recommender systems can support classroom integration because learners can discuss the reasons behind recommendations rather than treat them as fixed commands. Teachers can encourage learners to compare system recommendations with their own goals and to use explanations as prompts for reflection. This supports learner agency while still benefiting from adaptive guidance.

Ethically, transparency must be balanced with privacy and fairness. Systems should explain data use clearly, avoid stigmatizing learners based on errors, communicate limitations, and provide ways to correct or contest recommendations. Designers should avoid presenting the recommender as perfectly accurate. Instead, the system should communicate uncertainty and invite appropriate learner judgment.

Limitations and future research

This conceptual article has limitations. It synthesizes existing literature and proposes a framework, but it does not provide empirical results from a completed intervention. Future studies should test the framework in real EFL or ESL classrooms, compare explanation types, examine how AI literacy affects learners' use of explanations, and investigate long-term trust calibration. Future work should also explore open learner models, privacy-preserving personalization, and fairness-aware vocabulary recommendation.

CONCLUSION

AI-driven vocabulary personalization can support efficient practice and durable retention, but prediction accuracy alone is not sufficient. Learners need to understand why recommendations appear, how their data are used, and how they can adjust the system when recommendations do not fit their goals. This paper shows that transparency can support vocabulary learning through perceived control, calibrated trust, and sustained adoption. Trustworthy vocabulary recommenders should therefore combine concise pedagogical explanations with learner control so that adaptive technology strengthens self-regulated learning rather than replacing it.

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