

One-Topic-Doesn't-Fit-All: Transcreating Reading Comprehension Test for Personalized Learning

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Abstract

Personalized learning has gained attention in English as a Foreign Language (EFL) education, where engagement and motivation play crucial roles in reading comprehension. We propose a novel approach to generating personalized English reading comprehension tests tailored to students' interests. We develop a structured content *transcreation* pipeline using OpenAI's gpt-4o, where we start with the RACE-C dataset, and generate new passages and multiple-choice reading comprehension questions that are linguistically similar to the original passages but semantically aligned with individual learners' interests. Our methodology integrates topic extraction, question classification based on Bloom's taxonomy, linguistic feature analysis, and content transcreation to enhance student engagement. We conduct a controlled experiment with EFL learners in South Korea to examine the impact of interest-aligned reading materials on comprehension and motivation. Our results show students learning with personalized reading passages demonstrate improved comprehension and motivation retention compared to those learning with non-personalized materials.

1 Introduction

Personalized learning has the potential to improve educational outcomes by offering learning content that meets the unique needs of individual learners (Bloom, 1984; Zhang et al., 2020). Personalized learning is defined by four key aspects: (1) cognitive—encompassing skills, knowledge, and self-regulation; (2) affective—relating to emotions, attitudes, and regulation; (3) socio-cultural—shaped by context, identity, and social agency; and (4) motivational—driven by interest, goal orientation, and autonomy. Our study focuses on motivational factors, particularly topic interest, which

has been shown to positively influence students' engagement, motivation, and knowledge acquisition across various educational contexts (Kahu et al., 2017; Alzubi and Nazim, 2024; Lee and Pulido, 2017). Personalized learning based on interest has been applied in structured subjects such as mathematics (Yadav et al., 2023; Høgheim and Reber, 2015), where concepts are largely universal and require minimal localization. Instead, English reading education presents greater adaptability through diverse reading materials that can be tailored to students' needs. However, in EFL education, textbooks often present imbalanced content with Western-centric perspectives (Kang-Young, 2009; Lee, 2009; Alawlaqi and Basya, 2023). This imbalance can lead to a decline in reading comprehension (Toti and Hamid, 2022) or result in materials that are misaligned with the interests of non-Western EFL students. Despite the importance of personalized reading materials, most AI-driven educational content research has focused on question generation and assessment (Lu et al., 2023; Lamsiyah et al., 2024), leaving a critical gap in the development of reading materials tailored to individual learners' interests.

Advancements in large language models (LLMs) offer a promising solution for creating personalized learning materials that were once deemed impractical due to cost and logistical constraints. Specifically, a growing concept in NLP-based content adaptation is transcreation, which involves adapting content across cultural and contextual settings while preserving its intended meaning. Prior studies have primarily focused on cultural transcreation (Conia et al., 2024; Khanuja et al., 2024), with limited attention to its broader educational applications. While Khanuja et al. (Khanuja et al., 2024) introduced transcreation in math word problems, their modifications were surface-level, such as unit conversions, rather than substantive content adaptation. By expanding transcreation to personalized

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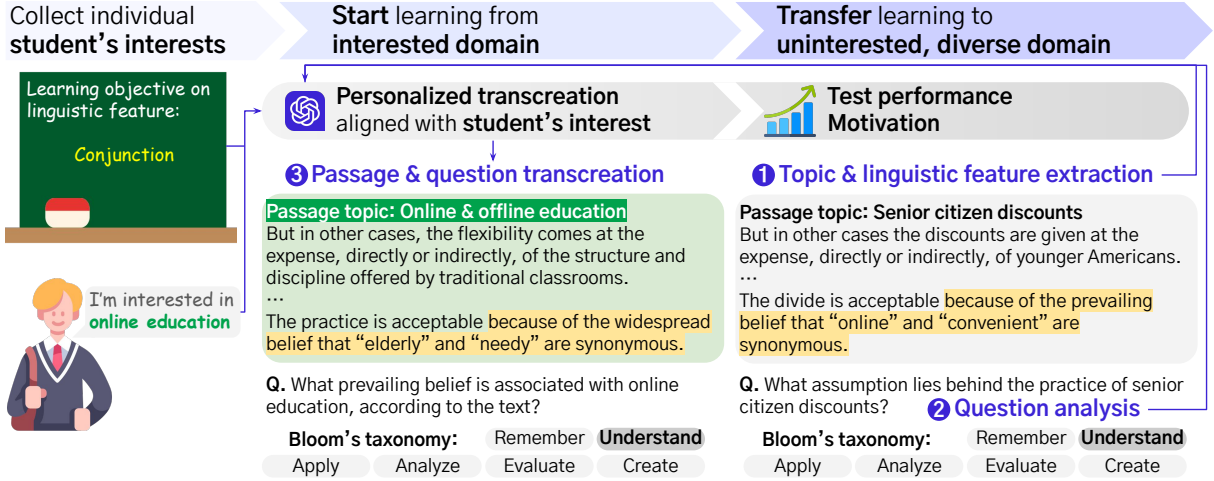


Figure 1: Transcreated reading passage and question. A source data with the uninterested topic (right) is transcreated into the student's interested topic (left).

learning, our study adapts reading materials to align with individual interests. We suggest that LLM-driven transcreation enhances comprehension and motivation retention in English reading education.

2 Method

We suggest a personalized transcreation pipeline (§2.1) and examine the impact of tailored content on EFL learners (§2.2).

2.1 Personalized Transcreation

We propose a systematic pipeline for generating personalized learning materials through LLM-driven transcreation. Using the RACE-C dataset as a source, our approach adapts reading passages and multiple-choice questions to align with individual student interests. The process is structured into five steps, each leveraging gpt-4o from OpenAI¹ with an English teacher system prompt to ensure pedagogical quality.

Step 1. Topic Extraction We first analyze the topic of the reading passage in RACE-C. We incorporate nine categories and 33 subcategories from the educational curriculum by the Ministry of Education in South Korea (Ministry of Education, South Korea, 2022).

Step 2. Question Analysis Building on the prior research (Hwang et al., 2024; Scaria et al., 2024), we classify the question types from the original reading passage using six categories of Bloom's taxonomy (Bloom, 1956): *Remember*, *Understand*, *Apply*, *Analyze*, *Evaluate*, and *Create*.

Step 3. Linguistic Feature Extraction In this step, we aim to identify and extract key linguistic features from the original reading passage. We hypothesize that the sentences supporting the questions are essential for comprehending the text. Therefore, we employ 41 special tags to highlight these key linguistic features, as defined by the Ministry of Education in South Korea (Ministry of Education, South Korea, 2022). We incorporate special tokens to be placed after sentences that support answering the questions for LLM to recognize important linguistic elements in Step 4.

Step 4. Reading Passage Transcreation We transcreate the original reading passage into a new version, adapting the topic to better align with student interests. When transcreating the passage in the extracted topic (Step 1) into the student's interested topic, we ensure consistency in the key linguistic features of the original passage (Step 3).

Step 5. Question Transcreation We transcreate questions, options, and answers using the question type information of the original question set from Step 2. Since the main content of the reading passage changed, the corresponding questions and answer choices must also be adapted accordingly. By maintaining alignment with the original question types, we ensure that the revised questions reflect the same cognitive demands and assessment items.

Validation After transcreation, we have an English expert validate the reading passage and question sets. This expert holds Secondary School Teacher's Certificates (Grade II) for English, licensed by the Ministry of Education, Republic of Korea. The expert ensures that each question is answerable based on the given passage. Among the

¹All following experiments using gpt-4o in this paper were conducted from Feb 1, 2025 to Feb 18, 2025 under OpenAI API services.

transcreated questions, 2.8% were deemed unanswerable, all stemming from a single question that required understanding the temporal relationship between two events. This issue arises because current LLMs struggle with temporal reasoning, which relies on multiple cognitive skills (Xiong et al., 2024). To address this, the expert modified the reading passages when necessary to make the questions answerable. On average, 1.7 words were added per modified passage, all of which were time-related, including years and temporal conjunctions.

	Test 1		Test 2
	Group A	Group B	
# words	387 $\pm$ 94.68	372.45 $\pm$ 66.55	394 $\pm$ 78.35
TTR	0.59 $\pm$ 0.05	0.59 $\pm$ 0.04	0.52 $\pm$ 0.45
FRES	31.24 $\pm$ 16.86	34.02 $\pm$ 11.39	52.20 $\pm$ 11.36

Table 1: Analysis on reading passages of each test

We employ an automated approach to further evaluate the quality and difficulty of transcreated reading passages and questions. Specifically, we use the LLM-as-a-Judge method (Zheng et al., 2024) to assess whether the transcreated questions align with the same cognitive level in Bloom’s taxonomy. The evaluation results indicate an average accuracy of 0.72 and a Cohen’s Kappa score of 0.29, suggesting a fair level of agreement. Table 1 shows linguistic features and difficulty level of the reading passages, measured by the word counts, type-token ratio (TTR), and Flesch Reading Ease Score (FRES) (Flesch, 1979).

2.2 Student Experiment

We recruit EFL learners from a college in South Korea, selecting participants with scores from internationally standardized English proficiency tests such as TOEFL. The student cohort comprises 20 Korean students with a gender distribution of 10 females and 10 males. To ensure a balanced level of English proficiency across groups, we divide the students into two groups of 10 while maintaining a similar distribution of TOEFL scores. The average TOEFL score for Group A is 92.15 $\pm$ 14.95, and for Group B is 93.13 $\pm$ 12.09.

Students first take the transcreated test (Test 1) and then take the original test sourced from RACE-C (Test 2). We assess their comprehension and motivation retention with uninteresting topics in Test 2 compared to Test 1. This design is based

on the idea that exposure to diverse topics is essential for EFL students (Little and Aglinskas, 2022), as focusing solely on personally interesting topics may hinder overall knowledge expansion. Each test comprises four passages with five questions each, totaling 100 points. Before the test, we collect students’ individual interests in 33 topics using a 7-point Likert scale. Additionally, students provide open-ended responses identifying their top four most interesting topics, while their least interesting topics are selected through a multiple-choice format from the 33 given topics. Group A receives transcreated reading materials with randomly selected topics, while Group B is given transcreated reading materials aligned with their stated interests. Specifically, a single original text from the RACE-C dataset is transcreated into randomly selected topics for Group A and into each student’s preferred topic for Group B. For the source test, we select four less preferred passages from the RACE-C, guided by a preliminary survey: 2.b (family events, holidays, household chores, and daily family life), 5.a (cultural differences among generations and genders), 4.c (social events—meetings, community events, graduations, weddings, and funerals), and 6.b (democratic and global citizenship—human rights, gender equality, global etiquette, and peace)

After completing each test, students are given time to review and reflect on the given task. This review session allows them to analyze their mistakes and reinforce their understanding of the content. Additionally, the student submits open-ended answers on their learning experience. Regarding the written reflection, the study employed a thematic approach to examine patterns of engagement, comprehension, and motivation across two test phases. This allowed for a comparative assessment of how personalized versus non-personalized reading materials influenced learners’ experiences. Students complete the Instructional Materials Motivation Survey (IMMS) (Keller, 2010) on a 7-point Likert scale after Test 1 and Test 2.

3 Experimental Result

We present quantitative results on comprehension and motivation and qualitatively analyze students’ open-ended responses to their test impressions.

Quantitative Result All the following significance tests are conducted with a p value of 0.01. Figure 2 shows group test scores for 20 questions, totaling 100 points. The Wilcoxon Signed-Rank

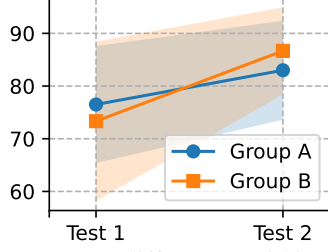


Figure 2: Test score differences within Group A/B

test demonstrates that Group B, which received personalized reading materials, achieves a significant improvement in performance ($73.33_{\pm 15.12} \rightarrow 86.67_{\pm 8.28}$). In contrast, Group A, given randomly assigned reading materials, does not exhibit a significant difference ($76.50_{\pm 11.11} \rightarrow 83.00_{\pm 9.39}$). In particular, Group B reports significant improvements in the *Analyze* questions ($+1.33_{\pm 0.71}$) compared to Group A ($+0.00_{\pm 0.45}$), out of five points on average. This suggests that Group B excels in high-level analytical questions, as such questions above the *Analyze* level are rare in the source dataset (5%). Furthermore, Group B significantly reduces their test turnaround time after reading personalized materials ($30.78_{\pm 7.60} \rightarrow 27.78_{\pm 5.30}$ minutes), compared to Group A ($24.50_{\pm 11.04} \rightarrow 32.00_{\pm 17.77}$ minutes).

It also correlates with IMMS, which captures students’ motivational perceptions. Across all groups, Test 2, containing less engaging topics, is perceived as less motivating. However, the Mann-Whitney U test confirms that Group B shows better motivation retention ($4.68_{\pm 0.66} \rightarrow 4.61_{\pm 1.04}$) than Group A ($4.82_{\pm 0.38} \rightarrow 4.44_{\pm 0.85}$) on a 7 Likert scale. Specifically, Group B reports increased confidence as they encounter similarly structured articles ($4.30_{\pm 0.66} \rightarrow 4.57_{\pm 1.19}$), while Group A becomes less confident as topics change ($5.01_{\pm 0.82} \rightarrow 4.30_{\pm 0.66}$). These results further reinforce the efficacy of personalized reading materials in enhancing engagement in EFL education.

Qualitative Result In the written responses, Group B participants demonstrate sustained engagement and consistent performance, even as external motivational factors diminish. In contrast, Group A exhibits a deepening disengagement over time, highlighting the cumulative impact of non-personalized content on learner motivation. Participants in Group A, who receive non-personalized materials, consistently report low engagement. In the initial phase, A1 and A2 mention that they often solve problems without thoroughly reading the passages. This lack of deep engagement may con-

tribute to reduced concentration, as indicated by A3, who experiences a significant decline in focus as the test progresses. Over time, this disengagement becomes more pronounced. After Test 2, A2 and A4 explicitly describe the reading tasks as unengaging, attributing their disinterest to the repetitive structure of the passages. This suggests that a lack of personalized content not only results in immediate disengagement but may also lead to a cumulative decline in motivation across tasks.

In contrast, participants in Group B, who initially receive interest-aligned reading materials, exhibit higher engagement. Early responses indicate that four participants (B1, B2, B3, B4) found the readings well-matched to their interests, leading to greater satisfaction (B2) and enhanced comprehension (B4). This alignment appears to foster an initial sense of motivation and involvement. However, engagement in Group B was not entirely stable. While interest-aligned content generally enhances motivation, some participants (B4, B5) experience a mismatch between their expectations and the actual content. For example, B5’s initial interest in tennis leads to a passage about younger generations’ enthusiasm for the sport, but they later realize that their true interest lies in improving tennis skills rather than broader discussions about the topic. This suggests that interest-based content is most effective when it precisely reflects the learner’s expectations, rather than broadly aligning with a general topic of interest. Despite the removal of interest-aligned content in the later phase, participants in Group B (B3, B6, B7) remain engaged.

4 Conclusion

Our study demonstrates that LLM-driven personalized transcreation significantly enhances comprehension in English reading education by aligning reading materials with individual student interests. The initial motivation from personalized content can carry over, helping learners sustain engagement even when motivation-related factors (interest-aligned content) are removed. Future research should explore a fine-grained interest alignment to mitigate misalignment and evaluate longitudinal outcomes for the sustained impact. We also suggest expanding LLM-driven personalized learning to incorporate cultural and cognitive factors.

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