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Affective Trajectories and Learning Outcomes in Russian Language Learning among Chinese-English Bilingual Learners Using Personalized AI Learning Software

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Abstract. Generative artificial intelligence (GenAI) is entering the field of language learning. However, longitudinal evidence remains limited for Chinese-English bilingual learners studying a third language such as Russian. This study examines affective trajectories and learning outcomes in foreign language learning supported by personalized AI software. A four-week longitudinal pilot study followed 30 Chinese-English bilingual learners as they used a personalized AI application to learn Russian. Weekly questionnaires measured enjoyment, anxiety, motivation, perceived personalization, and perceived progress, and a Russian test was administered at the end of the study. The results showed that, during AI-supported learning, learners' anxiety declined, enjoyment and perceived progress increased, perceived personalization rose slightly, and motivation remained stable. Multilevel models showed that perceived personalization was associated with a faster decline in anxiety (interaction term = -0.178, $p < .001$), and this result remained robust after baseline anxiety was controlled. These findings suggest that visible personalization in AI-supported early L3 learning may function less as a direct route to short-term achievement and more as an affective support mechanism, especially for anxiety reduction. The study provides practical evidence for third-language teaching and for the design of AI-based educational tools that attend to learners' emotional experience.

Keywords: perceived personalization, third-language acquisition, Russian as a foreign language, longitudinal study, generative artificial intelligence

1. Introduction

With rapid advances in science and technology, GenAI is now widely used in language learning. Tools such as Gemini, Duolingo, and Busuu offer conversational feedback, pronunciation practice, adaptive exercises, and self-directed learning. Research on AI-supported language learning has grown [1], but it still focuses mainly on English and other second languages [2-7]. Personalization is often treated as a technical or multimedia feature rather than learner-centered adaptation [8, 9]. This distinction matters because learners need to perceive that tasks, feedback, and progress cues respond to their current level. Studies of AI and language-learning emotions also concentrate on English and single-wave designs [5, 6, 10], while longitudinal evidence on enjoyment and anxiety remains

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limited [3, 11]. Yan et al. showed that positive emotion, anxiety, and learner beliefs interact dynamically in AI-supported learning [3]. Evidence on how affect and outcomes unfold when learners use AI for a third language (L3) is still scarce [3, 12]. For English majors in China, Russian is often learned from zero as an L3, making it a useful context for examining this issue.

This study examines three issues: changes in enjoyment, anxiety, motivation, perceived personalization, and perceived progress over four weeks of personalized AI-supported Russian learning, the association between perceived personalization and affective change, and the association between affective trajectories and final achievement. H1 predicted a faster increase in enjoyment, H2 predicted a faster decline in anxiety.

2. Research design and methods

2.1. Research model and participants

This study constructed an exploratory longitudinal model of affective change in AI-supported L3 learning. Time was modeled as a within-person predictor. Enjoyment, anxiety, motivation, perceived personalization, and perceived progress were measured repeatedly, while perceived personalization was also examined as a relatively stable person-level predictor. The final Russian achievement was treated as the endpoint outcome. Thirty undergraduate English majors from one university were recruited by convenience sampling. Eligible students were Chinese first-language speakers, sophomores or above, they had passed the Test for English Majors Band 4 (TEM-4), had no systematic Russian study, and did not recognize the Cyrillic alphabet. TEM-4 scores were 60-69 (n = 5), 70-79 (n = 11), 80-89 (n = 11), and 90 or above (n = 3). Russian beginner status was confirmed by self-report and screening.

All participants used the English-interface Russian course in Busuu for four weeks [13]. In Week 1, background information, screening results, and baseline measures were collected. In Weeks 2 to 4, weekly measures of affect, perceived personalization, and usage behavior were administered. In Week 5, repeated measures were collected again, together with a follow-up measure of technology acceptance. After Week 5, participants completed a final Russian test.

2.2. Instruments and measures

Enjoyment, anxiety, and motivation were measured using adapted versions of a foreign language enjoyment scale, the short form of the Foreign Language Classroom Anxiety Scale, and a simplified L2 motivational self-system scale, respectively. Technology acceptance was measured with items based on the Technology Acceptance Model, covering perceived usefulness, perceived ease of use, and intention to continue using the tool [14].

Perceived personalization was adapted from Komiak and Benbasat's perceived personalization scale [8]. The measure covered four dimensions: understanding learner needs, matching content to the learner, targeted feedback, and dynamic adjustment. Perceived progress was measured using Likert-type seven-point items. Weekly usage duration, functions used, and help-seeking frequency were also recorded. Language aptitude was measured with a 20-item Cyrillic letter-learning task, scores ranged from 14 to 20 (M = 18.00, SD = 1.51).

Reliability analyses were conducted in SPSS 27.0. Cronbach's alpha and McDonald's omega were calculated by wave. Reliability values were as follows: enjoyment, .62-.83, anxiety, .75-.89, perceived personalization, .79-.85, and perceived progress, .68-.76. Technology acceptance was measured only in Week 1 and Week 5, with alpha values of .675 and .795, respectively. Motivation

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showed lower reliability (alpha = .51-.68), and was therefore interpreted mainly as a descriptive background variable.

2.3. Data analysis

Given that each of the 30 learners contributed five nested observations, multilevel models with random intercepts were employed. Random slopes were additionally retained whenever supported by likelihood-ratio test results. Time was coded from W0 to W4, and perceived personalization was grand-mean centered when used as a person-level predictor. Models estimated time effects and perceived personalization by time interactions. Individual affective slopes and the Cyrillic letter-learning aptitude score were then used to predict final achievement. Given the small Level-2 sample, results are exploratory. Baseline anxiety was controlled in one model, and perceived personalization was decomposed into between-person and within-person components.

3. Results

3.1. Descriptive trajectories

Across five waves, anxiety decreased from 3.84 to 2.83, enjoyment increased from 4.53 to 5.40, perceived progress from 4.43 to 5.51, and perceived personalization from 4.70 to 5.22. Motivation changed little (4.91 to 5.12). Paired comparisons showed significant changes in anxiety (Delta = -1.01, t = -4.80, p < .001, d = -0.88), enjoyment (Delta = +0.87, t = 4.76, p < .001, d = 0.87), perceived personalization (Delta = +0.51, t = 3.49, p = .002, d = 0.64), and perceived progress (Delta = +1.08, t = 5.32, p < .001, d = 0.97). Motivation did not change significantly (Delta = +0.21, t = 1.55, p = .132, d = 0.28). Figure 1 summarizes these trajectories.

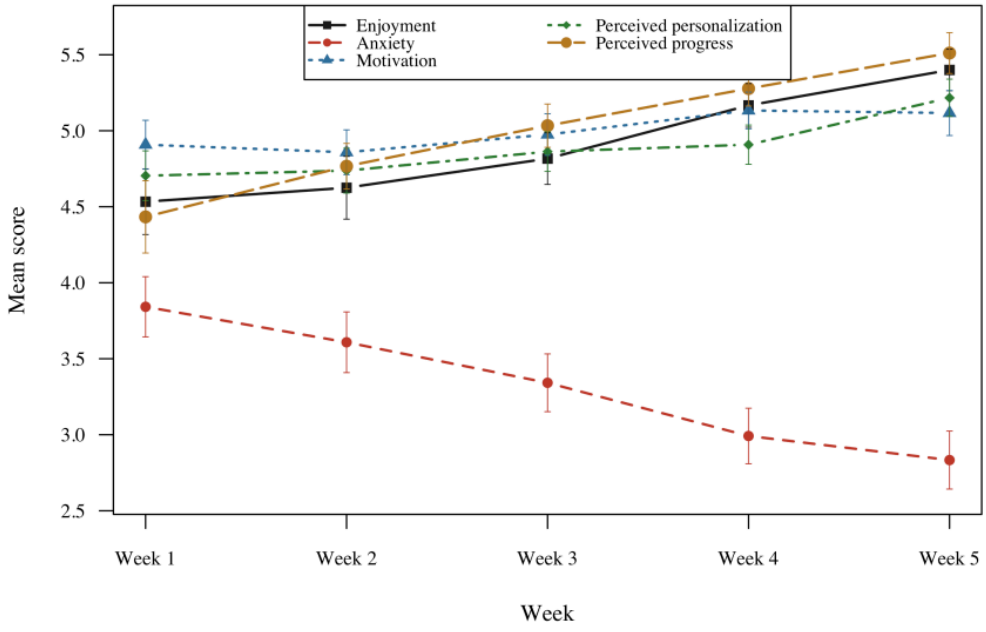

Figure 1. Five-wave means with standard errors for affect and perceived progress

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3.2. Time effects in the multilevel models

Fixed time effects were significant for anxiety (-0.26 per wave), enjoyment (+0.23), perceived progress (+0.27), and perceived personalization (+0.12), all $p < .001$. Motivation increased by +0.07 ($p = .004$) but is reported descriptively. Intraclass correlations were .59 for anxiety, .64 for enjoyment, .71 for motivation, .70 for personalization, and .48 for progress. Random slopes improved fit for enjoyment, motivation, and progress, but not anxiety. All these results are summarized in Table 1.

Table 1. Fixed time effects, intraclass correlations, and random slopes from the multilevel models (N = 30, 150 person-wave observations)

Variable	Fixed slope beta (per week)	p	ICC	Random slope (LRT)
Enjoyment	+0.23	< .001	.64	Yes (p < .001)
Anxiety	-0.26	< .001	.59	No (p = .244)
Motivation	+0.07	.004	.71	Yes (p = .005)
Perceived personalization	+0.12	< .001	.70	Not tested
Perceived progress	+0.27	< .001	.48	Yes (p < .001)

Note. Perceived personalization entered the multilevel models as a person-level predictor based on each participant's mean score, therefore, its random slope was not estimated.

3.3. Perceived personalization and the rate of affective change

The key interaction was found for anxiety. The interaction between perceived personalization and time was -0.178 ($p < .001$), indicating that learners who experienced the application as more personalized tended to show a faster reduction in anxiety, H2 was therefore supported. The corresponding interaction for enjoyment was -0.070 ($p = .103$). It was not significant and, because its direction was negative, H1 was not supported.

After W1 baseline anxiety was controlled, the static association between perceived personalization and anxiety decreased from 0.820 ($p = .003$) to 0.190 ($p = .224$). However, the interaction with time remained -0.178 ($p < .001$). This suggests that the key association lies in the rate at which anxiety changed over time rather than in a simple cross-sectional relationship with anxiety level.

When personalization was decomposed, the between-person component by time was -0.153 ($p = .001$) and the within-person component by time was 0.224 ($p = .013$). The between-person effect was not driven by same-week covariation, although the within-person term cannot establish temporal order in this single-group design. Figure 2 shows anxiety trajectories for high- and low-personalization groups.

Two explanations are possible. First, personalized feedback may reduce evaluative threat and uncertainty when learners make errors, making the learning process feel more controllable. This is consistent with Wang's finding that trust is negatively associated with anxiety [5] and Ballıdağ and Aydın's finding that AI-based chatbot interaction can address speaking anxiety [15]. Second, learners with lower anxiety may be more willing to perceive the software as personalized. Although baseline anxiety was controlled, the single-group design cannot rule out reverse causality or common-method bias. Enjoyment did not show the same association, suggesting that perceived personalization does not affect all emotions uniformly. This is consistent with Pan and Zhang's conclusion that enjoyment and anxiety are not mirror images [11].

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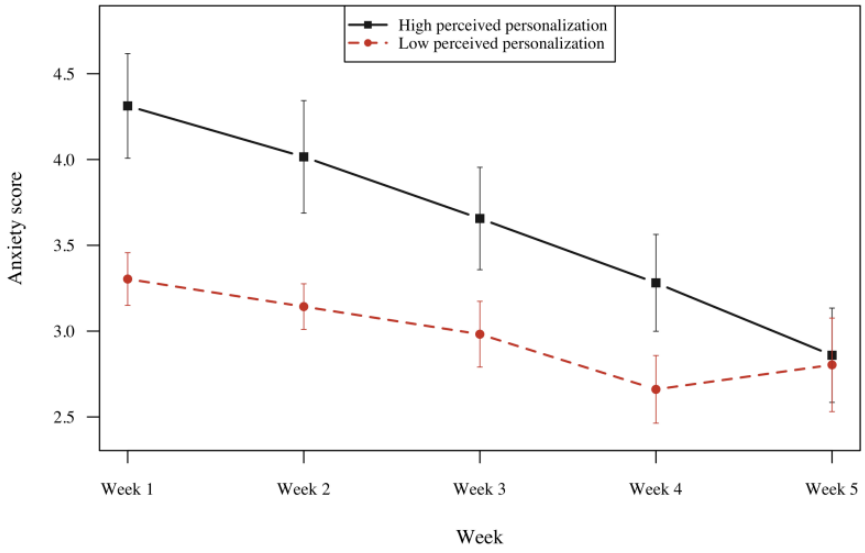

Figure 2. Anxiety trajectories by perceived-personalization group

3.4. Affective trajectories and learning outcomes

Affective slopes were not significantly associated with final Russian achievement: anxiety r = .165 (p = .382), enjoyment r = .016, and perceived progress r = -.024. In a regression with the three slopes and Cyrillic letter-learning aptitude, only Cyrillic letter-learning aptitude was significant (b = 1.55, p = .024, R^2 = .212). The model without aptitude explained little variance (R^2 = .031, F(3, 26) = 0.275, p = .843), after aptitude was added, the overall model remained non-significant (adjusted R^2 = .086, F(4, 25) = 1.686, p = .185). Final scores ranged from 70 to 97 (M approximately 82), suggesting that short-term affective change was weakly related to achievement in this small pilot.

4. Conclusion

Over four weeks, learners showed lower anxiety, higher enjoyment and perceived progress, slightly higher perceived personalization, and stable motivation. The clearest model-based finding was that perceived personalization was associated with a faster decline in anxiety, even after baseline anxiety was controlled. It was not reliably associated with enjoyment change, and affective trajectories did not predict final achievement. These findings are exploratory because the single-group design and small Level-2 sample limit causal inference. Nevertheless, perceived personalization tracked the pace of anxiety reduction rather than enjoyment change or final achievement, separating emotional support from achievement gains. AI-supported language tools should therefore make personalization visible by linking feedback to learners' own errors, adjusting difficulty transparently, and showing progress clearly. Such cues may be especially useful for beginners. Several limitations should be noted. The study used a single-group design without a non-personalized control condition. The Level-2 sample included only 30 learners, and the range of final achievement scores was restricted. Future studies should include a comparison condition without personalization, recruit larger samples, and extend the tracking period. Future studies should also combine questionnaire data with behavioral logs, such as time on task, feedback use, repeated practice, and help-seeking behavior, so that perceived personalization can be compared with actual learning behavior. Despite these

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limitations, the present findings identify visible personalization cues as a possible pathway for reducing beginner anxiety. Feedback that refers to the learner's own errors, adjusts difficulty dynamically, and makes progress visible may help improve AI-supported personalized learning while also protecting the psychological well-being of foreign language learners.

References

[1] Wang, Y. (2026). Reviewing the influence of AI-related technologies on the intrinsic motivation of students to learn English as a second language. *SHS Web of Conferences, 228*, 01010. https://doi.org/10.1051/shsconf/202622801010

[2] Li, M., Wang, Y., & Yang, X. (2025). Can generative AI chatbots promote second language acquisition? A meta-analysis. *Journal of Computer Assisted Learning, 41*, e70060. https://doi.org/10.1111/jcal.70060

[3] Yan, J., Wu, C., Tan, X., & Dai, M. (2025). The influence of AI-driven personalized foreign language learning on college students' mental health: A dynamic interaction among pleasure, anxiety, and self-efficacy. *Frontiers in Public Health, 13*, 1642608. https://doi.org/10.3389/fpubh.2025.1642608

[4] Wang, F., Cheung, A., Neitzel, A., & Chai, C. S. (2024). Does chatting with chatbots improve language learning performance? A meta-analysis of chatbot-assisted language learning. *Review of Educational Research*. https://doi.org/10.3102/00346543241255621

[5] Wang, X. (2026). Second language learners' trust in AI feedback: An empirical study based on the current application of AI technology in second language learning. *SHS Web of Conferences, 228*, 02001. https://doi.org/10.1051/shsconf/202622802001

[6] Bin-Hady, W. R. A., Ali, J. K. M., & Al-humari, M. A. (2024). The effect of ChatGPT on EFL students' social and emotional learning. *Journal of Research in Innovative Teaching & Learning*. https://doi.org/10.1108/jrit-02-2024-0036

[7] Zhai, X., & Wu, C. (2025). Unpacking beliefs and engagement in AI-assisted Chinese learning: A latent profile analysis of Malaysian Chinese as a foreign language learners. *European Journal of Education*. https://doi.org/10.1111/ejed.70101

[8] Komiak, S. Y. X., & Benbasat, I. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS Quarterly, 30*(4), 941-960. https://doi.org/10.2307/25148760

[9] Li, C. (2016). When does web-based personalization really work? The distinction between actual personalization and perceived personalization. *Computers in Human Behavior, 54*, 25-33. https://doi.org/10.1016/j.chb.2015.07.049

[10] El Shazly, R. (2021). Effects of artificial intelligence on English speaking anxiety and speaking performance: A case study. *Expert Systems, 38*(3), e12667. https://doi.org/10.1111/exsy.12667

[11] Pan, C., & Zhang, X. (2021). A longitudinal study of foreign language anxiety and enjoyment. *Language Teaching Research, 27*(6), 1552-1575. https://doi.org/10.1177/1362168821993341

[12] Sysoyev, P. V., & Filatov, E. M. (2024). Artificial intelligence in teaching Russian as a foreign language. *Russian Language Studies, 22*(2), 300-317. https://doi.org/10.22363/2618-8163-2024-22-2-300-317

[13] Rosell-Aguilar, F. (2018). Autonomous language learning through a mobile application: A user evaluation of the Busuu app. *Computer Assisted Language Learning, 31*(8), 854-881. https://doi.org/10.1080/09588221.2018.1456465

[14] Hsu, H.-T., & Lin, C.-C. (2022). Extending the technology acceptance model of college learners' mobile-assisted language learning by incorporating psychological constructs. *British Journal of Educational Technology, 53*(2), 286-306. https://doi.org/10.1111/bjet.13165

[15] Ballıdağ, M., & Aydın, S. (2025). A comparison of the effects of AI-based chatbots and peer interactions on speaking anxiety among EFL learners. *Future in Educational Research, 3*(2), 224–238. https://doi.org/10.1002/fer3.70005