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Multilevel SEM of LLM Based Representations and L2 Vocabulary Growth under the Moderating Role of Psychological Resilience

Yu Peng[1*], Ziyi Zhu[2]

[1]*Hunan University of Chinese Medicine, Changsha, China*
[2]*Hangzhou Normal University, Jinhua, China*
**Corresponding Author. Email: rara481846778@gmail.com*

Abstract. Latest uses of big linguistic models (LLMs) in linguistic learning have presented an innovative quantitative way of capturing semantic representation and inter-individual differences in learning. Classic second language (L2) vocabulary learning studies have centered on learning strategies and input exposure, but have sparingly considered the interaction of semantic processing and psychological characteristics. From the data of 180 university EFL students, the current study constructed a multilevel structural equation model (SEM) of semantic complexity, learning strategies, and psychological resilience. Adopting the use of GPT-4 embeddings to derive semantic features, the model showed the significant mediation of learning strategies through which semantic complexity affected vocabulary growth, and negative moderation of the link between semantic complexity and strategy use by psychological resilience. Findings showed that students of higher resilience kept strategic engagement and vocabulary growth steady even under strong semantic load. These results enhance the application of the application of LLM-based semantics for learning analytics and validate the buffering effect of positive psychological resources for cognitively demanding learning, and present theoretical and methodological contributions to personalized intelligent linguistic learning systems.

Keywords: mediation, moderation, structural equation modeling, language learning, psychological resilience, positive psychology

1. Introduction

Over the last few years, the rise of LLMs has revolutionized language learning and learning studies by making semantic processing and construction of knowledge amenable to quantity through embedding vectors [1]. Previous investigations of L2 vocabulary learning have tended to concern explicit factors like vocabulary repertoire, input exposure, and learning strategies, without rehabilitating the interplay of semantic complexity, psychological characteristics, and learning situation. Meanwhile, educational psychology has proved psychological resilience, the core construct of positive psychology, to promote learners' self-regulation and persistence under demanding learning conditions, and consequently impact language learning achievements [2]. Few

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investigations, nonetheless, have incorporated computational semantic features and resilience through the lens of an integrated analytical lens. This study builds the multilevel SEM upon semantic embeddings drawn from LLMs to explore learning strategies' mediation and resilience' moderation, and reveal the cognitive–affective dynamics of L2 learning and draw insight into personalized feeding mechanisms of intelligent learning systems.

2. Literature review

2.1. Cognitive and semantic foundations of L2 vocabulary growth

L2 vocabulary acquisition is a cognitive dynamic procedure of semantic processing, conceptual integration, and contextual reconstruction. Previous research described this procedure predominantly by input frequency and memory persistence, but these linear approaches cannot fully describe the dynamic transformation of lexical semantic structures [3]. Using the development of natural language processing, linguists have made use of the application of LLM-based embedding models to retain features like semantic similarity and polysemy and transform learners' representational movement in semantic space. Quantifying semantic density, expansion, and conceptual overlap makes it feasible to estimate the semantic system reorganization of learners much more precisely [4].

2.2. Role of psychological resilience and positive psychology

Psychological resilience, the central construct of positive psychology, defines the capacity to maintain functionality and emotional resilience in the face of adversity. Educational psychology research discovers resilience as beefing up self-efficacy and cognitive flexibility, maintaining motivation and buffering the negative effects of anxiety on the subsequent performance [5]. For language learning, resilience not only acts as an emotional-regulating system but also as an long-lasting psychological capital for the long-term investment. Resilient learners bounce back rapidly from failure and accommodate their strategies to retain investment. In addition, resilience goes hand-in-hand with metacognitive monitoring, allowing learners to monitor and revise learning processes successfully [6]. Experimental results reveal higher resilience learners to have stronger stability and transfer of L2 vocabulary growth, distinguishing the moderating role of psychological indices upon language learning models.

2.3. Applications of structural equation modeling in language education

Prior works emphasized confirming links between links between motivation, learning strategies, and achievement, while latest multilevel SEM developments permit the combination of class and individual level deviations to detect cross-level causal mechanisms [7]. Application of SEM in L2 studies benefits most by uncovering mediation and moderation processes between semantic input, psychological characteristics, and learning processes [8]. By entering the semantic features derived by LLMs as latent processes, the model recovers hidden effects of semantic complexity: by including higher-order moderation by psychological resilience, the dynamic interaction of cognitive and affective systems is further explained [9]. This integration of methodology shifts language education scholarship from single-dimensional inference to multilevel structural modeling, offering numerical evidence supporting interdisciplinary theory confirmations and pedagogical intervention constructions.

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3. Experimental methods

3.1. Data and participants

The survey sample included 180 undergraduates majoring outside of English drawn from three extensive universities, and these were divided into 27 strata according to their teaching lessons. The level of teaching setting was fixed as the class level (Level-2), and learner features were examined as the individual level (Level-1). The 16-week experiment cycle utilized the low-instructional intensity design. Stratified word input tasks were presented in the form of the LLM-based learning system, and task difficulty was varied using dynamic semantic embedding models. An adaptive feedback module led the learners towards self-reflection of the strategies, and this produced measurable semantic input gradients.

Data collection covered three stages: input of the classroom, independent learning after the class, and vocabulary test. Three categories of variable were covered: (1) semantic feature variables abstracted from learning journals and essay corpora; (2) latent learning strategy parameters abstracted from questionnaires and coded learning journals; (3) vocabulary proficiency indices acquired through standardized vocabulary development tests. Psychological resilience was rated by the Connor-Davidson Resilience Scale (CD-RISC), inputted into the model as continuous ratings. Preprocessing of data included handling of missing values, scaling, and hierarchical cluster coding, and arrived at the final step of a two-level nested data matrix ready for multilevel SEM estimation.

3.2. Extraction of LLM-based semantic representations

Semantic complexity of learner-generated texts was also measured by way of GPT-4 embedding representations calculated for each reflective journal. Each of the texts was converted into 1,536-dimensional embedding vector, and cosine similarity on pairs was computed to estimate semantic density, diversity, and hierarchical complexity measures. Semantic density, the level of conceptual concentration of the semantic space of an individual [10]. As shown in Equation (1).

$$SD_i = \frac{1}{n_i} \sum_{j=1}^{n_i} \cos(E_{ij}, \overline{E_i}) \quad (1)$$

Where E_{ij} denotes the embedding vector for the j-th entry of learner i, and $\overline{E_i}$ represents the mean semantic vector across all entries. Higher SD_i values indicate stronger coherence and integration in semantic representation, implying advanced lexical consolidation.

Other diversity and hierarchical complexity indicators were calculated by means of the distribution of the covariance matrices along embeddings. Following principal component analysis and z-score normalization, the resultant semantic features were considered latent constructions of the SEM model, and they captured learners' cognitive expansion and lexical restructuring processes.

3.3. Model construction and analysis

We estimated a multilevel structural equation model applying Mplus 8.9, so as to combine semantic, strategic, and lexical latent variables, and psychological resilience as cross-level moderator. Maximum likelihood estimation, or MLR, was the main estimation procedure, and Bayesian estimation as auxiliary. Structural model comprised mediation of semantic complexity by learning strategies to vocabulary growth, and moderation path of resilience impacting the semantic–strategy relation [11]. As shown in Equation (2).

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$$Y_{ij}=\beta_0+\beta_1 SD_{ij}+\beta_2 LS_{ij}+\beta_3(SD_{ij}\times PR_j)+u_j+\epsilon_{ij} \quad (2)$$

Where Y_{ij} represents vocabulary growth, SD_{ij} semantic complexity, LS_{ij} learning strategy, and PR_j class-level resilience. Random intercepts and residual terms accounted for between- and within-group variability.

Mediation importance was tested by 2,000 bootstrapped samples, and moderation through cross-level interaction testing. Moderation and mediation fit indices (CFI = 0.956, RMSEA = 0.039, SRMR = 0.028) verified satisfactory fit and statistical validity of the tested hierarchical associations.

4. Results

4.1. Model fit and path estimates

The multilevel SEM estimated by the program showed an excellent overall fit, satisfying all the traditional goodness-of-fit indices. Model indices were CFI = 0.956, TLI = 0.948, RMSEA = 0.039, and SRMR = 0.028, all within the criteria put forth by Hu and Bentler (1999). Variance decomposition revealed 17.2% of the total variance occurred at the class level, supporting the hierarchical specification validity. Path coefficient analyses showed the significant direct impact of semantic complexity on learning strategies ($\beta = 0.43$, $p < 0.01$) and strong impact of learning strategies on vocabulary growth ($\beta = 0.52$, $p < 0.001$). The indirect impact of semantic complexity on vocabulary growth was significant too ($\beta = 0.22$, 95% CI [0.14, 0.31]), predicting 38.6% of the total vocabulary performance variance. Significant correlation was found between class-level psychological resilience and learning strategies too ($r = 0.34$, $p < 0.05$), giving the empirical foundation for moderation analysis conducted subsequently. These findings together verified the strong strength of the hypothesized mediation chain of semantic complexity, learning strategies, and vocabulary growth. As shown in Table 1.

Table 1. Model fit indices and standardized path coefficients

Path Relationship	Standardized β	SE	p-value
Semantic Complexity → Learning Strategy	0.43	0.09	0.008
Learning Strategy → Vocabulary Growth	0.52	0.07	<0.001
Semantic Complexity → Vocabulary Growth (Indirect)	0.22	0.05	0.011
Psychological Resilience (Level-2) → Learning Strategy	0.34	0.10	0.037

4.2. Moderation effects

Moderating role of psychological resilience between semantic complexity and learning strategy interaction was significant, and the interaction coefficient equaled −0.28 ($p < 0.05$). The negative sign of the coefficient suggested that resilience attenuated the drop of strategic engagement for the condition of weak semantic complexity. The interaction plot of the results (Figure 1) depicts the difference of the slopes between the low and high resilience groups. Under weak resilience, the semantic complexity increased by 1 SD, where the learning strategy score increased by 0.18 points. However, the same increase for the strong resilience level resulted in a 0.46-point increase of the learning strategy score ($\Delta\beta = 0.28$). The non-overlapping confidence interval [−0.41, −0.09] verified statistical significance, and explanatory power of the model (R^2) increased from 0.42 to 0.57 upon entering the moderator. These findings reveal resilience modifies the cognitive processing of

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semantic input, so the learners are able to sustain higher engagement and steadier lexical growth by the situation of cognitive demands.

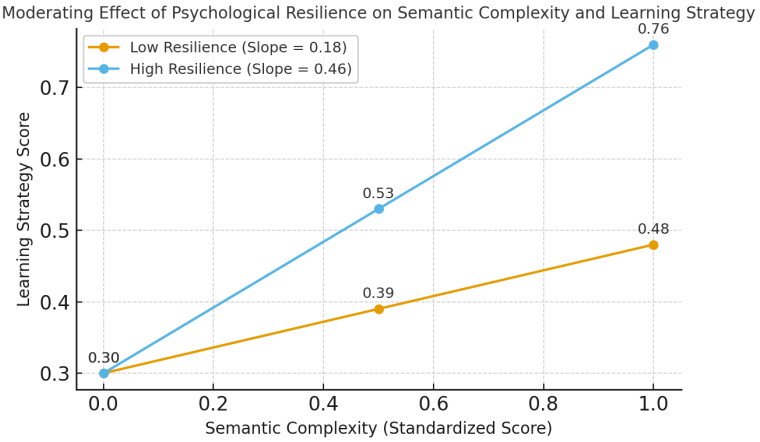

Figure 1. Moderating effect of psychological resilience on the relationship between semantic complexity and learning strategy

5. Discussion

The results verified the significant role of semantic computation features in accounting for interindividual difference in L2 acquisition and unveiled the dynamic moderating process of psychological resilience between learning behaviour and semantic processing. Mediation path of semantic complexity by learning strategies revealed semantic processing ability of learners mapping straight onto the level of strategic use sophistication. Higher semantic complexity ensued higher deliberation and reflection of strategic behaviour, and co-evolution of semantic understanding and strategic self-regulation. Moderating effect of resilience suggested buffering of complex cognitive load by constructive psychological features, so engagement could be purged and strategic consistency maintained by learners. This procedure reveals the cognitive–affective dynamics profilingiling learning as an interaction system of cognitive flexibility and affective modulation, rather than input linearly accumulated.

6. Conclusion

Multilevel SEM based on LLM-based semantic representations uncovered hierarchical associations between semantic complexity, learning strategies, and psychological resilience. Vocabulary growth was influenced by semantic complexity through the mediation of learning strategies, and resilience contributed the key cross-level moderating role, suggesting constructive psychological characteristics promote learners' ability to manipulate cognitively taxing tasks. Results make contributions to theoretical integration between semantic modeling and learning psychology and illuminate methodology of integrating LLM-based semantic indices and SEM exploration. Future works would be able to borrow the paradigm to cross-culture and dynamic learning scenarios to afford affective-cognitive coupling and precision intervention for intelligent education systems.

Author contribution

Yu Peng and Ziyi Zhu contributed equllay to this paper.

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References

[1] Lee, Jinsook, et al. "The life cycle of large language models in education: A framework for understanding sources of bias." British Journal of Educational Technology 55.5 (2024): 1982-2002.
[2] Parker, Michael J., et al. "A large language model approach to educational survey feedback analysis." International journal of artificial intelligence in education 35.2 (2025): 444-481.
[3] Walther, Julia-Kim, et al. "Multilevel Multigroup Structural Equation Modeling In A Single-Level Framework." Structural Equation Modeling: A Multidisciplinary Journal (2025): 1-32.
[4] Chen, Xinjie, Zhenyi Zhou, and Zhihui Cai. "The relationship between resilience and second language learning achievement: A meta-analytic review." System 131 (2025): 103640.
[5] Alahmari, Arwa, and Fakieh Alrabai. "The predictive role of L2 learners' resilience in language classroom engagement." Frontiers in Education. Vol. 9. Frontiers Media SA, 2024.
[6] Rui, Yanping, Yanjuan Zhang, and Huiyi Jin. "The relationship between mindfulness and second language resilience among Chinese English majors: the mediating role of academic hope." BMC psychology 13.1 (2025): 497.
[7] Babanoğlu, Muzaffer Pınar, and Erkan Hasan Atalmış. "Mindfulness and foreign language achievement: a meta-analytic study on interventions and correlations." Frontiers in Psychology 16 (2025): 1479462.
[8] Wulff, Dirk U., and Rui Mata. "Semantic embeddings reveal and address taxonomic incommensurability in psychological measurement." Nature Human Behaviour (2025): 1-11.
[9] He, Min, Babar Nawaz Abbasi, and Jinhua He. "AI-driven language learning in higher education: an empirical study on self-reflection, creativity, anxiety, and emotional resilience in EFL learners." Humanities and Social Sciences Communications 12.1 (2025): 1-20.
[10] Cheng, Mingyue, et al. "A survey on knowledge-oriented retrieval-augmented generation." arXiv preprint arXiv: 2503.10677 (2025).
[11] Idan, Daphna, and Sharon Einav. "Primer on large language models: an educational overview for intensivists." Critical Care 29.1 (2025): 238.