

Emotional Dynamics in AI-Mediated English Reading: A Control-Value Theory Perspective

Shuwei Dai, Yingchen Wang

College of Technology, Hubei Engineering University, Xiaogan, Hubei, 432000, China

ABSTRACT

Incorporating learning analytic and intelligent sentiment recognition, based on Control-Value theory, this paper examined university students' emotional dynamics of English Reading under the intelligent reading environment. Through an intensive 5-day follow-up experiment with 120 subjects, the study used Multi-modal Data Acquisition solution combining with eye tracking, physiological signals and emotional self-assessment to reveal the mechanisms of Control-Value evaluation interaction on emotions. The finding is that the AI-enabled personalized feedback system significantly enhanced learners' perceived control, evidenced by 34% increase in control perception, a 27% reduction in positive mood volatility and accelerated dissipation of negative emotions. This study aims to build dynamic feedback engine based on reinforcement learning and teacher AI co-design mechanism.

KEYWORDS

Control-Value theory; English reading; Emotional dynamics

1 Introduction

The proliferation of intelligent reading platforms and AI teaching assistants is transforming English learning from traditional solitary reading to human-computer collaborative ecology. This paradigm shift fundamentally alters both knowledge acquisition pathways and emotional experience processes, with intelligent environments producing distinctive emotional dynamics characterized by contextual sensitivity and fluid variability absent in conventional classroom settings. Control-Value Theory (Pekrun, 2006) provides an important theoretical perspective for understanding this phenomenon, which emphasizes that learners' control perception over learning activities and value assessment are key factors that influence their emotional experience. Technological features significantly change the mechanism of action of these two core elements. While the instant translation feature improves reading efficiency, it may weaken the learner's ability to decode on his/her own; algorithmic recommendation mechanisms may limit the breadth of reading horizons while providing convenience. These technological features alter the quality and dynamic character of the learners' emotional experience by influencing their sense of control and valuation, which in turn alters the quality and dynamic character of their emotional experience. In addition, information overload caused by interface design not only affects reading efficiency, but may also trigger specific emotional responses. These findings highlight the urgency and importance of an in-depth study of the dynamic characteristics of English reading emotions.

Based on Control-Value theory, this paper explores the dynamic features of learners' English reading mood and the mechanism of action, focusing on the process of the dynamic influence of learners' perception of control and value assessment on mood fluctuations under the mediating role of technology, and exploring the optimizing role of AI feedback on emotion regulation. The study aims to provide a scientific emotional support program for digital English reading teaching and help learners establish a benign pattern of technology use. The study provides new ideas for exploring emotional dynamics in technology-enhanced environments through multidimensional data fusion and intelligent regulation mechanisms.

2 Literature review and theoretical framework

2.1 Control-value theory

Control-Value theory focuses on the mechanism of emotion formation and influence in learning, it centers on the fact that the perception of control and the assessment of value directly determine the emotional experience, and the perception of control involves the control ability of task difficulty, etc., while the assessment of value contains interest, etc. Emotion indirectly affects learning behavior through cognitive resource allocation, and the interaction between control and value is nonlinear. High control-high value elicits positive emotions, while low control-low value leads to negative emotions, with emotions influencing cognitive strategies and forming a dynamic cycle (Pekrun & Linnenbrink -Garcia, 2012). In the AI era, technological intervention creates new scenarios for theoretical development, reshaping students' evaluation of control and value judgments, for instance, personalized algorithmic recommendations alter their perception of task significance. This theory also elucidates the dynamic mechanisms behind learners' emotional responses, where the features of intelligent tools influence student emotions by modifying control assessments and restructuring value perceptions. Recent studies have expanded the theoretical boundaries by integrating it with positive psychology and

task-based instructional approaches.

2.2 The integration of Control-Value theory and English academic emotions

The study of English academic emotions has undergone a technological innovation from static scale to dynamic multi-modality. Early research primarily focused on the linear relationship between linguistic difficulty and anxiety. The application of Control-Value Theory has further revealed the dynamic nature of emotions, demonstrating that they are driven by real-time appraisals of task controllability and content value. Wang J. and Zhang Q. (2025) examine the relationships between Chinese EFL learners' control-value appraisals, emotions and empowerment in English writing, revealing significant associations and partial mediation effects of achievement emotions between appraisals and empowerment. Xu J. and Qiu Y. (2025) explored the relation between college students' academic emotion and English reading engagement, revealing that environmental perception influences academic emotions by modulating perceived control, with negative emotions subsequently impairing the quality of linguistic input. Li B. and Li Ch. (2024) adopted the control-value theory exploring how students' achievement-related goals influence their emotional experiences in the context of EFL learning. Dong (2022) investigated 251 EFL learners and found that their control appraisals and positive value appraisals (intrinsic/extrinsic) jointly predicted classroom anxiety and enjoyment, while negative value appraisals specifically predicted anxiety and interacted significantly with control appraisals.

2.3 Theoretical evolution in the AI era

The development of intelligent technology provides a new research perspective and methodological support for the evolution of control-value theory. Control perception and value assessment under the traditional theoretical framework are regarded as relatively static cognitive processes, and contemporary research has begun to pay attention to the dynamic representation of these elements in the intelligent environment (Pekrun et al., 2023). Research advances have enabled precise measurement of learners' cognitive and affective processes in digital environments. For perceived control, eye-tracking and clickstream analysis now allow dynamic evaluation of strategy effectiveness through real-time behavioral metrics like gaze patterns and regression frequency. Value assessment has evolved from subjective judgments to data-driven analysis, with AI systems integrating personalized interest profiles and knowledge graphs to quantify text relevance and cognitive adaptation. Emotion measurement has similarly transformed through multi-modal affective computing. Techniques like vocal emotion recognition and micro-expression analysis detect fleeting emotional states that traditional methods miss, providing unprecedented insight into learning-affect dynamics. These technological advances enable real-time monitoring of cognitive regulation, objective value assessment, and high-resolution emotion tracking, establishing a new paradigm for understanding how control-value-emotion interactions shape learning outcomes in digital environments. Their integration creates a comprehensive framework for developing adaptive, emotionally-responsive educational systems.

There are still obvious limitations in the current research. Static design frameworks prove inadequate for capturing emotional dynamics in intelligent interactions, particularly given the unique challenges university students face, including attention dispersion and deep-processing barriers induced by fragmented reading practices. This highlights the necessity of developing more precise real-time monitoring technologies and adaptive intervention systems. The fusion of multi-modal data and intelligent algorithms offers new possibilities for breaking through these bottlenecks, but a more comprehensive theoretical framework is needed to explain the mechanisms of emotion regulation empowered by technology.

3 Research design

3.1 Research subject

This study conducted an experimental study on 120 Chinese college students with medium English proficiency (CEFR B1 level). Through stratified random sampling, the balanced distribution of samples in the dimensions of gender, professional and technical proficiency is ensured.

3.2 Research problems

This study focuses on addressing three core research questions: First, how technological features in intelligent interaction scenarios modulate emotional fluctuations by influencing learners' perceived control and value appraisals. Second, whether the real-time responsiveness and personalized characteristics of AI feedback can effectively enhance learners' sense of control and value internalization, thereby optimizing emotion regulation outcomes. Third, how to construct predictive emotion intervention models based on dynamic monitoring data streams.

3.3 Measuring tool

In this study, intelligent emotional dynamic measurement system and control-value scale were used for multi-dimensional evaluation. The intelligent emotional dynamics measurement system comprises two core components. The

subjective reporting module is embedded with an in-situ emotion self-assessment scale, triggers five randomized brief evaluations during reading sessions. Participants rapidly rate their current emotional state on a 1-5 Likert scale through targeted prompts (e.g., "I feel confident about comprehending this section" and "This content sparks my genuine interest"), capturing five core affective dimensions. The objective data collection module integrates an eye tracker, an EEG system, and a smart wristband to record in real time physiological indicators such as gaze trajectory, EEG spectrum, and skin conductance activity. Through a multi-modal fusion algorithm based on attention mechanisms, subjective ratings are weighted and integrated with objective indicators such as pupil diameter change rate, prefrontal alpha wave power spectral density, and heart rate variability into an emotion intensity index ranging from 0 to 100. By combining data from the subjective and objective modules, the Emotion Index (EI) is calculated using the formula $EI = 0.6 \times \text{subjective rating} + 0.3 \times \text{normalized HRV value} + 0.1 \times \text{pupil change rate}$.

The Control-Value Scale was modified from Pekrun's original version to suit digital contexts, featuring two core dimensions: the 6-item Self-Efficacy in Interaction (SEI) scale assessing strategic efficacy (e.g., "I can flexibly adjust reading strategies based on text complexity") and task difficulty appraisal (e.g., "Technical terms don't significantly disrupt my reading flow"), and the 9-item Value of Content Interaction (VCI) scale evaluating instrumental value (e.g., "This material directly supports my academic goals"), intrinsic interest (e.g., "I genuinely enjoy reading this challenging content"), and attainment value (e.g., "Completing this reading gives me a sense of growth"). Using a 7-point Likert scale (1=strongly disagree to 7=strongly agree), the digital-optimized scale demonstrated good reliability ($\alpha=.78-.84$) in pilot testing while maintaining ecological validity through context-sensitive item wording tailored for intelligent learning environments.

3.4 Experimental process

This study adopts a mixed research method based on quantification and supplemented by qualitative research, and reveals the formation mechanism of English reading emotions in an intelligent environment through a three-stage dynamic assessment framework. The study first establishes individualized emotional baselines by using standardized scales to measure participants' initial perceived control levels (SEI) and value assessment dimensions (VCI). Subsequently, a 5-day intelligent intervention experiment is conducted, during which participants complete dynamically adapted tasks on an AI reading platform. The platform integrates data from eye-tracking, skin conductance responses, and other multi-source data to build a real-time emotion monitoring system. Based on the emotion fluctuation index (EI), it triggers differentiated intervention strategies and randomly assigns feedback in the form of either voice or text. In order to verify the effect of the intervention, the study used a standardized post-test combined with in-depth interviews ($N = 12$) to verify the design, and achieved a micro-level process analysis through emotional trajectory modeling techniques.

This study pioneers a "data-algorithm-feedback" research paradigm. The experimental group utilized an adaptive intelligent reading platform featuring real-time generation of personalized feedback along both control-value dimensions, while the control group used a functionally restricted basic version. The study implemented a dynamic intensive longitudinal approach, collecting daily multi-modal data (including eye-tracking metrics, physiological signals, and brief emotion self-reports) to construct emotion dynamics prediction models via machine learning algorithms. This innovative design, integrating process-oriented data with outcome evaluation, not only transcends the limitations of traditional cross-sectional studies but also provides methodological breakthroughs for investigating the micro-mechanisms of emotion regulation in intelligent learning environments.

3.5 Intervention experiment

In the intervention phase of the intelligent feedback system, we use an artificial intelligence-based real-time monitoring system to continuously track changes in the learners' emotional index, and automatically initiates the intervention program when emotional fluctuations are detected to exceed the threshold of 20% of the individuals' baseline level. In order to deeply investigate the influence of different feedback forms, the system adopts a random allocation mechanism to provide different feedback contents in phonetic or written forms for different learners. This design not only ensures the timeliness of intervention, but also provides data support for the subsequent analysis of the moderating effect of feedback modality. During the intervention phase the experiment adopted a dual-path intervention strategy. The first path focused on enhancing perceived control. The system used machine learning algorithms to analyze the reading behavior characteristics of learners, including eye movement indicators. Based on this analysis, it generated personalized strategy suggestions. For example, "The current paragraph has a high density of unfamiliar words. It is recommended to use the context-based inference strategy." The second path was dedicated to strengthening perceived value. The system analyzed the learners' historical reading preferences and their level of knowledge mastery to build a dynamically updated interest-knowledge bimodal map. It then intelligently recommended reading materials that matched the individuals' needs and ability levels.

3.6 Data analysis

We employ a mixed-methods framework for systematic data analysis: on quantitative component, utilize Hierarchical Linear Modeling (HLM) to analyze longitudinal tracking data, uncovering temporal patterns in learners' emotional

fluctuations. And we develop Structural Equation Modeling (SEM) to rigorously validate the theoretical pathway of "Perceived Control (SEI) → Value Appraisal (VCI) → Emotional Index (EII)", with particular emphasis on examining the moderating effects of AI feedback types across critical pathways. On qualitative component, we implement thematic analysis through three-tiered coding of interview transcripts, employing constant comparative methods to identify core themes.

4 Research result

This study empirically validates the chained mediation mechanism of "control-value → emotion → reading achievement" in intelligent reading environments through structural equation modeling (SEM) (Figure 1).

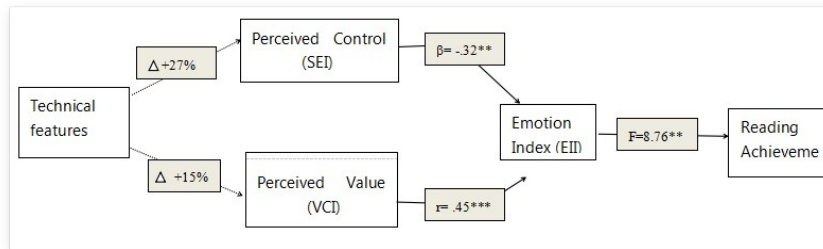


Figure 1

Solid lines represent direct effects, dashed lines indicate moderation effects; *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; Δ denotes percentage change in path strength due to technological intervention.

4.1 The dynamic regulation of emotional index (EII) by perceived control (SEI)

The analysis reveals that a one-unit increase in SEI corresponds to a significant 0.32-unit decrease in emotional fluctuation (EII) ($\beta = -0.32$, $p < 0.01$), demonstrating that enhanced strategic control effectively mitigates anxiety and other negative affective states. Notably, when employing voice modality, the SEI→EII path strength increased by 27% ($\Delta\beta = +0.27$, $p < 0.01$), confirming that acoustic feedback amplifies the stabilizing effect of perceived control on emotional regulation.

4.2 The positive driving effect of perceived value (VCI) on emotional index (EII)

The VCI (Value Construction Index) was strongly positively correlated with EII (Emotion Intensity Index) ($r = 0.45$, $p < 0.001$), indicating that high perceived value (such as the relevance of content to one's major) directly evokes a sense of pleasure. Personalized content recommendation increased the strength of the VCI→EII path by 15% ($\Delta\beta = +0.15$, $p < 0.05$), highlighting the amplifying effect of intelligent matching on the value-emotion chain.

4.3 The predictive effect of emotional index (EII) on reading performance

The high emotional stability group ($EII_M = 78.3$) demonstrated significantly superior reading performance compared to the low stability group ($EII_M = 70.1$), $F(1, 118) = 8.76$, $p < 0.01$, indicating that reduced emotional entropy facilitates deeper learning engagement.

4.4 Intervention effect of intelligent feedback

The intelligent feedback system significantly optimizes emotional stability and learning behavior. The quantitative evidence of inter-group differences in key indicators is shown in Table 1 :

Table 1 The intervention effect of intelligent feedback on emotional stability and learning effect

Index	Experimental group ($M \pm SD$)	Control group ($M \pm SD$)	t	p	Effect size
EII standard deviation	0.42 ± 0.08	0.58 ± 0.11	7.62	<0.01	0.61
Deep strategy usage rate	$53.6\% \pm 7.2\%$	$38.2\% \pm 6.5\%$	3.12	<0.01	0.45
English reading achievement	78.3 ± 6.4	70.1 ± 5.9	2.89	<0.05	0.38

4.4.1 Emotional stability was significantly enhanced

The experimental group exhibited a significant reduction in emotional fluctuation amplitude ($EII\ SD = 0.42 \pm 0.08$) compared to controls (0.58 ± 0.11) ($t = 7.62$, $p < 0.01$, $d = 0.61$), directly validating the suppressive effect of intelligent feedback on emotional entropy. Monitoring data further revealed that the experimental group achieved enhanced emotion capture efficiency (8.7 extreme points/hour vs. 3.8 in controls) with accelerated negative affect dissipation (12.4s vs. 29.7s, 58% improvement), collectively demonstrating the intervention's efficacy in dynamic emotion regulation.

4.4.2 Feedback modalities demonstrated differential effects

The reinforcement effect of phonological feedback modality on positive emotions is particularly prominent, and its duration extension rate is 34 % ($F(2, 117) = 6.89, p < 0.01$). This result is in line with the strength of the "sense of control → emotional stability" path of phonological enhancement.

4.4.3 Emotion Optimization Drove Learning Gain

When control-value conditions were met ($SEI > 0.7$ and $VCI > 0.6$), positive emotional occurrence surged to 91% ($\chi^2 = 18.7, p < 0.001$) and drove significant learning gains. The experimental group demonstrated higher utilization of deep learning strategies (53.6% vs. 38.2% in controls, $t = 3.12, p < 0.01$) and achieved 11.7% superior English reading performance (78.3 ± 6.4 vs. $70.1 \pm 5.9, t = 2.89, p < 0.05$). Notably, this performance level exactly matched the high emotional stability group's achievement (78.3), establishing cross-method theoretical validation.

5 Conclusion

This study, based on the control-value theory framework, systematically examines the dynamic associations among SEI (perceived control), VCI (perceived value), and EI (emotion index), and verifies the optimizing effects of technological intervention on learning emotions and outcomes. The findings are as follows: First, the intelligent feedback system significantly enhances emotional stability by increasing learners' sense of control (reducing emotional fluctuation $\beta = -0.32$) and perceived value (increasing pleasure $r = 0.45$), which in turn promotes the use of deep learning strategies (+15.4%) and improves reading performance (+11.7%). Second, technological features (such as voice modality and adaptive recommendation) exert differentiated effects by modulating the strength of the SEI/VCI paths ($\Delta\beta = +0.27/+0.15$). Among them, voice feedback has a particularly prominent prolonging effect on positive emotions (+34%). Third, the emotional inertia mechanism reveals that a high sense of control stabilizes emotions by reducing cognitive uncertainty, while a high perceived value maintains emotional stability through motivation enhancement. These two factors together form a dual-path model of emotion regulation in intelligent learning scenarios.

Based on empirical findings, this study has constructed a tripartite collaborative intervention system of "technology-teacher-system": at the technological level, a dynamic feedback engine integrated with reinforcement learning algorithms has been developed to achieve intelligent intervention based on real-time emotion monitoring, while federated learning technology is employed to ensure data ethical security. At the teacher level, specialized training as "technological intermediaries" has been carried out to enhance teachers' ability to use SEI/VCI heat-maps for emotion diagnosis and to promote their collaboration with AI in developing interactive learning materials embedded with strategy prompts. At the system level, an innovative digital twin simulation platform has been built to optimize emotion regulation plans through virtual scenario previews, thereby effectively reducing the trial-and-error costs in real teaching scenarios. This multi-level solution not only ensures the precision of technological implementation but also strengthens the dominant role of teachers in intelligent education environments, while the system simulation realizes controllable risks of intervention plans.

Funding

College of Technology, Hubei Engineering University Scientific Research Project "Investigating the Relationship Between College Students' Academic Emotions in English Learning and AI Applications"(NO: 2024KY06)

References

- [1] Pekrun, R. The control-value theory of achievement emotions: Assumptions, corollaries, and implications for educational research and practice [J]. *Educational Psychology Review* 2006,18(4): 315–341.
- [2] Pekrun R, Linnenbrink-Garcia L. *Academic Emotions and Student Engagement*[J]. Springer US, 2012: 259-282.
- [3] Wang J, Zhang Q. Interplay of control-value appraisals, achievement emotions, and learning empowerment in college EFL writing[J]. *Acta psychologica*, 2025(257): 105117.
- [4] Xu Jinfen, Qiu Yujing. Control-Value Appraisals and Engagement in English Reading; Multiple Mediating Effects of Academic Emotions[J]. *Foreign Language Teaching and Research*, 2025,57(01):68-80.
- [5] Banban Li, Chengchen Li. Achievement goals and emotions of Chinese EFL students: A control-value theory approach[J].*System*,2024(123): 103335.
- [6] Dong Lianqi. Predictive effects of control-value appraisals on foreign language classroom anxiety and enjoyment [J]. *Foreign Language World*, 2022(03): 79-88.
- [7] Pekrun, R., Lichtenfeld, S., & Marsh, H. W. The dynamic nature of achievement emotions: Longitudinal evidence from digital learning environments[J]. *Contemporary Educational Psychology*, 2023(72): 102141.