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From Anxiety to Autonomy: Examining Automated Feedback Systems Shape Reading Motivation and Emotional Engagement Worldwide

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Abstract

The automated feedback systems, spread worldwide through digital reading platforms, have not only changed access to education but have also not been insufficiently studied in terms of their effects on learner's emotional and motivational pathways, especially their ability to transition anxiety to autonomy across cultures. The purpose of the study was to investigate the roles of AI-based feedback systems in shaping reading motivation, emotional involvement, and self-regulated autonomy among diverse learners worldwide. The study employed a quantitative pre-post experimental design with N = 500 adult participants of 10 countries, stratified by age, education, and culture region. For structured tasks, participants were randomly assigned to receive either personalized AI feedback or static reading material. Key measures included the Reading Anxiety Scale, Emotional Engagement Scale, Reading Motivation Questionnaire, and the Perceived Autonomy Index. Findings showed that automated feedback significantly reduced reading anxiety and increased emotional engagement, with effects persisting at four-week follow-up. Cultural individualism mediated autonomy gains more strongly, revealing 81.5% more effects in western samples. Personalization intensity accounted for 31.2% of the variance in intrinsic motivation, and biometric integration doubled the mediated interaction between anxiety and autonomy. These results support a Dynamic Anxiety-to-Autonomy Continuum Model, where culturally adaptive, physiologically responsive AI serves as a driving force for equitable reading development. The findings imply the need for inclusive edtech tool design and a research approach that is longitudinal and multimodal to maximize global learning outcomes.

Keywords: Affective Computing, Anxiety, Cultural Moderation, Automated Feedback Systems, Emotional Engagement, Reading Motivation, Self-Determination Theory, Global Education,

Introduction

Automated Feedback Systems are a novel category of technologies in the digital age that has changed the face of education, specifically, by improving the degree of reading using AI-based machines that can give a student real-time, customized feedback (Feng et al., 2025). Examples of these systems include Duolingo and adaptive e-readers which can be used globally since they provide scalable solutions without discrimination of different learning requirements under different situations (Cao & Phongsatha, 2025). Nevertheless, their proliferation does not result in a lack of gaps in the understanding of their effect on reading motivation both intrinsic and extrinsic aspect and emotional involvement, and negative feedback may cause anxiety, and specific support may create a sense of independence (Zhan and Yan, 2025). More current research suggests that automated feedback has the ability to reduce the anxiety of reading by adjusting to personal performance levels, even though there is still a gap in empirical research on the emotional effects of the one between the breakdown of anxiety at the first stage of reading to the sense of empowerment in self-directed learning (Mejeh et al., 2024). This negligence is more pronounced within global contexts, in which any cultural and socioeconomic consideration may balance these impacts resulting in an unreasonable distribution of educational technology implementation (Lan and Zhou, 2025). It is important to address these gaps because analyzing the emotional processes unexplored by them can limit the potential of automated systems to facilitate sustained reading practices in the world (Ali et al., 2025; Alhebaishi et al., 2025).

This study is based on the Self-Determination Theory (SDT) to suggest that autonomic feedbacks-based systems could influence reading motivation by addressing the primal psychological needs of autonomy, competence, and relatedness which could actually shift the learning students towards the avoidance in anxiety mode to autonomous engagement (Singh and Aziz, 2025). According to SDT, intrinsic motivation increases when the feedback is perceived to improve the perceived competence via positive reactions and their adaptation to improvement, which drops the mood-based blockers encountered in the reading assignments (Singh and Aziz, 2025). In line with their complement, Flow Theory explains the involvement of emotions as a state of ideal immersion when a balance is achieved between challenges and skills, facilitated by automated systems, which reduce self-referential anxiety and offer a continuous transition between anxiety and autonomy (van der Linden et al., 2021). Here, automated feedback has an intermediary role that will offer feedback in time that matches the task demands and capabilities of the learners, which creates flow states marked by enhanced engagement and lowered emotional turbulence (van der Linden et al., 2021). By combining these theories, the theory of anxiety to autonomy progression is modelled as a kind of dynamism; the first (initial anxiety due to the overwhelming responses) and the second (autonomy due to the adaptability of the systems to develop respective competence) transformations is dynamic and finally makes the development of self-regulated reading possible (Lan and Zhou, 2025). This school of thought highlights the importance of empirical scrutiny of the impact of AI-driven mechanisms on these psychological infrastructures in a variety of educational environments (Rojas Vistorte et al., 2024).

The global nature of this study underscores the need to have an inclusive and fair technology in reading education where the automated feedback should consider cultural differences in pursuit of motivation and emotional reactions to prevent creating an inequality gap among nations (Lan and Zhou, 2025). As an example, feedback on personal accomplishment can strengthen autonomy in Western individualistic, but more relational factors might have a superior effect in reducing anxiety and promoting engagement in Eastern collectivist cultures (Singh and Aziz, 2025). This is not only relevant to policy and practice, but fair technology integration potential would fill disparities in reading achievement between low resource and digital technology zones, facilitating life long learning as the digital divide continues to widen (Cao and Phongsatha, 2025). Additionally, through the analysis of emotional engagement in the world, the paper will lead to sustainable educational development, which would be more in line with international ambitions of inclusive quality education (Alhebaishi et al., 2025). Eventually, the awareness of these dynamics will be crucial to the idea that cognitive outcomes are progressed with the help of automated systems, but such systems will also be helpful in the context of emotional well-being, thus contributing to resilient and adapted learning environments in an interlinked world (Rojas Vistorte et al., 2024).

In order to investigate in a systematic way, the relationship between automated feedback and reading dynamics, the research questions that shall be used in the study are as follows: RQ1: How automated feedback systems can reduce reading-related anxiety and improve emotional engagement among different global learners? RQ2 What are the cultural moderating effects in the effect of automated feedback on reading motivation and the transition to autonomy? RQ3: How well do individualized AI capabilities within feedback systems forecast change in intrinsic and extrinsic motivation among varying learning settings? RQ4: What is the impact of the integration of biometric data in automated systems on the continuum between anxiety and autonomy when reading tasks? Question 5: What are the effects of automated feedback in self-regulated reading behaviors in the long term across the globe? Hypotheses that correlate are (H1) Automated feedback will be found to have a significant impact on reducing anxiety and more emotional engagement, though mediated by perceived competence (per SDT; Singh and Aziz, 2025). H2: The autonomy-promoting influence of feedback will be positively mediated by the cultural individualism and will produce more motivation gains among the Western samples (Lan and Zhou, 2025).

The main goal of the study is to research the mechanisms of how the automated feedback systems turn reading experiences no longer anxiety, but dynamism driven, demonstrating the emphasis on motivation and emotional involvement on a global level (Mejeh et al., 2024). The secondary objectives are the determination of cross-cultural differences in these processes to guide the design of inclusive AI tools, the analyzing of the effectiveness of adaptive features to eliminate emotional obstacles, and practical advice that can be offered to educators and developers to maximize the feedback of learners with different backgrounds (Feng et al., 2025). By means of these objectives, the research will provide theoretical views on the introduction of edtech models and will make part of providing practical inputs on achieving equal education on reading globally (Zhan and Yan, 2025).

This article is designed in a way to identify in detail the role of automated feedback in the dynamics of reading: after the introduction, relevant literature can be summarized, including current research on the subject of motivation and engagement; then, the methods section follows, outlining the mixed methodology using international samples; results will represent empirical data on the shifts between anxiety and autonomy; the discussion will clarify the implications of the results in the theoretical frameworks chosen; finally, the conclusion will define the way to move forward with the global development of edtech (Alhebaishi et al., 2025).

Automated Feedback Systems

Automated feedback systems constitute one of the notable technological innovations in education, based on an artificial intelligence (AI) interface that provides real-time and personalized feedback, which can be used to help improve the process of learning, especially reading (Alfian et al., 2025). Such systems may be divided into two primary types, namely, formative feedback, which suggests continuous feedback to enhance performance in the course of tasks, and summative feedback, which analyzes the results at the conclusion of the tasks, which is often included in AI-controlled reading technologies like adaptive e-readers and language programs (Chen and Wang, 2025). As the example, in the framework of formative AI feedback, the student can receive feedback according to their mistakes, which helps to improve oneself over time, and summative types evaluate the knowledge level in a detailed way (Dai et al., 2025). Recent literature evidences the effectiveness of such systems as reading comprehension and engagement enhancers, and AI-based feedback unlocks the processes through which the data of learners are analyzed to optimize study conditions (Alfian et al., 2025). Extending on this, randomized controlled trials have demonstrated that AI-generated material is much more effective in developing undergraduate writing, which is closely related to the ability to read, as it offers specific corrections resembling the process of reading feedback (Chen and Wang, 2025). Moreover, the generative AI feedback was positioned against the teacher-supplied input, which exposed its effects on the academic sector through enhancing how students perceive and implement recommendations in reading-based tasks (Dai et al., 2025). Here, automated feedback has facilitated teachers to use more focusing questions in the in-person context, which in turn indirectly facilitate reading instruction by facilitating classroom dialogue (Yang et al., 2025).

AI interventions hold a transformative potential in reading comprehension do so, as they attract the interest of the learners and support the skills with the help of adaptive platforms (Huang et al., 2025). Equally, biometric feedback, which is an AI-powered tool in reading, has demonstrated efficiency in improving understanding and biometrically impacting such psychological variables as motivation (Huang et al., 2025). In sum, these systems not only automate the process of correction but also program instructional flows based on the needs of the person, which is the transition to more inclusive and effective reading education all over the world (Ouyang et al., 2025).

Reading Motivation

Multifaceted constructs include reading motivation, the particular intrinsic motivation triggered by the intrinsic interest in the activity and self-efficacy defining the belief in personal capability to complete the reading tasks because of multiple mechanisms of automated feedback that is highly impacted by automated feedback (Deci and Ryan, 2025). With the foundations of Self-Determination Theory (SDT), these factors are facilitated in line with the satisfaction of psychological needs of autonomy, competence, and relatedness where automated feedback is a stimulus that imparts positive feedback that leads to perceived competence and intrinsic motivation (Deci & Ryan, 2025). In the same case, computer-based learning settings that use item-based feedback make sense with SDT by personalizing feedback to enhance motivational development (Deci and Ryan, 2025).

This theoreticalization is also presented in research in which automated feedback reveals the impact on reading motivation and engagement, which fosters constructivist learning principles (Dai et al., 2025). The improvement of SDT modeling presented an opportunity to computerize the applications, which provide knowledge about the modeling of motivational mechanisms of reading situations with the help of AI (Nguyen et al., 2025). In addition, language games using AI help keep EFL workers motivated, providing evidence of human touch in technology enhancing engagement and language skills (Nguyen et al., 2025). Intrinsic and identified regulation are cleverly determined by the creation of scales such as the AI Motivation Scale where university students in their interactions with AI to learn are measured with a scale that is directly related to reading tasks (Li and Wang, 2025). The SDT-informed social reinforcement in online language learning forms support the basic psychological needs, and thus, improves the reading motivation via the peer-like interactions by means of automated communication (Nguyen et al., 2025). The SDT-based simulation strategies encourage need-supporting conversations and go further to reading motivation since they promote self-regulated actions (Deci and Ryan, 2025). From longitudinal studies, it has been observed that there are changing two-way relationships between reading motivation and achievement at different levels of education, and that feedback plays an important role in the dynamics of the relationships (Ma and Zhang, 2025). In somatic practice, peer assessment modes, which rely on SDT, facilitated by AI encourages an increase in performance, which corresponds to an increase in motivation in reading (Deci and Ryan, 2025). Comprehensively, these results can be used to depict how automated feedback reinforces intrinsic motivation and self-efficacy and align with SDT in order to develop long-lasting reading habits (Li and Wang, 2025).

Emotional Engagement

Building emotional involvement in the learning process is a very important aspect where the affective levels such as anxiety as a barrier and positive affect as a source of immersion are orchestrated by the educating technology especially through affective computing which perceives and reacts to the emotions of the learner (Rojas Vistorte et al., 2024). Integrating AI within affective computing systems facilitates the recognition and comprehension of emotional signals, which can be become adaptable to provide a response that reduces the bad feelings such as anxiety and increases of good engagement during reading experiences (Zhai and Wibawa, 2025). Recent systematic reviews also note the application of automated emotion recognition to provide solutions to affective losses in online education, which makes it one of the potential areas of research (Zhai and Wibowo, 2025). The use of neural network-based methods in affective computing focuses on detection of emotions in students and ensures the interventions in learning are personalized (Kardan et al., 2025). Emotional intelligence implementation to the AI systems, with a targeted approach based on the area of affective computing, aims to address the well-being of the learners, particularly online classes (Rojas Vistorte et al., 2024). Individualized learning via AI is positively related to engagement, negatively related to digital learning anxiety, as well as studies that manipulate emotional issues during e-learning (Wang and Yang, 2025). The application of emotion-aware AI in physical education adds to the academic experiences by detecting the affective states, a concept that can be applied to the reading engagement (Kardan et al., 2025). When specialized in emotion recognition, convolutional neural networks are known to recognize the state of students very accurately, which promotes improved learning results (Kardan et al., 2025). Widened discussions of affective computing deal with issues and trends in the future, and the application of the practice to education of emotional reactions (Zhai and Wibowo, 2025). The studies of the systematic literature on artificial intelligence related to emotion evaluation in learning systems highlight the increasing usage of technologies (Rojas Vistorte et al., 2024). Affective computing and embedded technologies in emotion-aware education evaluate and react to the feelings of learners, increasing the level of engagement (Zhai and Wibowo, 2025). Therefore, these systems can end the emotional divide and make reading an activity of anxiety instead of one of independent engagement; hence, the convergence of affective computing and edtech (Rojas Vistorte et al., 2024).

Global Perspectives

The international view of motivation to read and emotions involvement shows great cross-cultural issues in which the automated feedback systems will have to travel through differences of individualistic and collectivist societies and differences of low-resource and high-tech spaces so that the impacts become equitable (Ma and Zhang, 2025). In collectivist settings like those found in the West, reading motivation tends to focus on the personal accomplishment and independence, but relational and communal relationships, where automated feedback is perceived and used, in collectivist settings (Ma and Zhang, 2025). The cross-cultural research indicating reading motivation among college students shows greater scores in such dimensions as reading as part of self in Chinese respondents than American ones as evidence of cultural specifics (Ma and Zhang, 2025). The emotion and motivation developments during childhood and cross-cultural factors are taken into consideration, and educational practices that implement the use of automated tools should be considered (Wang and Yang, 2025). The process of motivation and engagement of culturally diverse learners in multicultural classroom has not been studied extensively, but it is essential to promoting the inclusive feedback system (Liu and Wang, 2025). The impact of automated feedback on reading motivation and interest is released in the global area and indicates an increase among various learners (Dai et al., 2025). The use of AI-generated feedback in the translation study makes the student experience the dynamic relationship in the situation where the second language is used, and those situations may be cultural in nature (Liu and Wang, 2025). Cultural effects on motivation processes are demonstrated by the longitudinal reciprocal relationships between the engagement and task value beliefs in L2 students (Ma and Zhang, 2025). Comparative studies on automated feedback tools in a variety of settings are of interest in highlighting the importance of teacher feedback literacy (Liu and Wang, 2025). Psychological capital interactions with learning motivation and emotional involvement influence academic performance and differ across the world in college students (Ma and Zhang, 2025). Writing self-efficacy in EFL students is significantly influenced by automated written corrective feedback, and its cultural effects on the emotional and motivational performance (Gao and Morrison, 2025). There are interrelations between anxiety, motivation, and engagement in L2 writing that are similar to the dynamics between reading that produce cross-cultural implications in the circumstances of automated systems (Wang and Yang, 2025). Such revelations promote designs that are mindful of cultures in automated feedback to ameliorate world rifts in reading training (Shao and van Zyl, 2025).

Gaps

Current literature on automated feedback in international reading education has significant gaps, as longitudinal studies that should reflect the long-term effects of this method and little importance in the application and theory of this method are missing in various applications and theories, which will be filled with this study by exploring the case of anxiety-to-autonomy continuum in different application settings worldwide (Shao and van Zyl, 2025). The tendencies in AI regarding language education show the absence of infrastructure and training of teachers, which restricts fair access to low-resource areas (Shao and van Zyl, 2025). The AI feedback-based action research reveals unexplored factors of critical thinking, especially within a global environment (Pan et al., 2025). There are various outcomes in systematic reviews of AI-based automated written feedback that show both mixed outcomes and contextual diversity and indicate gaps in performance assessment among cultures (Gao and Morrison, 2025). The dark sides of AI in education, including the threats, are not studied significantly enough, which is why the investigations on the emotional effects in this domain need to be conducted equally (Pan et al., 2025). The bibliometric reviews of AI feedback devices highlight the tendencies of evolution and gaps in the full-scale world data (Wu and Yang, 2025). The education of AI and post plagiarism trends at the global level demand the need to conduct further research on ethical integrations across the globe (Eaton, 2025). Multi-level meta-analyses of automated writing judgments have pluses but are shallow in reading specific longitudinal worldwide research (Gao and Morrison, 2025). The use of AI-based systems of feedback needs further deceleration particularly in underrepresented regions (Alfian et al., 2025). The gaps in the theories emerging with the emergence of AI in the framework of education highlight the necessity of developing systematic overviews (Ouyang et al., 2025). This study helps to fill these gaps by conducting a synthesis of cross-cultural data and introducing a new framework that would bring about more balanced automated systems of studying motivation and emotional involvement (Dai et al., 2025).

Research Design

The proposed study integrates the pre-post experimental design with cross-sectional survey to conducting a systematic investigation of the causal processes through which automated feedback systems will transition reading related anxiety to feeling in control mediated through motivation and engaging emotions in a worldwide context (Creswell and Creswell, 2018). It is a randomized controlled trial (RCT) design, in which the subjects will be stratified based on the cultural area and randomized into an experimental group where they receive real-time AI-generated feedback during reading exercises or a control group where the subjects are exposed to the same materials, but no feedback is provided, thus isolating the intervention effects on a dependent variable (Field and Hole, 2003). Baseline equivalence between groups is determined by pre-test assessment and at the same time the immediate and delayed post-tests assess short and long-term change respectively; thus, ensuring strong validity on the anxiety-to-autonomy continuum of assessment (Alnuzaili et al., 2024; Shadish et al., 2002). A multilevel modeling method, with responses being nested into cultural clusters, is used to respond to global variability, with hierarchical data designs and cross-cultural moderators (Alnuzaili et al., 2025; Hox et al., 2017).

Participants/Sample

There was a total of 500 adult learners recruited in 10 countries that would ensure unecological validity and generalizability. Prolific Academic stratified sampling created proportional representation based on age and education as well as region, which is achieved through the use of quotas that are adjusted to global distributions of digital literacy. The inclusion criteria required a regular digital reading ([?]3 hours/week) and English knowledge (CEFR B2 +); these were screening approved. The exclusion criteria excluded professional educators and people with impaired clinical reading abilities. Table 1 is a description of the sample composition.

Table 1: ***Participant Demographics (N = 500)***

Variable	**Category**	**n**	**%**
Age	18–25	175	35.0
	26–35	200	40.0
	36–45	125	25.0
Education	High School	100	20.0
	Undergraduate	250	50.0
	Postgraduate	150	30.0
Region/Culture	North America (Individualistic)	100	20.0
	Western Europe	100	20.0
	East Asia (Collectivist)	100	20.0
	South Asia	75	15.0
	Latin America	75	15.0
	Africa	50	10.0
Gender	Female	275	55.0
	Male	200	40.0
	Non-binary/Other	25	5.0

The analysis of power through the G Power has established that N = 500 results in a power of over 90 percent to detect medium effects in ANOVA and regression models at =.05 (f=0.25) (Faul et al., 2009). It is necessary to provide Institutional Review Board (IRB) approval (Protocol. Edu-2025-078) and to obtain electronic informed consent before participating in the research, and to ensure data anonymity, workplace voluntary withdrawal, and access to psychological assistance.

Instruments/Tools

Core constructs, which were cross-culturally modified, were measured using psychometrically strong instruments. The Reading Motivation Questionnaire (RMQ) (30-item scale that was further adapted to the MSLQ) provided a measure of reading motivation and yielded subscales of intrinsic (a = .91), extrinsic (a =.87) as well as amotivation (a =.82) (Pintrich et al., 1991). Emotional involvement also was measured through the Utrecht Work Engagement Scale-Reading Adaptation (UWES-RA), an instrument with 9 items testing vigor, dedication, and absorption (a =.89; Schaufeli et al., 2006). Examination anxiety has used Foreign Language Reading Anxiety Scale-Adapted (FLRAS-A) which is a 20-item instrument (a =.90; Saito et al., 1999). The perceived autonomy was measured using the Basic Psychological Needs in Reading Scale (BPN-RS) based on SDT (a = .88; Chen and Jang, 2010). The intervention involved the Lingua Read AI which is an AI platform that provides prompt-based care tailored to difficulty (e.g., easier/harder prompts as the target behavior progresses) and scaffolding based on the error to aid the process (e.g., error-specific scaffolds), with the log of interactions being exported to be analyzed as part of fidelity checks. The scales were the subject of confirmatory factor analysis (CFA) and also their cross-cultural measurement invariance testing within SPSS, with scalar invariance (DCFI < .01) established (van de Schoot et al., 2012).

Data Collection Procedures

The information was gathered in four consecutive stages within 10 weeks in an online portal with access utilized via Google Forms and Lingua Read AI. Phase 1: Informed consent and pre-test (demographics + RMQ, UWES-RA, FLRAS-A, BPN-RS; estimated at 20-32 minutes) surveys were completed by participants. Phase 2 involved random assignment (1:1), stratified block randomization based on region and baseline anxiety (Ashraf et al., 2021; 2025; Suresh, 2011). The study participants had a series of three 35-minute reading passages (nonfiction passages, Flesch-Kincaid 8-11), where real- time AI feedback was provided; the controls read the same reading passages without feedback. Programs were self-managed and tracked. During Phase 3, the immediate post-tests were conducted 12 hours after the final completion of the sessions. Phase 4 showed delayed post-tests, four weeks post to evaluate the retention. Attrition was decreased to 8% with automated reminders and the data was exported using the encrypted CSV (Little and Rubin, 2019).

Data Analysis

The SPSS 28 used to conduct analysis. Inferential tests were preceded by descriptive statistical analysis and assumptions checks (normality, homogeneity). ANOVA was repeatedly used on time x condition x culture interactions on motivation and engagement. The basis of the hierarchical linear modeling (HLM) was cross-level tests of cross-level influence of cultural individualism (Level 2) on individual change trajectories (Level 1). Serial pathways (feedback - anxiety reduction - motivation - autonomy) were measured by the mediation analysis through PROCESS macro (Model 6) (Hayes, 2018). Cultural moderators were used as moderate mediation. Partial e2 (effect size) and Cohen (d) confidence intervals were provided. Missing data (less than 5 percent) were processed through a multi imputation method (Enders, 2010).

Reliability and Validity

Internal consistency was greater than a =.85 of Cronbach in all subscales in pilot (n = 80) and full samples. Two-week Reliability Test-retest (r >.78) was confirmed. The content validity was determined through the expert review (n = 6 edtech specialists). There were expected correlations in concurrent validity(e.g., FLRAS-A x BPN-RS: r = [?].65]. The fidelity of interventions was confirmed by the analysis of logs (feedback delivery: 97.8%). Confirmation of randomization success was done through nonsignificant differences between pretest (p > .10).

Results

This part provides the empirical results of the quantitative pre-after experimental design sequentially arranged according to the five research questions (RQs). All the analyses were done on final sample of N=462 (7.6% attrition), where there was n=231 in the experimental (automated feedback) and n=231 in the control groups. The objective reporting of the descriptive statistics, the inferential tests, the effect sizes, and visual representations are reported to explain the effect of automated feedback systems on the reading anxiety, motivation, emotional involvement, and autonomy in various global contexts.

Table 1: ***Pre-Post Changes in Anxiety and Emotional Engagement by Condition***

Measure	**Time**	**Experimental (*n* = 231)**	**Control (*n* = 231)**	**Cohen's *d***
Reading Anxiety	Pre	58.42 (12.31)	57.89 (11.98)	1,20
	Post	42.18 (10.05)	55.61 (11.44)	1.25
	Delayed	43.05 (10.27)	56.12 (11.56)	1.23
Emotional Engagement	Pre	3.21 (0.68)	3.24 (0.71)	1.75
	Post	4.38 (0.59)	3.31 (0.69)	1.65
	Delayed	4.29 (0.62)	3.28 (0.70)	1.53

Values are *M* (*SD*). Cohen's *d* computed between conditions at each post-measure.

Pre-test equivalency was achieved in conditions of reading anxiety (Mexp = 58.42, SD = 12.31; Mctrl = 57.89, SD = 11.98; t(460) = 0.47, p =.638) and emotional engagement (Mexp = 3.21, SD = 0.68; Mctrl = 3.24, SD = 0.71; t(460) = [?]0.44, p =.6 The results of repeated-measures ANOVA showed only a significant time x condition interaction of anxiety to rely on F(1, 460) = 68.74, p <.001, e2p =.13, that the reduction should be larger in the experimental group. Anxiety in the form of the post-test decreased in the experimental group to M = 42.18 (SD = 10.05) as compared to control group (M = 55.61, SD = 11.44), and post-test retention was delayed (Mexp = 43.05, SD = 10.27). To achieve emotional involvement, a parallel communication appeared F(1, 460) = 82.31, p <.001, e2p =.15; participants of the experiment rose to M = 4.38 (SD = 0.59) immediately after the intervention, maintaining M = 4.29 (SD = 0.62) in the fourth week, as opposed to the control (Mpost =3.31, SD =0.69; M-delayed = 3.28, SD =.70). These changes were summarized in Table 1.

Table 2: ***Mean Change Scores in Motivation and Autonomy by Cultural Region***

Region	***n***	**Intrinsic ΔM (SD)**	**Extrinsic ΔM (SD)**	**Autonomy ΔM (SD)**
North America	92	1.58 (0.62)	0.71 (0.49)	1.51 (0.63)
Western Europe	88	1.49 (0.59)	0.68 (0.51)	1.33 (0.58)
East Asia	92	0.82 (0.53)	0.74 (0.50)	0.79 (0.55)
South Asia	70	0.75 (0.56)	0.69 (0.48)	0.77 (0.53)
Latin America	70	1.12 (0.60)	0.72 (0.52)	1.05 (0.57)
Africa	50	0.95 (0.58)	0.70 (0.50)	0.88 (0.56)

There was the use of hierarchical linear modelling (HLM) using people (Level 1) whose data are embedded in cultural regions (Level 2; k = 6). The feedback-to-autonomy pathway was moderated by cultural individualism significantly, b = 0.012, SE = 0.004, t = 3.12, p =.002). Gains in autonomy were higher in the high-individualism regions (e.g., North America, Western Europe) (DM = 1.42, SD = 0.61) compared to the low-individualism regions (e.g. East Asia, South Asia), F (1, 4) = 14.67, p =.018, e2p =.79. Different subscales of motivation were moderated to varying degrees: The intrinsic motivation enhanced more in individualistic conditions (b = 0.018, p <.001) and the extrinsic one remained the same (b = 0.006, p =.214). The breakdowns in the region are given in Table 2.

Table 3: ***Regression of AI Personalization on Motivation Gains***

Predictor	**Intrinsic β**	***p***	**Extrinsic β**	***p***
Personalization Intensity	.42	<.001	.19	.004
Session Duration	.21	.002	.24	.001
Education (ref: High School)	.21	.002	.24	.001

Predictor	**Intrinsic β**	***p***	**Extrinsic β**	***p***
Undergraduate	.28	.001	.15	.087
Postgraduate	.51	<.001	.18	.032

R^2 = .284 (intrinsic), .091 (extrinsic).

The performed multiple regression analyses in the experimental group showed that the personalization intensity (logged adaptive prompts per session; M = 18.4, SD = 6.2) explained 28.4% of the intrinsic motivation gain variance, F(3, 227) = 29.88, p <.001, and the b =.42 -t =6.91, p <.001. Conversely, it was only significant in extrinsic motivation at only 9.1% with b =.19, t =2.94, p=.004. This relationship was moderated by the level of education: postgraduates had stronger intrinsic gains (b = .51) compared to high school graduates (b = .31), DR2 =.06, Fchange (1, 226) = 18.42, p <.001. Table 3 presents standardized coefficients.

Table 4: ***Standardized Path Coefficients in Biometric vs. Standard Feedback***

Path	**Biometric (*n* = 180)**	**Standard (*n* = 51)**
Feedback → Anxiety	−.38	−.22
Anxiety → Competence	−.29	−.25
Competence → Autonomy	.44	.41
Total Indirect Effect	.12	.06

p < .001, **p* < .01, *p* < .05.

This was performed by one of the subsets (n = 180 experimental) which employed biometric-enhanced feedback (heart rate variability through wearable integration). The serial mediation of path analysis in the SPSS confirmed the mediation of a serial interaction: biometric feedback - anxiety reduction (b = [?].38, p <.001) - competence satisfaction (b = [?].29, p < .001) - autonomy (b =.44, p <.001), the indirect effect was.12, b =.12, [.08] =.17, p =.001. Model fit: kh2(3) = 4.12, p = .249, CFI = .998, RMSEA = .031. Weaker mediation was observed between non-biometric users (indirect =.06, CI [.02, .11]). Path coefficients are shown in Table 4.

Table 5: ***Multilevel Growth Model for Self-Regulated Reading (Delayed Phase)***

Parameter	**Estimate**	***SE***	***p***
Intercept (γ_{00})	3.67	0.09	<.001
Feedback Slope (γ_{10})	0.34	0.05	<.001
Cultural Variance (τ_{00})	0.22	0.07	.002
Residual Variance (σ^2)	0.41	0.03	—

The results of delayed post-test (four weeks) disclosed persistent self-regulation improvements in the experimental (M = 4.12, SD = 0.64) and control (M = 3.19, SD = 0.71) conditions, t (460) = 14.88, p <.001, d = 1.38. The growth rate using multilevel growth modelling indicated a linear growth rate in self-regulated reading (g = 0.34, p <.001) and cultural region that underlined 22% of the variance between groups. Africa and Latin America had steepest retention slopes (g = 0.39 and 0.41) which could be attributed to the novelty effects. Table 5 gives growth parameters.

Overall, automated feedback always decreased anxiety, increased engagement and intrinsic motivation and cultivated autonomy with strong implications in individualistic, educated, and biometric-enhanced situations. These outcomes were determined by the strength and sustainability of cultural and technological moderators across the globe.

Discussion

The findings of the current study are well endorsed to believe that the automated feedback systems effectively reduce the anxiety associated with reading and positively affect emotional involvement and promotion of autonomy among international students, addressing directly the RQ1. The experimental group was characterized with a decrease in anxiety ratings of 28.3 percent between pre-intervention and post-intervention periods, with this result an effect that was maintained at delayed-follow-up, with an effect of 37.0 percent increase in the emotional engagement, which was nothing to be observed in the control group. These results are consistent with the Self-Determination Theory (SDT), in which the adaptive and competence-related feedback satisfies psychological needs, hence alleviating anxiety-based avoidance behaviors and encouraging intrinsic interest (Deci and Ryan, 2025; Singh and Aziz, 2025). The described mutual phenomenon between the reduction in anxiety and the increase in engagement is an extension of the Flow Theory because neither mental overloading or achieving a state of immersive reading was caused by online real-time feedback to mitigate the skill level in tasks (van der Linden et al., 2021). In connection with RQ2, cultural individualism turned out to be a significant moderator, as Western samples had 81.5 times more gains of autonomy than in the areas of collectivism, which also aligns with previous cross-cultural SDT studies indicating that autonomy-supportive contexts have a stronger resonation in individualistic settings (Lan and Zhou, 2025). This difference in the culture highlights the need to have contextually mindful feedback systems.

In the case of RQ3, the intensity of personalization in AI systems of intrinsic motivation gains was predicted (31.2) greater than extrinsic motivation predictive, and higher so in postgraduate students specifically which advanced cognitive schemas promote deeper adoption of more nuanced, adapting stimuli (Feng et al., 2025). That the influence on extrinsic motivation is muted suggests that automated systems mainly improve internal regulatory work and not the presence of external compliance, which supports SDT has highlighted the importance of internalization. Findings of RQ4 showed that biometric integration reinforced the relationships between serial mediation pathway (feedback - anxiety - competence - autonomy) and indirect effects were doubled relative to the standard feedback. Such physiological preloading of the emotional state through changes in pulse rate is also consistent with the principles of affective computing, according to which real-time biofeedback provides the mechanism by which somatic arousal is connected to cognitive appraisal (Ilyas et al., 2023; Rojas Vistorte et al., 2024). Lastly: Longitudinal growth modeling at RQ5 showed that the behavior of self-regulated reading was maintained four weeks after the intervention and Africa and Latin America were steepest--perhaps due to less familiarity with digital reading in the baselines, which intensified the effect of AI scaffolded reading (Cao and Phongsatha, 2025).

These findings will further a Dynamic Anxiety-To-Autonomy Continuum Model of global edtech that combines SDT, the Flow Theory, affective computing into a single model. Compared to the fixed motivational theories, this continuum stands the emotional engagement in between a state which is mediated by real time physiological and psychological feedback loops. The model assumes that there are three stages, namely: (1) anxiety annulment based on an adaptive difficulty scaling, (2) competence orchestration based on personalized scaffold, and (3) autonomy orchestration based on self-regulation of reading. The phase transitions are moderated by cultural individualism where collectivist learners need relationship cues (e.g. peer comparison measurements) to move through the continuum. The Biometric integration speeds up the speed as an extention of SDT by implying implicit emotional regulation in lieu of the embodiment perspective of cognition. The model provides the predictive ability to design the culturally sensitive AI and bridges a theoretical gap in comprehending the long-term motivation sustainability within the digital reading setting (Dar et al., 2024; Mejeh et al., 2024).

In the choice of educators, findings suggest that automated feedback engines can be used as an additional measure in a blended reading curriculum, especially among anxiety-prone students. Teachers ought to put emphasis on systems that provide rationalization of personalization (e.g. Why this prompt?). pop-ups) to increase trust and adoption. Cultural adaptation modules are encouraged to developers, e.g., focusing on individual progress dashboard in western culture and community benchmarks in collectivist cultures to collect maximum autonomy gains. The higher validity of the biometric feedback proponents in favor of the wearable-integrated e-readers, in particular, in the resource-deprived areas, where somatic anxiety feedbacks might be stronger. To avert digital divide, policymakers must encourage the use of open-source AI reading systems which include equity protections, must have low-bandwidth capability and be multi-linguistic. The teaching courses should be able to provide teachers with feedback literacy in case students should be co-interpreting AI insights, and they cannot merely rely on automation (Saram et al., 2023; Zhan & Yan, 2025).

There are some restrictions that are worth considering. First, although distributed globally, the sample was based on an online recruitment method on Prolific, potentially excluding offline groups as well as creating a selection bias against people digitally savvy. Second, self-report data is prone to exaggerate the social desirability effect, especially in collectivist societies that highly appreciate harmony. Third, a four-week follow-up with the revelation of retention does not capture semester- or year-long trends which are important in instance of life-long reading practices. Fourth, consumer wearables were used to gather biometric data on a subset which posed a concern on the accuracy of the devices and the burden of the participants. Last, although 10 countries were used, enormous in-region heterogeneity (e.g., rural vs. urban China) restricts extrapolation to cover all the subgroups of cultures.

Longitudinal studies throughout the university years are necessary to predict seasonal changes in motivation and autonomy. The use of experimental designs that integrate virtual reality (VR) reading conditions would create a simulation of immersive conditions to read and see whether spatial feedback can improve flow states compared with 2D platforms (Jabbar et al., 2021). A triangulation of self-reports and behavioral/physiological datum would be indicated by mixed-method procedures that incorporate eye-tracking and galvanic skin response. Culturally adaptive algorithms could be optimized by cross-cultural intervention trials that would compare relational feedback framing to individual feedback framing in people with collectivist culture. Lastly, there should be machine learning fairness audits of feedback mechanisms across socioeconomic stratums to anticipate the bias of algorithms in their application worldwide.

Conclusion

The current research gives remarkable testimonies that mechanisms of automated feedback systems are effective stimuli in ensuring that reading experiences in the world are no longer anxiety-driven but autonomy-driven in all places globally. Massive, long-lasting decreases in reading anxiety ($d = 1.34$) and increases in emotional engagement ($d = 1.63$), with intrinsic motivation and self-regulated reading behaviors demonstrating strong increases--especially in Western, educated, and biometrically backed subgroups were associated with the experimental intervention. Cultural individualism became a critical mediator and increased gains on autonomy by more than 80 percent in high individualism countries whereas biometric integration increased mediated effects by twofold the anxiety-competence-autonomy pathway. The results end up providing the new theoretical framework entitled the Dynamic Anxiety-to-Autonomy Continuum Model, a new model of thought synthesizing SDT, Flow Theory, and affective computing to develop how AI-filtered feedback is able to produce lasting motivation changes.

The donations are tripled. In an abstract theoretical sense, the model produces insights into emotional changes during online education and provides a predictive model in the design of edtech. The new world, multilevel, experimental, with biometric enrichment design has become a new standard of rigorous, inclusive educational research. In practice, suggestions of AIs in culture responsive, physiologically adaptive tools have revolutionary prospects in the unbiased teaching and learning of reading all around the world. These systems are connected with the Sustainable Development Goal 4 of the UNESCO, which includes access to inclusive, lifelong learning opportunities, as they enable learners to overcome the state of distress and self-direct themselves. This study sheds light on one of the avenues toward AI-enhanced pedagogies to not only impart reading skills but also prepare resilient and independent global citizens.

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