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Beauty in the Minds of Language Learners: A Portray of the Nexus between AI Psychological Flow, Grit Tendencies, Mental Health, and Critical Thinking

Tahereh Heydarnejad[1*]
Behruz Lotfi Gaskaree[2]
Sajjad Zahedi Moghaddam[3]
Ali Mavaddat Kakhki[4]

[*1]Assistant Professor of Applied Linguistics, Department of English Language, Faculty of Literature and Humanities, University of Gonabad, Gonabad, Iran
[2]Assistant Professor of Applied Linguistics, Department of English Language, Faculty of Literature and Humanities, University of Zabol, Iran
[3]M.A. in Applied Linguistics, Department of English Language, Faculty of Literature and Humanities, University of Zabol, Zabol, Iran
[4]M.A. in Applied Linguistics, Department of English Language, Faculty of Literature and Humanities, Hakim Sabzevari University, Sabzevar, Iran

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CORRESPONDING AUTHOR

E-mail: heydarnejad@gonabad.ac.ir

ABSTRACT

The incorporation of Artificial Intelligence (AI) into language development has garnered considerable interest, especially within the realm of English as a Foreign Language (EFL) education. Psychological flow is regarded as a pivotal element that affects learning outcomes; however, its significance in the context of AI-assisted language learning has yet to be thoroughly investigated. This study examines the relationship between psychological flow induced by AI, tendencies of fortitude, mental health, and critical thinking among 214 university students enrolled in EFL programs who utilized AI-integrated language learning aids. Data were gathered via structured online surveys, and the relationships among the variables were examined utilizing Structural Equation Modeling (SEM). The findings suggest that the psychological flow induced by AI has a substantial impact on learners' levels of fortitude, mental well-being, and critical thinking. The findings indicate that when learners engage in AI-assisted language learning and experience a state of flow, they exhibit elevated levels of perseverance, improved mental well-being, and enhanced critical thinking. These outcomes underscore the dual function of flow in AI-assisted language learning, as it not only augments learners' cognitive engagement but also fosters positive emotional states that are conducive to improved mental health and enhanced problem-solving abilities. The findings of the study possess significant pedagogical implications, indicating that AI-based platforms ought to be developed to promote a state of fluidity by integrating personalized learning trajectories, real-time feedback mechanisms, and engaging features.

KEYWORDS: AI psychological flow; Grit tendencies; Mental health; Critical thinking; EFL learners

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1. Introduction

The integration of AI in language education has sparked a growing interest in understanding its impact on learners' psychological and cognitive processes (Wang & Xue, 2024; Xiao et al., 2024). A notable concept that has gained prominence in this context is AI psychological flow, a state of deep immersion and intrinsic motivation that enhances learning experiences (Norsworthy et al., 2023; Zhai et al., 2024). AI-assisted language learning (AIALL) has the potential to facilitate psychological flow by providing personalized and adaptive learning environments allowing learners to engage in meaningful and enjoyable tasks (Payant & Zuniga, 2022). However, the effectiveness of AIALL in fostering psychological flow is contingent on various individual and contextual factors, including grit tendencies, mental health, and critical thinking skills (Zhai et al., 2024).

Grit, characterized by perseverance and passion for long-term goals, has been identified as a crucial determinant of success in educational settings (Duckworth et al., 2007). In the realm of language learning, grit has been linked to sustained motivation, engagement, and achievement (Zhang et al., 2022). Language learners with high levels of grit are more likely to persist in their studies despite challenges, demonstrating resilience and a strong commitment to their goals (Namaziandost et al., 2024). The interplay between grit and AIALL presents an intriguing avenue for exploration, as the adaptive nature of AI tools may either enhance or hinder learners' perseverance depending on their individual tendencies (Zhai et al., 2024).

In addition to grit, mental health is a critical factor influencing language learning outcomes. Positive mental health contributes to academic success, while poor mental health can hinder cognitive functioning and motivation (Chen & Kim, 2024). The pressures of language learning, coupled with the challenges of adapting to AI-driven environments, may exacerbate mental health issues such as anxiety and stress (Wu, 2023). Nevertheless, AI technologies offer opportunities for mental health support through personalized interventions and virtual companions, which can alleviate some of the psychological burdens faced by learners (Long & Lin, 2023).

Critical thinking (CT), another essential component of effective language learning, involves the ability to analyze, evaluate, and synthesize information (Halpern, 2003). The development of CT skills is vital in AI-assisted learning environments, where learners should navigate vast amounts of information and engage with interactive technologies in meaningful ways (Namaziandost et al., 2023). Studies suggest that AI tools, when used appropriately, can enhance critical thinking by providing learners with opportunities to engage in problem-solving, debates, and self-directed learning (Liu & Wang, 2024; Shen & Teng, 2024). However, concerns have been raised regarding the potential for AI to foster passive learning and reduce opportunities for deep cognitive engagement (Wang & Xue, 2024).

Notwithstanding the increasing corpus of studies on AI in education, understanding the interactions among psychological and cognitive factors in the framework of AIALL still lags. The present study aims to bridge this gap by exploring how AI psychological flow interacts with learners' grit tendencies, mental health, and CT, ultimately shaping their language learning experiences and outcomes. This choice of factors is based on their direct connection to the motivating and cognitive states of learners, which are essential for maximizing the results of language learning. The incorporation of these factors is also affected by their potential to direct the design of AIALL settings. By critically examining these relationships, this study seeks to provide valuable insights for educators, policymakers, and technology developers, ensuring that AIALL environments are designed to optimize learners' psychological and cognitive well-being. A nuanced understanding of these factors will contribute to the development of more effective, engaging, and supportive AI-driven language learning experiences. Keeping these stands points in the mind, the following research questions are proposed:

RQ1: Does AI psychological flow among EFL learners affect their grit tendencies in the voyage of AI-assisted language learning?

RQ2: Does AI psychological flow among EFL learners affect their mental health in the voyage of AI-assisted language learning?

RQ3: Does AI psychological flow among EFL learners affect their CT skills in the voyage of AI-assisted language learning?

2. Theoretical framework

2.1. AI psychological flow

Csíkszentmihályi first described the concept of flow in the book "Beyond Boredom and Anxiety" and has since explored it across various domains, such as art, sports, and work (Csikszentmihalyi, 2000). Furthermore, Shernoff and Csikszentmihalyi (2009) describe flow as the "subjective buoyancy of experience when skillful and successful actions seem effortless, even when a great deal of physical or mental energy is exerted" (p. 137). Psychological flow can play a significant role in language learning. Second-language researchers have investigated the interaction between second-language classroom dynamics and a diverse array of individual difference factors and language tasks, both in traditional classroom settings and online environments, employing various implementation variables (Amini et al., 2016; Ibrahim, 2020; Norsworthy et al., 2023; Payant & Zuniga, 2022). Moreover, Zuniga

(2023) confirmed that high school students who reported frequent flow experiences were more likely to develop skills and perform better in activities related to art, music, athletics, math, and science. Studies in language learning indicated that reaching a flow state can significantly improve language acquisition and retention. Individuals who regularly experience flow are more inclined to immerse themselves in the material, resulting in enhanced proficiency and increased satisfaction with the learning experience (Ibrahim, 2020). Amini et al. (2016) discovered a positive correlation between flow experiences and vocabulary knowledge gains. Similarly, Engeser et al. (2005) found positive correlations between flow experiences during a French L2 class and results on a final exam.

2.2. Grit tendencies

Grit, defined as perseverance toward long-term goals despite setbacks (Duckworth et al., 2007), is critical in language learning's iterative nature. Duckworth's model emphasizes two components: Perseverance of Effort, which is a sustained practice despite challenges, and Consistency of Interest, which is a stable commitment to fluency goals (Duckworth et al., 2007). The Triarchic Model of Grit (Datu et al., 2018) expands this by integrating resilience and psychological capital. AI tools have the potential to scaffold grit through adaptive reminders, progress visualizations, and encouragement, fostering resilience and self-efficacy (Datu et al., 2018). Overall, grit could reinforce flow by maintaining effort during challenging tasks and indirectly buffer mental health by promoting a growth mindset. In recent years, a growing body of research has begun to explore the significance of grit in language development. Furthermore, Shafiee Rad and Jafarpour (2022) found that efficient emotion management positively impacts grit, emotion control, and resilience in the process of learning English. Similarly, Ghanbari and Abdolrezapour (2021) discovered that positive emotions and perseverance of EFL learners in L2 were beneficial to their academic development. Researchers have also found that individuals with high levels of grit tend to have a positive attitude in their working life (Lan, 2022) and higher ability to focus on their goals and try harder to achieve them (Hejazi & Sadoughi, 2022). Additionally, the literature suggest that grit is a strong predictor of motivation to study, engagement with learning, and success in the English language (Wei et al., 2019; Zhang et al., 2022; Zhao & Wang, 2023). Gao et al. (2024) and Zhai et al. (2024) have underlined that learners exhibiting more significant levels of grit are more inclined to consistently engage with learning technologies, suggesting that grit may play an essential role in the adoption and effective utilization of AI-driven language learning tools.

2.3. Mental health

Mental health is a fundamental aspect of human well-being, encompassing a holistic state where individuals can realize their potential, cope with life's stresses, work productively, and contribute to their communities (Newson et al., 2024). Mental health in AI-ALL can be framed through the Task-Orientation vs. Self-Orientation dichotomy (Rogers, 1961). Task-oriented learners focus on goal-driven activities, which enhance self-efficacy, whereas self-orientation correlates with anxiety over perceived inadequacies (Rogers, 1961). Positive mental health could enable flow states, sustain grit, and create a safe environment for critical thinking. Although Tucker and Leriche (1964) mentioned that defining mental health is complex and subjective, this multifaceted construct is characterized by positive feelings about oneself and life, resilience in the face of adversity, and the ability to maintain healthy relationships (Manderscheid et al., 2010). Positive mental health is widely recognized as a crucial factor in coping with adversity and promoting positive developmental outcomes (Moore et al., 2023).

Despite its importance, millions of individuals worldwide struggle with mental health issues (Wu, 2023). This challenge is particularly prevalent among college and university students, whose emotional and mental well-being is closely linked to their academic performance, course completion, and overall success in higher education (Cage et al., 2018). The prevalence of mental health issues among students, mainly EFL learners, can be attributed to several interrelated factors. A significant concern is academic pressure, where high levels of anxiety, depression, and stress are reported, with study-related worries being the most impactful (Thang et al., 2022). Additionally, the problematic use of social media has been linked to increased foreign language anxiety and academic burnout, further exacerbating mental health challenges (Shu, 2023). Furthermore, barriers to accessing mental health support within university settings contribute to the persistence of these issues (Cage et al., 2018).

Moreover, various research has identified several factors that contribute to or exacerbate mental health issues among university students. These include the academic pressures of studying, the culture and systems within educational institutions, and the overall stress associated with the university experience (Neves & Hillman, 2019; Lee & Kim, 2018; Winzer et al., 2018). Furthermore, Chen and Kim's (2024) study found a strong correlation between students' mental health scores and their English language achievement, highlighting the interconnectedness of emotional well-being and academic success. As technology continues to advance, the landscape of mental health support for college students is also evolving. One emerging trend is the integration of AI into the field of mental health care (Wu, 2023). Additionally, AI-powered online psychological counseling services can provide students with access to mental health support at any time and from any location, addressing the challenges of limited on-campus resources and the stigma associated with seeking help (Moore et al., 2023).

2.4. Critical thinking

CT is a complex and multifaceted construct that has been the subject of extensive research and theoretical frameworks. Socrates is widely recognized as the first philosopher to conceptualize and promote critical thinking as a fundamental component of human cognition and learning (Paul, 1988). Halpern (2003) defines CT as a type of higher-order thinking that results from cognitive mechanisms and mental practices. This emphasis on cognitive skills and dispositions underscores the importance of CT in modern education, as it prepares students for the evolving job market, enhances informed citizenship, and addresses the gap between employer demand and graduate preparedness, particularly in the context of increasing AI-driven job automation. Theoretically, CT encompasses a range of cognitive skills, including problem-solving, inference formulation, probability assessment, and decision-making (Li & Heydarnejad, 2024). The assessment of the cognitive process, the rationale underlying the conclusions reached, and the multiple aspects considered during decision-making are also central to the conceptualization of CT (Halpern & Dunn, 2023). The integration of AI introduces a new layer of complexity to the study of CT. Studies have indicated that AI-driven interventions, such as using generative AI for interactive quizzes and debates, can lead to statistically significant improvements in CT abilities compared to traditional methods (Heydarnejad & Çakmak, 2024; Liu & Wang, 2024). Additionally, the interplay between CT, self-directed learning, and AI-assisted writing highlights the importance of fostering independent learning to mitigate over-reliance on AI tools (Shen & Teng, 2024). Furthermore, the responsible integration of generative AI in language teaching necessitates clear guidelines to ensure that these technologies enhance rather than replace CT and human interaction (Cogo et al., 2024).

3. Methodology

3.1. Participants and settings

This survey included 214 university students, and the data was collected in the second semester of the 2024 academic year. The sample included students from three major academic disciplines: Teaching English as a Foreign Language (TEFL), Translation Studies, and English Literature at the MA level at universities of Khorasan Shomali, Khorasan Razavi, and Tehran. The students were chosen using a non-random, convenience selection technique. All participants confirmed their active use of AI-assisted language learning tools throughout their education, based on responses from a pre-study questionnaire and course records. The participants ranged in age from 18 to 25 years (136 female, 78 male), predominantly identifying as non-native English speakers. They were in the first or second year of their Master's program and hailed from various ethnic backgrounds, including Persian, Kurdish, and other prevalent ethnic groups in the region. Socioeconomic status was diverse, with students from both urban and suburban regions. The research sought to encompass a diverse array of learners about their academic and cultural experiences.

3.2. Instruments

The AI Psychological Flow Scale (AIPFS) was implemented by Norsworthy et al. (2023) to evaluate the emotions and thoughts that students may have encountered during the application of AI. This scale comprised nine items in a seven-point Likert scale: Absorption, Intrinsic Reward, and Effort-less Control. The grit inclinations of the students were assessed using the language-domain-specific grit scale (LDSGS), which was developed by Teimouri et al. (2020). This scale comprises 12 items: six items to evaluate perseverance of effort and six items to evaluate the consistency of interest on a five-point Likert scale that ranges from 1 (not at all like me) to 5 (very much like me). The Mental Health Quality of Life Questionnaire (MHQoL) evaluates the participants' mental health and quality of life (van Krugten et al., 2022). The MHQoL consists of seven items that address self-image, independence, mood, relationships, daily activities, physical health, and future outlook, organized into 26 items rated on a six-point Likert scale. The CT of the participants was evaluated using the Watson–Glaser Critical Thinking Appraisal Form A, developed by Watson and Glaser (1980). This scale has five sections: inference (16 items), detecting assumptions (16 items), making deductions (16 items), interpretation (16 items), and assessment (16 items). The reliability and validity of the applied instruments were assessed and reported on Table 1.

Table 1. Report on construct reliability and validity

Constructs		Average Variance Extracted (AVE)	Cronbach's Alpha	Composite Reliability
AI Psychological Flow	Absorption	0.786	0.872	0.922
	Effort-less Control	0.694	0.890	0.929
	Intrinsic Reward	0.793	0.881	0.925
	total	0.758	0.758	0.892
L2 Grit	Consistency of Interest	0.728	0.815	0.889
	Perseverance of Effort	0.653	0.821	0.882
	total	0.685	0.773	0.898

Mental Health	Self-image	0.749	0.889	0.923
	Independence	0.651	0.821	0.881
	Mood	0.593	0.705	0.816
	Relationships	0.610	0.729	0.826
	Daily Activities	0.631	0.819	0.872
	Physical Health	0.631	0.724	0.825
	Future	0.579	0.749	0.808
	total	0.635	0.760	0.879
Critical Thinking	Inference	0.505	0.920	0.931
	Recognizing Assumptions	0.528	0.894	0.904
	Making Deductions	0.502	0.932	0.939
	Interpretation	0.546	0.814	0.798
	Evaluation	0.511	0.848	0.869
	total	0.518	0.738	0.808

Table 1 presents critical reliability and validity indicators for the constructs used in the investigation. The AVE, Cronbach's Alpha, and Composite Reliability values are displayed for each construct and its related components, offering insight into the internal consistency and convergent validity of the metrics. The components of the AI Psychological Flow construct—Absorption, Effortless Control, and Intrinsic Reward—exhibit robust dependability, with Cronbach's Alpha values ranging from 0.872 to 0.890, signifying good internal consistency. The Composite Reliability ratings go from 0.922 to 0.929, indicating a high level of consistency among the components. The overall AVE for this construct is 0.758, signifying strong convergent validity. The L2 Grit construct, consisting of Consistency of Interest and Perseverance of Effort, has an overall Composite Reliability of 0.898 and a total AVE of 0.685, which is satisfactory although somewhat inferior to that of AI Psychological Flow. Cronbach's Alpha scores demonstrate robust internal consistency across the components, ranging from 0.773 to 0.821. The Mental Health construct's constituent components, including Self-image, Independence, and Mood, exhibit good to moderate reliability, with Cronbach's Alpha values between 0.705 and 0.889, and Composite Reliability scores ranging from 0.808 to 0.872. The overall AVE of 0.635 signifies satisfactory convergent validity. The CT construct's individual subscales—Inference, Recognizing Assumptions, Making Deductions, Interpretation, and Evaluation—exhibit high Cronbach's Alpha values, between 0.814 to 0.932, indicating exceptional internal consistency.

3.3. Data collection

Data was gathered over the course of three months in the second semester of the 2024 school year. Participants in the research were given access to an online survey platform via their course teachers. The study included a set of standardized questions assessing AI psychological flow, grit inclinations, mental wellness, and critical thinking abilities. Each of the instruments were developed to evaluate students' self-reported experiences with AI-assisted language acquisition and their corresponding psychological states.

3.4. Data analysis

The data were analyzed using Smart PLS (Partial Least Squares), a statistical software that is frequently employed to analyze data with non-normal distributions, as a result of the non-normality of the data distribution. The selection of Smart PLS was based on its capacity to estimate the parameters of the model using the Partial Least Squares method, which is robust in situations where data deviate from normality, and to manage intricate relationships between variables. The relationships among AI psychological flow, grit tendencies, mental health, and critical thinking skills were tested using SEM via Smart PLS in the study. The SEM model was developed to investigate the direct and indirect effects between the constructs. The procedure of analysis consisted of various stages: Using indices such as Cronbach's alpha, composite reliability, and average variance extracted (AVE), the validity and dependability of the constructs were evaluated.

4. Results

To decide about the appropriate data analysis procedure, firstly, the Kolmogorov-Smirnov test was applied.

Table 2. Kolmogorov-smirnov test

	Kolmogorov-Smirnov Z	Asymp. Sig. (2-tailed)
Absorption	0.179	0.000
Effort-less Control	0.121	0.000

Intrinsic Reward	0.115	0.000
AI Psychological Flow	0.064	0.034
Consistency of Interest	0.099	0.000
Perseverance of Effort	0.112	0.000
L2 Grit	0.074	0.007
Self-image	0.094	0.000
Independence	0.081	0.002
Mood	0.090	0.000
Relationships	0.081	0.002
Daily Activities	0.092	0.000
Physical Health	0.159	0.000
Future	0.206	0.000
Mental Health	0.157	0.000
Inference	0.085	0.001
Recognizing Assumptions	0.105	0.000
Making Deductions	0.072	0.008
Interpretation	0.142	0.000
Evaluation	0.070	0.013
Critical Thinking	0.152	0.000

The Kolmogorov-Smirnov test findings (Table 2) indicate that most variables display non-normal distributions, suggesting the necessity of nonparametric statistical approaches for subsequent analysis.

Table 3. Report on the t-statistics and factor loadings

		Questions	Original Sample	T -Statistics
AI Psychological Flow	Absorption	A1	0.898	30.185
		A2	0.845	53.551
		A3	0.915	74.121
	Effort-less Control	A4	0.664	15.934
		A5	0.825	26.650
		A6	0.980	66.992
	Intrinsic Reward	A7	0.750	19.715
		A8	0.949	51.274
		A9	0.957	60.985
L2 Grit	Consistency of Interest	S1	0.874	56.422
		S2	0.882	49.384
		S3	0.802	24.277
	Perseverance of Effort	S4	0.753	22.803
		S5	0.876	46.160
		S6	0.851	33.586
		S7	0.743	15.233
Mental Health	Self-image	M1	0.866	37.516
		M2	0.897	69.259
		M3	0.849	29.828
		M4	0.850	47.393
	Independence	M5	0.762	17.173
		M6	0.809	21.203
		M7	0.857	37.766
		M8	0.796	20.399
	Mood	M9	0.702	13.082
		M10	0.894	54.364
		M11	0.837	33.231
		M12	0.616	14.252
	Relationships	M13	0.651	14.323
		M14	0.814	18.490
		M15	0.806	21.220
		M16	0.839	29.669
	Daily Activities	M17	0.839	26.452
		M18	0.788	17.743
		M19	0.767	14.147
		M20	0.781	19.293

	Physical Health	M21	0.671	15.140
		M22	0.862	31.049
		M23	0.785	22.518
		M24	0.845	32.568
	Future	M25	0.833	32.368
		M26	0.746	21.957
		M27	0.674	11.108
		M28	0.782	22.799
Critical Thinking	Inference	C1	0.630	11.428
		C2	0.722	27.124
		C3	0.698	16.539
		C4	0.817	31.500
		C5	0.626	14.583
		C6	0.769	26.270
		C7	0.639	15.713
		C8	0.696	14.915
		C9	0.556	13.831
		C10	0.742	26.234
		C11	0.709	23.907
		C12	0.812	38.157
		C13	0.821	31.567
		C14	0.734	26.571
		C15	0.750	29.001
		C16	0.579	5.034
	Recognizing Assumptions	C17	0.727	23.445
		C18	0.756	23.648
		C19	0.886	33.967
		C20	0.817	28.910
		C21	0.729	24.985
		C22	0.590	13.039
		C23	0.658	16.832
		C24	0.758	23.253
		C25	0.704	20.388
		C26	0.661	15.334
		C27	0.806	30.581
		C28	0.795	23.105
		C29	0.603	13.195
		C30	0.895	42.811
		C31	0.573	8.138
		C32	0.542	7.148
	Making Deductions	C33	0.666	13.906
		C34	0.773	24.134
		C35	0.783	26.903
		C36	0.724	24.593
		C37	0.668	13.105
		C38	0.706	20.590
		C39	0.798	24.324
		C40	0.782	24.531
		C41	0.708	21.115
		C42	0.654	14.205
		C43	0.677	13.989
		C44	0.623	13.650
		C45	0.720	24.550
		C46	0.737	24.129
		C47	0.672	13.690
		C48	0.604	13.846
	Interpretation	C49	0.685	15.541
		C50	0.811	32.965
		C51	0.796	22.726
		C52	0.694	11.890
		C53	0.832	42.685
		C54	0.698	12.719
		C55	0.607	12.449
		C56	0.836	41.770
		C57	0.824	40.549

	C58	0.788	33.469
	C59	0.543	8.595
	C60	0.748	20.526
	C61	0.620	11.135
	C62	0.899	40.378
	C63	0.563	10.351
	C64	0.765	20.624
	C65	0.810	40.114
Evaluation	C66	0.833	35.376
	C67	0.773	22.143
	C68	0.830	37.461
	C69	0.619	11.705
	C70	0.732	17.534
	C71	0.550	7.765
	C72	0.672	14.436
	C73	0.669	12.803
	C74	0.635	11.954
	C75	0.716	15.204
	C76	0.758	26.180
	C77	0.730	19.589
	C78	0.694	18.796
	C79	0.771	35.242
	C80	0.564	10.746

Table 3 displays the T-statistics and factor loadings for items associated with psychological dimensions, including AI Psychological Flow, Intrinsic Reward, L2 Grit, Mental Health, and CT, among others. Each item is assessed for its contribution to its particular construct via T-statistics, with elevated T-values signifying greater associations between the item and the underlying component. In AI Psychological Flow, all three items (A1, A2, A3) have exceptionally high T-statistics, ranging from 30.185 to 74.121, demonstrating their substantial significance to the construct. Likewise, Effort-less Control and Intrinsic Reward have significant factor loadings, with T-statistics between 15.934 and 66.992, so affirming the strength of the association between the items and their corresponding constructs. The L2 Grit construct is effectively represented, with Consistency of Interest items (S1, S2, S3) exhibiting T-statistics between 24.277 and 56.422, and Perseverance of Effort items (S4, S5, S6, S7) displaying T-values from 15.233 to 46.160, all of which are statistically significant.

The Self-image items (M1, M2, M3, M4) under the Mental Health construct have significant T-statistics, ranging from 13.082 to 69.259, whilst the Independence items (M5, M6, M7, M8) likewise present elevated T-values between 17.173 and 37.766. The Mood items (M9, M10, M11, M12) and Relationships items (M13, M14, M15, M16) have comparable robust correlations, with T-statistics predominantly over 13, indicating their significant contributions to their respective variables. The Daily Activities and Physical Health variables have substantial loadings, with T-statistics between 11.108 and 32.568, affirming their significance in the model. The Future components (M25, M26, M27, M28) have T-values ranging from 11.108 to 32.368, further demonstrating their contribution to the construct. Within the CT domain, questions pertaining to Inference, Recognizing Assumptions, Making Deductions, Interpretation, and Evaluation display a variety of T-statistics, predominantly characterized by elevated T-values, exemplified by C12 (38.157) and C30 (42.811).

Table 4. Correlation analysis

	AI Psychological Flow	Social Isolation	Mental Health	Critical Thinking
AI Psychological Flow	0.871			
L2 Grit	0.640**	0.917		
Mental Health	0.747**	0.523**	0.766	
Critical Thinking	0.821**	0.578**	0.540**	0.801

Correlation is significant at the 0.01 level (2 tailed) **

Table 4 presents the correlation matrix for four constructs: AI Psychological Flow, L2 Grit, Mental Health, and CT. The correlation values provide insights into the strength and direction of the relationships between these constructs, with significant correlations noted at the 0.01 level (two-tailed). The AI Psychological Flow construct shows strong positive correlations with L2 Grit (r = 0.640) and CT (r = 0.821). These significant correlations suggest that higher levels of psychological flow are associated with greater grit and CT abilities. Additionally, AI Psychological Flow is moderately correlated with Mental Health (r = 0.747), indicating a strong positive relationship between psychological flow and mental well-being. L2 Grit has a very strong correlation with CT (r = 0.917), suggesting that individuals with higher levels of grit tend to display better CT skills. It is also positively correlated with Mental Health (r = 0.523), though this correlation is somewhat weaker compared to its relationship with CT. The Mental Health construct shows moderate positive correlations with both CT (r = 0.540) and AI Psychological Flow (r = 0.747), highlighting that individuals who are mentally healthier tend to engage more in psychological flow and perform better in critical thinking tasks.

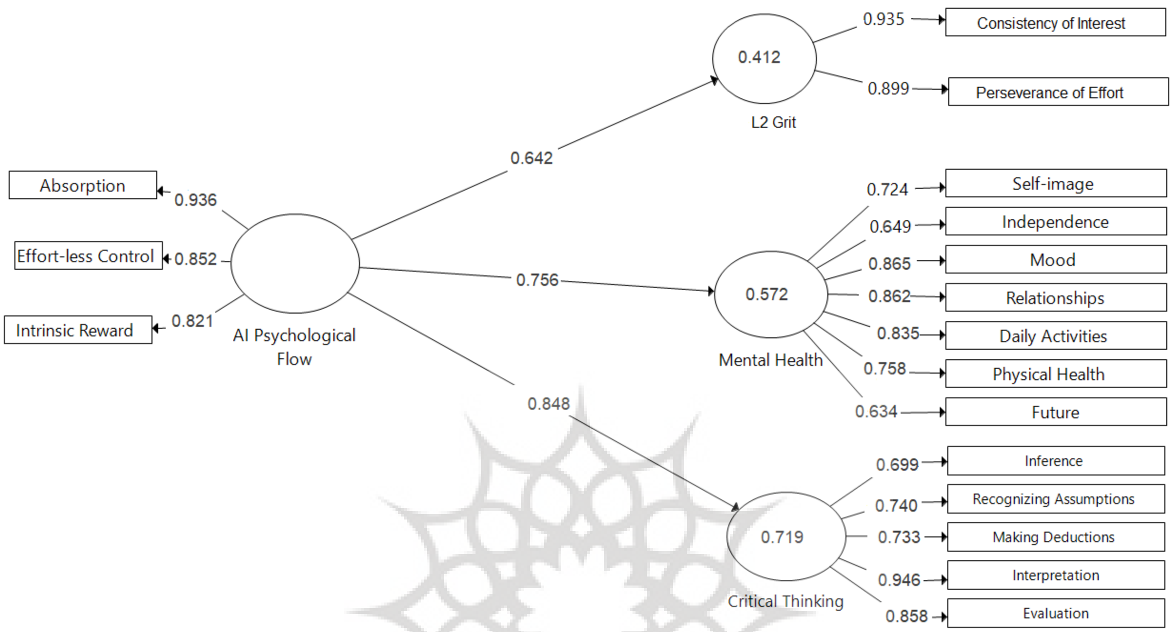

Figure 1. Factors coefficients and path coefficient of the first research model

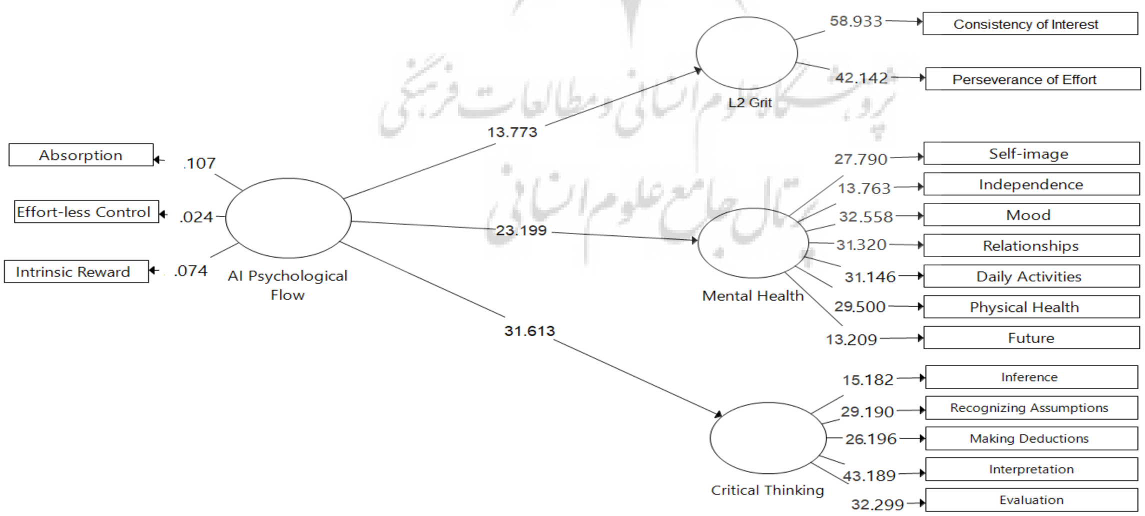

Figure 2. The value of the first research model's path coefficients

Table 5. The report on path coefficients and test results

Paths	Path coefficient	T Statistics	Test results

AI Psychological Flow	→	L2 Grit	0.642	13.773	Supported
AI Psychological Flow	→	Mental Health	0.756	23.199	Supported
AI Psychological Flow	→	Critical Thinking	0.848	31.613	Supported

Based on Figures 1 and 2 as well as Table 5, the path coefficient from AI Psychological Flow to L2 Grit is 0.642, with a highly significant T-statistic of 13.773. This result indicates a strong and statistically supported positive relationship between AI Psychological Flow and L2 Grit, suggesting that greater engagement in psychological flow is associated with higher levels of grit. Similarly, the relationship between AI Psychological Flow and Mental Health has a path coefficient of 0.756, with a T-statistic of 23.199, indicating a very strong and statistically significant positive relationship. This suggests that higher levels of psychological flow are strongly linked to better mental health outcomes. The path from AI Psychological Flow to CT shows an even stronger path coefficient of 0.848, with an impressive T-statistic of 31.613, confirming a highly significant and positive relationship.

Table 6. The model fit indexes (model 1)

	R^2	Q^2
L2 Grit	0.412	0.252
Mental Health	0.572	0.284
Critical Thinking	0.719	0.331

GOF=$\sqrt{0.707 * 0.568}$ =0.634

Table 6 displays the R^2 and Q^2 values for the domains L2 Grit, Mental Health, and Critical Thinking, in addition to the Goodness of Fit (GOF) assessment. These metrics provide insights into the model's explanatory capacity and predictive usefulness. The R^2 values indicate the percentage of variance elucidated by the model for each construct. The R^2 score for L2 Grit is 0.412, indicating that around 41.2% of the variation in grit is accounted for by the model. The R^2 score for Mental Health is 0.572, indicating that 57.2% of the variation in mental health is explained by the model. The CT component has the highest R^2 value of 0.719, indicating that the model accounts for 71.9% of the variation in critical thinking. The Q^2 values evaluate the model's predictive relevance, with higher values indicating superior predictive ability. L2 Grit has a Q^2 of 0.252, indicating modest predictive significance. Mental Health has a Q^2 of 0.284, indicating a somewhat enhanced predictive significance. The CT construct has the highest Q^2 value of 0.331, indicating that the model possesses the most robust predictive relevance for CT. The GOF is determined by taking the square root of the product of the mean R^2 and Q^2 values. The GOF is computed as $\sqrt{0.707 * 0.568}$ = 0.634. A GOF value over 0.36 is seen indicative of a satisfactory fit, indicating that the model exhibits an acceptable overall alignment.

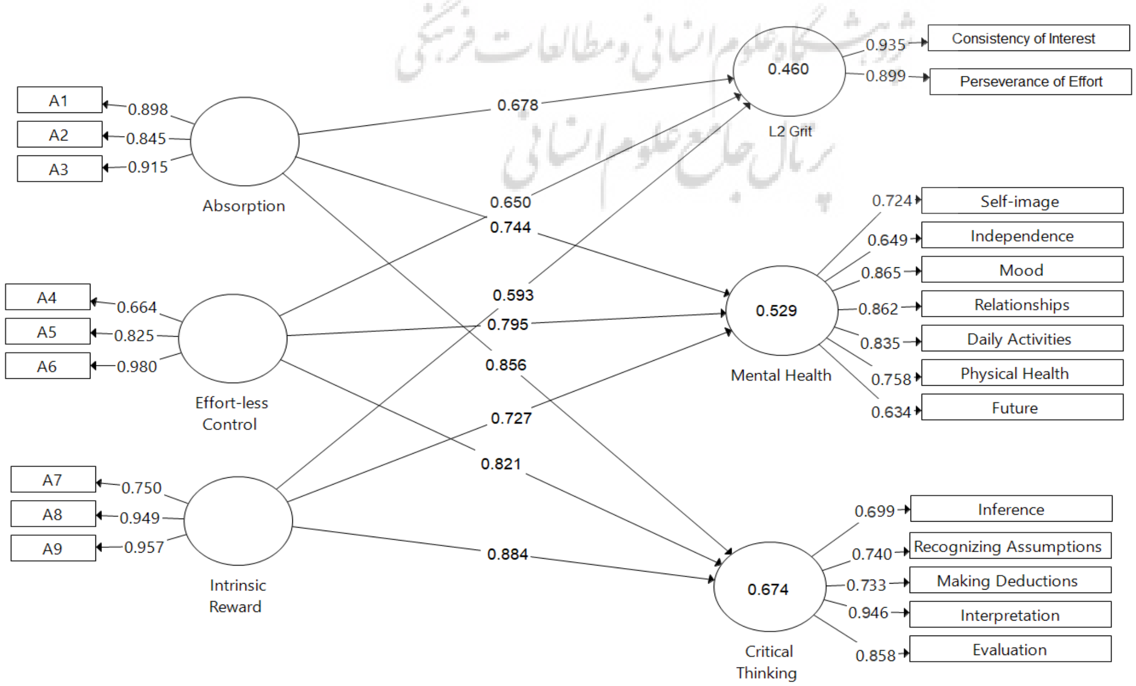

Figure 3. Factors coefficients and path coefficient of the second research model

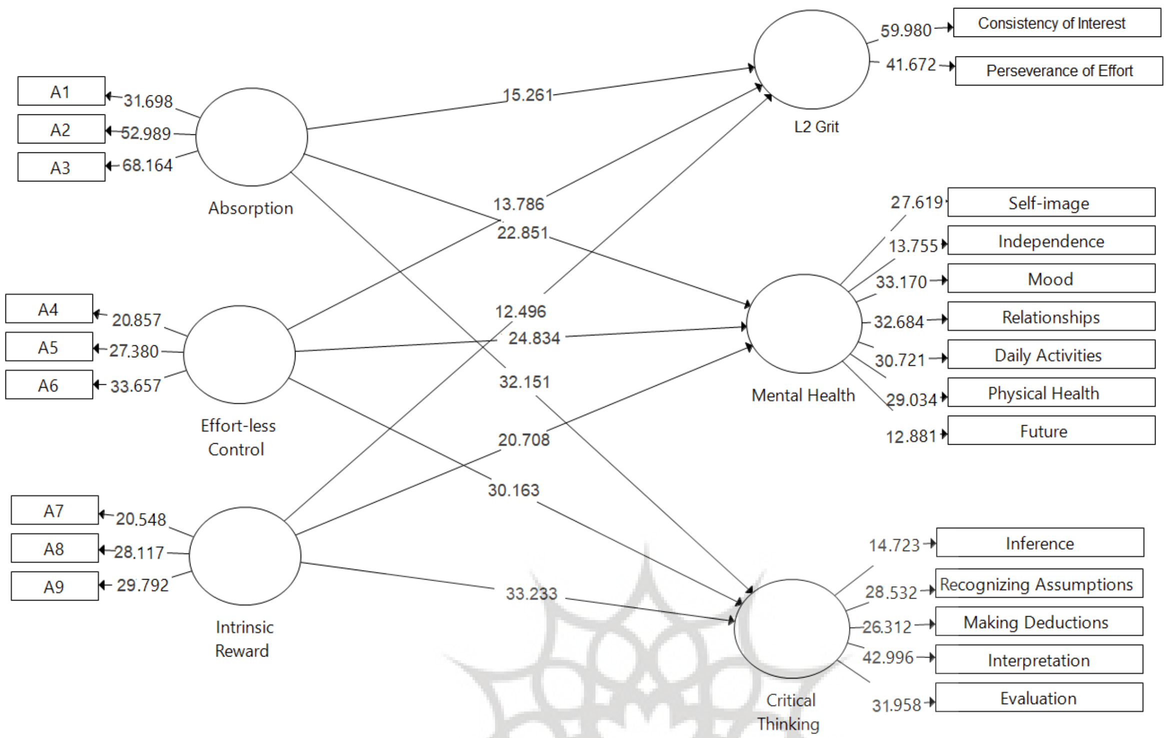

Figure 4. The value of the second research model's path coefficients

As shown in Figures 3 and 4, this report analyzes the connections between L2 grit, mental health, and critical thinking and absorption, effort-less control, and intrinsic reward. Strong impacts of these conceptions on the measured outcomes are suggested by the data's substantial path coefficients and T statistics. Starting with the association between absorption and L2 grit, the path coefficient of 0.678 suggests a strong correlation, suggesting that higher levels of grit are associated with deeper activity involvement. This assertion is supported by the T statistic of 15.261, which shows a statistically significant impact. Likewise, effort-less control has a path coefficient of 0.650 and a T statistic of 13.786, highlighting the fact that people who feel in control of their work are more likely to be persistent and determined. A path coefficient of 0.593 and a T statistic of 12.496 demonstrate the significant contribution of intrinsic reward to the development of L2 grit. The importance of internal motivation in accomplishing long-term objectives is further supported by this study, which implies that the intrinsic pleasure gained from activities encourages consistent effort and devotion. With a route coefficient of 0.744 and a T statistic of 22.851, absorption once again plays a critical part in the study of mental health outcomes, showing that immersive experiences may greatly improve mental health. With a path coefficient of 0.795 and a T statistic of 24.834, effort-less control has an even greater impact, emphasizing how crucial feeling in control is to preserving mental health. With a path coefficient of 0.727 and a T statistic of 20.708, intrinsic reward also has a favorable impact on mental health, highlighting the importance of internal drive. Moreover, absorption significantly improves CT skills, as shown by absorption's path coefficient of 0.856 and T statistic of 32.151. Strong beneficial effects are also shown for intrinsic reward and effort-less control, with T statistics of 30.163 and 33.233 and path coefficients of 0.821 and 0.884, respectively.

Table 7. The model fit indexes (model 2)

	R^2	Q^2
L2 Grit	0.460	0.259
Mental Health	0.529	0.278
Critical Thinking	0.674	0.305

$GOF=\sqrt{0.724 * 0.554}=0.633$

Based on Table 7, the R^2 values show how well the model explains the variation for each construct. The R^2 score for L2 Grit is 0.460, indicating that the model explains 46% of the variation in grit. The model explains 52.9% of the variation in mental health, as shown by a somewhat lower R^2 value of 0.529. The model explains 67.4% of the variation in critical thinking (R^2=0.674). The R^2 values indicate that the model has moderate to high explanatory power, especially for CT. The Q^2 values evaluate the model's predictive relevance, with higher values suggesting more predictive potential. L2 Grit has a Q^2 score of 0.259, indicating modest predictive significance. Mental health has a Q^2 value of 0.278, suggesting somewhat higher predictive importance. CT has the greatest Q^2 of 0.305, indicating that the model best predicts CT. In this model, GOF is determined as $\sqrt{0.724 * 0.554}$= 0.633. A GOF score more than 0.36 indicates a strong model fit, and a value of 0.633 suggests that the model is adequate for expressing the connections between the components.

5. Discussion

This study aimed to examine the associations between AI psychological flow, grit inclinations, mental health, and CT abilities in EFL learners, emphasizing the impact of these aspects on the efficacy of AI-assisted language development. To this end, a SEM analysis was conducted among EFL university students. The results of the initial study question indicate a substantial positive correlation between AI psychological flow and grit tendencies in EFL learners. Specifically, learners who experience psychological flow when utilizing AI technologies are more inclined to exhibit elevated levels of grit—characterized by tenacity and love for long-term objectives—during their language development process. These findings correspond with theoretical frameworks that highlight the significance of emotional involvement and intrinsic motivation in promoting sustained effort and determination in learning (Duckworth et al., 2007; Csikszentmihalyi, 2000). Psychological flow denotes a mental state in which individuals are completely engrossed in a task, characterized by experiences of delight, challenge, and mastery. In AI-assisted language learning, flow is achieved when AI technologies customize assignments to align with the learner's proficiency, providing an ideal challenge that boosts engagement while avoiding irritation.

The flow experience is crucial in AI-assisted learning as it fosters an environment that enhances intrinsic motivation and profound cognitive engagement .This corroborates the findings of the present study, which indicate that AI psychological flow enhances grit tendencies. Specifically, learners who attain a state of flow are more inclined to demonstrate endurance, a fundamental component of grit, when confronted with obstacles in language acquisition (Namaziandost et al., 2024). The results of this research align with studies regarding the significance of grit in educational environments. In 2024, Zhai, et al. discovered that grit substantially enhanced students' resilience in online and AI-driven learning settings, especially when learners exhibited elevated levels of engagement and flow. This suggests that AI systems that facilitate flow can significantly contribute to cultivating grit, allowing learners to remain dedicated to their long-term language acquisition objectives. The practical implications of these findings indicate that AI-assisted language learning tools ought to be developed with an emphasis on fostering psychological flow. Vygotsky's (1978) Zone of Proximal Development (ZPD) posits that learners excel when confronted with challenges that slightly exceed their existing abilities, yet remain attainable with appropriate assistance. In accord to these findings, Halkiopoulos and Gkintoni (2024) discovered that real-time feedback systems in AI language learning platforms resulted in increased learner engagement and perseverance, especially among students who attained flow states.

Furthermore, the results of this study demonstrate that AI psychological flow significantly impacts the mental health of EFL learners during AI-assisted language learning sessions. It implies that students who experience psychological flow exhibit enhanced mental health outcomes, including less anxiety, greater emotional well-being, and lowered stress levels. Upon achieving this equilibrium, learners encounter positive feelings and intrinsic motivation, which correlate with enhanced mental well-being. AI tools that provide personalized and autonomous learning experiences enable learners to perceive themselves as more in command of their educational journey and proficient in mastering the requisite tasks. Furthermore, in the realm of AI-assisted learning, the pleasure and involvement linked to the state of flow can foster the development of psychological resources that serve as a protective barrier against adverse emotions, including anxiety and tension, thereby enhancing overall mental health.

The findings of this research are consistent with those of other recent studies that suggest AI-mediated flow may have a beneficial emotional impact on learners and minimize language development-related stress. For instance, the individualized characteristics of AI tools guarantee that learners are neither inundated nor insufficiently stimulated, hence fostering a favorable emotional experience and enhanced mental well-being (Lin & Chen, 2024). In a comparable vein, a study by Qu and Wu (2024) revealed that AI applications aimed at fostering a state of flow in language development significantly alleviated feelings of frustration. This, in turn, contributed to enhanced emotional well-being and cultivated more favorable attitudes toward the learning process.

Moreover, the finding that AI psychological flow positively influences CT skills among EFL learners can be expanded upon through a deeper understanding of the cognitive processes involved in flow and CT. In AI-assisted language learning, when learners are engaged in activities that induce flow, they are often required to assess and adapt their strategies in real time, which inherently promotes CT. Thus, the experience of psychological flow can act as a catalyst for the development of these advanced cognitive skills. Furthermore, AI-driven platforms, often using adaptive learning systems, offer learners with activities that require CT and creative problem-solving. These platforms may modify the difficulty level according to learners' performance, therefore sustaining an ideal challenge that fosters engagement. As learners attain elevated levels of flow, they are prompted to investigate many linguistic and conceptual avenues, therefore enhancing their cognitive flexibility. This corresponds with the results of Shen and Teng (2024), who observed that adaptive AI learning systems promote CT by necessitating that learners interact with knowledge at several levels of complexity, so improving their reasoning and problem-solving skills. Higher cognitive engagement results from the process of seeing and assessing many answers to a problem in a flow state, so CT is naturally included into the educational process. AI-driven language platforms that facilitate a state of flow are particularly adept at maintaining learners' motivation, as they present tasks that are both engaging and suitably challenging. When learners exhibit motivation to remain engaged in these tasks, they are more inclined to actively employ CT skills in the resolution of problems and the analysis of language usage.

Taken together, the findings of this study underscore the profound impact that AI psychological flow can have on learners' cognitive and emotional development in AI-assisted language learning environments. AI systems that successfully induce flow can foster greater perseverance, improve mental health, and enhance CT skills, all of which are crucial for effective language development. These results offer important insights for the design and implementation of AI-driven learning platforms, suggesting that personalized, adaptive, and engaging tasks that promote flow are vital for optimizing both language learning and the development of key cognitive and emotional skills. In conclusion, this study provides compelling evidence that AI psychological flow is a pivotal factor in supporting learners' grit, mental health, and CT, making it a powerful tool in the language learning process.

6. Conclusion

This research sought to investigate the correlation between AI-induced psychological flow, grit characteristics, mental health, and CT abilities among EFL learners in AI-enhanced language learning contexts. The results demonstrate that AI psychological flow significantly enhances grit, mental health, and CT among EFL learners. The research revealed that EFL learners who experience flow during AI-assisted learning exhibit increased tenacity, improved mental health, and heightened CT skills. The favorable results indicate that psychological flow is a crucial factor in enhancing engagement and cognitive advancement in language acquisition. In summary, the ability of AI systems to facilitate a state of flow through appropriately challenging tasks, personalized feedback, and interactive learning experiences creates an optimal environment for learners to thrive. As learners become progressively engaged in their language development endeavors, they not only surmount challenges but also cultivate the cognitive flexibility essential for CT and problem-solving.

The study's results have significant pedagogical implications for instructors and developers of AI-assisted language learning systems. As AI keeps evolving educational methods, understanding the psychological processes that drive student performance, such as the idea of psychological flow, becomes more important. For instructors, using flow-inducing tactics may greatly improve student motivation, engagement, and overall language learning success. To promote flow, educators and developers should emphasize the design of learning assignments with an appropriate amount of complexity. In addition to increasing engagement, AI-assisted platforms should include learners' emotional well-being. As flow experiences improve mental health results, AI systems should include stress and anxiety-reduction characteristics. This may be accomplished by encouraging students, ensuring that they are confident in their talents, and giving them a feeling of control over their learning experience. Creating an emotionally supportive learning environment may help reduce frustration and exhaustion, resulting in greater language retention and a more pleasurable overall learning experience.

To successfully incorporate AI psychological flow into language development, many pragmatic ways may be used by educators and platform developers. Personalizing the learning experience is one of the most successful ways. Personalized learning enhances engagement and guarantees that learners operate within their ideal difficulty zone, essential for sustaining flow. AI-driven systems have to be engineered to provide customized learning trajectories aligned with each learner's ability, requirements, and preferences. AI systems can facilitate a learning environment that constantly achieves flow by dynamically altering task complexity in accordance with the learner's progress. Moreover, AI systems may include interactive components including gamification and scenario-based learning. Gamification components such as badges, leaderboards, and awards may enhance motivation, whilst scenario-based assignments or simulations can engage learners in authentic language problems. Another essential element for encouraging flow and cultivating CT is real-time feedback. AI systems need to provide students prompt, helpful feedback so they can recognize their errors, hone their tactics, and advance their language proficiency. AI platforms may challenge learners' thinking and broaden their language comprehension by fostering collaboration among them and exposing them to a variety of viewpoints. Finally, AI platforms ought to incorporate mindfulness tools or stress-reduction activities, such as guided meditation or brief intermissions, to assist learners in managing anxiety and maintaining concentration on their tasks. By providing emotional support to learners, AI systems can cultivate a harmonious educational atmosphere that promotes both cognitive and emotional growth.

Notwithstanding its merits, this study is not without certain shortcomings: This research concentrated on a particular cohort of 214 university students enrolled in EFL programs who utilized AI in their academic pursuits. Future research endeavors may aim to broaden the sample population to encompass a more diverse array of learners representing various educational levels and cultural contexts. This would facilitate a more thorough comprehension of the impact of AI-induced psychological flow on diverse learner profiles and enhance the generalizability of the results. Comparative studies conducted across diverse cultural contexts may elucidate the influence of culture on learners' experiences with AI. Additionally, the study did not take into consideration the particular characteristics of the AI tools utilized by the learners, nor the pedagogical approaches implemented within the context of AI-assisted language learning. Future research endeavors should investigate the particular attributes of AI tools that most effectively facilitate psychological flow and enhance learner outcomes. Researchers may examine which characteristics, such as adaptive learning algorithms, interactive simulations, or real-time feedback, are most efficacious in promoting a state of flow. Furthermore, subsequent research could investigate the influence of various instructional methodologies and explore how educators might incorporate AI tools into their pedagogical practices to augment the flow of learning and enhance student engagement.

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