Research Article

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Intrinsic and Extrinsic Motivation in AI-Supported EFL Learning: A Mixed-Methods Study

Abdelghani Remache

Wafa A. Hazaymeh

Abdeljalil Bouzenoun

Bushra S. Abusini

Mohammad Hussein Faqeeh

College of Education, Humanities and Social Sciences, Al Ain University, UAE

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Abstract

AI-assisted language-learning tools are shaping learners' experiences of motivation when they complete English-based coursework. Using a mixed-methods approach, this study investigated how 120 undergraduates at an English-medium private university in the United Arab Emirates perceived intrinsic and extrinsic motivation while using AI-supported drafting, revision, oral rehearsal, and tone-development tools. Survey results indicated associations between motivational orientations, patterns of AI use, perceived feedback usefulness, and gamified elements. Semi-structured interviews with 28 students explored autonomy, competence, relatedness, flow, pressure, and self-regulation. Quantitative results showed positive relationships between intrinsic motivation, perceived usefulness of feedback and chatbot use. Results also indicated positive relations between extrinsic motivation, perception of gamification, and streak length. Analysis of the interview data showed that most students considered AI-generated feedback as competency nurturing; however, some also described feeling pressure with regard to grades, family expectation, employability, and visual performance metrics. Students described strategies for retaining control over their learning, including taking breaks from metrics, reframing goals, and seeking teacher guidance on task criteria. Based on these findings, the authors propose the AI-Mediated Motivational Balance (AIMMB) Framework as a teacher-facing model for designing EFL courses that balance useful feedback, autonomy support, and carefully constrained rewards in AI-assisted task completion.

Keywords: *AI-supported EFL learning, motivation, gamification, self-determination theory, mixed-methods, EFL pedagogy, teacher-facing framework.*

1. Introduction

Artificial Intelligence (AI) has become part of everyday foreign-language learning. Foreign language learning in English as a Foreign Language (EFL) courses increasingly incorporates Artificial Intelligence (AI). Today's learners have access to an expanding array of tools that

provide immediate feedback on their writing, support revision, prepare them for speaking assessments, track progress, and add interactive features to the course environment.

Although technologies provide immediate feedback to students including points earned, progress levels, grades, or time spent on completion of a task, they may also divert students' focus from the learning process (Dicheva et al., 2015; Shortt et al., 2023). Motivation remains one of the key factors of second-language development because it influences learners' willingness to put forth effort, persevere when faced with challenges, and develop strategies for overcoming obstacles associated with learning a new language (Alamer, 2022; Papi & Hiver, 2020).

In addition to being motivated by their own goals, learners are influenced by the signals provided through computer-assisted instructional environments. These signals are delivered through the tone of technological feedback, the adaptive nature of the challenges presented, and the extent to which learners can compare their performance with that of other users of the same technology.

2. Literature Review

2.1 Motivation in the Study of Foreign Languages: Historical Paradigms Through the Modern Era

Over time, foreign language motivation research has undergone changes in theoretical paradigm. Early social-psychological models (Gardner & Lambert, 1972) identified two distinct orientations toward language acquisition. The first was identified as an "integrative" orientation when learners identify with the culture and individuals whose language(s) they are attempting to learn and an "instrumental" orientation when learners study a language primarily for some tangible advantage such as good grades, employment, prestige etc. While both of these initial dichotomies have their place in history, further research has developed learner motivation into additional dimensions including cognitive, affective, situational and dynamic aspects.

Since Dörnyei's (1994) work examining the role of classroom based factors (task specific effort, teacher practice, and the total classroom learning environment), additional research has focused on(SDT) and its application to student motivation. In accordance with SDT (Deci & Ryan, 1985; Ryan & Deci, 2017), student motivation is closely linked to a students perceived autonomy, competence, and relatedness. SDT also indicates that the conditions surrounding technology mediated learning may either support or hinder the development of the three fundamental psychological needs identified above.

The most recent studies have highlighted the interdependence of intrinsic/extrinsic motivations among English language learners. As opposed to viewing learners as only having one type of motivational orientation (intrinsic or extrinsic), SDT views motivation as occurring across a continuum of self-determined regulation (Noels et al., 2000; Ryan & Deci, 2017). Furthermore, a number of studies have shown that the interaction among the above-mentioned elements has been examined in educational AI settings (e.g., Godwin-Jones, 2022; Guo & Li, 2024; Liu & Yu, 2022).

2.2 Gamification and Engagement

As gamification is becoming increasingly prevalent in popular mobile and AI-assisted English Language Learning (ELL) programs, examples like Duolingo and Memrise utilize a variety of point systems, badges, leader boards, levels and streaks to provide a never-ending cycle of feedback for users about their performance. Within this cycle, users are continuously completing very short tasks individually and receiving instant positive reinforcement after completion.

Behavioral psychologists would describe these loops as reinforcing: Visible rewards can produce stable patterns of practice. However, according to SDT, the degree to which a reward

produces motivation depends upon whether the reward is viewed as informative or competence-supportive feedback versus as a controlling external force (Deci et al., 1999; Ryan & Deci, 2017).

Mekler et al. (2017) demonstrated that points, levels and leaderboards can increase the amount of performance generated by learners, yet their effect on intrinsic motivation depends on how learners perceive the reward. Therefore, as there is potential for the same badge, score or streak to represent either positive encouragement or negative surveillance within an EFL AI-supported context; the interpretation of gamification rewards is critical to AI-supported EFL learning design.

Additionally, gamification intersects with flow theory (Csikszentmihalyi, 1990). Clearly defined objectives, immediate feedback and manageable challenges can support learner engagement by allowing learner focus on the process. Conversely, poorly-timed notifications, "streak" pressures or over-comparison may prompt learners to disengage from learning.

The literature surrounding the application of automated and AI-based technologies to assist in providing writing feedback has similarly described conflicting forces. Intelligent writing assistance can aid students in identifying their need for improvement, and subsequently improve the student's ability to revise independently. However, as Godwin-Jones (2022), Kohnke et al. (2023), and Liu and Yu (2022) noted, such technological assistance may simultaneously lead to increased dependence upon the technology, and a reduction in the learners' agency in the revision process.

2.3 Intrinsic Motivation: Flow Experience, Perceived Competence, and Autonomy in AI Settings

Learners' levels of intrinsic motivation can be fostered through the use of AI-based systems in ways that empower learners to make relevant decisions, provide informative feedback and help learners achieve a state of flow, i.e., an optimal level of challenge where the task is neither too simple nor too complex. Such technologies cannot always provide conditions supportive of intrinsic motivation (Deci & Ryan, 2000; Godwin-Jones, 2022).

For example, while personalized feedback, visualized progress through graphs, charts, and progress bars, and real-time feedback can enhance learners' perceptions of competence, such information must be perceived as supporting learner autonomy rather than being controlling (Godwin-Jones, 2022).

2.4 Extrinsic Motivation: Rewards, Recognition, Feedback, and Accountability

As with the fostering of intrinsic motivation, AI technologies can also promote extrinsic motivation through rewards and recognition provided through visible measures of accomplishment such as scores, progress bars, reminders, etc. While these components can lead to the development of routine behaviors among learners, controlled behavior may result if learners continue to engage in the activity solely to meet measurable performance requirements. Similarly, anxiety regarding loss of progress may develop if learners are overly focused on maintaining consistent performance.

Engaging learners over time on an ongoing basis will require some connection between measures of learner success and personal meaningfulness of those same successes, along with opportunities to reflect on that process (Deci et al., 1999; Ryan & Deci, 2017).

2.5 Balancing Factors: Overreliance and Cognitive Offloading

Due to the nature of AI technologies as being user-friendly interfaces that can encourage learner engagement, it is essential to acknowledge potential trade-offs between ease-of-use and development of metacognitive abilities including error identification within AI-assisted

assignments, establishment of self-directed learning goals, and assessment of one's own strategic growth (Gilbert et al., 2023; Risko & Gilbert, 2016).

One risk related to complacency in using AI-supported learning environments relates to reduced learner ownership of more demanding tasks. Without achieving satisfaction derived from successfully completing more challenging tasks, learner engagement may be largely dependent on the AI system as opposed to continued development of learner competency (Dörnyei & Ushioda, 2021). Thus, while researchers recognize the value of using AI in educational settings; the primary question is not whether AI should be utilized, but rather how to design AI-based support so that it enhances learner autonomy. In particular, two design principles appear to be especially important:

Effort Transparency: Learners need to be able to clearly see what they have done during an activity. This can occur by having them explain why they accepted, rejected, or revised each suggestion made by the AI system.

Adaptive Friction: AI-supported tasks should include some productive struggle. They must be designed so that there is a small amount of productive struggle in terms of delayed help (or "hints"), prompts that ask students to think about their own learning processes (reflection), or rationales for why a student's answer was incorrect. While the idea behind AI-supported tasks is to reduce friction in order to make learning easier, if we remove all friction from the task, then convenience becomes the primary motivator for cognitive offloading (Kohnke et al., 2023).

2.6 Toward an Integrated Model of Motivational Synergies

Collectively, research shows that AI-supported language learning can be represented as a dynamic motivational system. As such, many AI features can simultaneously serve both intrinsic and extrinsic purposes. The ultimate design challenge is not to select between intrinsic and extrinsic motivation but to structure external incentives to support internalization, competence and learner ownership as opposed to substituting them.

3. Theoretical Foundation

3.1 Intrinsic vs. Extrinsic Motivation

For nearly five decades, researchers investigating second-language (L2) motivation have drawn extensively on Gardner and Lambert's (1972) integrative/instrumental orientation. The integrative motivation dimension describes learner interest in and identification with a particular language community.

Instrumental motivation describes practical benefits derived from knowing a foreign language, such as better grades, improved job prospects, and increased social standing. However, according to Self-Determination Theory (SDT), these orientations represent a continuum of behaviors ranging from externally regulated (externally driven behavior) to autonomously-motivated (internally driven) behaviors (Ryan & Deci, 2017).

3.2 Extrinsic vs Intrinsic Motivation Based on SDT

In terms of extrinsic motivation, there are different levels of motivational orientation. According to SDT (Deci & Ryan, 1985; Ryan & Deci, 2017), extrinsic motivation can vary from external regulation — where individuals act solely based on receiving reward or penalty — to internalization — where individuals take on external goals as their own and act based on personal relevance.

For instance, while some students study English in order to receive better grades at school,

others may develop an appreciation of bilingualism because it aligns with their identity or future career aspirations (Noels et al., 2000; Ryan & Deci, 2017). In contrast, intrinsic motivation exists when individuals engage with a task based on personal interest. A considerable body of research demonstrates that intrinsic motivation has strong positive associations with deep-level learning.

3.3 Application of Self-Determination Theory to Technology-Based Learning Environments

Since technology-based learning environments utilizing AI may affect individuals' perceptions of autonomy, competence, and relatedness, SDT offers an effective theoretical framework for examining their impact. Specifically, AI-based platform feedback can enhance learners' perceptions of their ability to develop skills when that feedback informs them about how they can improve their abilities.

Similarly, learner choice regarding content selection, task sequence, and/or pacing can promote autonomy when those choices are relevant rather than simply cosmetic. Moreover, technology-based systems generally provide only limited support for relatedness among learners — particularly when social features are provided in comparative rather than cooperative formats (Deci & Ryan, 2000; Godwin-Jones, 2022; Ryan & Deci, 2017).

Thus, autonomy-supportive technology design must provide more than just personalized learning experiences. Learners must be provided with opportunities to assess their usage of AI-driven suggestions — as opposed to passively accepting those suggestions (Alamer, 2022; Guo & Li, 2024; Kohnke et al., 2023).

3.4 Focus of Study

While several investigations have demonstrated that AI gamification systems result in increases in learner engagement — very few investigate how learners' emotional states shape their perceptions of the various aspects of AI-based technologies. While this issue is important to both identify whether or not AI-based systems stimulate learner motivation — and to what degree — it is equally important to understand how factors such as learners' prior confidence in their abilities, anxiety about their performance, goal attainment expectations, and social pressures shape whether learners will perceive AI-based feedback as encouraging and supportive or discouraging and surveillance-oriented (Dörnyei & Ushioda, 2021; Papi & Hiver, 2020).

If learners perceive themselves as independent, confident, and self-regulated, they tend to perceive system feedback as beneficial; whereas if learners perceive themselves as being anxious or dependent upon others for direction, similar system feedback is perceived as restrictive and controlling.

Based on the two-way relationship between learners' emotions and technology — through which they jointly produce motivation — this investigation adopts this interactive framework. The way in which intrinsic and extrinsic motivations coexist in an AI-based English language-learning environment;

- The way in which intrinsic and extrinsic motivations coexist in an AI-based English language-learning environment;
- The way in which design elements help learners internalize motivation;
- And the risks and strategies involved in balancing intrinsic and extrinsic motivation over time.

4. Methodology

4.1 Study Design

This study employed a convergent mixed-methods design (Creswell & Plano Clark, 2018) because it was necessary to identify motivational patterns and examine learners' interpretations of AI-supported English as a Foreign Language (EFL) task performance. Quantitative data were collected through surveys measuring intrinsic motivation, extrinsic motivation, and perceived affordances of AI.

Qualitative data were collected through semi-structured interviews in which learners described their experiences of feedback, autonomy, competence, pressure, and overreliance. A mixed-methods approach was chosen because motivation in an AI-supported learning environment consists of both quantifiable patterns and contextualized understandings. The quantitative strand examined large-scale associations between types of motivation and perceived AI features.

The qualitative strand interpreted how learners made sense of these features. Convergence enabled findings from the quantitative strand, including statistical associations among motivation scales, to be clarified and expanded through narrative accounts from the same learners. This process produced a more comprehensive understanding of how intrinsic and extrinsic drives intersected in practice. Because the quantitative strand was exploratory and associative in nature and did not seek to establish causality or direction, no causal or directional claims are made.

4.2 Participants and Context

Twenty-eight of the thirty participants invited for interviews through purposeful maximum variation sampling of survey profiles participated in 30- to 40-minute interviews. Participant characteristics and AI-use profiles are listed in Table 1. Variability was operationalized using a median split on the survey distribution (higher vs. lower IM, higher vs. lower perceived feedback usefulness, and higher vs. lower reliance on gamified indicators).

Table 1. Participant Characteristics and AI-Use Profile (N = 120).

Characteristic	Category / Statistic	n (%) or M ± SD / Median [IQR]
Gender	Female	74 (61.7%)
	Male	46 (38.3%)
Course level	English 1	62 (51.7%)
	English 2	58 (48.3%)
English proficiency (IELTS band)	5.0	28 (23.3%)
	5.5	37 (30.8%)
	6.0	34 (28.3%)
	6.5	21 (17.5%)
Chatbot use for coursework	Yes	86 (71.7%)
	No	34 (28.3%)
Weekly AI use	<1 hour	18 (15.0%)

	1–2 hours	39 (32.5%)
	3–5 hours	41 (34.2%)
	6+ hours	22 (18.3%)
Days/week using AI	Mean ± SD	3.6 ± 1.5
Streak length (days)	Median [IQR]	18 [6–39]

4.3 Instruments

4.3.1 Quantitative Instruments

The quantitative component used a revised form of the Language Learning Orientation Scale (LLOR) associated with SDT-based L2 motivation research (Noels et al., 2000). The instrument contained two subscales:

Intrinsic Motivation (IM): Twelve items assess participants' enjoyment, curiosity, and perceived competence in the context of learning a second language. The Cronbach alpha coefficient for the IM subscale was .87. McDonald's omega was not computed in this analysis.

Extrinsic Motivation (EM): Ten items assess participants' external regulation (grades, recognition) and introjected/identified regulation (self-activated expectations) in the context of learning a second language. The Cronbach alpha coefficient for the EM subscale was .83. McDonald's omega was not computed in this analysis.

Participants answered the items using a five-point Likert-type scale (1 = Strongly Disagree, 2 = Somewhat Disagree, 3 = Neutral, 4 = Somewhat Agree, 5 = Strongly Agree).

Additionally, a portion of the questionnaire asked participants to describe their perceptions of the motivational aspects of AI-based systems, including gamification (e.g., "I am motivated by badges and levels"), immediate feedback, and autonomy in adapting tasks (Cronbach's alpha = .81).

Other demographic variables included participants' gender, major, number of hours per week spent using AI-based systems, and length of participation in a given chat session.

Reliability and Validity: Reliability was assessed using Cronbach's alpha for each multi-item scale. Convergent validity was assessed using expected correlational relationships (e.g., usefulness of feedback with intrinsic motivation; perceived gamification with extrinsic motivation).

No structural modeling (e.g., CFA/HTMT) or regression claims are made unless explicitly reported in the Results; accordingly, the quantitative analyses are presented as exploratory and correlational.

4.3.2 Qualitative Instruments

Each semi-structured interview lasted approximately 30 to 40 minutes and addressed the following areas:

- Participants' emotional responses to AI-based feedback.
- Perceptions of learners' roles in relation to rewards, streaks, and visualizations of progress.
- Perceptions of learners' self-efficacy and autonomy when working on AI-based tasks.
- Perceptions of overreliance and complacency in the use of AI-based systems.

All questions were open-ended in order to elicit reflective narratives from participants (e.g., "Can you recall a time when AI-based feedback elicited pride or frustration in you?"). Audio recordings of each interview were transcribed verbatim and analyzed using NVivo 14.

4.4 Procedure

Data collection occurred over eight weeks. Weeks 1-2 consisted of an online survey. Weeks 3-6 consisted of participants engaging in observational journaling. Participants were required to spend at least fifteen minutes daily using their preferred AI-based platform(s) and recording a brief account of what motivated them to continue using the platform. Weeks 7-8 consisted of Zoom interviews.

Quantitative analysis was performed using SPSS 28 to compute descriptive statistics and correlations. Qualitative analysis was performed using reflexive thematic analysis (Braun & Clarke, 2023) following six stages of iteration: familiarization, coding, theme generation, review, definition, and synthesis. Journal entries were used to support participant reflection and inform interview prompts; they were not analyzed as a separate dataset.

Participants were encouraged to record brief weekly reflections to document their motivation triggers in real time and to assist in recalling their motivations during the interviews. The journal entries were considered contextual qualitative data used for triangulation and interview probing rather than a separate dataset for producing independent claims; all qualitative findings reported in the Results section are derived from the interview transcripts.

4.5 Analytical Approach

Integration of Strands: Quantitative results provided broad patterns of motivation; qualitative results provided explanations for why those patterns existed. Integration occurred at three levels:

Data Connection: Participants in the interviews were selected based on their motivation scores.

Data Comparison: Patterns of similarity and dissimilarity were mapped across the two methodologies.

Meta-Inference: Final interpretation reconciled statistical trends with qualitative evidence following mixed-methods integration principles (Fetters et al., 2013).

The qualitative themes were used to qualify and reframe the quantitative associations. For example, where a correlation indicated the activation of both intrinsic and extrinsic motivation, the qualitative data clarified whether this activation represented an autonomy-supportive environment or a metrics-driven environment of pressure. The meta-inferential approach explained survey trends at the level of mechanisms rather than using the qualitative findings as confirmatory evidence.

Quantitative results are reported with associations and 95% confidence intervals to facilitate practical interpretation; all necessary assumptions were checked using common diagnostic procedures.

Qualitative Rigor and Reflexivity: Interview data were analyzed through reflexive thematic analysis across six stages: familiarization, coding, theme development, review, refinement, and definition. The primary coder maintained a reflexive memo log detailing analytical decisions and assumptions. Credibility was enhanced through peer debriefing on emerging themes, maintenance of an audit trail (codebook and memo versions), and purposeful searches for contradictory evidence within each theme. Integration with quantitative results was used to evaluate similarity and dissimilarity, rather than having one strand confirm the other.

5. Results

5.1 Quantitative Findings

Reporting Note: In addition to p-values, we report 95% confidence intervals and effect sizes (r^2 for correlations; effect size estimates) to provide practical interpretation in an education/instructional systems (IS) context. Results are reported for N = 120 complete cases on the variables in Tables 2–3.

5.1.1 Descriptive Statistics

Table 2. Descriptive statistics of motivation and AI-affordance variables (N = 120). Note. 95% CIs are t-based (df = 119). Cronbach's α: IM = .87; EM = .83; AI-affordances = .81.

Variable	Mean	SD	95% CI	Range	Interpretation
Intrinsic Motivation (IM)	4.12	0.58	[4.02, 4.22]	2.6–5.0	High
Extrinsic Motivation (EM)	3.84	0.66	[3.72, 3.96]	2.0–5.0	Moderately high
Gamification perception	4.05	0.70	[3.92, 4.18]	1.8–5.0	Positive
feedback usefulness	4.22	0.61	[4.11, 4.33]	2.4–5.0	Very positive
Autonomy support	3.95	0.68	[3.83, 4.07]	2.0–5.0	Positive

High overall motivation was evident: 91% of the sample reported values greater than the midpoint on both subscales, suggesting widespread engagement. Both AI-based feedback and gamification were highly rated, suggesting that learners viewed these features as motivational drivers.

Table 3. Key exploratory associations used to contextualize qualitative themes (descriptive).

Association	r (95% CI)	r^2	p	Interpretive note (for triangulation)
IM ↔ EM	0.62, 95% CI [0.50, 0.72]	0.38	<.001	Intrinsic and extrinsic motives co-occurred.
IM ↔ feedback usefulness	0.54, 95% CI [0.40, 0.66]	0.29	<.001	feedback aligned with intrinsic engagement.
EM ↔ Gamification perception	0.49, 95% CI [0.34, 0.62]	0.24	<.001	rewards aligned with extrinsic drive.
Streak length ↔ EM	0.30, 95% CI [0.13, 0.45]	0.09	.004	Streaks aligned with extrinsic orientation.

Chatbot use ↔ IM	0.27, 95% CI [0.10, 0.43]	0.07	.009	Chat-based practice aligned with interest.

5.1.2 Correlation Analysis

The correlation results were interpreted as exploratory associations between perceived AI features and motivational orientations. Consistent with competence need satisfaction, perceived feedback usefulness was positively associated with intrinsic motivation. Perceived autonomy support was also positively associated with intrinsic motivation. These patterns are descriptive and do not establish causal effects.

The main exploratory associations were as follows:

IM-EM: $r = 0.62$, 95% CI [0.50, 0.72], $r^2 = 0.38$, $p < .001$, suggesting that intrinsic and extrinsic motives co-occurred rather than excluding one another.

IM-feedback Usefulness: $r = 0.54$, 95% CI [0.40, 0.66], $r^2 = 0.29$, $p < .001$.

EM-Gamification Perception: $r = 0.49$, 95% CI [0.34, 0.62], $r^2 = 0.24$, $p < .001$.

Streak Length-EM: $r = .30$; $p = .004$.

5.2 Qualitative Findings

The qualitative data revealed four main themes that help explain how students experienced AI-assisted learning in relation to perceived competence, gamification, autonomy, and learner agency. These include:

Theme 1. Perceived Competence Support Through AI Feedback

Participants frequently described how AI-assisted feedback helped them identify areas needing correction, verify improvement, and determine future actions. Thus, Theme 1 offers some insight as to why there was such a strong positive correlation between the participants' perceived usefulness of the feedback and their levels of intrinsic motivation.

Theme 2. Commitment and Pressure Generated by Gamification

An example of potential student engagement in activities that represent surface-level engagement is student reporting of "I complete the easy lessons just for the points." This represents surface-level engagement rather than engagement in communicative practice. In these cases, students' primary focus appeared to be achieving system metrics rather than engaging in communicative practice. Therefore, Theme 2 offers some insight into why gamification perceptions and streak length were more strongly correlated with students' levels of extrinsic motivation.

Theme 3. Autonomy and Overreliance on Convenience

Several participants expressed that they prefer to have many choices and like things to happen fast. Some accounts noted that using tools designed to provide convenience can limit learners' reflective time. An example of this is provided in one of the interview excerpts where a participant state: "It corrects me so I don't really need to think too much about it." This quotation illustrates the autonomy paradox: Learners may feel autonomous because they can select the tool they use and the pace at which they work; however, the tool used may also reduce the independent cognitive processing required during learning.

The above quotation illustrates the autonomy paradox: learners may feel autonomous because they can select the tool they use and the pace at which they work; however, the tool may also reduce the independent cognitive processing required during learning.

Theme 4. Maintaining Agency with AI-assisted Learning Tools.

Besides noting the many ways that students maintained agency when using AI-assisted learning tools, Theme 4 provided several examples of student strategies for maintaining agency in learning. Some of those strategies included (a) deliberately turning off tracking systems so they could take breaks from monitoring their performance metrics; (b) reframing the goal to develop an ability or skill instead of building a streak; and (c) establishing limits on when and how they could use AI-assisted feedback based on teacher-established guidelines.

5.3 Commentary on Interpretation of Gamification

Participants described gamification as having dual roles: providing visible progress and encouraging routine practice, while also causing anxiety about failure or losing points. This qualitative account supports a cautious view of gamification; it may scaffold engagement, but it should not define success solely through engagement metrics.

Rewards from gamification act as tangible expressions of a learner's effort. For some learners, quantifying effort reduced their uncertainty about achieving success and made the experience of progressing appear more tangible. For other learners, the emphasis had changed from developing language skills toward accumulating metric-based achievements. The fact that some students completed "easy lessons for points" indicates that external scaffolding can lead to surface-level engagement when communication objectives are removed from those efforts.

This study does not claim to definitively extend Self-Determination Theory (SDT). Instead, it presents a tentative threshold interpretation: gamified incentives may provide competence-supportive and routine-enhancing benefits when used appropriately, but they may become detrimental if learners view them as controlling or if they substitute for reflective effort.

5.4 Commentary on Interpretation of Autonomy and Convenience

Learners expressed a preference for choosing topics, pacing, and revision routes. At the same time, several learners described surrendering portions of their cognitive effort to AI. The quote, “It corrects me; therefore, I do not have to think about it for a long time,” illustrates how convenience may occur in conjunction with lessened reflection. The paradox illustrated here supports the cognitive-offloading concern (Gilbert et al., 2023; Risko & Gilbert, 2016).

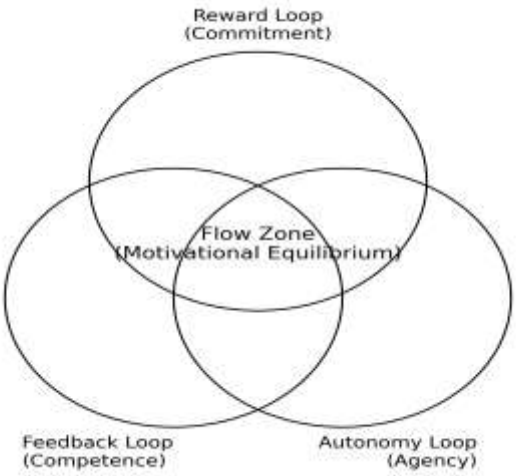
This phenomenon can be understood within the framework of Self-Determination Theory (SDT). Learners' pseudo-autonomy is demonstrated when they have option selections at the interface level; however, learners are directed by default settings, predictive feedback and suggestions provided by the tool. Thus, authentic autonomy requires that learners demonstrate reflective control over decision-making processes.

When learners provide critical evaluations of suggested alternative choices via AI-assistants, AI-assistants can promote self-regulated learning behaviors. Conversely, when learners do not deliberate before accepting suggested alternative choices offered via AI assistants, AI assistants can support compliant behavior. Accordingly, teacher mediation and revision rationales are necessary safeguards to prevent overreliance on AI-assistant systems.

5.5 Integration Between Mixed Methods

The AI-Mediated Motivational Balance (AIMMB) Model is presented as an interpretive theoretical framework, not as a statistically validated model. AIMMB was developed by integrating Self-Determination Theory, Flow Theory, reward psychology, and the exploratory results of this study. Therefore, additional studies that incorporate larger sample sizes, longitudinal designs and confirmatory modeling will be necessary before AIMMB can be considered validated.

Figure 1 illustrates the conceptual model of AI-Mediated Motivational Balance (AIMMB), which describes the interaction between feedback loops, autonomy loops, and reward loops in achieving and maintaining a state of motivational balance.



The Competence Feedback Loop provides immediate and ongoing feedback that helps learners feel competent by showing how their learning efforts produce improvement. Learners who receive frequent and relevant feedback will feel more competent because they can see the direct result of their effort. Agency Loops (Autonomy) allows learners to develop their own learning environment through customized options. They also give them the opportunity to describe the rationale for their choices and assess whether the recommendations provided by AI are correct. Students also need to link tasks to personally endorsed goals.

A Reward Loop (Commitment) provides gamification-based rewards that encourage initial commitment and ongoing practice when those rewards remain informational, are provided privately when appropriate, and align with mastery instead of competition. The central overlap among all three loops is referred to as Motivational Equilibrium. Motivational Equilibrium is a fragile state in which internal interests and external supports coexist. To preserve agency, automation should not make students overly dependent. Likewise, extrinsic supports should remain in place only as long as they help intrinsic motivators develop. This perspective should be viewed as a conceptual integration grounded in exploratory research, not as a causal framework.

6. Discussion

In an era where artificial intelligence is increasingly shaping learning environments, the role of motivation within those spaces requires reassessment.

The results of this study suggest that instead of merely enhancing student motivation, AI-supported platforms may actually influence the ways in which students experience motivation.

Positive relationships between both types of motivation ($r = .62$) found in this study suggest that students who exhibit strong levels of one type of motivation frequently demonstrate some level of the other.

Qualitative responses from the students in this study suggest that most students

experienced multiple motivating factors simultaneously (e.g., enjoyment, feedback, rewards, accountability), while fewer students experienced each factor individually.

When AI-supported platforms provide real-time feedback on student performance and present opportunities for advancement that seem feasible with effort, the combination of timely feedback, reasonable challenges, and measurable progress can promote motivational alignment.

However, such alignment may be tenuous. The same characteristics that promote a sense of competence may also lead to dependency or metric chasing if opportunities for self-reflection or reflective dialogue are absent.

6.1 From Feedback to Flow: AI as a Motivational Multiplier

Quantitatively, this study found that the only AI-related affordance associated with intrinsic motivation was the degree to which students believed the AI provided useful feedback.

Qualitatively, students indicated that useful feedback provided insight into performance gaps and allowed them to see how improvements could be made.

When learners perceive system feedback as informative for improvement, feedback can act as a motivational amplifier. In the current study, learners were able to report associations with feelings of success or failure when correcting errors and reporting increases in perceived competence.

However, none of these factors demonstrated causality. Based on the findings of this study, the motivational value of AI appears to lie not in gamification alone, but in creating environments where learners can access meaningful feedback and appropriately calibrated challenges. Although many AI-based learning tools are designed to encourage students to continuously track their progress and performance using rewards such as points and streaks due to the immediate gratification afforded to the user, the results suggest that adaptive feedback was more closely associated with learners' self-reported interest and perceived competence than points or streaks.

Table 5. AIMMB loops and teacher-facing implementation options for EFL tasks.

AIMMB loop	Primary need/pathway (SDT/flow)	What the AI feature does	Instructor-facing implementation choices (General English course examples):
feedback loop (Competence axis)	Competence signaling; informational feedback; flow support	Immediate, specific feedback; adaptive difficulty; progress visualization	Provide feedback as dialogue: Ask students to describe 2-3 correction(s) they will make in a weekly revision memo (i.e., Paragraph Revision Memo, Summary Draft, Email Revisions, etc.). Assess reflection quality, not only correctness.

Autonomy loop (Agency axis)	Autonomy support; self-endorsed goals; internalization	Choice of topics/pacing; personalization; goal prompts	Allow students to choose from menus for AI-supported practice (Example: Alternative prompts for revising an email sent to an instructor. Alternative prompts for clarifying a paragraph. Alternative prompts for creating two versions of summaries.) Include short "Why I Chose This" prompts that help protect their agency.
Reward loop (Commitment axis)	Extrinsic scaffolding that can be internalized; accountability	Badges, streaks, points, reminders, leaderboards	Keep rewards informational and voluntary: Allow them to track their own progress privately. Do not tie their grade to their use of the streak metric. Utilize mastery checkpoints (Example: Version History shows improvement on a particular task in Course Writing and Revision Tasks)

Table 6. AIMMB implementation toolkit for university-wide EFL courses: design choices, activities, and assessment.

AIMMB lever	What to tune in the AI tool	In-class activity (General English example)	Instructor monitoring	Assessment / rubric cue
Autonomy guardrails	Require learner choice (prompt options + self-rationale); limit one-	Rewrite an email to an instructor: choose a tone goal (polite/requesting/clarifying) and justify edits.	Watch for overreliance; collect 2–3 rationale notes	Quality of rationale; alignment with audience and purpose

	click completion			
Competence feedback	Timely, specific feedback; revision cycles; exemplars	Paragraph revision (English 1/2): two rounds using AI feedback	Spot-check revision changes; confirm feedback is used thoughtfully (not copied)	Improvement across drafts; evidence-based use of feedback
Challenge calibration	Progressive constraints; reduce streak pressure	Revision escalation: add constraints (tone, evidence, clarity) to an argument paragraph	Monitor frustration vs engagement; quick pulse checks	Problem framing under constraints; clarity and completeness
Reward rebalancing	Shift rewards from streaks to mastery; reflection badges	"Mastery badge" earned by fixing an error pattern across tasks	Track recurring issues; acknowledge correction patterns	Mastery evidence; fewer repeated errors
Flow protection	Chunked tasks; limited interruptions; deep-work windows	20-minute drafting block; feedback only at the end	Observe time-on-task; reduce notifications	Coherence, unity, and organization of the final draft
Anti-offloading	Require explanation; avoid full-solution outputs; disclosure of AI assistance	Explain-your-edit: annotate five AI-suggested changes	Audit annotations; detect superficial acceptance	Metacognitive annotation quality; originality retained

6.2 Practical and Pedagogical Implications

The findings have several implications for the design of AI-assisted language-learning environments and for teachers who incorporate such systems into English as a Foreign Language (EFL) classes.

6.3 For Designers of AI-Supported Language-Learning Environments

Informational Feedback Structure: Instead of providing purely evaluative feedback, such as "wrong," AI systems should provide learners with competence-supportive feedback, such as "You improved by 10% this week."

Adaptive Friction: Developers should add pauses, hints, or uncertainty zones so that

learners have time to reflect on their choices rather than relying on the system for cognitive offloading.

Optional Metacognitive Prompts: When developing applications utilizing AI, developers should embed optional metacognitive prompts into those applications that require learners to think critically about their thought processes. Examples of metacognitive prompts might include "What was your reasoning?" and "How did you arrive at this answer?" These types of prompts assist in promoting learner self-reflection and internalization.

6.3 Implications for Educational Policy and Practice

6.3.1 Pedagogical Implications

Educators will now need to go beyond simply adopting new technologies to enhance teaching practices. As educators begin to integrate AI-powered language tools into formal curricula, educators will need to develop more pedagogically-sound methods for integrating technology into educational settings. Three implications for teacher practice and student learning emerged from the findings:

First, educators will need to consider AI as an assistant to teaching, not as a replacement for teachers' role in facilitating student learning. By explicitly framing AI-based feedback as an extension of educator-based feedback, instead of an alternative form of teacher feedback, educators can leverage the immediacy of AI-based feedback while maintaining interpretive authority.

After students receive grammar suggestions from AI, for example, a reflective debrief can ask them to articulate the underlying grammar rules that correspond to each suggestion, thereby transforming passive receipt of feedback into active metalinguistic reasoning.

Second, educators should embed autonomy-supportive structures into the use of AI. For example, assignments can include learner-created goals ("Select one feature you want to improve this week") and self-tracking journals that relate app data to learners' own reflections. In this way, educators can transform motivational components of AI, such as visualizations of progress and adaptive challenges, into self-regulatory behaviors.

Third, educators need to guard against over-gaming the use of AI. While using the gamification elements such as leaderboards and streaks may motivate learners, these need to be optional or at least tied to some form of mastery criteria. If the AI is used as the sole basis for determining grades or participation points, then students are much more likely to develop controlled motivations for learning (for example, to get good grades) and therefore learn for external reasons. By combining the formative aspects of AI-based feedback with some narrative commentary ("You have developed your vocabulary") you can maintain the informative aspect of the feedback while also encouraging learners to feel competent in their ability to learn.

6.3.2 Implications for Design and Technology Development

The developers and designers of technologies using artificial intelligence in education have a shared responsibility with teachers to promote pedagogically informed design practices. These practices support the development of motivational strategies when designing learning technology. Key design considerations for developing technologies using AI in education include:

Transparency: Systems should clearly state what types of information they collect from users and how this information is processed. Additionally, systems should be transparent regarding how a decision was reached. When transparency is incorporated into learning technologies, users tend to view the AI system as a collaborative partner in the learning experience, as opposed to viewing the AI system as authoritative (Godwin-Jones, 2022; Yan, 2024).

Feedback as Dialogue: AI systems should provide users with reasons for the evaluations they generate. Instead of generating a simple evaluation (correct/incorrect), an AI system can generate a scaffolded explanation or rationale for revising an evaluation. Research suggests that when an AI system provides a rationale for a revision, learners may be more likely to develop understanding and mastery (Godwin-Jones, 2022; Liu & Yu, 2022; Remache & Remache, 2025).

Range of adaptive difficulty levels: Designers can create a threshold-reflection component within a learning environment to pause the AI's adaptive difficulty adjustments after several consecutive successful experiences.

7. Limitations

The findings are situated within a single private, English-medium university in the UAE; institutional assessment regimes, sociocultural expectations, and performance-pressure dynamics may shape motivational interpretations, and transferability to other contexts should be made cautiously.

8. Conclusion

AI does not replace instructional judgment; it changes the motivational conditions in which everyday language-learning work occurs. When AI feedback is framed as dialogic, informative, and mastery-oriented, it may help sustain effort while supporting durable engagement rather than simple compliance. The AIMMB framework and accompanying toolkit offer an exploratory, teacher-facing way to integrate feedback, autonomy, and reward loops in AI-supported EFL tasks. The goal is not to remove extrinsic motivators, but to integrate them into learning designs that encourage responsibility, reflection, and ownership.

AI-Use Statement

ChatGPT was utilized as a means of assisting with language editing while revising this manuscript. ChatGPT was not utilized in generating the data for this study; analyzing the data; creating participant quotes; creating false or fabricated citations; nor producing results for this study. All intellectual property, interpretation(s), analysis(s), reference(s), conclusion(s) were reviewed and validated by the authors.

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