



## **The relative importance of self-determined motivation for engagement in generative AI-supported English language learning: Insights from Japanese university students**

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### **Abstract**

Both motivation and engagement play pivotal roles in second language (L2) learning within the fields of applied linguistics and digital applied linguistics. While previous studies in applied linguistics have accumulated findings on the motivation-engagement nexus, there remains a paucity of empirical research in digital applied linguistics grounded in robust theoretical frameworks for understanding the comprehensive relationship of both constructs due to its relatively recent emergence. The current study addresses the gap by employing a self-determination theory to investigate the relationship between self-determined motivation and engagement in L2 learning with the use of generative artificial intelligence (GenAI). Data were collected using a questionnaire from a total of 98 university students learning English as a foreign language in Japan. Results from correlation analysis showed that autonomous forms of regulation were strongly associated with three dimensions of engagement (i.e., behavioral, cognitive, and emotional). Furthermore, a series of multiple regression analysis with supplemental use of dominance analysis and random forest plots revealed that, while the total variance explained in each engagement ranged from 52.8% to 59.6%, autonomous motivation accounted for around 80% of the proportion explained within the regression models. The findings highlight the key role of autonomous motivation, especially identified regulation, in facilitating active participation in L2 learning with GenAI. This article concludes with theoretical and pedagogical implications, emphasizing the viability of SDT in conceptualizing the motivation-engagement nexus in GenAI-supported L2 learning and the critical roles of teachers in helping students recognize the value of L2 learning with GenAI.

**Keywords:** motivation; engagement; self-determination theory; generative AI; multiple regression analysis; open science

Both motivation and engagement have garnered significant attention from second language (L2) researchers and practitioners over the past 25 years (e.g., Dörnyei & Kormos, 2000; Yamazaki & Hiver, 2024). Motivation serves as a driving force behind subsequent behavior and provides insight into *why* students invest their energy into particular actions. In contrast, engagement reflects energy in action, offering a lens through which researchers and practitioners can understand *how* students actively participate in tasks. Integrating these two perspectives enables a more comprehensive understanding of students' L2 learning processes. A large body of studies in traditional applied linguistics has emphasized the positive interdependence between motivation and engagement (Kashimura & Hiromori, 2024; Liu, 2022; Namkung & Kim, 2024). Self-determination theory (SDT; Ryan & Deci, 2017) provides a theoretical framework for this relationship by emphasizing that varying degrees of self-determined motivation can trigger behavioral, cognitive, and emotional engagement. SDT posits that students who are more autonomously motivated are likely to demonstrate higher levels across all three dimensions of engagement.

One of the significant shared characteristics of the two constructs is their context-specific nature: both are shaped by their surrounding social contexts. Specifically, in today's educational settings, the exponential rise of generative artificial intelligence (GenAI) has brought about a drastic shift in L2 learning practices. GenAI such as ChatGPT is a powerful tool capable of generating, understanding, translating, and paraphrasing language (Han, 2024). It is increasingly establishing itself as a game-changer in education, and students can use it to learn L2 more effectively in an individualized way, both within and beyond the classroom, compared to conventional classroom settings. Furthermore, several recent studies have revealed that GenAI-supported L2 learning positively influences students' motivation and engagement (e.g., Huang & Mizumoto, 2025; Shen & Teng, 2025; Yuan & Liu, 2025). These findings imply that researchers and practitioners should reconsider how L2 students are motivated and engaged in learning with GenAI. However, research on motivation and engagement in GenAI-supported L2 learning remains relatively new, resulting in a dearth of empirical studies that are strongly grounded in robust theoretical frameworks. This highlights the urgent need to investigate the motivation-engagement nexus based on theoretical foundations tailored to digital applied linguistics.

The present study adopts SDT to examine the associations between motivation and engagement in English language learning with GenAI. Specifically, it investigates the relative importance of different types of self-determined motivation in predicting three dimensions of engagement (i.e., behavioral, cognitive, and emotional) by applying multiple regression analysis, supplemented by dominance analysis and random forest plots. Understanding the unique contributions of various motivational orientations to engagement will provide researchers with insight into the viability of SDT within digital applied linguistics and assist practitioners in identifying key variables to target in daily instruction.

## Literature Review

### *Self-determined Motivation*

SDT is an overarching theory for explaining human behavior in terms of various types of self-determined motivation (Ryan & Deci, 2017). SDT broadly categorizes motivation into three types: intrinsic motivation, extrinsic motivation, and amotivation. Intrinsic motivation represents that human beings behave based on their inherent interest and enjoyment. In contrast, extrinsic motivation indicates that people take actions which are triggered by external pressures and incentives. Specifically, organismic integration theory, one of the mini-theories of SDT, differentiates extrinsic motivation into four types based on varying degrees

of internalization, namely, a process of adjusting external pressure and resources to their own behaviors (Ryan & Deci, 2017). The most internalized type of extrinsic motivation is integrated regulation, which represents a state of fully assimilating a value into their own identity. It follows identified regulation (i.e., consciously upholding values or beliefs and reflecting them into their proactive behaviors) and introjected regulation (i.e., partial incorporation of external resources into their own). The least internalized type refers to external regulation. Those who are externally regulated behave to pursue rewards from others or avoid punishment. Beyond intrinsic and extrinsic motivation, SDT posits that amotivation is a lack of motivation, a state of being neither internally nor externally motivated. Originating in general psychology, L2 researchers have adopted this theory to explore the different reasons behind subsequent actions and achievement (Al-Hoorie et al., 2025).

Although extensive SDT-informed empirical research has established the theoretical foundations, several conceptual debates remain unresolved. One ongoing discussion concerns whether intrinsic motivation should be divided into three sub-components: intrinsic motivations to know (i.e., engaging in learning for the pleasure of acquiring knowledge), to accomplish (i.e., striving to complete moderately challenging tasks), and to experience stimulation (i.e., seeking excitement or pleasure from tasks). A few studies have examined intrinsic motivation from the tripartite subcomponent models. For instance, Noels et al. (2000), who took the initiative to introduce SDT into applied linguistics research, investigated intrinsic motivation from the tripartite subcomponent models. However, Howard et al. (2020) revealed that the three were highly strongly correlated with each other ( $\rho = .83-.86$ ), suggesting that intrinsic motivation may be examined as a unidimensional construct. Another is the relevance of integrated regulation as part of the continuum of a simplex structure. A large body of empirical studies have excluded integrated regulation, as it is often difficult to distinguish it from identified regulation. Regarding this point, Howard et al. (2021) suggested that the role of integrated regulation becomes more apparent when examining maladaptive outcomes (e.g., anxiety or boredom), thereby supporting its continued inclusion in SDT-informed motivation research. Finally, there is inconsistency regarding whether amotivation should be positioned at the lowest end of the continuum. Although SDT traditionally views amotivation as conceptually distinct from both intrinsic and extrinsic motivation, some researchers recommend that amotivation be included as part of the continuum. This stems from a person-centered approach, which has revealed

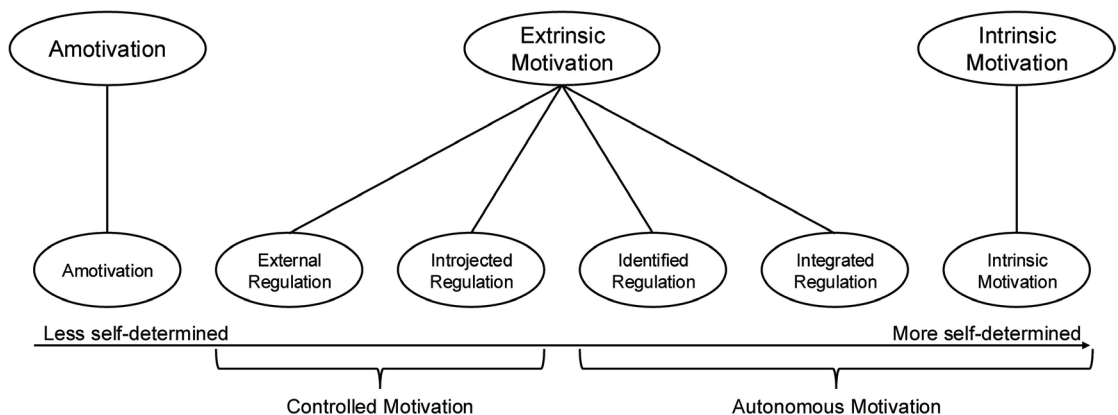


**Figure 1.** Illustrative representation of self-determined motivation.

Note. Adapted from Howard et al. (2017).

that even individuals who are intrinsically and/or extrinsically motivated have amotivation simultaneously (e.g., Howard et al., 2016). It is noted that, looking at the L2 domain, Leeming and Harris (2022, 2024) followed this line of inquiry including six types of regulation: intrinsic motivation as a unidimensional construct, four types of extrinsic motivation, and amotivation.

Based on the findings supported by educational and L2 research in traditional applied linguistics, the current study therefore considers student motivation from the six types of regulation (i.e., intrinsic motivation, integrated regulation, identified regulation, introjected regulation, external regulation, and amotivation; see Figure 1) for capturing various reasons behind GenAI-supported L2 learning behaviors.

### **Student Engagement**

Student engagement refers to active participation and involvement in tasks (Dörnyei & Kormos, 2000; Hiver et al., 2024). Fredricks et al. (2004) conceptualize student engagement from internal and external aspects, including behavioral, cognitive, and emotional dimensions. Behavioral engagement is observable actions from others that can be measured by language use, effort, and persistence. Cognitive engagement entails mental effort, representing strategy use, self-regulation, and focused attention. Emotional engagement pertains to manifestations of activated positive emotions such as enjoyment and interest. This tripartite conceptualization offers a multifaceted lens through which researchers and practitioners can better understand students' learning processes.

Although Reschly and Christenson (2012) state metaphorically this construct as the “new kid on the block” (p. 14), recent research syntheses (Hınız & Çelik, 2025; Hiver et al., 2024; Namkung & Kim, 2024; Wang & Hui, 2025) have recognized the increasing number of L2 engagement research, which may reflect entering a mature stage of development of the field. Dörnyei and Kormos (2000) conducted initial investigations about engagement in L2 learning. They examined the relationships between motivational variables and two behavioral indicators including number of words and turns in an oral argumentative task. The results revealed that students with high task attitudes demonstrated their behaviors, which suggested the interrelations between motivation and behavioral engagement. Following the publication of Dörnyei and Kormos (2000), a number of studies have explored engagement through one or two dimensions (e.g., Liu, 2022; Yamazaki & Hiver, 2024). For instance, Liu (2022) examined how autonomous and controlled motivation predicted behavioral engagement. Similarly, Yamazaki and Hiver (2024) focused on the extent to which motivational variables (e.g., self-efficacy and attributions) affected behavioral engagement in L2 reading tasks. These focused investigations on a certain dimension (e.g., behavioral engagement) can provide invaluable insight into conceptual understanding. However, given the complex nature of GenAI-supported L2 learning environments, a multidimensional investigation of engagement is necessary to fully capture L2 learning processes.

In sum, the current study adopts this tripartite model as the conceptual framework of student engagement in GenAI-supported L2 learning. Furthermore, it is hypothesized that the three dimensions are positively interrelated; that is, learners who demonstrate a high level of engagement in one dimension are likely to show high engagement in their other two dimensions as well.

### **Self-Determined Motivation and Engagement in L2 Learning**

As discussed above, research on self-determined motivation and engagement has an existing body of theoretical and conceptual knowledge in applied linguistics. Findings highlight that motivation and engagement are inextricably linked and go hand in hand. In other words, highly

motivated students in L2 classrooms tend to invest their energy into tangible actions. This close link has led some researchers to use these two constructs interchangeably. However, there is a growing consensus among L2 researchers that the two constructs are closely related but conceptually distinct. Hiver et al. (2024) emphasize this distinction by noting that “motivation represents initial intention and engagement is the subsequent action” (p. 223). The current study follows this line of research, and motivation and engagement are considered to be closely related but separate constructs.

Regarding the link of motivation and engagement, SDT postulates that varying degrees of self-determined motivation influence subsequent engagement (Ryan & Deci, 2017). In particular, autonomous forms of motivation more strongly promote engagement, as students who are autonomously motivated internalize the values and meaningfulness of learning. This internalization leads to greater persistence, deeper cognitive involvement, more positive emotional experiences during learning tasks, and ultimately higher achievement (Alamer et al., 2025; Howard et al., 2021). In contrast, when students are driven by controlled motivation, they may partially recognize the value of learning or act under external pressure. Such motivation tends to result in temporal engagement and lower levels of academic achievement (Alamer et al., 2025; Howard et al., 2021). Beyond autonomous and controlled motivation, students who have higher levels of amotivation lack clear intention and purpose of learning, often resulting in a minimal engagement. Overall, SDT emphasizes that, among the various types of self-determined motivation, autonomous forms of motivation are the most conducive to sustained engagement.

Building on these theoretical foundations, in traditional applied linguistics, an extensive body of empirical research has employed SDT as a theoretical framework to show that motivation and engagement are closely associated. Liu (2022) explored the relationship between motivation and engagement and moderating effects of emotions on it. Based on a total of 108 university students in China, regression analyses revealed a significant effect on engagement when considering autonomous motivation and positive emotion together. Furthermore, Li et al. (2022) extended the Liu’s (2022) findings in that they explored the motivation-engagement link and its association with achievement. Utilizing data from 532 university students in China, latent profile analysis revealed that participants with high autonomous and controlled motivations demonstrated higher test scores than others. These results suggest that both motivation and engagement can work synergistically in L2 learning, contributing to improved academic achievement.

Focusing on the Japanese context, Konno and Koga (2017) explored the relationship between various motivational variables and behavioral engagement during a decision-making task. They collected data from 114 university students through using psychometric scales for five motivational variables (effort, interest/enjoyment, value, perceived competence, and perceived relatedness) and two indicators of task behavioral engagement (number of words and turns). Correlation analysis revealed that both interest/enjoyment and value showed small-to-medium-sized associations ( $r = .22-.35$ ). Furthermore, the researchers deepened the results using cluster analysis to examine differences in the degree of engagement based on motivational profiles. The results showed that more intrinsically motivated learners were more behaviorally engaged in the task. In another study, Oga-Baldwin and Nakata (2017) conducted a longitudinal survey to investigate the close relationship between motivation and engagement. Rooted in SDT, they tested a hypothesized model of the effects of engagement on motivation. Based on data from 423 elementary school students in Japan, statistical analyses revealed that two autonomous types of regulation (intrinsic and identified regulation) were strongly and positively correlated with engagement ( $r = .57-.73$ ), whereas controlled types of regulation showed small-to-medium-sized associations ( $r = -.42-.23$ ).

Overall, a substantial body of research has demonstrated the close link between motivation and engagement in L2 learning. Prior research suggests that, when students are autonomously motivated to learn an L2, they are more likely to be actively engaged. Furthermore, autonomous types of motivation serve as a trigger for subsequent learning behaviors. These findings underscore the importance for researchers and practitioners to support students' intrinsic motivation to learn an L2. Additionally, they should help students recognize and internalize the value of L2 learning, which in turn fosters greater engagement.

### ***Self-Determined Motivation and Engagement in GenAI-supported L2 Learning***

The ongoing exponential rise of GenAI has caused an unexpected shift in educational contexts, prompting researchers to pay increasing attention to how GenAI can be integrated into language learning and teaching (e.g., Huang & Teng, 2025; Shen & Teng, 2025; Shi & Lai, 2025). In this regard, Wang et al. (2025) conducted a scoping review to reveal L2 research trends by synthesizing 43 studies published between 2022 and 2024. The authors found that approximately half of the reviewed studies focused on teachers' and students' perceptions of L2 teaching and learning with GenAI. This line of research may be understandable, as it is essential to recognize how the users feel and experience in L2 learning with novel tools such as ChatGPT. As a notable finding from the review, the authors identified that 46.5% of the studies did not employ or explicitly report any theoretical frameworks adopted, and thus Wang and colleagues call for more theory-driven research by emphasizing that "it is essential that GAI [generative artificial intelligence] studies explicitly define their theoretical foundations in the future" (p. 16). This suggests that one promising avenue for future research is to employ robust theoretical frameworks (e.g., SDT) to better understand the psychological mechanisms (e.g., motivation and engagement) in GenAI-supported L2 learning.

Although the number of empirical studies that adopted theoretical frameworks remains limited, digital applied linguists have gradually begun applying SDT to examine the nexus between L2 students' motivation and engagement in GenAI-supported learning environments (e.g., Nakamura et al., 2024; Teng, 2025; Yuan & Liu, 2025). For instance, Yuan and Liu (2025) conducted an experimental study to investigate the effects of the use of GenAI on motivation (intrinsic motivation, identified regulation, introjected regulation, external regulation, and amotivation) and engagement (cognitive and emotional dimensions). Data were collected from 412 students in China, who were randomly assigned to experimental and control groups. A series of one-way analysis of covariance revealed that both scores of motivation and engagement significantly increased in the experimental group, suggesting that GenAI can play an important role in positively influencing students' L2 motivation and engagement.

Similarly, Nakamura et al. (2024) investigated the associations among motivation (intrinsic motivation, introjected regulation, and external regulation), engagement (behavioral, cognitive, and emotional dimensions), and learning styles in English language learning with GenAI. Cluster analysis based on data collected from 103 university students in Japan showed that groups with higher scores for introjected and external regulation were highly engaged behaviorally, cognitively, and emotionally. In contrast, the group with high intrinsic motivation demonstrated moderate engagement, highlighting the importance of students understanding the value and meaningfulness of using GenAI in L2 learning to enhance their engagement.

Overall, both studies of Yuan and Liu (2025) and Nakamura et al. (2024) suggested SDT as a prospective theoretical framework for capturing students' motivation and engagement in GenAI-supported L2 learning. However, these two studies addressed motivation as a unidimensional construct or part of the continuum. Furthermore, there were inconsistencies in how engagement dimensions were operationalized across the studies. This indicates that

there needs to be further research that examines the relationships between all six types of self-determined motivation and the tripartite dimensions of engagement in order to fully capture the interrelations between motivation and engagement in GenAI-supported L2 learning.

### Current Study

SDT is an overarching theory for understanding students' motivation across wider research domains, including educational psychology as well as L2 research. Furthermore, both researchers and practitioners can gain comprehensive insight into students' tangible actions through the lens of engagement. Although previous studies on the motivation-engagement nexus have drawn attention to traditional educational contexts, recent drastic changes of the contexts caused by the introduction of GenAI highlight the need of updating our understanding about students' motivation and engagement. However, research on motivation and engagement in GenAI-supported L2 learning is relatively new, which may lead to a lack of theory-driven empirical studies that focus on the relationships between the two constructs in the domain of digital applied linguistics. Based on this background, the current study provides initial evidence of the viability of SDT in the field of digital applied linguistics by investigating the comprehensive relationships between motivation and engagement in GenAI-supported L2 learning. The following two research questions (RQs) were set out:

- RQ1: To what extent are different types of self-determined motivation and student engagement interrelated in GenAI-supported English language learning?
- RQ2: What is the relative importance of different types of self-determined motivation in predicting student engagement in GenAI-supported English language learning?

## Method

### Participants

Employing a convenience sampling approach, 98 university students learning English as a foreign language participated in the survey. Of these, 70 students were male, 19 were female, and the remaining nine preferred not to disclose their gender. The majority were freshmen ( $n = 94$ ), with three second-year students and one third-year student. They were enrolled in two general English classes in a Japanese university, which originally included a total of 128 students. Given the purpose of the present study, 30 students who had never used GenAI in English language learning were excluded. The participants had low-to-intermediate English proficiency, based on the researcher's (i.e., the teacher of the courses) observation during the classes.

The participants completed a paper-and-pencil questionnaire at the beginning of the first semester in 2025. Prior to data collection, the researcher provided all participants with written informed consent, informing that participation in the survey was entirely voluntary, would have no effect on their course grades, and that they could withdraw at any time, even partially.

It is noteworthy that, to calculate a statistical power for multiple regression analysis (as discussed later), this study preliminarily performed a post hoc power analysis by using *G\*Power* (version 3.1.9.6; Faul et al., 2009). With the conditions of effect sizes of  $f^2$  being 0.15, the  $\alpha$  value being 0.05, the sample size being 98, and the number of predictors being six, the power was shown to be 0.80. This value is a “medium-effect” size (Cohen, 1988, p. 413), indicating that the sample size of the present study was sufficient to detect the medium-sized statistical power in multiple regression analysis.

## Instruments

### Language Learning Orientation Scale Japan

Student motivation for English language learning using GenAI was assessed using the Language Learning Orientation Scale Japan (LLOS-J) validated by Leeming and Harris (2024). LLOS-J includes a total of 33 items to evaluate six regulations consisting of intrinsic motivation (7 items; *The reason I study English using generative AI is because I like using English*), integrated regulation (5 items; *The reason I study English using generative AI is because learning English is a part of who I am*), identified regulation (5 items; *The reason I study English using generative AI is because I think it's a good idea to know some English*), introjected regulation (5 items; *The reason I study English using generative AI is because I feel an obligation to learning English*), external regulation (6 items; *The reason I study English using generative AI is to get the course credit*), and amotivation (5 items; *With regards to studying English using generative AI I think that studying English is a waste of time*). Leeming and Harris (2024) demonstrated that LLOS-J had high reliability (i.e., person reliability of each subscale ranged between .70 and .90). It is noteworthy that the original scale (Leeming & Harris, 2024) was developed in the conventional L2 contexts, and thus, I modified it into English language learning using GenAI. All items were written in Japanese to ensure the participants' comprehension. The participants completed it on a 6-point Likert scale (1 = *strongly disagree*; 6 = *strongly agree*).

### Second Language Classroom Engagement Scale

This study adapted the L2 engagement scale from Hiver et al. (2020) to evaluate student engagement with English language learning with GenAI. It includes 12 items for assessing three dimensions of behavioral (4 items; *When I cannot understand English language learning using generative AI, I stay focused until I do*), cognitive (4 items; *I go through the work for English language learning using generative AI carefully and make sure that it's done right*), and emotional (4 items; *I enjoy learning new things in English language learning using generative AI*). As with the motivational scale described above, this study revised the original into assessing engagement toward English language learning using GenAI. It is to be noted that a previous study (Nakamura et al., 2024) used the modified version and showed that the subscales were highly reliable ( $\alpha = .82-.86$ ). The participants completed the scale written in Japanese on a 6-point Likert scale (1 = *strongly disagree*; 6 = *strongly agree*).

## Data Analysis

The statistical analyses were conducted using statistical software *R* (version 4.4.3; R Core Team, 2025). Prior to analyses for RQs, Cronbach's  $\alpha$  with its 95% confidence intervals was checked for each subscale to assess its internal consistency. In addition, to explore overall characteristics of the participants, descriptive statistics were calculated in terms of mean, standard deviation, skewness, and kurtosis. If values of skewness and kurtosis ranged between  $\pm 2$ , the data could be judged as normally distributed (Roever & Phakiti, 2018).

To examine the overall relationships between self-determined motivation and engagement (RQ1), correlation analysis was performed. With a reference to Plonsky and Oswald (2014), this study considered Pearson's correlation coefficients of .25, .40, and .60 as small, medium, and large, respectively.

Subsequently, multiple regression analysis was conducted to investigate the relative importance of six types of regulations (i.e., predictor variables) for three dimensions of engagement (i.e., outcome variables) (RQ2). Notably, I followed Mizumoto's (2023) methodological guidelines

regarding the appropriate interpretation of beta coefficients in multiple regression analysis and recommendations for the supplementary use of dominance analysis and random forest modeling. These two approaches can identify which predictors within regression models are more influential while taking into account the interrelations among predictors. More specifically, dominance analysis is useful for examining the relatively important predictors by assessing changes in explained variance ( $R^2$ ) across different combinations of them. Random forest with the Boruta algorithm is a nonparametric approach that offers a different perspective from dominance analysis. This approach aims to identify important predictors in multiple regression models by comparing with shadow variables, which are meaningless but can provide valuable insight into predictors’ significance. Notably, these two approaches are rooted in different paradigms, which helps researchers double-check their results. Since the publication of Mizumoto (2023), an increasing number of articles have employed dominance analysis and random forest modeling as supplemental procedures, possibly reflecting L2 researchers’ growing attention to the precise interpretation of beta coefficients (e.g., Mikami & Shiozawa, 2024; Teng & Mizumoto, 2024). For readers interested in these techniques, Mizumoto (2023) offers an accessible introduction tailored to L2 research.

Transparency and Openness

Recent scholars in psychology (American Psychological Association, 2024) and applied linguistics (Al-Hoorie et al., 2024; Marsden & Morgan-Short, 2023; Plonsky, 2024) have placed strong emphasis on open science. As a representative development within this movement, the American Psychological Association recommends including a “Transparency and Openness” subsection at the end of the Method section to report the transparency of relevant information, such as the sharing of data, code, and materials. In line with this emerging trend, the author (i.e., an early-career researcher) understand this initiative, and all data, R code, and materials used in the current study are available on the Open Science Framework (<https://doi.org/10.17605/OSF.IO/EF3B5>), allowing readers to reproduce the results of the current study.

Results

Before conducting statistical analyses for RQs, several preliminary analyses were performed. First, Cronbach’s  $\alpha$  for each subscale was calculated. As shown in Table 1, the values ranged

Table 1. Descriptive statistics and reliability

| Variable    | <i>M</i> | <i>SD</i> | Skewness | Kurtosis | $\alpha$ | 95% CI     |
|-------------|----------|-----------|----------|----------|----------|------------|
| Intrinsic   | 3.51     | 1.02      | 0.41     | 0.40     | .94      | [.91, .95] |
| Integrated  | 3.04     | 1.09      | 0.36     | −0.47    | .92      | [.89, .94] |
| Identified  | 3.67     | 1.10      | 0.25     | −0.22    | .91      | [.88, .93] |
| Introjected | 3.28     | 0.92      | 0.50     | 0.65     | .83      | [.77, .88] |
| External    | 3.02     | 0.99      | 0.17     | −0.47    | .86      | [.81, .90] |
| Amotivation | 2.29     | 1.04      | 0.66     | 0.26     | .93      | [.91, .95] |
| Behavioral  | 3.61     | 0.95      | 0.36     | 0.00     | .88      | [.84, .91] |
| Cognitive   | 3.60     | 0.99      | 0.49     | 0.08     | .90      | [.87, .93] |
| Emotional   | 3.54     | 1.00      | 0.44     | 0.11     | .89      | [.85, .92] |

Note. *N* = 98. CI = confidence interval.

from .83 to .94 for the motivation scale and from .88 to .90 for the engagement scale. These results showed that both had moderate-to-high internal consistencies. Furthermore, the skewness and kurtosis fell within the range of  $\pm 2$ , indicating that the data were normally distributed. Regarding characteristics of the participants, they held moderately autonomous types of motivation and were engaged in GenAI-supported L2 learning.

**RQ1: To what extent are different types of self-determined motivation and student engagement interrelated in GenAI-supported English language learning?**

Concerning RQ1, correlation analysis was performed to explore the associations between self-determined motivation and engagement (see Table 2). The results demonstrated simplex structures among six types of regulation: stronger correlations were found between adjacent variables than between more distant ones. Autonomous types of motivation (i.e., intrinsic, integrated, and identified) were positively and strongly correlated with one another ( $r = .56-.69$ ), while controlled types of motivation (i.e., introjected and external) were associated with a small-to-medium size ( $r = .49$ ). With regard to amotivation, its associations with other types of regulation were generally inconclusive, except for a moderate correlation with external regulation ( $r = .48$ ). In terms of engagement, the three dimensions were more strongly interrelated ( $r = .71-.83$ ). Furthermore, regarding the relationships between motivation and engagement, autonomous types of regulation showed stronger associations with engagement ( $r = .49-.72$ ) than did controlled types ( $r = .23-.46$ ).

**Table 2.** Correlations between self-determined motivation and engagement

| Variable       | 1      | 2          | 3          | 4          | 5           | 6           | 7            | 8            | 9           |
|----------------|--------|------------|------------|------------|-------------|-------------|--------------|--------------|-------------|
| 1. Intrinsic   | –      | [.57, .78] | [.53, .76] | [.32, .63] | [.02, .40]  | [–.28, .11] | [.47, .72]   | [.44, .70]   | [.61, .80]  |
| 2. Integrated  | .69*** | –          | [.41, .68] | [.19, .53] | [.01, .39]  | [–.13, .27] | [.36, .65]   | [.32, .63]   | [.43, .70]  |
| 3. Identified  | .66*** | .56***     | –          | [.27, .59] | [–.02, .36] | [–.35, .04] | [.52, .75]   | [.58, .79]   | [.54, .76]  |
| 4. Introjected | .49*** | .37***     | .44***     | –          | [.32, .63]  | [–.06, .33] | [.20, .54]   | [.10, .46]   | [.28, .60]  |
| 5. External    | .22*   | .21*       | .18        | .49***     | –           | [.31, .62]  | [–.09, .30]  | [–.16, .23]  | [.03, .41]  |
| 6. Amotivation | –.09   | .07        | –.16       | .14        | .48***      | –           | [–.43, –.06] | [–.48, –.31] | [–.27, .12] |
| 7. Behavioral  | .61*** | .52***     | .65***     | .38***     | .11         | –.25*       | –            | [.75, .88]   | [.66, .83]  |
| 8. Cognitive   | .59*** | .49***     | .70***     | .29**      | .04         | –.31***     | .83***       | –            | [.59, .79]  |
| 9. Emotional   | .72*** | .58***     | .67***     | .46***     | .23*        | –.08        | .76***       | .71***       | –           |

Note.  $N = 98$ . Pearson’s correlation coefficients are below the diagonal, and 95% confidence intervals [lower, upper] are above the diagonal.  
\* $p < .05$ . \*\* $p < .01$ . \*\*\* $p < .001$ .

**RQ2: What is the relative importance of different types of self-determined motivation in predicting student engagement in GenAI-supported English language learning?**

Regarding RQ2, this study performed multiple regression analysis with the conditions of behavioral, cognitive, and emotional engagement being outcome variables and six types of regulation being predictor variables (see Table 3). Notably, the three regression models demonstrated substantial explanatory power, accounting for 52.8% of the variance in behavioral engagement, 56.1% in cognitive engagement, and 59.6% in emotional engagement. Within each model,

**Table 3.** Multiple regressions with dominance analysis

|                | <i>b</i> | SE   | $\beta$ | <i>t</i> | <i>p</i> | R <sup>2</sup> | DW (%)        |
|----------------|----------|------|---------|----------|----------|----------------|---------------|
| (1) Behavioral |          |      |         |          |          |                |               |
| Intrinsic      | .187     | .109 | .201    | 1.714    | .090     | .528           | .131 (24.73%) |
| Integrated     | .143     | .091 | .164    | 1.566    | .121     |                | .101 (19.22%) |
| Identified     | .306     | .088 | .354    | 3.460    | < .001   |                | .185 (35.15%) |
| Introjected    | .080     | .098 | .077    | 0.819    | .415     |                | .047 (8.99%)  |
| External       | .033     | .092 | .034    | 0.364    | .717     |                | .010 (1.81%)  |
| Amotivation    | −.199    | .081 | −.217   | −2.463   | < .05    |                | .053 (10.10%) |
| (2) Cognitive  |          |      |         |          |          |                |               |
| Intrinsic      | .166     | .110 | .171    | 1.509    | .135     | .561           | .122 (21.84%) |
| Integrated     | .109     | .092 | .120    | 1.189    | .238     |                | .089 (15.95%) |
| Identified     | .440     | .089 | .488    | 4.947    | < .001   |                | .246 (43.90%) |
| Introjected    | −.023    | .098 | −.021   | −0.235   | .815     |                | .027 (4.81%)  |
| External       | .005     | .092 | .005    | 0.052    | .959     |                | .007 (1.34%)  |
| Amotivation    | −.212    | .081 | −.222   | −2.611   | < .05    |                | .068 (12.16%) |
| (3) Emotional  |          |      |         |          |          |                |               |
| Intrinsic      | .400     | .106 | .411    | 3.790    | < .001   | .596           | .213 (35.76%) |
| Integrated     | .090     | .088 | .099    | 1.024    | .308     |                | .116 (19.53%) |
| Identified     | .267     | .085 | .295    | 3.122    | < .01    |                | .179 (30.01%) |
| Introjected    | .077     | .094 | .071    | 0.810    | .420     |                | .064 (10.67%) |
| External       | .046     | .089 | .046    | 0.522    | .603     |                | .016 (2.74%)  |
| Amotivation    | −.031    | .078 | −.032   | −0.392   | .696     |                | .008 (1.29%)  |

Note. *N* = 98. DW = dominance weight.

approximately 80% of the proportion was attributable to autonomous motivation (intrinsic, integrated, and identified regulation).

Particularly, as for behavioral engagement, identified regulation emerged as the strongest predictor ( $\beta = .354, p < .001$ ; dominance weight [DW] = .185, 35.15%), which was followed by intrinsic motivation ( $\beta = .201, p = .090$ ; DW = .131, 24.73%) and integrated regulation ( $\beta = .164, p = .121$ ; DW = .101, 19.22%). For cognitive engagement, identified regulation again accounted for the largest proportion ( $\beta = .488, p < .001$ ; DW = .246, 43.90%), followed by intrinsic motivation ( $\beta = .171, p = .135$ ; DW = .122, 21.84%) and integrated regulation ( $\beta = .120, p = .238$ ; DW = .089, 15.95%). Finally, slightly different pattern was observed for emotional engagement: intrinsic motivation accounted for the largest proportion ( $\beta = .411, p < .001$ ; DW = .213, 35.76%). It was followed by identified regulation ( $\beta = .295, p < .01$ ; DW = .179, 30.01%) and integrated regulation ( $\beta = .099, p = .308$ ; DW = .116, 19.53%).

Additionally, the random forests were checked to complement the results of multiple regression analysis and dominance analysis (see Figure 2). For behavioral engagement, all motivational variables, except for external regulation, were important predictors. Amotivation emerged as the most significant variable, which was followed by autonomous types of motivation. In the

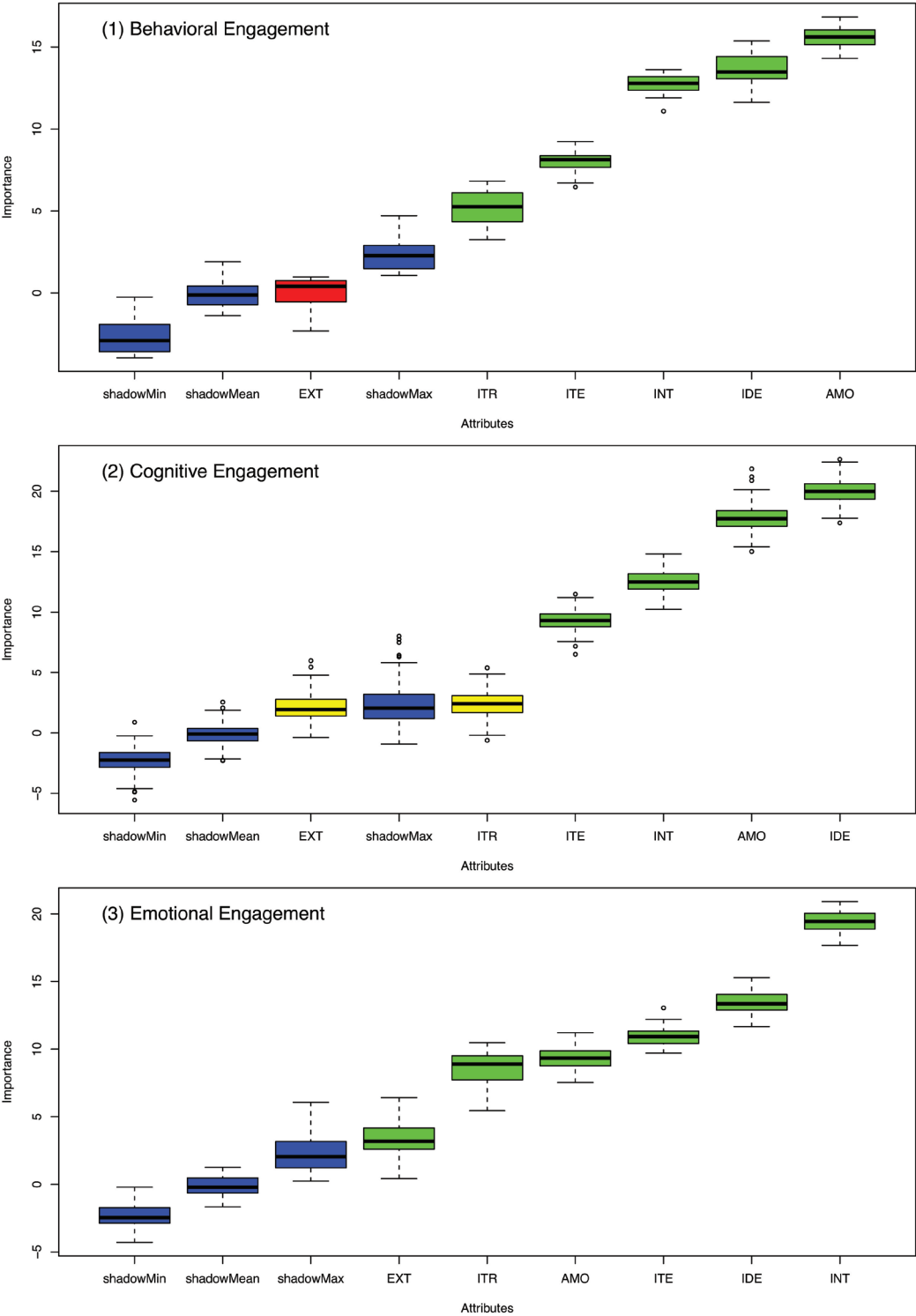


**Figure 2.** *Random forest plot.*

*Note.* INT = intrinsic motivation; ITE = integrated regulation; IDE = identified regulation; ITR = introjected regulation; EXT = external regulation; AMO = amotivation.

case of cognitive engagement, both autonomous motivation and amotivation were important, while the roles of two controlled types of regulation were tentative. Finally, in the same way as behavioral and cognitive engagement, autonomous motivation as well as amotivation were also crucial variables for emotional engagement. In contrast, introjected and external regulations were less important for emotional engagement.

Importantly, when comparing the results from dominance analysis and random forest modeling, similar yet slightly different findings were observed. Regarding behavioral engagement, while dominance analysis showed that the three autonomous types of regulation were the most dominant, the random forest identified amotivation as the most important predictor. Similarly, the random forest indicated that amotivation played a more important role in cognitive engagement compared to dominance analysis. It is noteworthy that, despite these differences, both analyses converge on the point that autonomous motivation (and the absence of amotivation) are key predictors of behavioral and cognitive engagement.

Overall, multiple regression analysis supplemented with dominance analysis and random forests indicated that autonomous types of regulation demonstrated larger proportions of the variance across the three dimensions of engagement. In contrast, controlled motivation and amotivation had relatively smaller accounts for engagement.

## Discussion

The present study posed two research questions to investigate the motivation-engagement nexus as well as the relative importance of self-determined motivation for engagement in GenAI-supported L2 learning. In particular, SDT was employed as a robust theoretical framework to examine qualitatively different types of motivation and their tangible manifestations through the lens of behavioral, cognitive, and emotional engagement among university students learning English in Japan. The findings generally corroborated the premises of SDT, demonstrating the important roles of autonomous motivation in triggering subsequent behaviors. However, a series of statistical analyses identified different effects among various types of regulation.

RQ1 concerned the overall relationships between six types of motivation and three dimensions of engagement in English language learning with GenAI. One of the most significant results from correlation analysis was that autonomous types of regulation had larger associations with engagement ( $r = .49-.72$ ) than controlled types of regulation ( $r = .04-.46$ ). This result indicates that, when students are motivated to learn English using GenAI for inherent joy or by assimilating the value of using the tools into their beliefs, they are likely to invest their energy into tangible actions. This finding aligns with previous studies (e.g., Nakamura et al., 2024; Yuan & Liu, 2025), emphasizing the positive synergy between autonomous motivation and engagement. In contrast, controlled types of regulation (introjected and external) had small-to-medium correlations with engagement. In this regard, Ryan and Deci (2017) explain that introjected regulation is a partial integration of values into their beliefs, which indicates that students learn English based on partially and incompletely internalized beliefs. Besides, external regulation pertains to a feeling of obligation driven by external pressures to avoid punishment. Therefore, individuals with introjected or external regulation may temporarily engage in English language learning using GenAI, even if practitioners allow them to use the tools to make L2 learning more effective. Overall, these findings confirm the SDT's proposition: autonomous motivation has stronger associations with engagement. This implies that SDT can be meaningfully applied into digital applied linguistics to understand the relationship between motivation and engagement in GenAI-supported L2 learning.

In addition to the relationship between motivation and engagement, this study found unique patterns of association among the six types of motivation and among three dimensions

of engagement. With a focus on interrelations among six types of regulation, correlation analysis showed that three autonomous types of regulation (i.e., intrinsic, integrated, and identified) were more strongly interrelated than two controlled types (i.e., introjected and external), which supported the findings of previous studies (Nakamura et al., 2024; Howard et al., 2021; Leeming & Harris, 2024). These findings imply that, once students internalize the value and meaningfulness of English language learning with GenAI, they are likely to remain autonomously motivated. This constellation of the three autonomous types of regulation can drive students to learn English with GenAI over a longer term. In sum, these findings support SDT's postulations of the simplex pattern of motivation, which posits that adjacent regulations on the self-determined continuum are more strongly interrelated, confirming that the simplex structure of motivation can be applied into GenAI-supported L2 learning contexts.

Concerning engagement, three dimensions displayed strong positive associations ( $r = .71-.83$ ), with a larger part of confidence intervals for the interrelations among them overlapped: .75–.88 for behavioral-cognitive, .66–.83 for behavioral-emotional, and .59–.79 for cognitive-emotional. The results imply that, if students actively participate in GenAI-supported English language learning in an observable manner, they demonstrate deliberate mental effort, and their emotional aspects are activated. These findings align with those in traditional applied linguistics research (e.g., Philp & Duchesne, 2016). In other words, regardless of whether students use GenAI in L2 learning, the three dimensions work in tandem. These positive interrelations among the three dimensions can extend conceptual understandings about engagement in traditional applied linguistics by demonstrating that the multidimensional construct remains robust and interdependent even within GenAI-supported L2 learning environments.

RQ2 addresses more specific relationships between the two constructs to investigate the relative importance of motivation for engagement in GenAI-supported English language learning. First, regarding behavioral engagement, dominance analysis revealed that identified regulation was the most dominant predictor, followed by intrinsic motivation. Notably, the random forest yielded a similar but slightly different result: amotivation emerged as the most significant predictor, which was followed by identified regulation, intrinsic motivation, and integrated regulation. Taken together, these findings highlight the promotive power of autonomous motivation and the detrimental effect of amotivation on behavioral engagement. These results are consistent with previous studies in traditional applied linguistics (e.g., Liu, 2022). In this regard, Howard et al. (2021) argued that, particularly in relation to persistent-related outcomes, identified regulation is of notable importance. This suggests that students' perceptions of the meaningfulness of learning are closely linked to tangible actions. It is especially relevant with L2 learning, since L2 learning processes require sustained effort over a long term. This study builds on this extensive body of research and extends it into the context of GenAI-supported L2 learning. The findings suggest that, once students can assimilate the value and meaningfulness of GenAI into their own beliefs, they are more likely to engage actively in L2 learning with the tools. Furthermore, given that statistical analyses revealed that identified regulation was more dominant than intrinsic motivation in predicting behavioral engagement, this highlights the importance of students' explicit understanding of the meaningfulness of GenAI-supported L2 learning, rather than relying solely on their enjoyment and interest in using the tools.

As for cognitive engagement, both dominance analysis and the random forest identified autonomous motivation and amotivation as central predictors. More specifically, both analyses emphasized the significant role of identified regulation. In accordance with theoretical and empirical studies (e.g., Ryan & Deci, 2017; Yuan & Liu, 2025), these results suggest that students who have internalized the value of using GenAI in L2 learning are more likely to be cognitively engaged. Given that cognitive engagement is operationalized as mental effort and

strategic learning (Fredricks et al., 2004), students who clearly understand the purpose of using such tools are more likely to engage in strategic and reflective ways. In contrast, amotivation was shown to be a negative predictor for cognitive engagement. This finding corroborates the theoretical framework (Ryan & Deci, 2017), which posits that individuals who have a lack of clear reasons or perceived value behind behaviors are unlikely to invest their energy into tangible actions. Thus, it is insufficient for researchers and practitioners to simply introduce a number of GenAI tools to their students, but they must also support students in recognizing their purposes.

With regard to emotional engagement, the findings diverged slightly from those for behavioral and cognitive engagement. Dominance analysis revealed that intrinsic motivation was the most important predictor. A possible explanation behind the result lies in the conceptual similarity between the two constructs. According to Reeve (1993), intrinsic motivation refers to inherent joy and interest in tasks, while emotional engagement entails activated positive emotion responses such as enjoyment and interest. This conceptual overlap suggests that intrinsically motivated students are naturally predisposed to emotional engagement. In addition to the relationship, both dominance analysis and the random forest highlighted identified regulation as a dominant predictor. When learners perceive the use of GenAI in L2 learning as personally valuable and aligned with their goals, they are likely to invest their energy into tangible actions for challenging tasks, which leads to foster greater enjoyment, interest, and satisfaction.

Overall, the present study confirms the utility of SDT as a theoretical framework for examining the relationship between motivation and engagement within GenAI-supported L2 learning environments. SDT provides a valuable perspective for differentiating qualitative differences in motivation and identifying which types are most conducive to enhancing student engagement. These findings demonstrate that, to effectively foster behavioral, cognitive, and emotional engagement in GenAI-supported L2 learning, researchers and practitioners should focus not only on GenAI-related tool introduction but also on promoting students' understanding of the value and purpose of using GenAI in their L2 learning.

### Theoretical and Pedagogical Implications

The present study provides initial substantiation for supporting the SDT's proposition of the simplex structure of motivation within the context of GenAI-supported L2 learning. While previous studies have established robust empirical foundations in traditional L2 learning, this study provides initial evidence for the viability of SDT in digital applied linguistics, particularly in understanding the relationship between motivation and engagement. Statistical analyses corroborated key premises of SDT: a simplex structure among self-determined motivation and stronger associations between autonomous motivation and engagement. Based on these findings, this study suggests that SDT can be meaningfully extended to examine students' motivation and engagement in GenAI-supported L2 learning.

This theoretical insight further implies a pedagogical significance of focusing on identified regulation in English language learning using GenAI. Even though researchers and practitioners recognize that GenAI can support L2 learning, it is not sufficient to merely introduce the benefits and practical functions of the various GenAI tools to their students. Rather, it is necessary to guide students in understanding why GenAI-supported L2 learning is highly meaningful and effective. Specifically, in Japanese educational contexts, where English is typically studied as a foreign language in classroom-based settings, the rapid advancement of GenAI is transforming the learning environment. Unlike in traditional learning environments, students can now use GenAI to learn English anytime and in an individualized way; for instance, receiving immediate feedback in writing, reinforcing vocabulary retention, and practicing speaking. Furthermore,

they can integrate these tools both within and beyond the classroom. To maximize such benefits that GenAI offers, researchers and practitioners should foster students' internalization of the value of using the tools, which enhances autonomous motivation and engagement in L2 learning with GenAI.

## Conclusion

Before concluding remarks, I should acknowledge several limitations involved in the current study. First, although the sample size of this study was enough to detect statistical powers for multiple regression analysis evidenced by a post-hoc power analysis, further studies are warranted to adopt advanced statistical methods (e.g., structural equation modeling) with larger sample sizes to investigate structural models and test causal pathways between motivation and engagement. Second, although this study collected data on motivation and engagement using a self-report questionnaire from Japanese university students, future research is recommended to incorporate indirect self-reported data and direct measures together to capture each construct from multiple perspectives (e.g., Hiver & Dao, 2025). Furthermore, given that both motivation and engagement are context-specific, it is advisable to replicate the findings of the present study with participants at different educational levels (e.g., elementary or secondary school students) in different countries (e.g., across various Asian regions). Third, this study investigated the motivation-engagement nexus from a variable-centered perspective. However, SDT posits that students possess various types of motivation simultaneously, and thus, it might be more beneficial to identify distinct motivational profiles among learners and their relations with engagement by employing person-centered approaches (e.g., latent profile analysis; Li et al., 2022). This line of research could provide both researchers and practitioners with insight into different types of motivational profiles and how they relate to active participation in learning (Howard, 2023). Finally, motivation and engagement are context-specific constructs; thus, longitudinal studies should be conducted to explore the dynamic nature and its effects on their English language learning using GenAI over the long term.

Despite these limitations, this study demonstrates initial investigation into the application of SDT for understanding the motivation-engagement nexus in the field of digital applied linguistics. While a growing body of research has accumulated the findings for strengthening SDT's propositions in traditional applied linguistics, there remains a dearth of empirical studies that investigated the relationship between six types of self-determined motivation and three dimensions of engagement in L2 learning with GenAI. This perspective is especially important in that students in the current digital era are surrounded by numerous GenAI tools including ChatGPT. The findings of this study generally align with existing evidence in applied linguistics and identify the crucial roles of autonomous motivation in triggering engagement. Furthermore, it highlights identified regulation as a central role in triggering subsequent tangible actions in GenAI-supported L2 learning. These findings indicate that, regardless of whether learners use GenAI in L2 learning or not, both researchers and practitioners should actively communicate the value and meaningfulness of GenAI in L2 learning. Such collective efforts can meaningfully contribute to our understanding of how students are proactively engaged behaviorally, cognitively, and emotionally with GenAI-supported L2 learning.

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