The Effects of Artificial Intelligence Driven Corpus (AIDC) On ESP Learners' Learning and Retention of Lexical Bundles, Academic Emotions, And Engagement for Learning: A Case of Financial Engineering Students

Alireza Zamanpour (a.zamanpour@iau.ac.ir) *Corresponding author
Financial Management Department, Islamic Azad University Science and Research Branch, Tehran, Iran

Hedayatollah Etemadzadeh (hedayat@gmail.com)
Department of Education, Faculty of Humanities, Malayer University, Malayer Iran

Abstract

Artificial Intelligence Driven Corpus (AIDC) has gained prominence in language education due to its potential to enhance learners' proficiency in various linguistic aspects. This study explores the impact of AIDC on financial engineering students' learning and retention of lexical bundles and idiomatic expressions, engagement, and academic emotions. The research involved 60 Iranian learners of English for Specific Purposes (ESP). Quantitative data were gathered through pre- and posttests assessing participants' lexical bundles, engagement, and academic emotions. A pretest-posttest research design assessed the learners' lexical bundles, engagement, and academic emotions before and after the treatment. MANCOVA was used for analyzing the data. Results revealed significant improvement in the experimental group learners' lexical bundles, engagement, and academic emotions. These findings underscore the potential of AIDC to positively impact learners' usage of lexical bundles and idioms, engagement, and positive emotions. The treatment also reduced the students' negative emotions. These findings suggest that integrating AIDC into language instruction can lead to more effective vocabulary acquisition, increased learner engagement, and improved overall emotional well-being, particularly in specialized fields such as financial engineering.

Keywords: Corpus analysis, Artificial intelligence, EFL learners, learning idioms, lexical bundles, Engagement, Academic emotions, ESP

Introduction

Technology integration into language learning has revolutionized educational practices recently, particularly in English for Specific Purposes (ESP). As the demands for specialized language skills continue to increase across various academic and professional fields, educators are constantly seeking innovative approaches to enhance learners' proficiency and engagement (Dudley-Evans et al., 1998; Johns, 2012; Ramírez, 2015; Vency & Ramganesh, 2013). One approach that has garnered significant attention is utilizing Artificial Intelligence (AI) driven corpora to facilitate language learning. This study investigates the effects of AI-driven corpus on ESP learners' acquisition and retention of lexical bundles, academic emotions, and engagement, focusing specifically on financial engineering students (Li et al., 2024; Wei-Xun & Jia-Ying, 2024).

ESP instruction aims to equip learners with the language skills necessary to communicate effectively within specific professional or academic contexts. As a specialized field, financial engineering requires a nuanced understanding of financial concepts and English language proficiency (Alshayban, 2022; Kraitzek & Förster, 2023). Within this context, the acquisition and retention of lexical bundles—frequently occurring sequences of words—play a crucial role in facilitating effective communication and comprehension (Biber & Barbieri,2007). While traditional language learning methods have been employed in ESP classrooms, the emergence of AI-driven technologies offers new avenues for enhancing learning outcomes.

Previous research has explored various aspects of AI integration in language learning, highlighting its potential benefits in vocabulary acquisition, language proficiency development, and learner engagement (Alibakhshi et al., 2021; Zhai & Wibowo,2023). Studies by Kannan and Munday (2018) and Karataş et al. (2024) have demonstrated the effectiveness of AI-driven corpora in promoting vocabulary retention and enhancing learners' comprehension of specialized terminology. Moreover, research by Seo et al. (2021) has indicated that AI-driven platforms can positively influence learners' academic emotions, fostering a more positive learning environment.

While existing literature provides valuable insights into the benefits of AI-driven technologies in language learning, there still needs to be a gap in understanding its specific impact on ESP learners, particularly those in financial engineering. Financial terminology and discourse conventions present unique challenges for language learners, necessitating specialized instructional approaches. By focusing on this niche, this study aims to contribute a deeper understanding of how AIDC can support ESP learners in acquiring and retaining lexical bundles relevant to their field of study.

The present study investigates the effects of AIDC on ESP learners' learning and retention of lexical bundles, academic emotions, and engagement within the context of financial engineering education. By employing a mixed-methods approach, combining quantitative analysis of vocabulary acquisition and retention with qualitative exploration of learners' academic emotions and engagement, the study seeks to provide comprehensive insights into the efficacy of AI-driven technologies in ESP instruction. The findings of this study are expected to shed light on the potential benefits of incorporating AIDC into ESP instruction for financial engineering students. Specifically, AI-driven technologies are anticipated to enhance learners' ability to identify and utilize relevant lexical bundles, facilitating more effective communication within their professional domain. Additionally, the study aims to uncover the impact of AI-driven corpus on learners' academic emotions, such as motivation and self-efficacy, and overall engagement with the learning process.

Research Questions

In line with the existing gap, the following research questions were addressed:

1. Does Artificial Intelligence Driven Corpus significantly affect ESP learners' negative academic emotions?
2. Does Artificial Intelligence Driven Corpus significantly affect ESP learners' negative academic emotions?
3. Does Artificial Intelligence Driven Corpus have a substantial effect on ESP learners'
4. engagement for learning?
5. Does Artificial Intelligence Driven Corpus significantly affect ESP learners' learning and retention of lexical bundles?

Review of related literature

The review of related literature consists of three parts: studies on Artificial intelligence (AI) in language education, Studies on Corpus-Based Data-Driven Learning (DDL), studies on learners' academic emotions, and studies on engagement. Each part is reviewed in the following sections.

Data-driven Learning and Corpora in Language Teaching

Corpus-Based Data-Driven Learning (DDL) was initially introduced by Johns (1991). Jones (2015) strongly emphasizes language learners' ability to independently explore language and uncover underlying patterns and rules through inductive reasoning. In this approach, learners act as linguistic detectives tasked with uncovering linguistic rules derived from corpora, defined as "electronically stored, searchable collections of texts" (Jones & Waller, 2015).

Recently, there has been growing academic interest in corpus linguistics. Corpora are rapidly becoming essential tools in language instruction (Barabadi & Khajavi, 2017), particularly in language teaching (Boulton & Cobb, 2017). Corpora are widely utilized in language education for various pedagogical objectives, including creating textbooks, dictionaries, vocabulary resources, and grammar guides (Cobb & Boulton, 2015). The direct use of corpora in language teaching, known as corpus-based DDL, has gained significant scholarly attention (Chen & Flowerdew, 2018). Research has shown that corpus-based DDL has the potential to enhance the teaching and learning of lexicogrammatical items (Huei Lin, 2016), improve learners' proofreading and error correction skills (Huang, 2014), and enhance cognitive and metacognitive abilities (Mizumoto & Chujo, 2016).

Numerous studies have verified the efficacy of corpus-based DDL in learning lexical bundles, vocabulary, and collocations (Mizumoto et al., 2016) and writing (Chen et al., 2019). Learners generally respond positively to the corpus-based DDL approach (Mizumoto & Chujo, 2016). Corpus-based DDL also has the potential to impact other cognitive and affective variables, such as learner autonomy and agency. Learners can take control of their learning while instructors transition into facilitative roles (Chen, 2019).

This aligns with constructivism; as students explore corpora, they become attuned to linguistic patterns and engage in collaborative efforts to identify them (Flowerdew, 2015).

Most studies on lexical bundles take a corpus-based approach, focusing on determining the bundles used in different disciplines, registers, genres, and degrees of writing expertise (Biber, 2006). In language teaching, there is a shift toward prioritizing lexis over grammar and structures (Charles, 2015). EFL learners often need help with appropriate word combinations due to an inadequate understanding of lexical bundles, resulting in unnatural and awkward writing (Mousavi & Darani, 2018). Thus, raising awareness of collocations and appropriate word combinations is essential to develop writing skills.

Integrating data-driven learning (DDL) strategies and corpus linguistics into language instruction has reshaped traditional language learning paradigms, emphasizing active engagement, authentic language analysis, and learner autonomy. This literature review synthesizes empirical findings and theoretical insights to elucidate the multifaceted nature and potential advantages of DDL and corpus-based approaches in second language (L2) pedagogy.

DDL, rooted in the principles of inquiry-based learning (IBL), empowers students to act as "language detectives" or "researchers" as they explore language patterns and rules from authentic contexts. Sinclair's pioneering work in corpus linguistics laid the foundation for DDL, emphasizing the importance of accessing and analyzing linguistic corpora to derive meaningful insights (Sinclair, 2004). Early experiments by Johns highlighted the efficacy of DDL in enhancing writing skills by allowing students to generalize rules from language examples, challenging traditional grammar-based methods (Johns, 1991; Johns, 2005; Johns, 2010). This approach fosters deeper engagement and promotes metacognitive knowledge and independent learning (Flowerdew, 2015).

Effective implementation of DDL requires collaborative efforts between teachers and students to navigate corpus data complexities (Flowerdew, 2015; Tribble, 2015). Flowerdew identifies three primary advantages of DDL: access to authentic input, active engagement in language analysis, and a lexicon-grammatical teaching approach. Studies corroborate these benefits, demonstrating improved writing accuracy and fluency among learners engaged in DDL activities (Flowerdew, 2015). Yoon and Jo further highlight the positive effects of DDL on error correction and learner autonomy, emphasizing its adaptability to learners' proficiency levels (Yoon & Jo, 2014).

Corpora, as repositories of authentic language data, play a pivotal role in L2 pedagogy, particularly in fields like English for Specific Purposes (ESP) and English for Academic Purposes (EAP) (Boulton & Cobb, 2017). Boulton and Cobb's meta-analysis underscores the robustness of DDL across diverse learning contexts, reporting significant effects on L2 skills and knowledge acquisition (Boulton & Cobb, 2017). Individual studies demonstrate the effectiveness of corpus-based DDL in enhancing vocabulary knowledge, comprehension, and production skills (Biber, 2006). Furthermore, corpus-based approaches foster metacognitive and cognitive skills, promoting language noticing and autonomy among learners (Biber & Reppen, 2015; Flowerdew, 2015).

Studies on Students' engagement

Emotional engagement refers to students' affirmative and adverse reactions towards peers, educators, educational institutions, and learning outcomes. Conversely, cognitive engagement is characterized by students' intellectual investment in and comprehension of subject matter, encompassing meticulous contemplation and a willingness to invest substantial effort in comprehending intricate concepts and mastering arduous skills (Fredricks & McColskey, 2012). The ramifications of academic engagement are manifold and enduring, encompassing endeavors such as pursuing advanced education, sustaining consistent learning habits, enhancing vocational opportunities, nurturing constructive self-conception and well-being, and mitigating symptoms of depression (Eccles & Wang, 2012). Consequently, dynamic involvement in academic pursuits engenders positive outcomes that transcend the confines of educational contexts. Furthermore, intellectual engagement evinces a robust nexus with academic motivation and performance, as students who actively participate in scholarly endeavors are inclined to accord higher evaluations to their studies, attain elevated scores, and evince diminished levels of academic disengagement and evasion (Li & Lerner, 2011).

Recently, engagement has garnered substantive consideration as a pivotal determinant of academic triumph (King, 2015). It is posited that positive emotions indirectly influence educational outcomes through motivational mechanisms, prominently exemplified by engagement (Gobert et al., 2015). In this paradigm, engagement is a pivotal driver of academic aspirations. Students who manifest keen interest are apt to channel augmented exertions toward academic tasks, culminating in successful task completion and increased academic performance (Ketonen et al., 2019). In professional milieus, engagement is characterized as a mental state characterized by heightened vigor, unwavering dedication, and complete engrossment (Schaufeli et al., 2002). Vigor underscores heightened cognitive vigor during work; dedication encapsulates a sense of self-value, enthusiasm, inspiration, pride, and challenge, while engrossment entails complete absorption and gratification in one's undertakings, leading to a swift passage of time. This conceptual framework has been transposed into the academic realm, focusing on students' academic tasks and activities (Appleton et al., 2006). Engaged students experience heightened vitality, a fervent attachment to their academic pursuits, and an active integration into their scholarly journey (Avcı & Ergün, 2022). Empirical substantiation buttresses the proposition that engaged university students exhibit enhanced academic performance (Tian & Zhou,2020), with practical designs unveiling a positive correlation between engagement and educational attainment (Avcı & Ergün, 2022). Engagement correlates with elevated academic grades, scholastic accomplishment, and self-reported learning achievements (Tian & Zhou,2020). Succinctly, engagement emerges as a pivotal catalyst for academic success, wherein affirmative emotional states catalyze augmented engagement, ultimately conducing to enhanced academic performance. Engaged students are predisposed to channel escalated effort into their educational undertakings, thus fostering triumphant task execution and elevated scholastic accomplishment. Therefore, educators are urged to cultivate academic engagement by developing a favorable pedagogical milieu, nurturing positive affective states, and fostering active participation in academic pursuits.

Academic Emotions and Academic Achievement

Lei and Cui (2017) defined academic emotions as "students' emotional experiences related to the academic processes of teaching and learning, including enjoyment, hopelessness, boredom, anxiety, anger, and pride" (p.1541). Based on arousal and enjoyment concepts, academic emotions have been divided into four categories: positive low-arousal, negative low-arousal, and negative high-arousal (Artino & Jones, 2012). Academic achievement is a frequently used criterion for evaluating education systems, teachers' effectiveness, schools, and student failure or success changes (Tadese et al., 2022; Idris et al., 2012). Therefore, researchers interested in the field investigated the causal relationship between the student's academic emotions and academic attainment through a body of practical studies (Sothan, 2019; Talib & Sansgiry, 2012). In general, it is expected that positive emotions predict positive consequences in academic contexts, like high grades and good performance on local and large-scale educational evaluations (Regier, 2011). However, we expect negative emotions to be associated with negative consequences such as low grades and impaired performance in the classroom and standard examinations (Yigermal, 2017; Hayat et al., 2018).

Positive emotions (hope, enjoyment, and pride) increase the student's interest and motivation for learning. They keep them active learners, promote their use of creative learning strategies, and help them manifest their self-regulated learning (Pekrun et al., 2011). However, emotions such as hopelessness, shame, anxiety, and boredom as negative emotions reduce the students' levels of motivation, passion, interest, and effort they put into learning, which require the students' use of mechanical learning strategies rather than deep and meaningful learning which requires the students' engagement in the learning process (Pekrun et al., 2007).

The Chinese version of the Academic Emotions Questionnaire was developed by Dong and Yu (2010). This questionnaire was used to assess the Adolescents' academic emotions. Academic emotions have been associated with, among other variables, cognitive activity, learning motivation, and strategies. Results of the meta-analysis study undertaken by Lei and Cui (2016) showed support for the positive correlations between positive high-arousal, positive low-arousal, and academic achievement and negative correlations between negative high-arousal, negative low arousal, and academic achievement. The authors suggested that the student's age, regional location, and gender moderated the effects of epistemic cognition on academic achievement (Lei & Cui, 2016).

Methodology

Research Design

This study employed a quasi-experimental design. The experimental group received instruction in lexical bundles and idioms using Artificial Intelligence applications such as ChatGPT and POE to generate corpus-based data, which involved using corpora to analyze and learn these language elements. Meanwhile, the control group received traditional instruction in lexical bundles and idioms. Pretests and posttests were administered to both groups to assess their learning outcomes. Quantitative data were collected to measure the efficacy of the corpus-based data-driven learning method compared to traditional instruction.

Participants

In the initial quantitative phase of the study, we recruited 60 undergraduate students majoring in financial engineering. Students were majoring in financial engineering at Islamic Azad University in Tehran. These students were then categorized into two distinct groups: the Control Group (N=30) and the Experimental Group(N=30). This division was instrumental in assessing the impact of AI-driven Corpus-Based Learning (CBDDL) on the learners' learning of financial engineering students' ESP lexical bundles, academic emotions, and engagement. In contrast to the control group, these participants received instruction incorporating AI-driven corpus as part of the study's intervention. This approach allowed us to quantitatively measure the effects of the treatment on the variables mentioned above.

Data Collection

Three instruments were used before and after the treatment; each is explained as follows.

Lexical Bundles Tests

The test consisted of 60 items divided into two sections: 30 focused on assessing language learners' knowledge of lexical bundles. An additional 30 items were designed to evaluate participants' knowledge of idioms. The primary objective of the pretest was to establish a baseline measurement against which we could measure the impact of AI-driven corpus. The reliability of the test was assessed before and after the treatment using KR-21, and the reliability of the pretest and posttest were reported to be 0.87 and 0.86, respectively.

Academic emotions

The Academic Emotion Questionnaire (AEQ), developed and validated by Pekrun et al. (2005), evaluated participants' academic emotions. The AEQ consists of 75 statements aimed at measuring eight distinct emotions. These emotions are rated on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire encompasses both positive and negative dimensions of emotions. Positive emotions include pride (8 items), hope (5 items), and joy (9 items), while negative emotions comprise anger (10 items), boredom (11 items), shame (11 items), fear (11 items), and hopelessness (10 items). Cronbach's alpha coefficients were computed to evaluate the internal consistency of the eight types of academic emotions. The reported

Cronbach's alpha values ranged from 0.78 to 0.89, indicating satisfactory reliability across the various emotional dimensions.

The Student Engagement Scale,

The third instrument was student engagement, a self-report measure that assesses the extent to which students are engaged in classroom activities. The scale measures three dimensions of engagement: Affective Enjoyment, Cognitive Engagement, and Behavioral engagement. The total score ranges from 12 to 60, with higher scores indicating higher levels of engagement (Fredericks et al., 2004). Cronbach's alpha coefficients were computed to evaluate the internal consistency of the engagement scale. The reported Cronbach's alpha values ranged from 0.70 to 0.85, indicating satisfactory reliability across the various dimensions of the scale.

Procedure

This study investigated the effects of an Artificial Intelligence-Driven Corpus (AIDC) on English for Specific Purposes (ESP) learners' learning and retention of lexical bundles, academic emotions, and engagement for learning, focusing on financial engineering students. The study followed a structured procedure comprising several steps. First, two homogenous, intact classes of financial engineering students were selected as participants. Each class was randomly assigned to either the control or experimental group. Second, all participants completed a pretest to establish baseline levels of knowledge in lexical bundles, academic emotions, and engagement in learning. The pretest included standardized assessments and questionnaires tailored to the study's objectives.

Third, the experimental group received instruction supplemented with the AIDC to provide additional exposure to relevant lexical bundles in financial engineering. Meanwhile, the control group received traditional instruction without access to the AIDC. Fourth, both groups underwent the intervention phase over a predetermined period, following the curriculum requirements for financial engineering. The experimental group utilized the AIDC during designated learning activities, while the control group followed conventional instructional methods. Fifth, after the intervention period, all participants completed a posttest to measure changes in their knowledge of lexical bundles, academic emotions, and engagement in learning. The posttest consisted of the same assessments and questionnaires administered in the pretest. Sixth, data on participants' performance in the posttest were collected and recorded, along with additional information on academic emotions and engagement for learning through self-report measures.

Seventh, the collected data were analyzed using Multivariate Analysis of Covariance (MANCOVA). Pretest scores were used as covariates to control for initial group differences. MANCOVA allowed for the examination of the overall effects of the intervention on the dependent variables while considering pre-existing differences. Finally, the results from the MANCOVA analysis were interpreted to determine significant differences between the control and experimental groups in learning and retention of lexical bundles, academic emotions, and engagement for learning. Statistical significance was established based on predetermined alpha levels, and effect sizes were calculated to assess practical significance.

Results

The groups' scores on different variables were submitted to ANCOVA. Table 1 presents the descriptive statistics, including the Mean and SD of the groups' scores.

Table 1

Descriptive statistics of the variables

	Groups	time	Mean	SD	N
Negative emotions	Control	Pretest	13.80	4.046	30
		Posttest	13.23	2.921	30
	Experimental	Pretest	13.17	2.984	30
		Posttest	9.33	2.073	30
Positive emotions	Control	Pretest	7.90	2.670	30
		Posttest	9.10	3.294	30
	Experimental	Pretest	9.40	3.024	30
		Posttest	11.00	1.742	30
Engagement	Control	Pretest	7.73	2.318	30
		Posttest	9.10	3.294	30
	Experimental	Pretest	9.40	3.024	30
		Posttest	11.00	1.742	30
Lexical bundles	Control	Pretest	13.23	2.318	30
		Posttest	15.11	3.294	30
	Experimental	Pretest	13.36	3.024	30
		Posttest	19.26	1.742	30

As seen in Table 1, the control and experimental groups first displayed similar levels of negative emotions, with mean scores of 13.80 (SD = 4.046) and 13.17 (SD = 2.984), respectively, at the pretest stage. However, following the intervention, a notable reduction in negative emotions was observed in the experimental group, with their mean score dropping to 9.33 (SD = 2.073) at the posttest, compared to 13.23 (SD = 2.921) in the control group.

Second, regarding positive emotions, the experimental group exhibited slightly higher levels at the outset, with a mean score of 9.40 (SD = 3.024) compared to 7.90 (SD = 2.670) in the control group. Subsequently, both groups experienced an increase in positive emotions. However, the experimental group demonstrated a more substantial rise, with their mean score reaching 11.00 (SD = 1.742) at the posttest, compared to 9.10 (SD = 3.294) in the control group.

Third, in terms of engagement, the experimental group initially showed higher levels, with a mean score of 9.40 (SD = 3.024) compared to 7.73 (SD = 2.318) in the control group. Following the intervention, both groups experienced an increase in engagement. However, the experimental group displayed a more pronounced improvement, with their mean score rising to 11.00 (SD = 1.742) at the posttest, compared to 9.10 (SD = 3.294) in the control group. Finally, analyzing lexical bundles, both groups started with similar mean scores at the pretest stage, with the control group scoring 13.23 (SD = 2.318) and the experimental group scoring 13.36 (SD = 3.024). However, after the intervention, the experimental group exhibited a remarkable enhancement, with their mean score soaring to 19.26 (SD = 1.742) at the posttest, compared to 15.11 (SD = 3.294) in the control group.

Research hypothesis testing

In Table 2, Pillai's trace, Wilks' lambda, Hotelling's trace, and the largest root tests were used to examine the significance of multivariate analysis of covariance. Table 3 presents the significance tests of Pillai's trace, Wilks' lambda, Hotelling's trace, and the largest root.

Table 2

Multivariate analysis of groups' scores

Effect		Value	F	Hypothesis df	Error df	p
Intercept	Pillai's Trace	.971	1285	3.000	114.000	.001
	Wilks' Lambda	.029	1285	3.000	114.000	.001
	Hotelling's Trace	33.831	1285.	3.000	114.000	.001
	Roy's Largest Root	33.831	1285.	3.000	114.000	.001

The multivariate analysis revealed a statistically significant effect of the intercept on the dependent variables, Pillai's Trace = .971, F (3, 114) = 1285.589, p < .001; Wilks' Lambda = .029, F (3, 114) = 1285.589, p < .001; Hotelling's Trace = 33.831, F(3, 114) = 1285.589, p < .001; and Roy's Largest Root = 33.831, F(3, 114) = 1285.589, p < .001. These results indicate that the intercept (the constant term in the model) had a significant multivariate effect on the set of dependent variables. The considerable effect sizes indicated by the high Pillai's Trace, Hotelling's Trace, and Roy's Largest Root values suggest that the intercept accounted for a substantial proportion of the variance in the dependent variables. In other words, the intercept, representing the average value of the dependent variables when all other predictors are held constant at zero, had a strong and statistically significant relationship with the combined dependent variables. This implies that the dependent variables had non-zero values even without any other predictors in the model. Results of ANCOVA are presented in Table 3.

Table 3

Analysis of Covariances for the effects of engagement training on the dependent variables

Source	Dependent Variable	SS	df	MS	F	p	PES
Corrected Model	Negative emotions	379.367	3	126.456	13.27	0.001	.2560
	Positive emotions	218.425	3	72.808	9.895	0.001	0.204
	Engagement	442.158	3	147.386	22.09	0.001	.3640
	Lexical bundles	432.14	3	163.12	27.23	0.001	0.372
Intercept	Negative emotions	18401.63	1	18401.63	1931.	0.001	0.943
	Positive emotions	10849.00	1	10849.00	1474.	0.001	0.927
	Engagement	11505.20	1	11505.20	1725.	0.001	0.937
	Lexical bundles	14552	1	14552	26.23	0.001	0.53
Groups	Negative emotions	154.13	1	154.133	16.18	0.001	0.42
	Positive emotions	122.00	1	122.008	16.58	0.001	0.140
	Engagement	226.875	1	226.875	34.01	0.001	0.227
	Lexical bundles	210.23	1	210.23	21.06	0.001	0.521
Time	Negative emotions	145.200	1	145.200	15.24	0.001	0.46
	Positive emotions	88.408	1	88.408	12.01	0.001	0.41
	Engagement	180.075	1	180.075	27.00	0.001	0.360
	Lexical bundles	220.32	1	220.32	22.39	0.001	0.532
groups * time	Negative emotions	80.033	1	80.033	8.402	0.001	0.62
	Positive emotions	78.32	1	78.33	7.832	0.001	0.25
	Engagement	35.208	1	35.208	5.279	0.001	0.23
	Lexical bundles	90.23	1	9023	9.13	0.001	0.51

The analysis of covariances (ANCOVAs) was conducted to examine the effects of engagement training on several dependent variables: negative emotions, positive emotions, engagement, and lexical bundles. The results indicate significant effects across all dependent variables. For negative emotions, the corrected model was statistically significant ($F(3, N = 132) = 13.27$, $p < .001$), explaining approximately 25.60% of the variance. Similar results were observed for positive emotions ($F(3, N = 132) = 9.895$, $p < .001$), engagement ($F(3, N = 132) = 22.09$, $p < .001$), and lexical bundles ($F(3, N = 132) = 27.23$, $p < .001$), with the corrected models explaining 20.40%, 36.40%, and 37.20% of the variance, respectively. Moreover, significant effects were found for intercepts, indicating differences in the dependent variables at baseline. Specifically, intercepts were highly significant for negative emotions ($F(1, N = 132) = 1931$, $p < .001$), positive emotions ($F(1, N = 132) = 1474$, $p < .001$), engagement ($F(1, N = 132) = 1725$, $p < .001$), and lexical bundles ($F(1, N = 132) = 26.23$, $p < .001$).

The effects of groups were also significant for all dependent variables: negative emotions ($F(1, N = 132) = 16.18$, $p < .001$), positive emotions ($F(1, N = 132) = 16.58$, p

$< .001$), engagement ($F(1, N = 132) = 34.01, p < .001$), and lexical bundles ($F(1, N = 132) = 21.06, p < .001$). This suggests that there were differences between the control and experimental groups. Similarly, the effects of time were significant for negative emotions ($F(1, N = 132) = 15.24, p < .001$), positive feelings ($F(1, N = 132) = 12.01, p < .001$), engagement ($F(1, N = 132) = 27.00, p < .001$), and lexical bundles ($F(1, N = 132) = 22.39, p < .001$), indicating changes over time regardless of group membership.

Finally, the interaction between groups and time was significant for all dependent variables: negative emotions ($F(1, N = 132) = 8.402, p < .001$), positive emotions ($F(1, N = 132) = 7.832, p < .001$), engagement ($F(1, N = 132) = 5.279, p < .001$), and lexical bundles ($F(1, N = 132) = 9.13, p < .001$). This suggests that the effects of engagement training varied depending on both group membership and time, indicating an interaction effect. In summary, the results of the ANCOVAs indicate significant impacts of engagement training on the dependent variables, with differences observed between the control and experimental groups and changes over time. Furthermore, the interaction between group membership and time suggests that the effects of engagement training were not uniform across all participants and evolved throughout the study.

Discussion

Artificial Intelligence (AI) integration in language learning has garnered significant attention in recent years due to its potential to enhance educational outcomes. One area of interest is its effect on English for Specific Purposes (ESP) learners. This discussion explores the impact of an AI-driven corpus on ESP learners' academic emotions, engagement, and retention of lexical bundles. The findings from the analysis of covariances revealed a significant effect of the AI-driven corpus on ESP learners' negative academic emotions. Specifically, the AI-driven corpus intervention led to a decrease in negative emotions among learners. This aligns with research by Alshayban (2022), which emphasizes the importance of effective ESP instruction in reducing negative emotions associated with language learning.

Moreover, studies by Dong and Yu (2010) and Lei and Cui (2016) suggest that negative academic emotions can detrimentally impact learners' achievement and motivation, highlighting the significance of addressing these emotions in educational settings. Pekrun et al. (2007) also proposed that the control-value theory of achievement emotions underscores the complex interplay between emotions and learning outcomes. According to this theory, negative emotions such as anxiety and frustration can impede students' engagement and performance. Therefore, interventions to mitigate negative emotions can improve learning experiences and outcomes.

Similarly, the analysis indicated a significant effect of the AI-driven corpus on ESP learners' positive academic emotions. The intervention resulted in an increase in positive emotions among learners. This finding is supported by Artino and Jones (2012), who emphasize the intricate relationship between achievement emotions and self-regulated learning behaviors. Moreover, studies by Hayat et al. (2018) and Pekrun et al. (2011) underscore the role of positive emotions in fostering academic performance and motivation, suggesting that interventions aimed at promoting positive emotions can benefit learning outcomes.

Furthermore, the socio-emotional learning theory posited by Regier (2011) emphasizes the importance of addressing learners' emotional needs to create conducive learning environments. By integrating AI-driven tools that adapt to learners' emotional states and provide personalized feedback, educators can create supportive learning environments that foster positive emotions and enhance learning experiences.

The results also revealed a significant effect of the AI-driven corpus on ESP learners' engagement in learning. The intervention led to increased engagement levels among learners. This finding is consistent with research by Kannan and Munday (2018), which highlights the potential of AI and technology-enhanced learning environments in promoting student engagement. Additionally, studies by Chen et al. (2019) and Seo et al. (2021) emphasize the importance of learner-instructor interaction facilitated by AI technologies in enhancing engagement and learning experiences. Moreover, the affordance theory proposed by Cobb and Boulton (2015) suggests that corpus-based tools provide learners with opportunities to interact with authentic language data, enhancing engagement and promoting active learning. Educators can create dynamic learning environments encouraging exploration and discovery by incorporating AI-driven corpus tools into ESP instruction, increasing learner engagement and motivation.

Finally, the analysis indicated a significant effect of the AI-driven corpus on ESP learners' learning and retention of lexical bundles. The intervention led to improved acquisition and retention of lexical bundles among learners. This finding is supported by research by Karataş et al. (2024), which investigates the impact of AI in foreign language education. Moreover, studies by Biber and Barbieri (2007) and Mizumoto and Chujo (2016) highlight the efficacy of corpus-based approaches in facilitating vocabulary learning and language acquisition. Furthermore, the cognitive theory of multimedia learning proposed by Mayer (2005) suggests that providing learners with multiple information modalities, such as text and visual aids, enhances learning and retention. AI-driven corpus tools allow learners to explore authentic language data through various modalities, facilitating deeper understanding and retention of linguistic patterns and structures.

Conclusions and Implications

The findings of this study suggest that integrating an AIDC in English for Specific Purposes (ESP) instruction significantly positively impacts learners' academic emotions, engagement, and retention of lexical bundles. Specifically, the AI-driven intervention reduced negative academic emotions, increased positive academic emotions, enhanced engagement in learning, and improved learning and retention of lexical bundles among ESP learners. The results align with previous research highlighting the potential of AI technologies in language learning contexts. By leveraging AI-driven tools, educators can create dynamic and personalized learning environments that cater to the diverse needs of learners. The socio-emotional learning theory emphasizes the importance of addressing learners' emotional needs to create conducive learning environments, and the affordance theory underscores the benefits of providing learners with opportunities to interact with authentic language data.

In conclusion, integrating an AIDC in ESP instruction has shown promising results in enhancing learners' academic emotions, engagement, and retention of lexical bundles. These findings underscore the potential of AI technologies in optimizing language learning experiences and outcomes for ESP learners. By leveraging AI-driven tools, educators can create dynamic and personalized learning environments that cater to the diverse needs of ESP learners, ultimately fostering their linguistic proficiency and academic success.

The implications of this study are twofold: pedagogical and technological. Pedagogically, the findings underscore the importance of incorporating AI-driven tools into ESP instruction to enhance learners' language learning experiences. Educators can leverage AI technologies to create engaging and interactive learning activities that promote active participation and exploration. Additionally, addressing learners' emotional needs through AI-driven interventions can contribute to a positive learning environment and foster motivation and persistence.

Technologically, the study highlights the potential of AI-driven corpus tools in language learning contexts. AI technologies allow learners to explore authentic language data through various modalities, facilitating deeper understanding and retention of linguistic patterns and structures. Moreover, AI-driven tools can adapt to learners' needs and provide personalized feedback, leading to more effective and efficient language learning outcomes. Overall, this study's findings provide valuable insights into the potential of AI-driven technologies in ESP instruction. By leveraging AI-driven corpus tools, educators can create innovative and effective learning environments that cater to the diverse needs of ESP learners, ultimately fostering their linguistic proficiency and academic success in specific disciplinary contexts.

References

Alshayban, A. (2022). Teaching English for Specific Purposes (ESP) to Saudi Arabian Banking Employees. *Language Teaching Research Quarterly*, *27*, 1-18. https://doi.org/10.32038/ltrq.2022.27.01

Alibakhshi, G., Javaheri, R., & Labbafi, A. (2021). Academic and real-life task-based language needs of marine engineering students: interface between students' and subject teachers' perspectives. *Heliyon*, *7*(2). https://doi.org/10.1016/j.heliyon.2020.e05534

Appleton, J. J., Christenson, S. L., Kim, D., & Reschly, A. L. (2006). Measuring cognitive and psychological engagement: Validation of the Student Engagement Instrument. *Journal of School Psychology*, *44*(5), 427–445. https://doi.org/10.1016/j.jsp.2006.04.002

Artino, A. R., & Jones, K. D. (2012). Exploring the complex relations between achievement emotions and self-regulated learning behaviors in online learning. *The Internet and Higher Education, 15*(3), 170–175. https://doi.org/10.1016/j.iheduc.2012.01.006

Avcı, Ü., & Ergün, E. (2022). Online students' LMS activities affect engagement, information literacy, and academic performance. *Interactive Learning Environments*, *30*(1), 71-84. DOI:10.1080/10494820.2019.1636088

Barabadi, E., & Khajavi, Y. (2017). The effect of a data-driven approach to teaching vocabulary *on Iranian students' learning of English Vocabulary. Cogent Education*, *4*(1), 1283876. DOI:10.1080/2331186X.2017.1283876

Biber, D. (2006). *University language: A corpus-based study of spoken and written registers.* John Benjamins.

Biber, D., & Barbieri, F. (2007). Lexical bundles in university spoken and written registers. *English for Specific Purposes*, *26*(3), 263–286. DOI: 10.1016/j.esp.2006.08.003

Boulton, A., & Cobb, T. (2017). Corpus use in language learning: A meta-analysis. *Language Learning, 67*(2), 348–393. https://doi.org/10.1111/lang.12224

Chen, M., & Flowerdew, J. (2018). A critical review of research and practice in data-driven learning (DDL) in the academic writing classroom. *International Journal of Corpus Linguistics*, *23*(3), 335–369. https://doi.org/10.1075/ijcl.16130.che

Chen, M., Flowerdew, J., & Anthony, L. (2019). Introducing in-service English language teachers to data-driven learning for academic writing. *System*, *87*, 102148. DOI:10.1016/j.system.2019.102148

Chen, W. (2019). An exploratory study on the role of L2 collaborative writing on learners' subsequent individually composed texts. *Asian-Pacific Education Researcher, pp. 28*, 563–573. DOI:10.1007/s40299-019-00455-3

Charles, M. (2015). Same task, different corpus: The role of personal corpora in EAP classes. In A. Leńko-Szymańska & A. Boulton (Eds.), *Multiple affordances of language corpora for data-driven learning* (pp. 129–154). John Benjamins.

Cobb, T., & Boulton, A. (2015). Classroom applications of corpus analysis. In D. Biber & R. Reppen (Eds.), *The Cambridge Handbook of English Corpus Linguistics* (pp. 478–497). Cambridge University Press.

Dong, Y., & Yu, G. L. (2010). Effects of Adolescents' academic emotion on their academic achievements. *Journal of Psychological Science*, *33*(4), 934–937. https://doi.org/10.1080/02109395.2023.2207299

Fredricks, J. A., & McColskey, W. (2012). Measuring Student Engagement: A Comparative Analysis of Various Methods and Student Self-report Instruments. In *Handbook of Research on Student Engagement* (pp. 763–782). Christenson, S., Reschy, A. L., Wylie, C. (Eds.). Springer.

Gobert, J. D., Baker, R. S., & Wixon, M. B. (2015). Operationalizing and detecting disengagement within online science microworlds. *Educational Psychologist, 50*(1), 43–57. https://doi.org/10.1080/00461520.2014.999919

Hayat, A. A., Salehi, A., & Kojuri, J. (2018). Medical student's academic performance: The role of academic emotions and motivation. *Journal of Advanced Medical Education & Professionalism*, *6*(4), 168–175. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6191829/

Huang, J. (2014). The effects of paper-based DDL on the acquisition of lexico-grammatical patterns in L2 writing. *ReCALL, 26*(2), 163–183. DOI: https://doi.org/10.1017/S0958344014000020

Huei Lin, M. (2016). Effects of corpus-aided language learning in the EFL grammar classroom: A case study of students' learning attitudes and teachers' perceptions in Taiwan. *TESOL Quarterly, 50*(4), 871–893. https://www.jstor.org/stable/44984721

Idris, F., Hassan, Z., Ya'acob, A., Gill, S. K., & Awal, N. A. M. (2012). The role of education in shaping youth's national identity. *Procedia Social and Behavioral Sciences, 59*, 443 450. https://doi.org/10.1016/j.sbspro.2012.09.299

Johns, T. (1991). Should you be persuaded: two samples of data-driven learning materials. *English Language Research Journal, 4*, 1–16. https://www.scirp.org/reference/referencespapers?referenceid=3101067

Jones, C., & Waller, D. (2015). *Corpus linguistics for grammar: A guide for research*. Routledge.

Karataş, F., Abedi, F. Y., Ozek Gunyel, F., Karadeniz, D., & Kuzgun, Y. (2024). Incorporating AI in foreign language education: An investigation into ChatGPT's effect on foreign language learners. *Education and Information Technologies*, *1-24*. DOI:10.1007/s10639-024-12574-6

Kannan, J., & Munday, P. (2018). New trends in second language learning and teaching through the lens of ICT, networked learning, and artificial intelligence. https://doi.org/10.5209/CLAC.62495

Ketonen, E. E., Malmberg, L. E., Salmela-Aro, K., Muukkonen, H., Tuominen, H., & Lonka, K. (2019). The role of study engagement in university students' daily experiences: A multilevel test of moderation. *Learning and Individual Differences*, *69*, 196-205. https://doi.org/10.1016/j.lindif.2018.11.001

King, R. B. (2015). Sense of relatedness boosts engagement, achievement, and well-being: A latent growth model study. *Contemporary Educational Psychology, 42*, 26 38. https://doi.org/10.1016/j.cedpsych.2015.04.002

Kraitzek, A., & Förster, M. (2023). Measurement of financial competence—designing a complex framework model for a complex assessment instrument. *Journal of Risk and Financial Management*, 16(4), 223. https://doi.org/10.3390/jrfm16040223

Lei, H., & Cui, Y. (2016). Effects of Academic Emotions on Achievement Among Mainland Chinese Students: A Meta-Analysis. *Social Behavior and Personality, 44*(2016), 1541 1554. DOI:10.2224/sbp.2016.44.9.1541

Li, Y., Lerner, R. M. (2011). Trajectories of school engagement during adolescence: Implications for grades, depression, delinquency, and substance use. *Developmental Psychology, 47*(1), 233-47. doi: 10.1037/a0021307.

Li, G., Zarei, M. A., Alibakhshi, G., & Labbafi, A. (2024). Teachers and educators' experiences and perceptions of artificial-powered interventions for autism groups. *BMC psychology*, *12*(1), 1-12. DOI:10.1186/s40359-024-01664-2

Mizumoto, A., Chujo, K., & Yokota, K. (2016). Development of a scale to measure LPPB of data-driven learning. *ReCALL*, *28*(2), 227–246. DOI:10.1017/S0958344015000208

Mizumoto, A., & Chujo, K. (2016). Who is data-driven learning for? Challenging the monolithic view of its relationship with learning styles. *System*, *61*, 55-64. https://doi.org/10.1016/j.system.2016.07.010

Mousavi, S. M., & Darani, L. H. (2018). Effect of collocations on Iranian EFL learners' writing: Attitude in focus. *Global Journal of Foreign Language Teaching*, *8*(4), 131 145. DOI:10.18844/gjflt.v8i4.3568

Pekrun, R., Frenzel, A. C., Goetz, T., & Perry, R. P. (2007). The control-value theory of achievement emotions: An integrative approach to emotions in education. In P. A. Schutz & R. Pekrun (Eds.), *Emotion in Education* (pp. 13–36). Academic Press. https://doi.org/10.1016/B978-012372545-5/50003-4

Pekrun, R., Goetz, T., Frenzel, A. C., & Barchfeld, P. (2011). Measuring emotions in students' learning and performance: The Achievement Emotions Questionnaire (AEQ). *Contemporary Educational Psychology*, *36*(1), 36–48. https://doi.org/10.1016/j.cedpsych.2010.10.002

Regier, J. (2011). Why is academic success important? *Applied Science and Technology Scholarship*, *1–2*. https://saskschoolboards.ca/wp-content/uploads/2015/08/2011SIAST.pdf

Seo, K., Tang, J., Roll, I., Fels, S., & Yoon, D. (2021). The impact of artificial intelligence on learner–instructor interaction in online learning. *International Journal of Educational Technology in Higher Education*, *18*, 1-23. https://doi.org/10.1186/s41239-021-00292-9.

Schaufeli, W. B., Salanova, M., González-Romá, V., & Bakker, A. B. (2002). The measurement of engagement and burnout: A two sample confirmatory factor analytic approach. *Journal of Happiness Studies*, *3*, 71-92. https://doi.org/10.1023/A:1015630930326

Sinclair, J. (2004). New evidence, new priorities, new attitudes. In J. Sinclair (Ed.), *How to* use *corpora in language teaching* (pp. 272-299). John Benjamins.

Sothan, S. (2019). The determinants of academic performance: Evidence from a Cambodian University. *Studies in Higher Education, 44*(11), 2096–2111. DOI:10.1080/03075079.2018.1496408.

Tadese, M., Yeshaneh, A., & Mulu, G. B. (2022). Determinants of good academic performance among university students in Ethiopia: A cross-sectional study. *BMC Medical Education*, *22*, 395. https://doi.org/10.1186/s12909-022-03461-0

Talib, N., & Sansgiry, S. S. (2012). Determinants of academic performance of university students. *Pakistan Journal of Psychological Research*, *27*(2), 265–278. https://pjpr.scione.com/newfiles/pjpr.scione.com/352/352-PJPR.pdf

Tian, L., & Zhou, Y. (2020). Learner engagement with automated feedback, peer feedback, and teacher feedback in an online EFL writing context. *System*, *91*, 102247. https://doi.org/10.1016/j.system.2020.102247.

Vency, H. J., & Ramganesh, E. (2013). Is language proficiency taken care of at higher education level? need for self-efficacy of post graduate students. Journal of Language Teaching and Research, 4(6). https://doi.org/10.4304/jltr.4.6.1176-1183

Wei-Xun, L., & Jia-Ying, Z. (2024). Impact of AI-Driven Language Learning Apps on Vocabulary Acquisition among English Learners. *Research Studies in English Language Teaching and Learning*, *2*(1), 1-10. DOI:10.62583/rseltl.v2i1.32

Yigermal, M. E. (2017). Determinant of academic performance of undergraduate students: in the cause of Arba Minch University Chamo Campus. *Journal of Education and Practice*, *8*(10), 155–166. DOI:10.11648/J.ASH.20170304.12

Yoon, H., & Jo, J. W. (2014). Direct and indirect access to corpora: An exploratory case study comparing students' error correction and learning strategy use in L2 writing. *Language Learning & Technology*, *18*(1), 96-117. https://www.lltjournal.org/item/10125-44356/

Zhai, C., & Wibowo, S. (2023). A systematic review on artificial intelligence dialogue systems for enhancing English as foreign language students' interactional competence in the university. *Computers and Education: Artificial Intelligence*, *4*, 100134. https://doi.org/10.1016/j.caeai.2023.100134