Brain, Digital, & Learning

pISSN : 2384-2474
eISSN : 2586-7490

RESEARCH ARTICLE

Behavioral Markers of Childhood Depression from a Neurodevelopmental Perspective: Linguistic Fragmentation and Hostile Projection in Chatbot Conversations

Sihoon Lee[1], Jaeyong Lee[2]*

[1]AI and Robotics Education Convergence Institute, Cheongju National University of Education

[2]Cheongju National University of Education

*Corresponding Author: Jaeyong Lee, educounsel@cje.ac.kr

ABSTRACT

This study investigates linguistic patterns in elementary students' chatbot conversations from a neurodevelopmental perspective. A total of 123 students interacted with an AI chatbot for two weeks. Using a dual-method strategy combining Latent Dirichlet Allocation and qualitative analysis, the study identified an exploratory three-stage behavioral spectrum corresponding to depression severity: (1) Situational Complaint & Playful Distraction (Mild), (2) Relational Ambivalence & Narrative Effort (Moderate), and (3) Structural Disintegration & Hostile Projection (Severe). As severity increased, patterns shifted from playful interaction to fragmented hostility, consistent with deficits in cognitive control and social pain processing. Although the study did not include direct physiological measurements, these linguistic behaviors can be interpreted within a neurodevelopmental perspective as conceptually relevant patterns. The findings suggest that chatbot dialogue serves as a meaningful process-based marker for tracking emotional shifts often missed by traditional screening, highlighting its potential for early risk detection in schools. Given the small moderate and severe subgroups, these findings remain exploratory but provide promising markers for future validation.

Keywords: Childhood depression, counseling chatbot, NLP, behavioral markers, neurodevelopmental perspective

Brain, Digital, & Learning
2025, Vol. 15, No. 4, 583-600
https://doi.org/10.31216/BDL.2025.15.4.4

Received: November 27, 2025
Revised: December 19, 2025
Accepted: December 22, 2025

Introduction

Recent advances in neuroscience conceptualize childhood depression not merely as an emotional problem but as a manifestation of developmental imbalance in neural circuits responsible for emotion regulation and cognitive integration. Dysregulation within the prefrontal–amygdala circuit has been linked to irritability, rumination, and negative attentional bias—core affective responses associated with depression. Moreover, hyperactivation of the Default Mode Network (DMN) has been shown to contribute to increased self-referential negative thinking

(Whitfield-Gabrieli & Ford, 2012). These neurodevelopmental vulnerabilities are also reflected in language use: depressed individuals tend to use more negative emotion words, rely heavily on first-person singular pronouns, and exhibit reduced lexical diversity (Rude et al., 2004). In addition, social threat cues such as peer rejection or conflict activate the so-called "social pain" network, including the anterior cingulate cortex (ACC) and insula (Eisenberger, 2012). Thus, elementary school students' repeated references to peer-related negative emotions during conversation may be closely tied to ongoing neural, social, and emotional developmental processes.

Against this backdrop, AI-based counseling chatbots have emerged as promising tools to complement existing limitations in school mental-health support. Chatbots offer anonymity and high accessibility, enabling children to express emotions without psychological burden (Okonkwo & Ade-Ibijola, 2021). Prior studies involving adolescents and adults have demonstrated that automated conversational agents can reduce early symptoms of depression and anxiety (Fitzpatrick et al., 2017; Heinz et al., 2025). For elementary-aged users, natural conversational data captured by chatbots provide unique developmental value: unlike one-time screening tests, chatbot interactions can longitudinally record emotional fluctuation, ruminative linguistic patterns, and peer-oriented affective expressions. The chatbot used in the present study was designed with a GPT-based empathetic conversational persona to facilitate natural dialogue, enabling the systematic collection of ecologically valid language data.

However, existing research has predominantly focused on user experience or intervention effects, while studies that analyze structural differences in linguistic and emotional expression across depression levels—particularly through the lens of neurodevelopmental and socioemotional brain models—remain scarce. Although certain conversational features in chatbot interactions may correspond to behavioral and neural markers of depression, these connections have seldom been systematically investigated.

To address this gap, the present study applies LDA topic modeling and negative affective word analysis to elementary students' counseling chatbot conversations in order to identify depression-related differences in linguistic and emotional expression. Furthermore, the findings are interpreted within the framework of childhood neurodevelopment and socioemotional neuroscience. Through this approach, we explore the potential of chatbot conversations to function as process-based emotional markers that reflect children's emotional and cognitive states, thereby offering new avenues for early detection of emotional risk within school settings.

Literature Review

Childhood Depression and Socioemotional–Neural Development

Child and adolescent depression is regarded not merely as a temporary mood disturbance but as a major risk factor with long-term consequences for mental-health trajectories extending into adulthood (Ministry of Health and Welfare, 2024; World Health Organization, 2012). Recent neuroscience research conceptualizes depression as arising from both functional abnormalities in emotion–cognition systems and developmental imbalances in the neural networks that support them. For example, when the prefrontal–amygdala emotion-regulation circuit fails to interact effectively, individuals exhibit heightened reactivity to negative stimuli, increased rumination, and attentional bias toward threat cues (Miller et al., 2007).

The DMN—a network implicated in self-referential thinking, autobiographical memory, and future simulation—also shows pronounced hyperactivation and hyperconnectivity in depression and anxiety disorders (Whitfield-Gabrieli & Ford, 2012). Such atypical DMN activation patterns contribute to persistent self-critical thought and the formation of negative self-schemas, and in developing children may pose risks for long-term cognitive and emotional impairment (Weir et al., 2012).

From a social–relational perspective, childhood depression is characterized by unique neuro–emotional sensitivity. Experiences of social rejection or exclusion—often described as "social pain"—activate neural circuits that overlap with physical pain processing, including the ACC and insula (Eisenberger, 2012). This suggests that peer exclusion operates not only as a psychological stressor but also as a neurobiological form of stress.

Considering elementary school children's developmental stage, depression may manifest through linguistic and emotional expressions that differ from those of adults. Because children's emotional clarity and labeling abilities are still developing, they may express distress not through explicit emotional words but through somatic complaints, fragmented statements, or indirect expressions (Kim & Baek, 2014). Accordingly, the emotion words, topic choices, and narrative styles children use in natural conversational contexts provide important indicators of their neural emotion-regulation processes and socio-cognitive development.

Grounded in this socioemotional–neural developmental framework, the present study interprets linguistic and emotional patterns in elementary students' counseling chatbot conversations as behavioral and developmental markers of depression. Because chatbots can collect children's naturalistic speech over extended periods, they offer a novel opportunity to capture subtle emotional signals that traditional screening assessments may overlook.

Language-Based Approaches to Depression Analysis

Language serves as a primary medium through which individuals externalize cognitive and emotional processes and thus has long been a central focus in mental-health research. Rude et al. (2004), through analysis of university students' essays, reported that depressed individuals—compared with non-depressed peers—exhibited (1) a higher proportion of first-person singular pronouns, (2) more frequent use of negative emotion words, and (3) reduced use of positive emotion words and overall lexical diversity. Subsequent meta-analytic findings have repeatedly validated these linguistic tendencies, supporting the notion that language functions as a behavioral indicator of vulnerability to depression (e.g., Tølbøll, 2018).

In online contexts, studies employing natural language to detect depression have grown substantially. De Choudhury et al. (2013) demonstrated that linguistic and behavioral patterns in social media posts can be used to predict depressive risk. Resnik et al. (2015) applied a supervised topic model incorporating depression-related linguistic features and showed that it yielded more clinically interpretable themes than conventional LDA. Collectively, these studies indicate that linguistic data provide valuable information beyond traditional self-report measures and highlight the expanding potential of natural language processing (NLP) techniques for depression detection.

Emotion lexicons are also widely used to quantify the affective tendencies of text. Notable examples include the NRC Emotion Lexicon (Mohammad & Turney, 2013) and VADER (Hutto & Gilbert, 2014) for English, and the KNU

Korean Sentiment Lexicon for Korean-language contexts (Park et al., 2018), which has been increasingly applied in educational and counseling settings. Lexicon-based approaches offer the advantage of transparent and reproducible affective analysis even when annotated training data are limited.

Topic modeling—an unsupervised learning method for inferring latent themes within corpora—has likewise been employed in depression-related language research. Latent Dirichlet Allocation (LDA; Blei et al., 2003) models the natural linguistic assumption that a document may contain multiple topics through a hierarchical document–topic–word structure. However, in environments dominated by short texts such as social media posts or chatbot utterances, sparse word co-occurrence patterns can diminish topic-inference accuracy. To address this issue, models optimized for short text, such as the Biterm Topic Model (BTM; Yan et al., 2013), have been developed, and recent analytical reviews have systematically synthesized advances in short-text topic modeling (Murshed et al., 2023).

In summary, language-based depression research across diverse corpora—including essays, online posts, and SNS text—has consistently documented increased negative emotion words, heightened self-referential language, and topic concentration patterns among individuals at higher depressive risk. However, most existing studies focus on adults, adolescents, or SNS users. Very few have examined the linguistic and emotional patterns that emerge in elementary school children's natural conversations—particularly interactions with counseling chatbots—and even fewer have integrated developmental and neuroscientific perspectives. To address this gap, the present study applies LDA topic modeling and negative emotion-word analysis to elementary students' chatbot counseling dialogues to investigate depression-related differences in linguistic and emotional expression and to interpret these findings through the lens of child developmental and neurobiological frameworks

Limitations of School-Based Emotional Support

Schools represent a primary developmental context in which children and adolescents spend the majority of their daily lives, and they serve as a critical setting for the early identification of emotional and behavioral difficulties. However, the emotional-support systems implemented in schools are constrained by numerous structural limitations. According to recent national surveys on child and adolescent mental health, the proportion of students experiencing emotional difficulties has continued to rise, yet only a small fraction receive professional counseling or clinical services (Ministry of Health and Welfare, 2024).

Most school-administered emotional and behavioral assessments, as well as screening tools for at-risk students, are conducted once per year as one-time evaluations. Such assessment structures limit the capacity to track students' emotional changes over extended periods. In addition, shortages of school counselors, substantial administrative workloads, and stigma perceived by students and parents regarding counseling service utilization all hinder accessibility to school-based emotional support (Lee & Son, 2015). For elementary school children in particular underdeveloped emotional articulation and linguistic structuring abilities make it difficult for them to respond accurately to self-report measures (Kim & Baek, 2014), resulting in the possibility that traditional assessment methods may fail to capture early or subtle emotional problems.

Counseling theories and child psychotherapy literature emphasize that the process through which children reconstruct their experiences and emotions in narrative form contributes to improved emotion regulation and enhanced self-understanding (Geldard & Yin, 2024). Yet, in school contexts—where counseling must be delivered within limited timeframes and constrained numbers of sessions—such process-oriented and narrative-based interventions are difficult to implement sufficiently. Consequently, school counseling often gravitates toward crisis intervention and short-term screening, leaving everyday emotional expression and subtle developmental changes underdocumented and underinterpreted.

Given these limitations, there is a growing need for complementary tools that allow students to express their emotions freely within everyday contexts and enable continuous monitoring of emotional changes through their linguistic patterns. With elementary students' increasing engagement with digital technologies, digital emotional-support tools that can be accessed from both school and home offer a promising means of supplementing existing school counseling systems. The counseling chatbot examined in the present study is positioned within this context, exploring its potential as an auxiliary system capable of supporting routine and longitudinal monitoring of children's emotional states.

Research Trends in AI Counseling Chatbots

AI-based counseling chatbots have gained increasing attention as tools capable of addressing gaps in existing mental-health services due to their advantages of 24-hour accessibility, low cost, and anonymity. Systematic reviews across educational and non-educational contexts have shown that chatbots serve multiple functions—including learning support, information provision, and emotional assistance—and demonstrate strengths in enhancing user engagement and delivering immediate feedback (Okonkwo & Ade-Ibijola, 2021).

In the mental-health domain, one of the most notable early studies is the Woebot trial, which demonstrated that automated conversational agents delivering cognitive–behavioral therapy (CBT)–based interventions can significantly reduce early symptoms of depression and anxiety (Fitzpatrick et al., 2017). More recently, randomized controlled trials (RCTs) using generative AI have emerged. The Therabot study, for example, provided a 4-week intervention for individuals with major depressive disorder or risk for anxiety and eating disorders, reporting meaningful symptom reduction and the formation of a positive therapeutic alliance (Heinz et al., 2025). These studies suggest that AI counseling chatbots may hold potential not only as self-regulation tools but also as components of clinically oriented interventions, while simultaneously highlighting the need for rigorous evaluation of long-term efficacy and safety.

In Korea, research has also expanded to school-specific chatbot applications. An AI counseling chatbot developed for elementary students demonstrated positive effects on emotional support and depression reduction (Lee & Lee, 2023). Another chatbot designed for school violence prevention showed that students can experience empathy and enhanced self-understanding through counseling-like digital interactions (Shin & Park, 2025). Such studies indicate that chatbots can function as practical auxiliary tools within school-based emotional and counseling support systems.

With the growing adoption of large language model (LLM)-based mental-health chatbots, discussions on safety and ethics have intensified. The World Health Organization (WHO, 2024) outlines essential principles for AI-driven mental-health systems—safety, effectiveness, privacy protection, accountability, and integration with human experts—emphasizing particularly the importance of crisis detection and immediate expert referral mechanisms. These international guidelines underscore that, when implementing AI counseling chatbots in educational settings, ethical and safety considerations must be systematically incorporated rather than treated as peripheral technical issues.

The counseling chatbot used in the present study employs a GPT-based LLM augmented with an empathetic persona grounded in Schwartz's universal value theory, enabling elementary school students to express their emotions naturally within a sense of psychological safety (Lee & Lee, 2023). Distinct from prior studies that primarily focused on evaluating the effectiveness of chatbot interventions, the present research collects a large corpus of actual chatbot conversations and analyzes linguistic and emotional patterns across depression levels, interpreting the findings through the lens of neurodevelopmental and socioemotional theory. This analytic approach offers a novel conceptual contribution by extending the potential of counseling chatbots as tools for early detection of emotional risk in school settings.

Materials and Methods

This study was designed to interpret the linguistic and emotional expressions that emerge in elementary students' counseling chatbot conversations through neurodevelopmental and socioemotional frameworks. All procedures were approved by the IRB (IRB No. 1301-202308-HR-0003-01). As summarized in Table 1, the research process comprised eight stages covering system development, data collection, and analysis. Ethical considerations were carefully addressed given the involvement of elementary school students and the sensitivity of emotional content. The counseling chatbot was designed as a supportive conversational tool for data collection and emotional expression, not as a substitute for professional counseling or therapeutic intervention. The system did not provide diagnostic feedback, treatment advice, or real-time crisis intervention, and no automated decisions or alerts were generated during student–chatbot interactions.

Potential emotional risk was assessed retrospectively based on the analysis of conversational logs and PHQ-based screening results. When patterns suggestive of elevated emotional risk were identified, the chatbot itself did not intervene or escalate responses. Instead, findings were used solely to inform post hoc discussions between teachers and school counseling professionals in accordance with existing school support protocols. This design ensured that responsibility for interpretation and intervention remained with qualified human practitioners.

To prevent students from misperceiving the chatbot as a human counselor or authority figure, the chatbot's role and limitations were explicitly explained to students prior to participation. The chatbot consistently adopted a non-directive, empathetic conversational style and avoided evaluative or prescriptive language. These safeguards were implemented to minimize ethical risk, prevent overreliance on the system, and ensure that the chatbot functioned strictly as an auxiliary tool supporting educators' judgment rather than replacing professional care.

A counseling persona was first constructed using a GPT-based LLM to support natural emotional expression in a psychologically safe environment. Drawing on Schwartz's universal value theory, elements of empathy, acceptance, and trust were embedded so the chatbot could function not merely as a question-answering tool but as an emotionally supportive conversational partner.

Depression levels were assessed using an adapted PHQ-9, with the suicide-ideation item removed for ethical reasons and the remaining eight items rewritten in child-friendly conversational formats suitable for elementary students (Hood & Kuiper, 2018). This adaptation aimed to reduce the burden of self-report assessments and promote more natural expression. The pre-assessment was administered in accordance with the school schedule, after which students conversed with the chatbot four to five times per week for about two weeks during their 30-minute morning activity period.

The chatbot system was implemented as a responsive web platform accessible from both classrooms and homes. All conversational data were anonymized, encrypted, and securely stored. Following the conversation phase, a post-assessment and brief satisfaction survey were conducted; however, this study focuses not on score changes but on analyzing thematic structures and emotional patterns in the conversational text.

Accordingly, LDA topic modeling and negative emotion-word analysis were conducted on the collected logs. LDA was used to quantify topic concentration and reduced linguistic flexibility—features frequently associated with depression (Rude et al., 2004). Negative emotion-word analysis examined how linguistic expressions associated with negative affect, as discussed in prior neurodevelopmental models (e.g., prefrontal–amygdala dysregulation or DMN-related processes; Miller et al., 2007), were reflected in students' spontaneous conversations with the chatbot. Given the short-utterance nature of the data, the LDA results are presented as supplementary descriptive evidence rather than as primary findings driving the study's central conclusions.

Table 1. Research process

Step 1	→	Step 2	→	Step 3	→	Step 4
Development of Counseling Chatbot		Reconstruction of PHQ-9 Items		Pre-test Administration		Chatbot Use by Participants
						↓
Step 8	←	Step 7	←	Step 6	←	Step 5
LDA Topic Modeling Analysis		Negative Emotion Word Analysis		Post-test and Survey		Collection of Dialogue Data

Research Participants

This study involved six classes of 5th- and 6th-grade students from three elementary schools in Cheongju, Chungcheongbuk-do. Students at this stage show rapid development in emotional clarity and linguistic expression but still experience difficulty articulating complex emotions directly (Kim & Baek, 2014). These developmental characteristics align with the study's aims, as children's natural speech provides an important indirect indicator of emotional states, making chatbot-based conversational data particularly valuable.

Because this study did not directly measure neurological indicators, interpretations linking linguistic patterns to neurobiological mechanisms are theoretical rather than causal, based on conceptual alignment with established neurodevelopmental models.

A preliminary system check with researchers and teachers was conducted from December 4 to 15, 2023, and the main student study proceeded for two weeks from December 21, 2023 to January 4, 2024. Of the 142 students who participated, 123 were included in the final analysis; exclusions were due to insufficient conversational data or missing assessments resulting from absences, field trips, or access issues.

As is typical in school contexts, the number of students classified as at risk for depression was small, and a similar pattern appeared in this study. This structural limitation necessitates interpreting analyses of the at-risk subgroup as exploratory.

Counseling Chatbot System

The counseling chatbot used in this study is an expanded version of the elementary student–focused system developed by Yang et al. (2025), designed to reliably collect naturalistic conversational data from children. The system comprises four components: a user interface, a dialogue management module, an LLM computation module, and a database management module, as illustrated in Fig. 1.

A GPT-based LLM was used to construct an empathetic and acceptance-oriented counseling persona capable of eliciting meaningful emotional expressions even from short or fragmented utterances typical of elementary students. This design was informed by prior findings that empathetic interactions support emotional regulation and reduce rumination (Miller et al., 2007), providing a strong foundation for capturing authentic linguistic and emotional data.

Student interactions included free conversation, daily-life dialogue, and PHQ-based exchanges, with PHQ items adapted into child-friendly conversational formats suitable for their comprehension level (Hood & Kuiper, 2018). This structure reduced the burden associated with traditional assessments while maximizing the detection of emotional cues, aligning closely with the aims of the study. All conversational data were anonymized and encrypted following removal of identifying information and were stored as primary materials for subsequent text analysis.

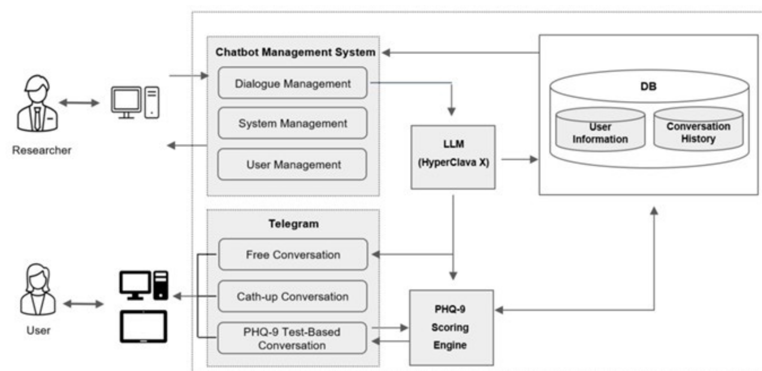

Fig. 1. Counseling chatbot architecture

Data Analysis

Data collection was conducted from December 21, 2023 to January 4, 2024. The final analysis included 123 students who completed both the pre- and post-assessments and provided sufficient conversational data. As shown in Table 2, pre-assessment PHQ results indicated that 80.5% of students (n = 99) fell within the normal range, 11.4% (n = 14) in the mild range, 3.3% (n = 4) in the moderate range, and 4.9% (n = 6) in the severe range. Reflecting the ecological distribution typically observed in school settings, the present study defined all students from the mild to severe categories (n = 24) collectively as the Clinical Attention Group. Analyses were focused on capturing the subtle linguistic variations within this group.

Table 2. Distribution of participants by depression level

Depression Level	N (%)
Normal	99 (80.5%)
Low	14 (11.4%)
Mid	4 (3.3%)
High	6 (4.9%)
Total	123 (100%)

The collected conversational texts were preprocessed through tokenization, morphological analysis, and the removal of special characters and stopwords. Given the characteristics of the dataset, a Dual-Method Strategy was adopted. In this study, the primary unit of discourse analysis was defined as a single student utterance, operationalized as each discrete text segment produced by a student between chatbot responses.

First, LDA topic modeling (Blei et al., 2003) was applied to identify the macro-level topical structure of conversations, which were predominantly produced by non-risk students. The optimal number of topics was determined using UMass and CV coherence metrics.

Second, to address the limitations of LDA in analyzing the Clinical Attention Group, whose conversations frequently exhibited linguistic fragmentation and short-text tendencies associated with higher depressive severity, a Qualitative Deep-Dive analysis was conducted. This allowed closer examination of contextual and emotional dynamics within individual utterances, offering insight into the topic narrowing and reduced linguistic flexibility commonly observed in depression (Rude et al., 2004).

For negative emotion-word analysis, both an established Korean sentiment lexicon and a custom affective term list were used. Emotion words were classified into Self-oriented, Peer-oriented, and Situation-oriented categories, reflecting neural evidence from social pain research (Eisenberger, 2012) and children's context-dependent emotional expression patterns (Kim & Baek, 2014).

To ensure classification reliability, a rigorous coding protocol was implemented. Operational definitions for five preliminary categories ("Self," "Family," "Friend," "Situation," and "Other") were established, and two trained coders independently coded approximately 15% of the data in a pilot phase to refine category boundaries. They then coded all negative emotion-word instances independently. Cohen's kappa was k = .81, indicating substantial agreement; discrepancies were resolved through discussion with input from a third reviewer when necessary.

PHQ scores were used as the reference measure for depressive level. The goal of the analysis was not to track score changes, but to identify qualitative shifts in topic structure and emotional expression across depression levels. By integrating LDA-based structural modeling with qualitative deep-dive analyses, the study developed a multifaceted analytic framework that interprets children's conversational patterns as process-based emotional markers of their internal emotional states.

Results

LDA Analysis

Within the dataset analyzed in this study, the Clinical Attention Group (n = 24) represented a relatively small sample, reflecting typical school distributions. Accordingly, LDA topic modeling was applied primarily to the Normal group to characterize the broader conversational landscape. For the Clinical group, LDA served only as a supplementary reference, as the limited number of utterances and short-text characteristics constrain the interpretive power of probabilistic topic models. Thus, analyses for this group were treated as exploratory, with the main clinical interpretation based on the Qualitative Deep-Dive analysis of contextual and emotional dynamics (Section 4.3).

After separating utterances by depression level, a Kkma-based morphological analysis was conducted to extract nouns, verbs, and adjectives, followed by normalization and stopword removal. Gensim's LdaModel was then applied with random_state = 42, passes = 10, alpha = 'symmetric', and eta = 'symmetric'. The number of topics (k) was varied from 2 to 10, and Coherence (c_v) scores were computed as shown in Table 3. Models with the highest coherence scores were selected as optimal, yielding 2 topics for the Normal and Mild groups, 4 for the Moderate group, and 5 for the Severe group.

Table 3. Coherence score results by depression level

Depression Level	Optimal Number of Topics (Coherence Score)
Normal	2 (0.6849)
Mild	2 (0.5843)
Moderate	4 (0.7116)
Severe	5 (0.6450)

These findings indicate that, unlike the Normal group, increases in depressive severity do not cause conversations to converge on a small set of stable themes. Instead, dialogue becomes dispersed into numerous small, fragmented topical units, leading to weakened thematic cohesion. As shown in Table 4, the Normal group maintained a coherent flow centered on two clear themes—play, quizzes, and hobbies—whereas the moderate and severe groups displayed discontinuous keyword combinations and more single-word utterances that did not form coherent semantic units. This structural shift reflects a prototypical pattern of topic fragmentation, where conversations consist of short, disconnected linguistic fragments rather than extended or elaborated content.

Table 4. Summary of topic modeling results by depression level

Level	Topic Name	Key Keywords	Core Content
None (Normal)	Play -centered interaction	Blue Dragon (0.134), I (0.099), Quiz (0.033), You (0.028), Today (0.023), Word-chain (0.021), We (0.020), Me (0.018), School (0.014)	Active interaction centered on quiz and play elements
	Play and hobbies	Word-chain (0.087), My (0.037), Fool (0.014), Study (0.014), YouTuber (0.012), Start (0.012), Drawing (0.011), Sims (0.010), Person (0.010)	Play elements and hobbies such as word-chain and YouTube
Low (Mild)	Play -centered interaction	Potato (0.098), Word-chain (0.046), Again (0.042), What (0.027), Exercise (0.026), Convenience store (0.025), Coupon (0.025), Contact (0.025), Smartphone (0.025)	Interactions centered on play such as quiz and word-chain
	Hobbies -centered	A little (0.061), Explanation (0.027), Name (0.023), Chatbot (0.022), Head (0.021), Content (0.018), Member (0.015), Jamdeul (0.012), Hello (0.011)	Interest in daily hobbies and activities
Mid (Moderate)	Unclear topics	Story (0.058), Again (0.022), Fruit (0.021), Other (0.013), Talk (0.013), If (0.013), Tomorrow (0.013), Ignore (0.013), Person (0.013)	Fragmented utterances rather than clear topics
	Expressions of surrounding relations	Keep (0.036), Sister (0.019), Parents (0.018), Friend (0.016), Head (0.014), Not really (0.014), Snack (0.014), Content (0.014), Chatbot (0.010)	Mentions of interactions or experiences with surrounding people
	Play-centered interaction	Word-chain (0.047), A little (0.024), Christmas (0.021), Lee○ (0.016), Friend (0.015), Stress (0.015), Once (0.013), What (0.013), Just (0.013)	Interactions centered on word-chain and quiz play
	Repetitive Peer Hostility	Friend (0.049), Reply (0.030), There (0.025), Parents (0.025), Hello (0.021), School (0.021), Today (0.017), Perhaps (0.017), Just (0.013)	Conversations centered on peer relationships
High(Severe)	Peer relations and play -centered	Friend (0.021), Just (0.020), Owner (0.019), Study (0.018), Today (0.017), Word (0.015), Word-chain (0.014), Worry (0.013), We (0.013)	Mentions about peer relations and play
	Fragmented Utterances	Failure (0.023), Every day (0.018), Degree (0.018), Perhaps (0.015), User (0.015), Almost (0.013), Lyrics (0.013), Fruit (0.011), Song (0.011)	Fragmented utterances without a specific topic

The fragmentation pattern observed in the moderate and severe depression groups conceptually aligns with neurodevelopmental models suggesting that as depression intensifies, emotional-processing demands increase while cognitive resources become more taxed. Prior studies indicate that reduced regulatory efficiency between the prefrontal cortex and amygdala disrupts the balance of negative emotion processing (Miller et al., 2007), which may lead to simplified or reduced linguistic expression and discontinuities in thought flow. Although the present study did not directly measure neurophysiological indicators, the structural features observed in the students' utterances show meaningful theoretical alignment with these neurodevelopmental explanations.

While clear differences in the number of topics emerged across groups, the qualitative content of the topics exhibited limited differentiation, with partial overlap and recurring keywords. This can be attributed to the short and context-poor utterances characteristic of the depression-risk group, which result in sparse word co-occurrence patterns—the foundation upon which LDA topic modeling operates. Whereas LDA performs effectively with longer contextual structures, the inherently short and fragmented nature of elementary students' conversational data constrains the model's interpretive power.

To address these methodological limitations, the next section supplements the analysis with an examination of the directionality of negative emotion words (Section 4.2), enabling a more refined exploration of structural differences in emotional expression across depression levels. This analysis is intended to complement aspects of emotional nuance that cannot be fully captured through LDA alone and to clarify how linguistic fragmentation interacts with patterns of emotional expression.

Negative Emotion Word Analysis

To complement the thematic discontinuities observed in the LDA analysis, negative emotion words appearing in the conversations were separately extracted and analyzed in terms of frequency and directional focus, as summarized in Table 5.

Table 5. Negative emotion words used in chatbot conversations

Category	Content
Words	hate, annoyed, bothered, fed up, angry, cry, scared, sick, anxious, depressed, sad, anger, bad, exhausted, dislike, quit, suicidal, tired, worn out, lonely, distressed

Following the criteria established in the Data Analysis section, emotion words were classified into five categories—Self, Family, Friends, Situation, and Others. The distribution of these categories across different depression levels was then compared, as presented in Table 6.

Table 6. Negative emotion words and their targets by depression level

Depression Level	Negative Emotion Word	Total Frequency (%)	Self	Family	Friends	Situation	Others
None (Normal)	angry	9 (75%)	2 (16.7%)	0	4 (33.3%)	1 (8.3%)	2 (16.7%)
	sick	3 (25%)	2 (16.7%)	0	0	1 (8.3%)	0
Low (Mild)	bothered	7 (50%)	1 (7.1%)	0	2 (14.3%)	3 (21.4%)	1 (7.1%)
	sad	4 (28.6%)	2 (14.3%)	0	0	1 (7.1%)	1 (7.1%)
	fed up	3 (21.4%)	1 (7.1%)	0	0	2 (14.3%)	0
Mid (Moderate)	depressed	10 (47.6%)	4 (19.0%)	0	2 (9.5%)	3 (14.3%)	1 (4.8%)
	exhausted	6 (28.6%)	2 (9.5%)	1 (4.8%)	1 (4.8%)	2 (9.5%)	0
	tired	5 (23.8%)	1 (4.8%)	0	1 (4.8%)	3 (14.3%)	0
High (Severe)	hate	15 (53.6%)	2 (7.1%)	1 (3.6%)	6 (21.4%)	3 (10.7%)	3 (10.7%)
	annoyed	8 (28.6%)	1 (3.6%)	0	4 (14.3%)	2 (7.1%)	1 (3.6%)
	scared	3 (10.7%)	1 (3.6%)	0	1 (3.6%)	1 (3.6%)	0
	anxious	2 (7.1%)	1 (3.6%)	0	0	1 (3.6%)	0

In the Normal group, low-intensity negative emotion words such as “angry” and “sick” appeared most frequently, with targets distributed relatively evenly across Self, Situation, and Friends (each about 30%). This indicates that negative emotions were not concentrated in a specific domain but dispersed across everyday contexts.

In the Mild group, avoidance- and discomfort-related terms such as “bothered,” “sad,” and “fed up” increased. Situation (35.7%) and Self (28.6%) were the most common targets, suggesting that early-stage negative emotions were internalized toward external circumstances or one’s inner states. Peer-directed expressions remained relatively low (14.3%).

In the Moderate group, higher-intensity emotion words such as “depressed,” “exhausted,” and “tired” were prevalent. Self and Situation each accounted for 33.3% of targets, while Friend-directed expressions rose to 19.0%, indicating a partial extension of negative affect into interpersonal domains.

The Severe group showed the clearest shift in both emotion type and target. Hostile terms such as “hate” and “annoyed” appeared frequently, with Friends becoming the dominant target (39.3%). Six of the fifteen instances of “hate” referred directly to a specific peer. By contrast, Self (17.9%) and Family (3.6%) were less frequent, reflecting a pronounced shift toward peer-directed negativity accompanied by intensified hostile evaluations.

Overall, these trends illustrate that as depressive severity increases, the direction of negative affect tends to shift from Self → Situation → Friends. Self-directed negativity appeared consistently across groups, consistent with known characteristics of childhood depression.

Repetition of emotion words, reduced lexical variety, and reliance on single-term expressions observed in the depression groups may reflect both difficulties in emotional clarity and typical linguistic features of 5th- and 6th-grade students. Given the small sample sizes in the Moderate and Severe groups, quantitative interpretation should be cautious. Nevertheless, the distinct peer-directed orientation observed in the Severe group provides exploratory insight into emotional patterns associated with escalating depression and offers a useful foundation for developing early-warning indicators for emotional risk detection.

Qualitative Analysis of the Clinical Attention Group

The LDA findings presented in Section 4.1 indicated that increasing depressive severity was associated with reduced topic cohesion and fragmented conversational structure. However, probabilistic topic models such as LDA depend heavily on word-frequency patterns and therefore cannot fully capture the clinical meaning or emotional dynamics underlying such fragmentation. To address this limitation, a dual-method strategy was adopted, combining LDA-based structural modeling with a Qualitative Deep-Dive analysis.

This qualitative analysis was conducted for all students in the depression-risk categories—Mild (n = 14), Moderate (n = 4), and Severe (n = 6)—to examine the contextual meaning of individual utterances and the directionality of negative affect. Through this approach, a three-stage spectrum of behavioral markers corresponding to depression severity was identified in Table 7.

Table 7. Qualitative behavioral markers in the clinical attention group

Behavioral Dimension	[Stage 1] Mild: Situational Complaints & Playfulness	[Stage 2] Moderate: Relational Concerns & Narrative Formation	[Stage 3] Severe: Structural Breakdown & Hostility
1. Linguistic Structure (Structural Integrity)	Conversational Coherence – Uses complete sentences ("I'm bored.") – Maintains turn-taking – Frequent use of slang, emojis, playful expressions	Narrative Appeal – Provides contextual explanations ("because…") – Longer and more complex sentences ("… but then…, so…") – Attempts to logically articulate emotions	Fragmented Outbursts – Isolated screams/insults without context – Mechanical repetition of single words ("I hate it") – Loss of linguistic self-regulation
2. Target of Emotion (Emotional Target)	External Situations – Academy, homework, weather, boredom – "Annoying," "Tired," "Sleepy" – Emotions are temporary and easily dissipated	Relationships & Self – Conflicts with friends, concerns about exclusion – "I want to make up, but I'm scared." – Self-blame about personality (e.g., shyness)	Hostile Projection – Hatred toward specific peers or the world – "I hate the kid next to me," "Wish they'd disappear" – Baseless, intense rejection without explicit reasons
3. Role of the Chatbot (Interaction Role)	Playmate – "Recommend a game," "I'm bored, play with me." – Casual chatting or simple information-seeking – Attempts to relieve distress through play	Counselor – "What should I do?" (seeking advice) – Expects comfort and empathy – Shows willingness to improve personal situations	Emotional Vent / Threat Target – "Go away," "You don't know anything." – Non-responsiveness or avoidance – Attacks or dismisses the chatbot
Example Utterances (Data Extracts)	(ID: low_3) "Ugh, too much academy homework. So annoying." "I'm bored. Recommend a game."	(ID: mid_4) "I got grouped with a friend… but honestly I want to be with someone else, so I'm conflicted."	(ID: high_1) "Just hate it." "I really hate the kid next to me." "Ugh, I hate Wednesdays the most."

As depressive severity increased, children's ability to verbally structure their emotional experiences progressively declined. Mild and moderate cases generally maintained coherent sentences, provided contextual explanations, and sought guidance—for example, "We changed seats today⋯ I want to work with other friends, but I don't know what to do" (Case Mid-4). In contrast, severe cases produced short, affectively charged utterances with little context, such as "Just hate it," "I really hate Wednesdays," or "No, I said no" (Cases High-1, High-6). These fragmented expressions align with neurodevelopmental models suggesting that reduced prefrontal regulatory functioning under depressive load limits children's capacity to articulate complex emotions, resulting in isolated fragments rather than coherent narratives (Miller et al., 2007).

A related shift occurred in the direction of negative affect. Mild-stage conversations focused on transient situational complaints ("too much homework," "tired," "bored"). In the moderate stage, negative affect became more internalized and directed toward peer relationships or self-evaluation, as seen in statements such as "I still feel uncomfortable around that friend" (Case Mid-4). In the severe stage, these concerns escalated into hostile projection toward peers, often without explanatory context—for example, "I hate the kid next to me," "Hate them so much" (Case High-2). This abrupt hostility is described here as a linguistic and interactional pattern characterized by intensified peer-directed negativity, without assuming direct correspondence to specific neural activation processes.

These linguistic and emotional changes were mirrored in children's interaction strategies with the chatbot. Mild cases treated the chatbot as a playmate, using light conversation or games for distraction. Moderate cases increasingly approached it as a counselor, asking solution-oriented questions (e.g., "What should I do?"). Severe cases, however, showed marked avoidance, abruptly shifting to trivial topics ("Let's play word-chain," "I'm going to watch YouTube") or disengaging entirely ("I don't know") (Cases High-3, Mid-2). This affective diversion suggests lowered tolerance for emotionally demanding content and a tendency to withdraw from distress-triggering dialogue.

Taken together, these patterns are presented as complementary descriptive evidence that helps contextualize linguistic and emotional tendencies across depressive severity, rather than as primary results driving the study's central conclusions. Whereas topic modeling captures surface-level fragmentation, the qualitative analysis highlights the emotional dynamics and cognitive load reflected in spontaneous language use. Two features in the severe group—linguistic fragmentation and peer-directed hostility—represent critical red flags indicating potential emotional crisis and requiring immediate attention from educators or school mental-health practitioners. These findings underscore the value of chatbot-based conversational data as process-based emotional markers, capable of detecting early warning signals that may not be visible through traditional screening tools.

Discussions

This study examined elementary school students' counseling chatbot conversations using a dual-method framework that combined quantitative and qualitative analyses. Rather than reiterating the specific linguistic patterns identified in the Results section, the present Discussion focuses on their broader interpretive significance and their alignment with neurodevelopmental and socioemotional models.

A central contribution of this study lies in demonstrating how depressive burden may alter children's capacity to organize emotional experiences into coherent linguistic forms. The progressive weakening of structural integrity in students' utterances is consistent with theoretical accounts of reduced prefrontal regulatory functioning. Such models argue that as cognitive resources become strained, children's ability to sustain narrative reasoning or contextual explanation diminishes. The resulting linguistic fragmentation can therefore be understood not merely as conversational variability but as a potential behavioral reflection of neurocognitive overload.

Changes in emotional directionality likewise suggest deeper shifts in socioemotional processing. The movement from externalized frustration toward more interpersonal forms of distress aligns with research on the development of social pain sensitivity. When peer-related cues are perceived as emotionally salient stressors, children may exhibit heightened vigilance and reactive hostility at the level of observable language and interaction patterns; however, such interpretations remain speculative, particularly given the small sample size of the severe group. Importantly, these expressions should be interpreted within a developmental framework: during late childhood, peer relationships become increasingly central to emotional life, and distortions in peer-related affect may signal emerging vulnerability in socioemotional regulation.

Interactional patterns observed in chatbot use further illuminate how emotional load influences children's engagement strategies. Avoidant or abrupt conversational withdrawal, for instance, can be interpreted through models of rumination and DMN-related cognitive capture, where sustained engagement with emotionally charged content becomes increasingly difficult. In such cases, fragmented or minimal responses are not merely stylistic features but may indicate reduced tolerance for affectively demanding interaction.

These interpretive insights highlight the potential value of chatbot-based conversational data as process-oriented indicators of emotional functioning. Unlike traditional self-report assessments, which depend on children's metacognitive ability to evaluate their own states, conversational data capture real-time fluctuations in linguistic coherence, emotional orientation, and engagement style—dimensions that may offer earlier or more sensitive markers of distress.

Practically, these findings underscore the importance of timely intervention within school counseling contexts. The presence of relational tension or ambivalent peer concerns may represent an actionable window for preventive support before such patterns escalate into overt hostility or withdrawal. Moreover, behaviors such as fragmented responses or silence should not be misinterpreted as oppositional but as possible manifestations of cognitive or emotional overload requiring alternative intervention strategies, such as play-based or nonverbal approaches.

Several limitations warrant consideration. The moderate and severe groups contained small sample sizes, reflecting the naturally low prevalence of high-risk students in school settings. As such, the findings should be interpreted as exploratory indicators rather than definitive characterizations of depressive expression. Future research using multi-site recruitment and larger clinical samples would strengthen the generalizability of the behavioral markers identified here. Incorporating multimodal data—such as typing patterns or response latency—may also provide a more comprehensive view of children's conversational microdynamics. Longitudinal designs would allow examination of the stability or variability of these patterns across developmental time.

Despite these limitations, this study offers empirical support for the utility of chatbot-based conversations as meaningful linguistic lenses into children's cognitive and emotional states. The broader interpretive patterns—capturing shifts in narrative organization, emotional orientation, and engagement capacity—point to promising applications for chatbot systems within school-based early warning frameworks for detecting emotional risk.

Conclusions

This study examined how depressive severity shapes linguistic and emotional expression in elementary school students' counseling chatbot conversations, interpreting these patterns within a neuro–emotional developmental framework. A key contribution of this work is identifying a coherent progression of behavioral markers that reflects shifting cognitive load, emotional orientation, and interactional capacity as depressive symptoms intensify.

Rather than focusing solely on topical or lexical changes, the findings reveal broader functional transformations in how children organize emotional experience—ranging from coherent narrative construction to substantial breakdowns in linguistic structure; from flexible emotional orientation to increasingly interpersonal forms of negativity; and from active help-seeking to avoidance-driven disengagement. These patterns can be interpreted as conceptually consistent with prior neurodevelopmental models of emotion regulation and social sensitivity, serving as an interpretive framework rather than evidence of directly measured neural mechanisms.

Practically, these insights highlight the unique value of chatbot-based conversational data as process-oriented emotional markers. Unlike one-time screening tools, chatbots capture moment-to-moment shifts in engagement and expression, enabling earlier detection of qualitative transitions in distress. Relational tensions observed in intermediate stages may represent a critical intervention window, whereas the emergence of peer-directed hostility signals the need for immediate support.

This study is not without limitations, particularly the small size of the moderate and severe subgroups. In addition, the relatively limited number of utterances in the severe group raises the possibility that certain linguistic patterns may be disproportionately influenced by a small number of individual cases. Furthermore, students' utterance length and structural characteristics may have been shaped in part by the chatbot's empathetic response style and conversational prompting, introducing an interactional influence that cannot be fully disentangled from students' spontaneous language production. The behavioral spectrum identified here should therefore be interpreted as exploratory. Future work should validate these markers through multi-site and longitudinal studies and by integrating multimodal behavioral signals to refine risk detection algorithms. Such studies may also benefit from experimental designs that systematically control or vary chatbot prompting strategies and response styles to more precisely assess their effects on children's linguistic and emotional expression.

Despite these limitations, the findings support the potential use of counseling chatbots in school settings. While this study does not directly assess neurodevelopmental or neural mechanisms, the neurodevelopmental perspective is adopted as a theoretical lens to aid interpretation of the observed behavioral and linguistic patterns. As naturalistic language data, chatbot conversations provide meaningful insight into children's emotional and social development and hold promise as a complementary tool for early warning systems in mental-health monitoring.

Future studies may therefore benefit from experimental designs that systematically control or vary chatbot prompting strategies and response styles to more precisely examine their effects on children's linguistic and emotional expression.

Conflicts of Interest

The author(s) declared no conflicts of interest.

References

Abd-Alrazaq, A. A., Alajlani, M., Alalwan, A. A., Bewick, B. M., Gardner, P., & Househ, M. (2019). An overview of the features of chatbots in mental health: A scoping review. International Journal of Medical Informatics, 132, 103978.

Abd-Alrazaq, A. A., Rababeh, A., Alajlani, M., Bewick, B. M., & Househ, M. (2020). Effectiveness and safety of using chatbots to improve mental health: systematic review and meta-analysis. Journal of Medical Internet Research, 22, e16021.
Bickmore, T., & Gruber, A. (2010). Relational agents in clinical psychiatry. Harvard Review of Psychiatry, 18, 119-130.
Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. Journal of Machine Learning Research, 3, 993-1022.
Cooper, M. (2008). Essential research findings in counselling and psychotherapy: The facts are friendly. London: SAGE Publications.
Cormier, L. S., & Hackney, H. (1999). Counseling strategies and interventions (5th ed.). Boston, MA: Allyn & Bacon.
Corey, G. (2016). Theory and Practice of Counseling and Psychotherapy (10th ed.). Belmon, CA: Brooks/Cole.
De, C. M., Gamon, M., Counts, S., & Horvitz, E. (2013). Predicting Depression via Social Media. In Proceedings of the International AAAI Conference on Web and Social Media (Vol. 7, No. 1, pp. 128-137).
Feldman, R., & Dagan, I. (1995, August). Knowledge Discovery in Textual Databases (KDT). In KDD (Vol. 95, pp. 112-117).
Fitzpatrick, K. K., Darcy, A., & Vierhile, M. (2017). Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (Woebot): a randomized controlled trial. JMIR Mental Health, 4(e7785).
Geldard, K., Geldard, D., & Foo, R. Y. (2024). Counselling children: A practical introduction (6th ed.). SAGE Publications.
Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. Proceedings of the National Academy of Sciences, 101, 5228-5235.
Heinz, M. V., Mackin, D. M., Trudeau, B. M., Bhattacharya, S., Wang, Y., Banta, H. A., ... Jacobson, N. C. (2025). Randomized trial of a generative AI chatbot for mental health treatment. NEJM AI, 2, AIoa2400802.
Hill, C. E., & Lent, R. W. (2006). A narrative and meta-analytic review of helping skills training: Time to revive a dormant area of inquiry. Psychotherapy: Theory, Research, Practice, Training, 43, 154.
Hong, J. S., Yang, J. M., Kim, J. H., & Lee, J. J. (2025). Association between mental health literacy and depression and suicidal ideation in Chungcheongnam-do, South Korea. Journal of Health Informatics and Statistics, 50, 47-56.
Hood, K., & Kuiper, P. K. (2018, January). Improving student surveys with natural language processing. In 2018 Second IEEE International Conference on Robotic Computing (IRC) (pp. 383-386). IEEE.
Hutto, C., & Gilbert, E. (2014, May). Vader: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text. In Proceedings of the International AAAI Conference on Web and Social Media (Vol. 8, No. 1, pp. 216-225).
Kim, K. H., & Baek, Y. M. (2014). The effects of alexithymia, emotional clarity on adolescent's somatization: Mediated effects of difficulties in emotional regulation. Korean Journal of Youth Studies, 21, 267-290.
Kottler, J. A. (2004). Introduction to therapeutic counseling. Brooks/Cole.
Kuhail, M. A., Alturki, N., Thomas, J., & Alkhalifa, A. K. (2024). Human vs. AI counseling: College students' perspectives. Computers in Human Behavior Reports, 16, Article 100534.
Lee, S. J., Choi, B. M., Cheon, Y. J., & Lee, J. Y. (2025). Topic modeling analysis of media discourse on senior employment and social activity support program (SESAP). Journal of the Korean Gerontological Society, 45, 519-547.

Lee, S. H., & Lee, J. Y. (2023). Development of artificial intelligence-based counseling chatbot for elementary school students and verification of effectiveness. Journal of the Korean Association of Information Education, 27, 425-432.

Lee, Y. A., & Son, E. Y. (2015). A narrative inquiry on school counselors' experience of adaptation in a school. Journal of Education & Culture, 21, 141-168.

Ministry of Health and Welfare. (2024). Report on the 2022 Survey of Child and Adolescent Mental Health in Korea. Ministry of Health and Welfare.

Mohammad, S. M., & Turney, P. D. (2013). Crowdsourcing a word–emotion association lexicon. Computational Intelligence, 29, 436-465.

Murshed, B. A. H., Mallappa, S., Abawajy, J., Saif, M. A. N., Al-Ariki, H. D. E., & Abdulwahab, H. M. (2023). Short text topic modelling approaches in the context of big data: taxonomy, survey, and analysis. Artificial Intelligence Review, 56, 5133-5260.

Okonkwo, C. W., & Ade-Ibijola, A. (2021). Chatbots applications in education: A systematic review. Computers and Education: Artificial Intelligence, 2, 100033.

Park, S. J., Choi, H. R., Choi, J. H., Kim, K. W., & Hong, J. P. (2010). Reliability and validity of the Korean version of the Patient Health Questionnaire-9 (PHQ-9). Anxiety and Mood, 6, 119-124.

Resnik, P., Armstrong, W., Claudino, L., Nguyen, T., Nguyen, V. A., & Boyd-Graber, J. (2015). Beyond LDA: Exploring Supervised Topic Modeling for Depression-Related Language in Twitter. In Proceedings of the 2nd Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality (pp. 99-107).

Röder, M., Both, A., & Hinneburg, A. (2015, February). Exploring the Space of Topic Coherence Measures. In Proceedings of the Eighth ACM International Conference on Web Search and Data Mining (pp. 399-408).

Rude, S., Gortner, E. M., & Pennebaker, J. (2004). Language use of depressed and depression-vulnerable college students. Cognition & Emotion, 18, 1121-1133.

Shin, S. K., & Park, D. B. (2025). An analysis of the cognitive and emotional effectiveness of a school bullying prevention chatbot. Journal of the Korean Association of Information Education, 29, 87-95.

Wing, S. D., & Sue, D. (2008). Counseling the Culturally Diverse: Theory and Practice. John Wiley & Sons, Inc.

World Health Organization. (2012). Adolescent mental health: Mapping actions of nongovernmental organizations and other international development organizations. World Health Organization.

Yan, X., Guo, J., Lan, Y., & Cheng, X. (2013, May). A biterm topic model for short texts. In Proceedings of the 22nd International Conference on World Wide Web (pp. 1445-1456).

Yang, J. W., Lee, S. J., Lee, S. H., & Lee, J. Y. (2025). Development and effectiveness analysis of an AI-based counseling chatbot for depression management in elementary school students. Korean Journal of Elementary Counseling, 24, 795-817.

Authors' Information

Sihoon Lee: AI and Robotics Education Convergence Institute, Cheongju National University of Education. Research Fellow, First Author.

Jaeyong Lee: Cheongju National University of Education. Professor, Corresponding Author.