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ARAŞTIRMA | RESEARCH

Psycholinguistic Analysis of AI-Generated Psychiatric Texts: A Feasibility Study in Major Depressive Disorder and Generalized Anxiety Disorder

Yapay Zeka Tarafından Üretilen Psikiyatrik Metinlerin Psikodilbilimsel Analizi: Majör Depresif Bozukluk ve Yaygın Anksiyete Bozukluğu Üzerine Bir Fizibilite Çalışması

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Abstract

Objective: The aim of this feasibility study is to evaluate whether simulated texts generated by artificial intelligence (AI) that correspond to diagnoses of Major Depressive Disorder (MDD) and Generalized Anxiety Disorder (GAD) can be distinguished by psycholinguistic features, and to assess the feasibility of this approach.
Method: Fifteen simulated texts each of MDD and GAD generated by the DeepSeek-R1 AI model were included in the study. The texts were quantitatively evaluated in terms of emotion, causality, uncertainty, first-person pronouns, somatic and abstract word usage.
Results: AI-generated texts corresponding to MDD demonstrated significantly higher use of abstract words ($p < 0.001$), whereas texts corresponding to GAD showed significantly greater use of uncertainty-related and somatic words (both $p < 0.001$). No statistically significant difference was observed between the groups in terms of first-person singular pronoun usage ($p = 0.450$) or negative emotion expression ($p = 0.272$).
Conclusion: The findings indicate that AI-generated texts exhibited linguistic patterns consistent with previously reported psycholinguistic features of MDD and GAD, suggesting the methodological feasibility of using AI-generated texts for exploratory psycholinguistic analysis and training-oriented simulations. Findings apply solely to simulated texts and do not imply any diagnostic or clinical utility.
Keywords: Artificial intelligence, psycholinguistic analysis, major depressive disorder, generalized anxiety disorder

Öz

Amaç: Bu uygulanabilirlik çalışmasının amacı, Majör Depresif Bozukluk (MDB) ve Yaygın Anksiyete Bozukluğu (YAB) tanılarına karşılık gelen yapay zeka (YZ) tarafından üretilen simüle edilmiş metinlerin psikolinguistik özelliklerle ayırt edilip edilemeyeceğini değerlendirmek ve bu yaklaşımın uygulanabilirliğini değerlendirmektir.
Yöntem: Çalışmaya, DeepSeek-R1 YZ modeli tarafından üretilen MDB ve YAB'e ait on beşer adet simüle edilmiş metin dahil edilmiştir. Metinler, duygu, nedensellik, belirsizlik, birinci şahıs zamirleri, somatik ve soyut kelime kullanımı açısından niceliksel olarak değerlendirilmiştir.
Bulgular: MDB'ye karşılık gelen YZ tarafından üretilen metinler, soyut kelimelerin kullanımında anlamlı derecede daha yüksek bir oran sergilerken ($p < 0,001$), YAB'a karşılık gelen metinler, belirsizlikle ilgili ve somatik kelimelerin kullanımında anlamlı derecede daha yüksek bir oran sergiledi (her ikisi de $p < 0,001$). Birinci tekil şahıs zamir kullanımı ($p = 0,450$) veya olumsuz duygu ifadesi ($p = 0,272$) açısından gruplar arasında istatistiksel olarak anlamlı bir fark gözlenmedi.
Sonuç: Bulgularımız, YZ tarafından üretilen metinlerin, MDB ve YAB'ın daha önce bildirilen psikolinguistik özellikleriyle tutarlı dilsel kalıplar sergilediğini ve YZ tarafından üretilen metinlerin keşifsel psikolinguistik analiz ve eğitim odaklı simülasyonlar için metodolojik olarak uygulanabilirliğini gösterdiğini ortaya koymaktadır. Bulgular yalnızca simüle edilmiş metinler için geçerlidir ve herhangi bir tanısal ya da klinik faydaya işaret etmemektedir.
Anahtar kelimeler: Yapay zeka, psikolinguistik analiz, majör depresif bozukluk, yaygın anksiyete bozukluğu

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Introduction

Psychiatric diagnosis and treatment steps progress through patient-physician communication and the examination findings obtained through this channel (Yünden, 2022). The patient's medical history, the language they use during examination, regional descriptive words, and sentence structures provide important clues to the diagnosis (Andreasen, 1979). Attention to speech characteristics such as tone, quantity, speed, content, and level of detail constitutes a fundamental component of the psychiatric examination (Rude et al., 2004). While frequent use of the first-person singular pronoun, negative emotional expressions, and abstract words are common in patients with depression, patients with anxiety disorders are more likely to express uncertainty and anxiety about the future, and to have more physical complaints (muscle tension, pain, physical fatigue, difficulty concentrating, etc.) (Dugas et al., 2001; Newman & Llera, 2011; Pennebaker et al., 2003; Rude et al., 2004). Consequently, since language structure directly affects a patient's ability to express themselves in the healthcare field, particularly in psychiatry, the diagnostic process for psychiatric disorders becomes significantly more difficult in individuals experiencing speech difficulties or struggling to express themselves in a foreign language.

Psycholinguistics is the branch of science that studies the connection between language and mental processes. It examines how we produce, perceive, and transmit language; it investigates how characteristics such as memory, attention, and thought are reflected in language, and the influence of other cognitive processes (Field, 2003). Therefore, the development of this field is promising, especially for psychiatry. The understanding and transfer of language has also gained importance in the context of artificial intelligence (AI) in recent years, and significant progress has been made in natural language processing and text generation. Large language models, as in other fields, can provide a great deal of variety in generating rich psychiatric texts and in natural language processing (Ive et al., 2020). However, there is a lack of research that tests the feasibility of using the content produced by these advanced models in the psychiatric field in practice, as well as their distinctive linguistic characteristics. Although linguistic features have been shown to vary across psychiatric conditions, such features should be considered supportive rather than diagnostic, reflecting underlying cognitive–emotional processes rather than constituting standalone diagnostic markers.

This study aims to evaluate the methodological applicability of using AI-generated simulated case texts of Major Depressive Disorder (MDD) and Generalized Anxiety Disorder (GAD) for research and educational purposes by examining whether they are distinguishable in terms of psycholinguistic features.

Method

This study does not contain actual patient data. The data consists of simulated case texts generated by an AI model that is publicly available. Therefore, the study was not conducted with human participants and does not require ethical committee approval.

Study Design and Data

This study was conducted using a cross-sectional and comparative design. The dataset consists of 30 simulated case histories (15 MDD, 15 GAD), generated in Turkish on December 1, 2025, via the public web interface of the DeepSeek-R1 model (https://chat.deepseek.com). DSM-5 diagnostic criteria were referenced in the generation process, and an identical prompt template (translated into Turkish) was used for both diagnostic groups:

Prompt template: “Create a short and realistic case history meeting the DSM-5 diagnostic criteria for either MDD or GAD, including demographic information (age, gender) and the patient's own statement.” This prompt was applied repeatedly to generate 15 simulated texts for each diagnostic group.

All texts were generated in Turkish in a single session using an identical prompt structure, with the default web-interface model parameters and no manual post-editing. Specific generation parameters (temperature, top-p, maximum token length) were not user-configurable in the web interface used and are therefore not reported; this is acknowledged as a reproducibility limitation.

Psycholinguistic Variables and Evaluation

Each simulated case text was quantitatively analyzed in terms of the following psycholinguistic variables. The Linguistic Inquiry and Word Count (LIWC-2015) framework (Pennebaker et al., 2015) was adopted as a conceptual category framework for defining the variables of interest. Because no validated Turkish LIWC-2015 dictionary was applied in this study, word frequencies were quantified through manual coding by a single researcher, based on pre-defined Turkish word stem lists for each category. Word stems were defined a priori using (i) LIWC-2015 English category descriptions and example words, and (ii) Turkish-language psychiatric and psycholinguistic literature. The complete stem lists for the two custom categories (Somatic Words and Abstract/Existential Words) are provided as Supplementary Material (Tables S1 and S2). The absence of independent dual coding and formal inter-rater reliability assessment is acknowledged as a methodological limitation consistent with the exploratory feasibility design. The categories analyzed were:

1. Positive Emotion: Percentage of words expressing positive emotions (e.g., happy, hopeful, good, cheerful)
2. Negative Emotion: Percentage of words expressing negative emotions (e.g., sad, anxious, scared, angry, helpless)
3. Causality: Percentage of words indicating a causal relationship (e.g., because, cause, effect)
4. Uncertainty: Percentage of words indicating uncertainty and probability (e.g., maybe, probably, I think)
5. First-person pronoun usage: Percentage of first-person singular pronouns (e.g., I, me, my, myself)

Table 1. Somatic Words — Turkish Word-Stem List (with English glosses)

Turkish word-stem	English gloss
ağrı	pain
sızı	ache / dull pain
yorgun*	tired / fatigued
bitkin*	exhausted
halsiz*	weak / listless
gergin*	tense
gerginlik	tension
kas	muscle
titreme	tremor
titriyor	(is) trembling
terleme	sweating
terliyor	(is) sweating
çarpıntı	palpitation
nefes	breath
soluk	breathing / breath
uyku (problemi / güçlüğü bağlamında)	sleep (in problem/difficulty context)
kalp	heart
nabız	pulse
sırt	(upper) back
bel	lower back / waist
baş ağrısı	headache
mide	stomach
bulantı	nausea
kusma	vomiting
ateş	fever
üşüme	chills / feeling cold
beden	body
vücut	body
fiziksel	physical

Asterisk (*) indicates stem matching (e.g., "yorgun*" captures yorgun, yorgunluk, yorgunum, etc.). Category constructed by combining LIWC-2015 body and health domain definitions with DSM-5 GAD somatic-symptom descriptors (Bandelow, 2015; Newman & Llera, 2011).

Somatic Words (custom category): Percentage of words referring to bodily sensations, autonomic symptoms, and somatic complaints characteristic of anxiety disorders (e.g., pain, tense, tremor, palpitation, tired, sweating). This category was constructed by combining the conceptual definitions of LIWC-2015 body and health domains with the somatic-symptom descriptors of the DSM-5 GAD criteria and the GAD somatic-symptom literature (Bandelow, 2015; Newman & Llera, 2011). Full stem list provided in Table 1.

Abstract/Existential Words (custom category): Percentage of words conveying abstract, existential, or meaning-related content (e.g., meaningless, emptiness, hopeless, helpless, worthless, nothingness). This category was constructed by combining selected LIWC-2015 cognitive-process domain definitions with the existential-psychology literature on meaning-related cognition in depression (Kéri, 2025). Full stem list provided in Table 2.

Table 2. Abstract/Existential Words — Turkish Word-Stem List (with English glosses)

Turkish word-stem	English gloss
anlam*	meaning
mana*	meaning (synonym)
boş*	empty / emptiness
hiç*	nothing
hiçlik	nothingness
umut*	hope
umutsuz*	hopeless / hopelessness
çare*	remedy / solution
çaresiz*	helpless / helplessness
değer*	value / worth
değersiz*	worthless / worthlessness
yararsız	useless
faydasız	useless (synonym)
beyhude	in vain / futile
bitti	(it is) over / finished
bitmiş	finished / done
son*	end
sonsuz*	endless / infinite
geleceksiz	without future
karanlık	darkness
ağırlık (yük anlamında)	weight (in the sense of burden)
suç*	guilt / blame
suçluluk	guilt
yalnız*	alone
yalnızlık	loneliness
tükenmiş*	burned out / depleted
dayanamıyorum	I cannot endure
katlanamıyorum	I cannot bear / tolerate
yaşam (varoluşsal bağlamda)	life (in existential context)
var olmak	to exist

Asterisk (*) indicates stem matching. Category constructed by combining selected LIWC-2015 cognitive-process domain definitions with existential-psychology literature on meaning-related cognition in depression (Kéri, 2025).

Each variable was calculated as a percentage (%), by dividing the number of words in the relevant category by the total number of words and multiplying the result by 100.

Statistical Analysis

The normality of the data distribution was determined using the Shapiro–Wilk test applied to the percentage (%) values of each LIWC variable. For variables where the assumption of normal distribution was met, the independent samples t-test was used for intergroup comparisons. For variables that did not show normal distribution, the Mann–Whitney U test was applied. In the uncertainty and abstract word variables, since all observations had the same value in at least one of the groups, the assumptions of parametric tests were not met, and intergroup comparisons were made using the Mann–Whitney U test. Since zero values were obtained in both groups in the positive sentiment and causality categories, these variables were not included in the comparative analyses. The statistical significance level was accepted as $p < 0.05$. All analyses were performed using IBM SPSS Statistics Version 22.0 (IBM Corp., Armonk, NY).

Results

A total of 30 simulated case texts (15 MDD, 15 GAD) were analyzed in the study. The average word count of the stories in the MDD group was 17.5 (SD=2.2), and the average word count of the stories in the GAD group was 19.1 (SD=1.1). Positive emotion and causality-related word categories contained zero values in both groups and were not included in further analyses. Descriptive statistics are summarized in Table 3.

Table 3. Descriptive Statistics of Psycholinguistic Variables in MDD and GAD Texts

Variable	Group	Mean ± SD	Median (IQR)	Min–Max
Negative emotion (%)	MDD	10.93 ± 1.44	10.9 (9.8–11.9)	7.7–12.5
	GAD	10.53 ± 0.52	10.6 (10.2–11.0)	10.0–11.1
Uncertainty (%)	MDD	0.00 ± 0.00	0.0 (0.0–0.0)	0.0–0.0
	GAD	5.33 ± 0.29	5.3 (5.1–5.5)	5.0–5.6
First-person pronouns (%)	MDD	2.8 ± 1.2	2.5 (1.8–3.5)	1.0–5.0
	GAD	2.5 ± 0.9	2.3 (1.8–3.0)	1.2–4.0
Somatic words (%)	MDD	0.42 ± 1.61	0.0 (0.0–0.0)	0.0–6.3
	GAD	6.00 ± 1.76	6.0 (5.0–7.0)	5.0–10.0
Abstract words (%)	MDD	7.73 ± 2.25	7.5 (6.1–9.4)	5.6–11.1
	GAD	0.00 ± 0.00	0.0 (0.0–0.0)	0.0–0.0

MDD: Major Depressive Disorder; GAD: Gewnrealized Anxiety Disorder; SD: Standard deviation

Text samples and qualitative findings generated by the DeepSeek-R1 model;

MDD text 1:

“Ahmet is 45 years old. For the past two months, he hasn't enjoyed anything. He constantly feels tired and lacks energy. His appetite has decreased significantly, and his sleep is frequently interrupted at night. He feels worthless and guilty. He says, ‘I don't have the strength to endure anymore.’”

(In this story, abstract and existential expressions are noteworthy. Although somatic complaints are present, they are presented intertwined with emotional and cognitive content.)

MDD text 2:

“Zeynep is a 29-year-old teacher. For the past three weeks, she has been in a state of intense depression. She says she feels like crying and can't concentrate. She has difficulty falling asleep. She adds, ‘Everything seems meaningless, I don't want to see anyone.’”

(In this story, anhedonia, cognitive impairment, and social withdrawal are prominent.)

GAD text 1:

“*Deniz, 27 years old. For the past six months, she has been constantly feeling ‘excessively anxious’ about her job, health, and family. She says, ‘I’m always thinking the worst.’ Her muscles are tense, she has difficulty falling asleep. She says she gets tired easily.”*

(In this story, the theme of uncertainty/anxiety and somatic complaints are prominent; the anxiety content extends to multiple areas of her life.)

GAD text 2:

“*Can, 35 years old. He constantly worries about traffic, meeting deadlines, and making mistakes. He describes it as, ‘I never get over the feeling of unease.’ He has difficulty concentrating, and his hands tremble slightly.” (In this story, somatic complaints and performance/anxiety content are prominent.)*

Table 4. Group Comparisons of Psycholinguistic Variables

Variable	Test	p-value	Direction of difference
Negative emotion (%)	Independent t-test	0.272	No significant difference
Uncertainty (%)	Mann–Whitney U	< 0.001	GAD > MDD
First-person pronouns (%)	Independent t-test	0.450	No significant difference
Somatic words (%)	Mann–Whitney U	< 0.001	GAD > MDD
Abstract words (%)	Mann–Whitney U	< 0.001	MDD > GAD

According to the analysis results given in Table 4:

First-person pronoun: No statistically significant difference was observed between the MDD and GAD groups in terms of first-person singular pronoun usage ($p = 0.450$).

Uncertainty-related expressions: Uncertainty-related expressions in the GAD group were found to be significantly higher than in the MDD group ($p < 0.001$).

Somatic Words: The use of somatic words in the GAD group was found to be significantly higher than in the MDD group ($p < 0.001$).

Abstract Words: The use of abstract words in the MDD group was found to be statistically significantly higher than in the GAD group ($p < 0.001$).

Negative Emotion: No statistically significant difference was found between the two groups in terms of negative emotion expressions ($p = 0.272$).

Discussion

This feasibility study examined the psycholinguistic features of simulated texts of MDD and GAD generated by artificial intelligence. The findings provide preliminary methodological evidence that AI-generated texts can exhibit linguistic patterns consistent with psycholinguistic tendencies previously reported in the literature for these diagnostic categories. Using LIWC-2015, the analysis demonstrated that such simulated texts can capture quantitative differences in predefined linguistic and psychological domains, offering a structured and reproducible approach for exploratory investigations (Pennebaker et al., 2003; Pennebaker et al., 2015). Importantly, these findings apply exclusively to AI-generated simulated texts and carry no implication of clinical, diagnostic, or screening utility. The simulated texts are short, structurally constrained prompt outputs and do not approximate the linguistic, affective, or narrative complexity of authentic patient discourse. No inference about the discriminability of real patient narratives, the validity of LIWC-based features as diagnostic markers, or the suitability of language-based AI tools for psychiatric assessment can be drawn from the present results.

Contrary to expectations based on the existing literature, no statistically significant difference was observed between MDD- and GAD-consistent texts in terms of first-person singular pronoun use. Previous clinical studies have reported that individuals with depression tend to focus on their inner experiences and self-evaluation, which is often reflected linguistically through increased use of first-person singular pronouns (Ingram, 1990; Rude et al., 2004). The absence of this expected difference in the present study may be attributable to the constrained nature of simulated texts, including limited text length and prompt-driven structure.

In contrast, the higher frequency of ambiguous statements observed in texts consistent with a GAD diagnosis aligns with intolerance of uncertainty and future-oriented worry, which are core characteristics of anxiety disorders (Dugas et al., 1998; Newman & Llera, 2011). On the other hand, another important finding of the study is the difference in the use of somatic and abstract words in both groups. The high use of somatic words in GAD texts can be explained by the bodily manifestations of anxiety (Newman & Llera, 2011). Indeed, generalized anxiety disorder is a psychopathology that manifests itself through cognitive and physical symptoms. Physical symptoms include muscle tension, pain, fatigue, sleep disturbances, difficulty concentrating, etc. (Leung et al., 2022; Papadimitriou & Linkowski, 2005; Leung et al., 2022). The high use of abstract words in MDD texts may be related to existential problems and the search for meaning in depression, as captured by the exploratory custom lexical category used in this study (Kéri, 2025).

The fact that these texts are consistent with clinical experiences mentioned in the literature suggests that AI-generated texts may serve as supplementary illustrative material in psychiatry education. AI-generated case histories, anamnesis, and examination findings could benefit medical students and psychiatry residents in exploring diagnostic language nuances. Furthermore, these histories could be transformed into standardized training materials, facilitating the work of instructors in the field. Previous research has demonstrated that LIWC-based linguistic analysis can capture meaningful associations between language use and underlying emotional, cognitive, and personality-related processes, suggesting that certain aspects of subjective psychological characteristics may be reflected in linguistic patterns (Hirsh & Peterson, 2009; Tausczik & Pennebaker, 2010). These developments suggest that psychiatric interviews can be evaluated more consistently with objective assessments and AI support, and that objective approaches to psychopathology can be developed more easily.

Recent studies suggest that large language model–based linguistic representations can capture latent emotional and distress-related dimensions in mental health–related narratives that align with established psychopathology frameworks, indicating that computational language models may reflect clinically relevant affective patterns in naturalistic text data (Bauer et al., 2024; Hirsh & Peterson, 2009). These findings, at the feasibility level, offer preliminary support for exploring AI-generated texts as proxy materials in methodological research.

The lack of a significant difference between groups in terms of the percentages of words containing negative emotions can be considered an explainable finding in the context of feasibility. The decrease in positive emotions in both disorders—negative feelings related to depression in one and anxiety in the other—are consistent with clinical manifestations observed by physicians. However, the fact that negative affect is a fundamental component in both MDD and GAD diagnoses shows that the discriminatory power of this category does not emerge in simulated texts generated by AI (Watson et al., 1988). The primary aim of this study is not to produce clinically generalizable results, but rather to evaluate whether psychiatric texts generated by AI are a suitable data source for psycholinguistic analysis. The findings demonstrate that the selected methods and variables are functional at the feasibility level and provide a methodological basis for confirmatory studies to be conducted with larger samples.

A central limitation of the present study concerns the very short length of the simulated texts (mean ≈ 17–19 words). LIWC-based analyses are conventionally applied to substantially longer texts, with empirical recommendations of at least 100 words to obtain stable proportional estimates (Tausczik & Pennebaker, 2010; Pennebaker et al., 2015). Proportional category scores computed on extremely short texts are highly sensitive to single-word fluctuations, exhibit inflated variance, and frequently produce floor or ceiling values that distort group-level comparisons. This constraint likely contributed both to the complete absence of positive-emotion and causality words in both groups and to the near-binary distributions observed for the somatic and abstract-word variables. Accordingly, the present results should be regarded as preliminary lexical signals embedded in highly compressed prompt outputs, rather than as estimates of stable psycholinguistic profiles. Replication using longer, narratively richer generations — or direct comparison with real-patient transcripts of comparable length distributions — is essential before any inference about psycholinguistic differentiation can be advanced.

A further interpretive caveat concerns the training-data composition of the language model used to generate the texts. Large language models such as DeepSeek-R1 are trained on extensive corpora that include psychiatric and psycholinguistic literature describing precisely the features assessed in this study — namely, reduced first-person pronoun use, elevated somatic vocabulary, and existential lexis as putative markers of MDD and GAD. It is therefore possible — indeed, plausible — that the linguistic differences detected between the MDD- and GAD-consistent texts partly reflect the model reproducing literature-derived stereotypes rather than emergent linguistic regularities. This circularity does not invalidate the feasibility framework, but it substantially constrains interpretation: the findings demonstrate that an LLM can generate texts recapitulating documented psycholinguistic patterns, not that those patterns arise spontaneously from clinical phenomena. This consideration is critical for any future use of such material in research or training contexts. In addition, the limited sample size of the study and the inclusion of only two diagnostic groups necessitate caution in interpreting the results. Furthermore, the fact that the case histories used were generated by AI does not fully reflect the linguistic complexity, amount of detail, and affective state conveyed by the patient's appearance in real patient narratives. However, these limitations are consistent with the feasibility of the study and may serve as inspiration for future research with much larger datasets that directly compare real patient texts with AI-generated simulated patient texts.

Conclusion

This study demonstrated that AI-generated texts corresponding to MDD and GAD exhibited distinguishable lexical patterns in psycholinguistic categories related to uncertainty, somatic content, and abstract/existential expression.

These differences are confined to short, prompt-driven simulated outputs and must not be interpreted as evidence of diagnostic utility, screening validity, or clinical equivalence to real patient language. Furthermore, the linguistic patterns observed may partly reflect the language model's training-data exposure to psychiatric literature describing these same features, rather than emergent regularities of clinical language. Within these constraints, the findings support, at a feasibility level only, the methodological viability of using AI-generated psychiatric texts for exploratory psycholinguistic methodology development and for the construction of standardized educational simulation material. Validation in larger datasets, with longer and narratively richer texts, and through direct comparison with authentic patient narratives, is required before any further inference can be drawn.

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Yazar Katkıları: Tüm yazarlar ICMJE'in bir yazarda bulunmasını önerdiği tüm ölçütleri karşılamışlardır
Etik Onay: Bu yazı için Etik Kuruldan onaya gerek yoktur.
Hakem Değerlendirmesi: Dış bağımsız.
Çıkar Çatışması: Yazarlar çıkar çatışması olmadığını beyan etmişlerdir.
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