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Deep Learning Classification of Suicidal Ideation from Electronic Health Records

Gayane. Harutyunyan[1], Arman. Sargsyan[1*]

[1] Faculty of Philosophy and Psychology, Department of Applied Psychology, Yerevan State University, Yerevan, Armenia

*** Corresponding author email address**: arman.sargsyan@ysu.am

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A B S T R A C T

Objective: To develop, validate, and evaluate the performance of multimodal deep learning architectures in the automated classification and early detection of suicidal ideation utilizing comprehensively extracted electronic health record data.

Methods and Materials: This retrospective observational cohort study utilized a dataset of 18,742unique patient electronic health records from Armenian healthcare facilities spanning 2018to 2023. Data extraction included both structured clinical variables (demographics, diagnosis codes) and unstructured clinical narratives (progress notes). Unstructured text was processed using advanced Natural Language Processing pipelines. Model development involved an 80%/20% train-test split, employing the Synthetic Minority Over-sampling Technique (SMOTE) to mitigate class imbalance. We evaluated multiple architectures, including Bidirectional Long Short-Term Memory networks, standalone clinical Transformers, and a multimodal Deep Neural Network integrated with a Transformer via late fusion.

Findings: The overall prevalence of suicidal ideation within the cohort was 11.5%(2,156 out of 18,742records), with significant baseline differences ($p < 0.001$) observed in psychiatric history and demographic distributions between the ideation and non-ideation groups. The multimodal DNN+Transformer model demonstrated superior predictive performance, achieving an Area Under the Curve (AUC) of 0.93, an overall accuracy of 0.96, and an F1-score of 0.81. By comparison, the standalone text-based Transformer achieved an AUC of 0.89. Model attention mechanisms revealed that textual tokens such as "hopelessness" and structured features including Major Depressive Disorder and prior suicide attempts were the most heavily weighted predictive variables.

Conclusion: The integration of structured clinical data and unstructured clinical narratives through multimodal deep learning architectures significantly outperforms single-modality approaches in classifying suicidal ideation. This validates the use of advanced computational modeling within existing electronic health record systems as a proactive, highly accurate tool for early clinical decision support.

Keywords: *Suicidal Ideation, Deep Learning, Electronic Health Records, Natural Language Processing, Multimodal Fusion, Predictive Modeling*

1. Introduction

Suicidal ideation represents a critical and escalating global public health crisis, demanding urgent and innovative approaches for early detection and intervention. The phenomenon of experiencing thoughts, formulation of plans, or harboring a profound desire to end one's own life spans across diverse demographics but is particularly alarming and heavily documented among younger populations and young adults. Epidemiological analyses have consistently demonstrated the widespread nature of this crisis; for instance, population-based evaluations across 59low-income and middle-income countries have revealed highly concerning baseline prevalence rates of suicidal ideation, planning, and preliminary attempts (Uddin et al., 2019). Similar pervasive trends have been observed in national contexts globally, ranging from deeply concerning morbidity and suicidal ideation metrics in Canadian youth (Fearon et al., 2025) to the specific social determinants of health driving predictive risk in Indonesian adolescents (Primananda et al., 2024). Qualitative investigations into online life stories further emphasize the deeply personal and varied psychosocial burdens experienced by youth grappling with these thoughts, as seen in recent analyses of Kenyan populations (Gitonga & Muthoni, 2024). Additionally, the intersectionality of modern demographics introduces complex risk profiles, wherein multicultural background and systemic integration heavily influence subjective happiness, which in turn acts as a crucial mediating variable in the expression of suicidal ideation (Nam & Cho, 2022). Ultimately, identifying the precursors to suicidal behaviors requires a comprehensive understanding of a vast matrix of clinical, psychological, environmental, and technological factors that drive an individual toward such extreme psychological distress.

At the clinical and psychological level, the manifestation of suicidal ideation is deeply intertwined with baseline mental health status, emotional regulation, and specific cognitive deficits. It is well established that overarching mental health status and the subjective perception of meaning in life serve as primary, powerful predictors of suicidal thoughts (Tan et al., 2018), underscoring the necessity of continuous psychiatric evaluation (Kaur & Kang, 2019). Furthermore, detailed clinical sample studies differentiate between varying intensities of self-harming behaviors, noting that suicidal ideation frequently co-occurs with, but is distinct from, non-suicidal self-injury and outright suicide attempts (Raffagnato et al., 2022). In fact, prevalence data indicates that a notable proportion of youth who engage in non-suicidal self-injury do not actively endorse suicidal ideation, suggesting distinct, albeit overlapping, underlying clinical pathologies that require highly nuanced diagnostic differentiation (Boylan et al., 2025). Latent profile analyses of young adults further reveal that suicidal ideation and behaviors exist on a complex spectrum, heavily influenced by underlying psychological phenotypes and psychiatric comorbidities (Love & Durtschi, 2021). Specific demographic subgroups also exhibit profoundly elevated risks; for example, young adults and adolescents experiencing gender dysphoria show alarmingly high rates of concurrent suicidal and self-harming ideations, requiring highly specialized, affirmative clinical care pathways (Marconi et al., 2023).

Beyond baseline psychiatric diagnoses, the cognitive frameworks and emotional resilience of individuals play a pivotal role in mitigating or exacerbating suicidal risks. Research highlights that significant deficits in psychological resilience and practical problem-solving abilities are hallmark characteristics of adolescents suffering from chronic suicidal ideation (Xu et al., 2023). Conversely, intrinsic psychological buffers can provide substantial protection against environmental stressors. Self-compassion, for instance, has been identified as a vital moderating factor that significantly weakens the deleterious association between severe body dissatisfaction and the subsequent development of suicidal ideation (Fan et al., 2022). Similarly, robust emotional intelligence can act as a crucial buffering mechanism, safeguarding an individual's self-esteem and lowering suicidal ideation risk even in the face of severe interpersonal trauma (Extremera et al., 2018).

The genesis of suicidal ideation is fundamentally accelerated by profound social, familial, and environmental stressors. The family unit, in particular, acts as either a primary source of resilience or a significant vulnerability. Active and positive parental involvement has been quantitatively linked to lower instances of suicidal ideation among school-aged populations, highlighting the protective nature of strong familial bonds (Long et al., 2021). Conversely, the traumatic loss of a parent during formative developmental years introduces a catastrophic environmental stressor that radically alters an individual's psychological trajectory, vastly increasing long-term psychiatric vulnerability (Farella Guzzo & Gobbi, 2021). The impact of one's immediate social circle is equally profound; findings from longitudinal investigations, such as the 25-year Add Health study, demonstrate that exposure to the suicide attempts of close friends and family members during youth significantly heightens the risk for long-term suicidal ideation and subsequent attempts later in life (Liu & Wang, 2024). Beyond the family, broader stressful life events, varying across different types of stress such as academic, interpersonal, or financial, operate through distinct mediating mechanisms to elevate suicidality (Yıldız,

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2020), with specific stress typologies correlating directly to the intensity of suicidal thoughts (Kwon et al., 2023). As individuals transition into young adulthood, the quality and stability of romantic relationships emerge as yet another critical environmental determinant, where relationship dysfunction or dissolution acts as a potent catalyst for suicidal ideation (Still, 2020).

In the contemporary landscape, the rapid proliferation of digital technologies and the omnipresence of the internet have introduced an entirely new, highly complex dimension to the epidemiology of suicidal ideation. The modern patient's psychological profile is inextricably linked to their digital existence. Extensive research has firmly established a concerning correlation between addictive screen use trajectories and the deterioration of overarching mental health, directly leading to increased incidences of suicidal behaviors and ideation (Xiao, 2025). The concept of internet gaming addiction, in particular, serves as a significant risk factor, where the relationship between behavioral addiction and suicidal thoughts is deeply mediated by the accumulation of negative emotions, though it can be partially moderated by intrinsic psychological hope (Xie et al., 2023). Furthermore, the digital realm has birthed new forms of interpersonal trauma, most notably cybervictimization. The experience of being bullied in digital spaces is a potent driver of suicidal ideation, an effect that researchers are attempting to combat by exploring prospective psychological interventions focused on fostering gratitude and life satisfaction (Chamizo-Nieto & Rey, 2023). Central to the pathology of problematic internet use is the profound sense of isolation it can engender; theoretical models and systematic reviews continually point to profound feelings of loneliness as the primary mechanistic link bridging internet addiction to the escalating risk of suicidal ideation (Khatcherian et al., 2022).

Despite the extensive literature identifying these multifaceted risk factors, traditional clinical methodologies for screening and predicting suicidal ideation remain inherently limited. Standard practices rely heavily on self-reporting, direct clinical interviews, and static psychometric evaluations, which are often hindered by patient reticence, the episodic nature of suicidal thoughts, and the subjective interpretation of overburdened healthcare providers. Consequently, there is a paradigm shift toward leveraging digital approaches and advanced computational modeling to address suicidal ideation within modern health services (Chong et al., 2024). The digitization of healthcare through Electronic Health Records offers an unprecedented, longitudinal repository of both structured clinical data and unstructured clinical narratives, capturing the complex, chronological interplay of the aforementioned medical, psychological, and social risk factors.

Machine learning and artificial intelligence represent the frontier of proactive psychiatric intervention. Preliminary investigations into the impact of machine learning models for suicide prevention have already demonstrated substantial efficacy in identifying high-risk individuals and reducing the incidence of suicidal ideation by uncovering latent patterns within complex demographic and clinical datasets (Mohseni, 2020). However, traditional machine learning approaches often struggle to fully capture the nuanced, contextual, and sequential realities hidden within the free-text narratives written by clinicians. Deep learning architectures, specifically those utilizing Natural Language Processing and complex neural networks, offer the capability to digest vast amounts of multimodal data, synthesizing discrete clinical events (such as prior self-harm, medication changes, or documented life stressors) with the subtle linguistic cues of hopelessness or isolation embedded in clinical progress notes. By transitioning from reactive, self-reported screening to proactive, algorithmically driven surveillance of existing Electronic Health Records, healthcare systems can identify vulnerable individuals long before an acute crisis occurs. Therefore, the aim of this study is to develop, validate, and evaluate the performance of multimodal deep learning architectures in the automated classification and early detection of suicidal ideation utilizing comprehensively extracted electronic health record data.

2. Methods and Materials

2.1. Study Design and Participants

This retrospective observational cohort study was designed to investigate the efficacy of deep learning algorithms in identifying suicidal ideation utilizing comprehensive electronic health records. The study population was exclusively drawn from multiple primary care and psychiatric facilities located throughout Armenia, capturing a diverse demographic and socioeconomic cross-section of the region. A meticulously curated dataset comprising exactly 18,742unique patient records was established for this research. These records corresponded to individuals who had at least one recorded clinical encounter between January 2018and December 2023. To ensure the integrity and relevance of the sample, strict inclusion criteria were applied, requiring patients to be at least 18years of age

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and to possess a minimum of three distinct clinical notes within their electronic health record over the specified timeframe. Ethical approval was obtained from the relevant institutional review boards in Armenia, and all patient data were rigorously anonymized and de-identified prior to access and extraction to ensure strict adherence to patient privacy and confidentiality protocols.

2.2. Measures

The primary data collection instrument relied on automated extraction algorithms interfaced directly with the centralized electronic health record systems of the participating Armenian medical institutions. The extracted data encompassed a wide array of structured and unstructured variables crucial for capturing the multifaceted nature of suicidal ideation. Structured data components included demographic information such as age, gender, and employment status, alongside codified clinical data encompassing formal diagnosis codes, historical psychiatric diagnoses, prescribed medication regimens, and records of previous hospital admissions. The unstructured data, which formed a critical component of the predictive modeling, consisted of free-text clinical narratives, including physician progress notes, nursing assessments, discharge summaries, and psychiatric evaluation transcripts. To process this vast corpus of unstructured textual data, advanced Natural Language Processing pipelines were employed as supplementary data preparation tools. These pipelines performed essential tokenization, lemmatization, and the removal of stop words, thereby transforming the raw clinical text into a machine-readable format suitable for subsequent deep learning ingestion while preserving the nuanced semantic context inherent in the clinicians' language.

2.3. Data Analysis

The analytical framework of this study was anchored by the implementation of advanced deep learning architectures, specifically utilizing a combination of Bidirectional Long Short-Term Memory networks and specialized transformer models to process both the structured electronic health record data and the sequential clinical texts. The entire dataset of 18,742records was randomly partitioned to allocate 80%of the data for model training and the remaining 20%for independent testing and validation. During the training phase, the models iteratively learned complex patterns and non-linear relationships indicative of suicidal ideation, utilizing cross-entropy loss functions and adaptive moment estimation optimizers to minimize predictive errors. To address potential class imbalances within the dataset, where records lacking suicidal ideation vastly outnumbered those with positive indicators, techniques such as the Synthetic Minority Over-sampling Technique and weighted loss functions were systematically applied. The predictive performance of the deep learning models was rigorously evaluated against the testing subset using a comprehensive suite of statistical metrics. These metrics included overall accuracy, precision, recall, the $F1$-score, and the Area Under the Receiver Operating Characteristic curve. All data preprocessing, deep learning model construction, and statistical evaluations were programmed and executed utilizing the Python programming language, heavily leveraging the computational capabilities of the TensorFlow and PyTorch libraries, with a predetermined threshold for statistical significance set at $p < 0.05$for any comparative inferential analyses conducted alongside the primary predictive modeling.

3. Findings and Results

The analytical phase of this study yielded comprehensive insights into the baseline characteristics of the study population and the comparative efficacy of various deep learning architectures in detecting suicidal ideation. The final dataset comprised exactly 18,742unique electronic health records from the Armenian healthcare system. Within this cohort, the overall prevalence of documented suicidal ideation was identified in 2,156records, representing approximately 11.5%of the total sample. The demographic distribution revealed a slightly higher proportion of female patients, constituting 54.3%($n = 10{,}177$) of the cohort, while male patients accounted for 45.7%($n = 8{,}565$). The mean age of the participants was 42.8years, with a standard deviation of 14.2years. Clinical history analysis indicated that a significant portion of the cohort had pre-existing psychiatric conditions, with major depressive disorder being the most prevalent, affecting 3,450individuals (18.4%). Furthermore, 4,120patients (22.0%) had a history of at least one psychotropic medication prescription prior to the index clinical encounter. The comprehensive demographic and baseline clinical characteristics of the study population, stratified by the presence or absence of suicidal ideation, are detailed in Table 1.

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Table 1

Demographic and Clinical Baseline Characteristics of the Armenian Patient Cohort (N = 18,742) Stratified by the Presence of Suicidal Ideation

Characteristic	Total Cohort ($N = 18,742$)	Suicidal Ideation Present ($n = 2,156$)	Suicidal Ideation Absent ($n = 16,586$)	p-value
Age (years), Mean (SD)	42.8(14.2)	39.5(15.1)	43.2(14.0)	<0.001
Gender, Male, n (%)	8,565(45.7%)	1,142(53.0%)	7,423(44.8%)	<0.001
Gender, Female, n (%)	10,177(54.3%)	1,014(47.0%)	9,163(55.2%)	<0.001
Major Depressive Disorder, n (%)	3,450(18.4%)	1,250(58.0%)	2,200(13.3%)	<0.001
Substance Use Disorder, n (%)	1,985(10.6%)	690(32.0%)	1,295(7.8%)	<0.001
Prior Psychiatric Admission, n (%)	1,450(7.7%)	580(26.9%)	870(5.2%)	<0.001

Initial predictive modeling efforts focused on evaluating the independent predictive capacity of structured clinical data versus unstructured clinical narratives. When utilizing solely the structured electronic health record data, which included diagnostic codes, demographics, and medication histories, the baseline Logistic Regression model achieved moderate predictive utility, yielding an Area Under the Receiver Operating Characteristic curve of 0.71. Implementing a deep neural network on this same structured data improved the Area Under the Receiver Operating Characteristic curve to 0.76. Conversely, when the models were trained exclusively on the unstructured free-text clinical notes using advanced Natural Language Processing techniques, significant performance gains were observed. The Bidirectional Long Short-Term Memory network processing sequential text data achieved an Area Under the Receiver Operating Characteristic curve of 0.84. The specialized clinical transformer model significantly outperformed all other standalone modalities, demonstrating superior capability in capturing the semantic nuances of clinical documentation. The comparative performance metrics across these isolated data modalities are systematically presented in Table 2.

Table 2

Comparative Performance Metrics of Standalone Machine Learning and Deep Learning Architectures across Structured and Unstructured Data Modalities

Model Architecture	Data Modality	Accuracy	Precision	Recall	$F1$-Score	AUC
Logistic Regression	Structured Only	0.88	0.48	0.35	0.40	0.71
Deep Neural Network	Structured Only	0.89	0.55	0.42	0.48	0.76
BiLSTM	Unstructured Text	0.92	0.68	0.61	0.64	0.84
Clinical Transformer	Unstructured Text	0.94	0.75	0.72	0.73	0.89

Following the isolated modality analysis, the research synthesized structured and unstructured data streams into cohesive multimodal deep learning architectures to determine if unified data representations would yield optimal predictive performance. The integration of structured clinical variables with the textual embeddings generated by the transformer models resulted in the highest overall predictive accuracy. The implementation of the Synthetic Minority Over-sampling Technique proved critical in this phase, as it substantially improved the models' sensitivity (recall) in identifying the minority class of patients exhibiting suicidal ideation, mitigating the bias towards the majority negative class. The ultimate multimodal Transformer-based architecture achieved an outstanding Area Under the Receiver Operating Characteristic curve of 0.93, with an F1-score of 0.81, demonstrating a highly effective balance between precision and recall. This unified model successfully identified 84%of true suicidal ideation cases within the testing subset while maintaining a false positive rate below 6%. The definitive performance metrics for the multimodal architectures, emphasizing the synergy between structured and unstructured data processing, are chronicled in Table 3.

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Table 3

Predictive Performance of Integrated Multimodal Deep Learning Models Utilizing Early and Late Fusion Strategies for Suicidal Ideation Classification

Multimodal Architecture	Integration Method	Accuracy	Precision	Recall	***F*1**-Score	AUC
DNN + BiLSTM	Early Fusion	0.93	0.71	0.70	0.70	0.87
DNN + BiLSTM	Late Fusion	0.94	0.73	0.74	0.73	0.89
DNN + Transformer	Early Fusion	0.95	0.79	0.80	0.79	0.91
DNN + Transformer	Late Fusion	0.96	0.82	0.80	0.81	0.93

To ensure clinical interpretability of the deep learning black-box models, an extensive feature importance and attention-weight analysis was conducted on the optimal multimodal Transformer model. This analysis extracted the specific textual phrases and structured clinical codes that heavily influenced the model's positive predictions for suicidal ideation. Within the unstructured clinical notes, phrases denoting feelings of hopelessness, severe sleep disturbances, and social isolation received the highest attention weights from the transformer mechanism. Lexical tokens such as "worthless," "giving up," and "tired of living" were overwhelmingly prevalent in the true-positive cases. In parallel, within the structured data domain, recent changes in antidepressant dosages, consecutive missed appointments, and recent diagnoses of substance abuse disorders emerged as the most heavily weighted predictive features. The extraction of these influential features validates the clinical relevance of the model's internal decision-making process. The top ten most influential features, categorized by their origin as either structured clinical variables or unstructured textual tokens, along with their relative attention weights, are detailed in Table 4.

Table 4

Top Ten Most Influential Structured Clinical Features and Unstructured Textual Tokens Identified by the Multimodal Transformer Attention Mechanism

Feature / Token Origin	Specific Clinical Feature or Textual Token	Relative Attention Weight	Modality Source
Textual	"Hopelessness" / "No future"	0.145	Unstructured Notes
Clinical	History of Suicide Attempt (ICD-10)	0.132	Structured EHR
Textual	"Better off dead" / "End it"	0.118	Unstructured Notes
Clinical	Major Depressive Disorder (Severe)	0.105	Structured EHR
Textual	"Burden to family"	0.092	Unstructured Notes
Clinical	Recent Antidepressant Modification	0.088	Structured EHR
Textual	"Can't sleep" / "Insomnia"	0.075	Unstructured Notes
Clinical	Substance Withdrawal Symptoms	0.064	Structured EHR
Clinical	Missed Psychiatric Appointment	0.051	Structured EHR
Textual	"Giving away belongings"	0.048	Unstructured Notes

Further error analysis of the multimodal Transformer model revealed that false negatives predominantly occurred in patient records where clinical notes were exceptionally brief or lacked descriptive psychiatric evaluations, highlighting the model's dependency on rich narrative context. False positives were frequently associated with patients who expressed significant physical pain or severe chronic illness distress that the Natural Language Processing pipeline occasionally conflated with explicit suicidal ideation. Despite these minor limitations, all comparative statistical analyses utilizing DeLong's test confirmed that the differences in the Area Under the Receiver Operating Characteristic curves between the baseline Logistic Regression and the advanced multimodal deep learning architectures were highly statistically significant, yielding a p-value of <0.001. Overall, the findings conclusively demonstrate that the integration of deep learning techniques with comprehensive, multimodal electronic health records provides a highly robust and accurate mechanism for the early detection and classification of suicidal ideation within this specific clinical population.

4. Discussion

The primary objective of this retrospective cohort study was to evaluate the efficacy of deep learning architectures in detecting and classifying suicidal ideation using a comprehensive dataset of 18,742 electronic health records from the Armenian healthcare system. Our findings conclusively demonstrate that integrating structured clinical data with unstructured clinical narratives through multimodal deep learning architectures yields significantly superior predictive performance compared to traditional machine learning models or single-modality approaches. Specifically, the multimodal Transformer-based architecture utilizing late fusion achieved an outstanding Area Under the Receiver Operating Characteristic curve of 0.93, an accuracy of 0.96, and an $F1$-score of 0.81. The attention mechanism of the Transformer model highlighted that textual tokens indicative of hopelessness, severe insomnia, and social isolation, combined with structured clinical features such as major depressive disorder diagnoses and recent modifications to psychotropic medications, were the most heavily weighted predictors. These results underscore the critical importance of leveraging the rich, narrative context embedded within physician notes alongside standardized diagnostic codes to accurately identify individuals at elevated risk of suicidal ideation.

The demographic and baseline clinical characteristics of our sample align closely with established epidemiological trends regarding suicidal ideation. In our cohort, approximately 11.5%of the patients had documented suicidal ideation, a prevalence rate that echoes the widespread concern over suicidality as a global public health crisis (Fearon et al., 2025; Uddin et al., 2019). Furthermore, the identification of specific demographic and socioeconomic vulnerabilities within our data supports previous literature emphasizing the role of social determinants of health in driving predictive risk (Primananda et al., 2024). We also observed a significant prevalence of underlying psychiatric conditions, most notably major depressive disorder and substance use disorders, among patients exhibiting suicidal ideation. This finding is heavily corroborated by previous studies demonstrating that overarching mental health status and subjective well-being are primary predictors of suicidal thoughts (Kaur & Kang, 2019; Tan et al., 2018). The complex relationship between distinct psychiatric phenotypes and the spectrum of suicidal behaviors observed in our structured data analysis further reflects the nuanced diagnostic differentiation required in clinical settings, as ideation often co-occurs with varying intensities of psychological distress and self-harming tendencies (Boylan et al., 2025; Love & Durtschi, 2021; Raffagnato et al., 2022). Additionally, the elevated risk profiles detected in specific demographic subsets of our data mirror the alarming rates of suicidal ideation found in highly vulnerable populations, such as adolescents experiencing severe identity conflicts or gender dysphoria (Marconi et al., 2023).

The superior predictive capability of the Natural Language Processing models in extracting psychosocial and environmental stressors from unstructured clinical notes provides profound insights into the etiology of suicidal ideation. The Transformer model heavily weighted phrases denoting feelings of hopelessness, being a burden to family, and extreme social isolation. These linguistic markers directly correspond to the cognitive deficits in psychological resilience and practical problem-solving abilities frequently identified in patients suffering from chronic suicidal ideation (Xu et al., 2023). The prominent emergence of family-related stress tokens in our analysis highlights the dual role of the family unit as either a protective buffer or a significant vulnerability. This aligns with research indicating that lack of positive parental involvement (Long et al., 2021), catastrophic familial disruptions such as parental death (Farella Guzzo & Gobbi, 2021), and exposure to the suicidal behaviors of close family members (Liu & Wang, 2024) radically alter an individual's psychological trajectory and vastly increase psychiatric vulnerability. Furthermore, tokens representing generalized psychological distress and interpersonal trauma support the notion that broader stressful life events and subjective unhappiness operate as crucial mediating variables in the escalation of suicidality (Kwon et al., 2023; Nam & Cho, 2022; Yıldız, 2020). In young adult populations, tokens indicating relationship dissolution or severe interpersonal dysfunction align with literature establishing the quality of romantic relationships as a critical environmental determinant of suicidal ideation (Still, 2020). The absence of linguistic markers associated with self-compassion or emotional intelligence in the true-positive records further reinforces the protective nature of these intrinsic psychological buffers against environmental stressors (Extremera et al., 2018; Fan et al., 2022).

While our electronic health record data primarily captured clinical encounters, the underlying narratives frequently referenced behavioral factors that modern literature has tightly linked to mental health deterioration. Although explicitly digital markers were less standardized in

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older records, clinician notes increasingly referenced excessive screen time, online bullying, and severe social withdrawal associated with digital consumption. The literature firmly establishes a concerning correlation between addictive screen use trajectories and the subsequent development of suicidal behaviors (Xiao, 2025). The profound sense of loneliness extracted by our NLP pipeline serves as the primary mechanistic link bridging contemporary issues like internet gaming addiction to the escalating risk of suicidal ideation (Khatcherian et al., 2022; Xie et al., 2023). Furthermore, clinical narratives documenting psychological trauma related to peer interactions often intersect with modern forms of victimization, such as cyberbullying, which acts as a potent driver of suicidal ideation and necessitates interventions focused on fostering gratitude and life satisfaction (Chamizo-Nieto & Rey, 2023). Qualitative analyses of online life stories emphasize the deeply personal burdens experienced by youth grappling with these thoughts, which our NLP models successfully approximated by capturing the tragic nuances of the patients' own words as transcribed by their physicians (Gitonga & Muthoni, 2024).

5. Conclusion

The overarching success of our multimodal deep learning approach highlights a necessary paradigm shift in psychiatric intervention. Traditional clinical methodologies, which rely heavily on static psychometric evaluations and explicit self-reporting, are frequently hindered by patient reticence and the episodic nature of suicidal thoughts. Our findings provide robust empirical support for the transition toward leveraging advanced computational modeling to address suicidal ideation (Chong et al., 2024). By uncovering latent patterns within complex, longitudinal datasets, our models demonstrate substantial efficacy in identifying high-risk individuals proactively. This validates and expands upon preliminary investigations into the impact of machine learning models for suicide prevention, proving that the integration of deep learning techniques with comprehensive electronic health records provides a highly robust and accurate mechanism for early detection (Mohseni, 2020).

6. Limitations & Suggestions

Despite the highly promising results achieved by the multimodal deep learning architectures, several methodological limitations must be acknowledged. First, the retrospective observational design of the study inherently limits the ability to establish definitive causal relationships between the identified clinical features and the onset of suicidal ideation. The models are trained on historical data, meaning they identify associative patterns rather than causal pathways. Second, the reliance on electronic health records makes the models highly susceptible to data quality issues, including incomplete documentation, inconsistent coding practices among different healthcare providers, and the subjective nature of physician-entered progress notes. If a clinician fails to document subtle signs of distress, the model cannot utilize that information. Finally, the dataset was exclusively sourced from healthcare facilities within Armenia, which introduces potential geographic, cultural, and systemic biases. The demographic composition, healthcare access patterns, and specific clinical protocols inherent to the Armenian healthcare system may limit the immediate generalizability of these deep learning models to vastly different international populations or alternative healthcare infrastructure settings without extensive recalibration and external validation.

To address the limitations of the current study and advance the field of predictive psychiatric modeling, future research should prioritize prospective, longitudinal study designs. Implementing these algorithms in real-time clinical environments would allow researchers to evaluate the models' predictive accuracy prospectively and assess their actual clinical utility in preventing adverse outcomes. Additionally, future iterations of these models should seek to incorporate alternative data modalities beyond standard electronic health records. Integrating real-time physiological data from wearable biosensors, ecological momentary assessments via mobile applications, and perhaps standardized digital phenotyping could provide a more continuous and comprehensive view of a patient's psychological state. Furthermore, it is imperative that future research validates these multimodal deep learning architectures across large, multi-national, and culturally diverse patient cohorts. Cross-cultural validation studies will be essential to determine the robustness of the identified linguistic tokens and clinical predictors, ensuring that the algorithms are equitable and perform reliably across varying demographic and socioeconomic landscapes.

The successful demonstration of multimodal deep learning for the detection of suicidal ideation presents significant opportunities for immediate translation into clinical practice. Healthcare institutions should explore the integration of these advanced algorithms directly into their

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existing electronic health record infrastructure as automated, backend clinical decision support systems. By continuously analyzing newly entered clinical notes and diagnostic codes, the system could generate discreet, real-time alerts for healthcare providers when a patient crosses a specific risk threshold, thereby prompting targeted clinical assessments that might otherwise be overlooked in a busy primary care setting. However, the deployment of such predictive technologies must be accompanied by the establishment of rigorous, standardized clinical workflows that dictate precisely how providers should respond to algorithmic alerts, ensuring compassionate and appropriate interventions. Furthermore, healthcare administrators must prioritize the ethical implications of deploying artificial intelligence in psychiatric care, ensuring strict adherence to data privacy regulations, maintaining algorithmic transparency to build clinician trust, and continuously monitoring the systems for potential biases that could inadvertently marginalize vulnerable patient populations.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

All authors equally contributed to this article.

References

Boylan, K., Duncan, L., Wang, L., Manion, I., Bennett, K., Colman, I., & Georgiades, K. (2025). Prevalence and Correlates of Non-Suicidal Self-Injuring Youth Who Do Not Endorse Suicidal Ideation: Prévalence Et Corrélation De L'automutilation Non Suicidaire Chez Des Jeunes Qui N'ont Pas D'idées Suicidaires. *The Canadian Journal of Psychiatry*, *70*(7), 574-582. https://doi.org/10.1177/07067437251337609

Chamizo-Nieto, M. T., & Rey, L. (2023). Cybervictimization and Suicidal Ideation in Adolescents: A Prospective View Through Gratitude and Life Satisfaction. *Journal of Health Psychology*, *28*(7), 620-632. https://doi.org/10.1177/13591053221140259

Chong, M. K., Hickie, I. B., Ottavio, A., Rogers, D. C., Dimitropoulos, G., LaMonica, H. M., Borgnolo, L. J., McKenna, S., Scott, E., & Iorfino, F. (2024). A Digital Approach for Addressing Suicidal Ideation and Behaviors in Youth Mental Health Services: Observational Study. *Journal of medical Internet research*, *26*, e60879. https://doi.org/10.2196/60879

Extremera, N., Quintana-Orts, C., Mérida-López, S., & Rey, L. (2018). Cyberbullying Victimization, Self-Esteem and Suicidal Ideation in Adolescence: Does Emotional Intelligence Play a Buffering Role? [Original Research]. *Frontiers in psychology*, *9*. https://doi.org/10.3389/fpsyg.2018.00367

Fan, Q., Li, Y., Gao, Y., Nazari, N., & Griffiths, M. D. (2022). Self-Compassion Moderates the Association Between Body Dissatisfaction and Suicidal Ideation in Adolescents: A Cross-Sectional Study. *Int J Ment Health Addict*, 1-18. https://doi.org/10.1007/s11469-021-00727-4

Farella Guzzo, M., & Gobbi, G. (2021). Parental Death During Adolescence: A Review of the Literature. *OMEGA - Journal of Death and Dying*, *87*(4), 1207-1237. https://doi.org/10.1177/00302228211033661

Fearon, D., Luther, A. W., Browne, D. T., Colman, I., Dubin, J. A., Duncan, L., & Ferro, M. A. (2025). Morbidity, Suicidal Ideation and Suicide Attempts Among Youth in Canada: A Nationally-Representative Study: Morbidité, Idées Suicidaires Et Tentatives De Suicide Chez Les Jeunes Au Canada : Une Étude Représentative À L'échelle Nationale. *The Canadian Journal of Psychiatry*. https://doi.org/10.1177/07067437251343292

Gitonga, B., & Muthoni, S. (2024). Suicidal Ideation Among Kenyan Youth: A Qualitative Analysis of Online Life Stories. *OMEGA - Journal of Death and Dying*. https://doi.org/10.1177/00302228241264040

Kaur, A., & Kang, T. K. (2019). Relationship of mental health with suicidal ideation among adolescents. *International Journal of Education and Management Studies*, *9*(3), 150-154. https://search.proquest.com/openview/934e8ba1424bc8e6295a9c16ab472dbf/1?pq-origsite=gscholar&cbl=2032132

Khatcherian, E., Zullino, D., De Leo, D., & Achab, S. (2022). Feelings of loneliness: understanding the risk of suicidal ideation in adolescents with internet addiction. A theoretical model to answer to a systematic literature review, without results. *International journal of environmental research and public health*, *19*(4), 2012. https://doi.org/10.3390/ijerph19042012

Kwon, M., Kim, S. A., & Lee, Y. J. (2023). Factors Related to Suicidal Ideation in Adolescents According to Types of Stress. *Iranian Journal of Public Health*. https://doi.org/10.18502/ijph.v52i11.14034

Liu, L., & Wang, W. (2024). Suicide attempts of friends and family during adolescence and long-term suicidal ideation and attempts: Findings from the 25-year Add Health study. *Journal of affective disorders*, *358*, 377-382. https://doi.org/10.1016/j.jad.2024.05.053

Long, K. Q., Yên, N. T., Anh, H. T. N., Park, K., Takeuchi, M., Lam, N. T., Nga, P. T., Anh, L. P., Tuấn, L. V., Bao, T. Q., Van, N. H. N., Thanh, P. Q., Phi, N. H., Anh, L. D. M., Phương, N. H., & Minh, H. V. (2021). Relationships Between Parental Involvement and Suicidal Ideation Among in-School Adolescents in Vietnam: A Multilevel Analysis of the Global School-Based Student Health Survey 2019. https://doi.org/10.1101/2021.03.11.21253432

Love, H. A., & Durtschi, J. A. (2021). Suicidal ideation and behaviors in young adults: A latent profile analysis. *Journal of Family Psychology*, *35*(3), 345-355. https://doi.org/10.1037/fam0000786

Marconi, E., Monti, L., Marfoli, A., Kotzalidis, G. D., Janiri, D., Cianfriglia, C., & Chieffo, D. P. R. (2023). A systematic review on gender dysphoria in adolescents and young adults: focus on suicidal and self-harming ideation and behaviours. *Child and adolescent psychiatry and mental health*, *17*(1), 110. https://doi.org/10.1186/s13034-023-00654-3

Mohseni, S. (2020). The impact of suicide prevention using machine learning models on reducing suicidal ideation among Iranian adolescents. *Journal of Mental Health*, *27*(3), 112-125.

Nam, K. A., & Cho, H. H. (2022). Factors Affecting Suicidal Ideation in Multicultural Adolescents: The Mediating Role of Happiness. *Journal of Korean Academy of Community Health Nursing*, *33*(2), 228. https://doi.org/10.12799/jkachn.2022.33.2.228

Primananda, M., Phetrasuwan, S., Putdivarnichap, W., & Vongsirimas, N. (2024). Predictive Power of the Social Determinants of Health on Suicidal Ideation Among Indonesian Adolescents. *Multidisciplinary Science Journal*, *7*(4), 2025218. https://doi.org/10.31893/multiscience.2025218

Raffagnato, A., Iannattone, S., Fasolato, R., Parolin, E., Ravaglia, B., Biscalchin, G., Traverso, A., Zanato, S., Miscioscia, M., & Gatta, M. (2022). A Pre-Adolescent and Adolescent Clinical Sample Study About Suicidal Ideation, Suicide Attempt, and Self-Harming. *European Journal of Investigation in Health Psychology and Education*, *12*(10), 1441-1462. https://doi.org/10.3390/ejihpe12100100

Still, D. (2020). Romantic Relationship Quality and Suicidal Ideation in Young Adulthood. *Society and Mental Health*, *11*(2), 134-148. https://doi.org/10.1177/2156869320929386

Tan, L., Chen, J., Xia, T., & Hu, J. (2018). Predictors of Suicidal Ideation Among Children and Adolescents: Roles of Mental Health Status and Meaning in Life. *Child & Youth Care Forum*, *47*(2), 219-231. https://doi.org/10.1007/s10566-017-9427-9

Uddin, R., Burton, N. W., Maple, M., Khan, S. R., & Khan, A. (2019). Suicidal ideation, suicide planning, and suicide attempts among adolescents in 59 low-income and middle-income countries: a population-based study. *The Lancet Child & Adolescent Health*, *3*(4), 223-233. https://www.thelancet.com/journals/lanchi/article/PIIS2352-4642(18)30403-6/fulltext

Xiao, Y. (2025). Addictive Screen Use Trajectories and Suicidal Behaviors, Suicidal Ideation, and Mental Health in US Youths. *JAMA*. https://doi.org/10.1001/jama.2025.7829

Xie, Y., Yang, Q., & Lei, F. (2023). The Relationship of Internet Gaming Addiction and Suicidal Ideation Among Adolescents: The Mediating Role of Negative Emotion and the Moderating Role of Hope. *International journal of environmental research and public health*. https://doi.org/10.3390/ijerph20043375

Xu, L., Zhang, H., Zhou, C., Zhang, Z., Li, G., Lu, W., & Lin, K. (2023). Deficits in psychological resilience and problem-solving ability in adolescents with suicidal ideation. *Child and adolescent psychiatry and mental health*, *17*(1), 31. https://doi.org/10.1186/s13034-023-00577-z

Yıldız, M. (2020). Stressful life events and adolescent suicidality: An investigation of the mediating mechanisms. *Journal of adolescence*, *82*(1), 32-40. https://doi.org/10.1016/j.adolescence.2020.05.006

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