BRAIN. Broad Research in Artificial Intelligence and Neuroscience
e-ISSN: 2067-3957 | p-ISSN: 2068-0473
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2025, Volume 16, Issue 4, pages: 542-557
Submitted: April 24th, 2025 | *Accepted for publication:* August 23rd, 2025

Forty Years of Knowledge Development on Emotional Abuse and Suicide – AI-Assisted Bibliometric and Empirical Insights

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Abstract: *This bibliometric study investigates worldwide research patterns on emotional abuse and suicide in 898 papers from 1985 to 2025 using data from the Web of Science Core Collection analysed with VOSviewer to study keyword co-occurrence, thematic clusters, temporal development, and country-level collaboration. Five primary research clusters focusing on suicide, childhood trauma, depression, risk factors among adolescents, and emotion regulation were revealed by the analysis. The USA, Canada, China, and England were found to be core contributors in worldwide co-authorship networks.Additionally, an empirical observational analysis was performed on 50 anonymised inpatients from the Socola Institute of Psychiatry in Iasi, assessing the severity of depression (HAM-D), suicidal ideation (BSS) and clinical follow-up results over a period of nine months.In the empirical arm of this study, which involved 50 anonymised inpatients, depression severity scores (HAM-D) and suicidal ideation (BSS) showed significant reductions from admission to nine-month follow-up ($p < 0.001$), while residual depressive symptoms at discharge (HAM-D T1) independently predicted persistent suicidality (OR = 1.12, 95% CI 1.02–1.23, $p = 0.014$). Results point toward the intricate, multidisciplinary nature of the field and the increasing concentration on trauma-informed prevention approaches.*

Keywords: *emotional abuse; suicide; childhood trauma; emotion regulation; HAM-D; BSS.*

How to cite: Vîşcu, L. I., Cădariu, I-E., Clifton, E.W.J., Constantin, A.-C., Delcea, C., & Siserman, C. V. (2025). Forty years of knowledge development on emotional abuse and suicide – AI-assisted bibliometric and empirical insights. *BRAIN. Broad Research in Artificial Intelligence and Neuroscience, 16*(4), 542-557. https://doi.org/10.70594/brain/16.4/33

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1. Introduction

Childhood emotional abuse has been identified for some time as a powerful risk factor for an array of negative mental health consequences, such as depression, self-injury, and suicidality. For example, Yang et al., (2024) discovered that depression mediates the link between childhood emotional abuse and non-suicidal self-injury in Chinese college students, with reciprocal filial piety serving as a moderator. Likewise, Ernst et al., (2022) determined that child maltreatment substantially heightens the risk of both non-suicidal self-injury and suicide attempts, largely via its influence on impaired personality functioning.

Corroborating these findings, Martins-Monteverde et al., (2019) described strong correlations between subtypes of early-life stress and depressive symptoms in adult psychiatric populations. Additionally, Silveira & Pereira, (2023) analysed data from Portuguese-speaking nations and determined that adverse childhood experiences (ACEs), specifically emotional abuse and neglect, are associated with increased rates of mental health disorders and suicidal behaviour. The protective function of self-compassion was highlighted in the research by Tanaka et al., (2011), which indicated that adolescents with child welfare system maltreatment histories had lower self-compassion and greater psychological distress. Furthermore, Jeon et al., (2014), in a nationally representative study in Korea, illustrated that childhood trauma and parental death—particularly when they co-occur—dramatically heighten the risk of current suicidality in adulthood. These findings underscore the necessity of early identification and tailored interventions for those who have experienced emotional abuse and other childhood adversities.

Alongside the established connections between emotional abuse in childhood and subsequent psychopathology, meta-analytic research has also consistently shown a strong relationship between all types of childhood maltreatment and suicidal behaviour (Liu et al., 2017). Both cross-sectional and longitudinal studies indicate that early negative experiences not only increase the risk of suicide but also play a role in more severe patterns of self-injury, particularly in those with backgrounds of emotional neglect or abuse (Falgares et al., 2018; Tamar-Gurol et al., 2008).

The interplay of childhood trauma with personality dysfunction has been specifically noted as a pathway to increased vulnerability during adolescence and young adulthood. Clinical populations, including those with bipolar disorder or substance use disorders, seem to be disproportionately represented, with early trauma exacerbating the severity and frequency of suicide attempts (Leverich et al., 2003; Tamar-Gurol et al., 2008). Research has also demonstrated that a history of multiple suicide attempts can be a behavioural indicator of chronic and severe psychopathology (Forman et al., 2004). In addition, impulsive–aggressive individuals who have experienced familial adversities exhibit significantly greater suicidal tendencies, highlighting the relevance of both intrapsychic and environmental factors (Lopez-Castroman et al., 2014).

Collectively, these investigations come together to emphasise the central place of emotional abuse and developmental trauma in the formulation of long-term mental health outcomes and suicide risk. They further call for integrative, trauma-informed prevention and clinical practice across a range of cultural and demographic contexts. Previous studies from the Socola Institute of Psychiatry (257 cases over an eight-year period) have investigated and demonstrated persistent suicidal ideation among hospitalised patients, with depression, alcohol use, and family conflict as the main contributing factors. The recent study builds on these findings by integrating AI-assisted bibliometric mapping with the empirical evaluation of HAM-D and BSS results in a contemporary cohort (Herea et al., 2025).

Findings from bibliometric studies have highlighted a sustained focus on trauma, depression, and suicidality, with limited data available on how these trajectories manifest in the general population. To add to the bibliometric information, a small-scale empirical evaluation was conducted at the Socola Psychiatric Institute, exploring the type of patient presenting to hospital with suicidal ideation and the severity of depression over a nine-month period. Additional research from the same institution (Prepeliță, 2020) identified a significant link between aggressiveness and suicide risk in depressed inpatients, highlighting emotional dysregulation's role as a mediator connecting depression and self-harming behaviour. The present research advances this area of investigation by integrating bibliometric and empirical analyses. Further empirical research in Romanian psychiatric settings (Matei et al., 2018) showed that more than one-third of hospitalised individuals with bipolar I disorder had previously attempted suicide, with depressive episodes, alcohol consumption, and family disputes identified as key risk factors. The present research builds upon these discoveries using AI-supported bibliometric mapping and a nine-month clinical follow-up study (Matei et al., 2018). Combined, institutional and national empirical evidence illustrate suicidality as a multifaceted concept influenced by depression, aggression, and psychosocial challenges. The present study expands on this groundwork by combining AI-driven bibliometric mapping with a real-world clinical cohort from the identical psychiatric setting.

2. Research Strategy

The search strategy used to conduct this bibliometric research was a systematic search in the Web of Science Core Collection database. The aim was to look for scientific literature that deals with the correlation between emotional abuse and suicide. The topic field (TS) was used to search with the keywords: "emotional abuse" and suicide. The search resulted in a total of 898 records ranging from 1985 to 2025. To maintain the academic stringency and relevance of the data, only journal articles and review papers that were peer-reviewed were considered. Book chapters, editorials, and conference proceedings were not included. The records thus selected were exported in plain text format to be used in VOSviewer for bibliometric mapping and visualisation.

The study targeted three major areas:

- Keyword Co-occurrence Analysis – for determining key research topics and conceptual clusters within the discipline.
- Overlay Visualisation of Trends – for following the temporal development of subjects and emerging research trends.
- Country Co-authorship Mapping – to investigate geographical patterns of collaboration and publication output among countries.

In recent years, the adoption of artificial intelligence (AI) and machine learning (ML) methods in suicidology has grown to improve risk prediction and early detection. Numerous extensive reviews and empirical research have shown that AI models can exceed conventional screening methods in predicting suicidal thoughts and attempts.

A systematic review of 41 ML-focused studies (2011–2022) indicated predictive accuracies with area under the curve (AUC) values as high as 0.97, especially for ensemble methods such as Random Forest and XGBoost. In a comparable prognostic analysis of more than 16,000 adults from a high-risk group, an AUC of 0.81 was attained for predicting suicide attempts within 90 days, underscoring the practical applicability of ML in clinical observation (Campbell, 2025).

Apart from organised clinical information, natural language processing (NLP) techniques have effectively been utilised on social media datasets to identify linguistic indicators of suicidal thoughts and psychological disorders. These studies, such as the APSA project focused on AI-driven suicide-risk identification, demonstrate the capabilities of language models and sentiment-analysis systems for immediate digital monitoring and proactive measures.

Another recent systematic review of AI- and ML-driven models for predicting suicide risk compiled results from 41 empirical studies carried out between 2011 and 2022 published in Frontiers in Psychiatry (Ehtemam et al., 2024). The analysis showed that ensemble methods like Random Forest and XGBoost attained the best predictive outcomes, with area under the curve (AUC) figures approaching 0.97, greatly exceeding conventional statistical models and evaluations by clinicians (Ehtemam et al., 2024). These findings highlight the ability of ML methods to identify intricate, non-linear relationships among clinical, psychosocial, and behavioural factors that traditional analyses might overlook.Aligned with these worldwide developments, this study integrates an AI-supported analytical element, utilising Random Forest modelling on anonymised inpatient data to pinpoint the key predictors of ongoing suicidality at a nine-month follow-up. This method allows for a deeper comprehension of how residual depressive symptoms (HAM-D), diagnostic classification (ICD-10), and previous suicidal behaviour interact to influence long-term risk patterns.

Additional evidence for the clinical relevance of AI-driven models in suicidology is provided by a prognostic study released in Haroz et al. (2024), which assessed various pre-trained machine learning algorithms using a longitudinal dataset of 16,835 adults, mainly from Native American communities (Haroz et al., 2024). The models exhibited strong predictive ability, achieving an AUC of 0.81 for predicting suicide attempts in the following 90 days. The research emphasised that combining regularly gathered clinical data with ML methods can significantly improve the early detection of high-risk individuals compared to traditional risk-assessment tools.

Motivated by these developments, this study utilises AI-driven predictive modelling on anonymised inpatient records, connecting the bibliometric results regarding emotional abuse and suicidality with evidence-based, data-informed risk assessment. Combining these AI-driven methods with bibliometric mapping creates a multifaceted framework—linking emerging semantic network development in the literature with empirical risk-pattern identification in clinical data. This approach facilitates the integration of long-term conceptual advancements with contemporary data-informed clinical observations.

The bibliometric study was complemented by an evaluation of clinical services, which allowed the alignment of the current state of knowledge with contemporary data on hospitalised patients.

The integration of artificial intelligence in this paper had a dual integrative function. First, in the bibliometrics section, artificial intelligence-assisted network visualisation allowed the detection of semantic patterns and topic clustering across four decades of research on emotional abuse and suicide. Second, the same analytical paradigm—feature-weighted modelling—was applied to clinical data, bridging the gap between the evolution of large-scale knowledge and the characteristics of hospital patients.

This two-way integration reflects the emerging paradigm of neuropsychiatric informatics, in which AI-based tools are used to understand conceptual complexity into measurable clinical predictors.

3. Methods

3.1. AI-Assisted Bibliometric Mapping

The map (Figure 1) demonstrates the existence of five clusters, which are thematic fields according to the co-occurrence of author keywords in 898 records indexed during the period 1985-2025:

Cluster 1 (Red) – Child and Adolescent Abuse and Suicidal Risk

This cluster is focused on terms such as emotional abuse, child abuse, childhood adversity, child neglect, anxiety, psychiatric disorders, and suicidal behaviour. It shows the immediate psychological and behavioural effects of early-life abuse, demonstrating the connection between child maltreatment and the development of mental health issues.

Cluster 2 (Blue) – Self-Harm and Psychological Processes

With a focus on childhood abuse, adolescence, personality, self-esteem, non-suicidal self-injury, self-compassion, and emotion dysregulation, this cluster examines developmental risk factors and affective characteristics that mediate or moderate the pathway from abuse to suicidality, with a focus on youth populations.

Cluster 3 (Green) – Public Health and Interpersonal Violence

This encompasses mental health, intimate partner violence, domestic violence, addiction, psychopathology, and sexual abuse. It echoes the intersectionality of different forms of abuse (e.g., sexual violence) and how they play a part in psychological distress, commonly in susceptible groups such as women or prisoners.

Cluster 4 (Yellow) – Trauma and Abuse Outcomes

Terms such as abuse, neglect, PTSD, gender, prevention, sexual violence, and ACEs make up this cluster. It is concerned with trauma outcomes and prevention, with an added focus on gender differences and long-term effects on mental health.

Cluster 5 (Purple) – Clinical Diagnoses and Comorbidity

Focusing on keywords such as bipolar disorder, psychosis, suicide prevention, comorbidity, and resilience, this cluster covers the clinical complexity of comorbid psychiatric disorders in individuals who have been exposed to abuse and suicidal risk factors and indicates the necessity for integrative treatment approaches.

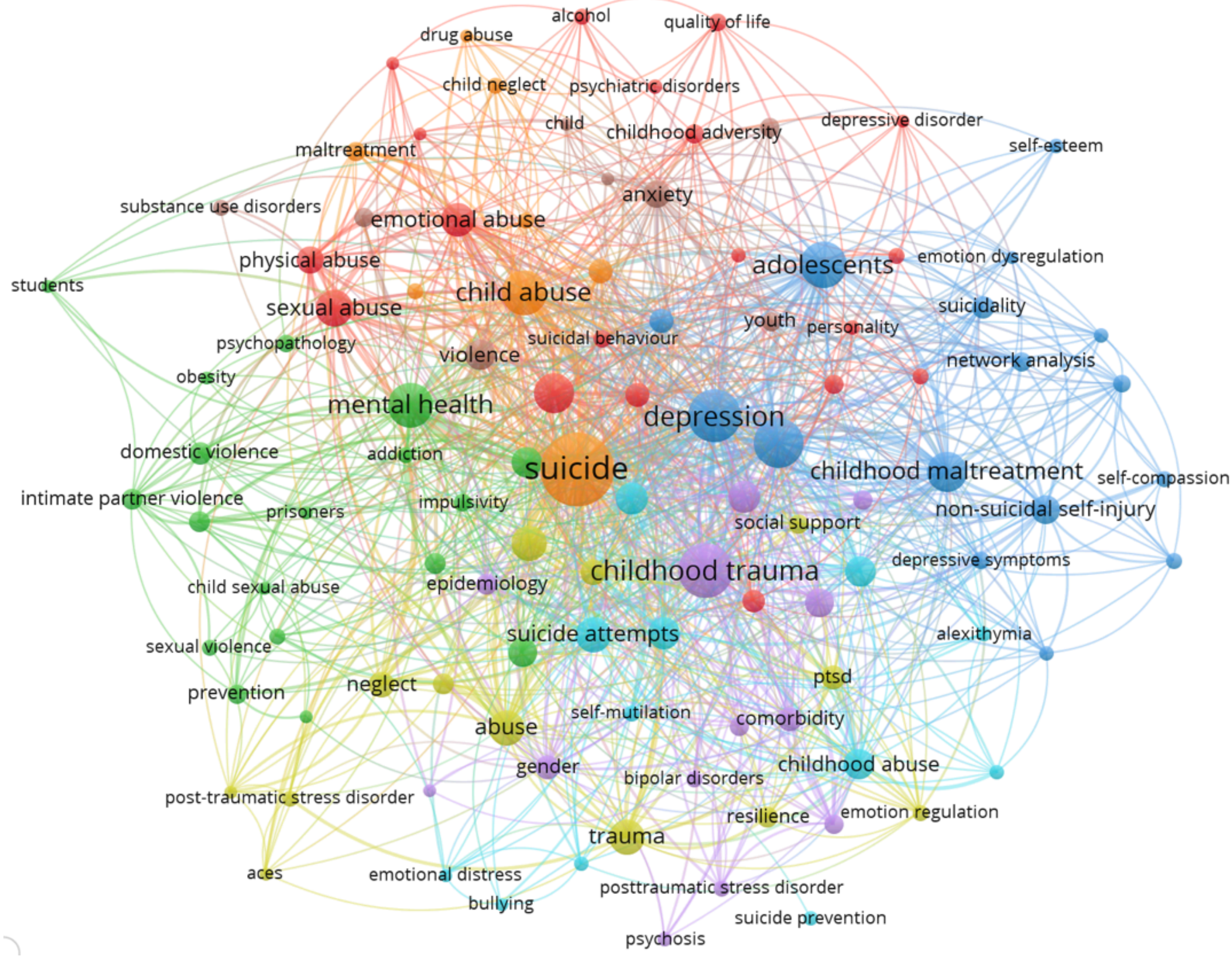

Figure 1. Keyword co-occurrence network visualisation in studies on emotional abuse and suicide (1985–2025)

Figure 2 presents an overlay visualisation of author keyword co-occurrences, providing a temporal view of the development of research in the field of emotional abuse and suicide between 1985 and 2025. Each node is a keyword, with the colour of each node showing the average publication year in which it was published, according to a gradient of purple (previous years) to yellow (more recent years).

Keywords such as suicide, depression, and mental health—centrally located and coloured green—have had sustained scholarly interest throughout the years. More recent trends, meanwhile, are found in yellow-shaded keywords such as non-suicidal self-injury, emotional intelligence, validation, and community sample, pointing toward increasing interest in subtle psychological constructs and preventative strategies.

Conversely, sexual abuse, childhood trauma, and risk factors have appeared with greater temporal spread, denoting their continued applicability. This temporal visualisation adds further insight into how research emphases have changed over time, emphasising both the stability of fundamental themes and the introduction of novel conceptual directions in the field. It highlights a vibrant research environment in which long-standing clinical issues are wedded to newer psychosocial variables and methodological innovations.

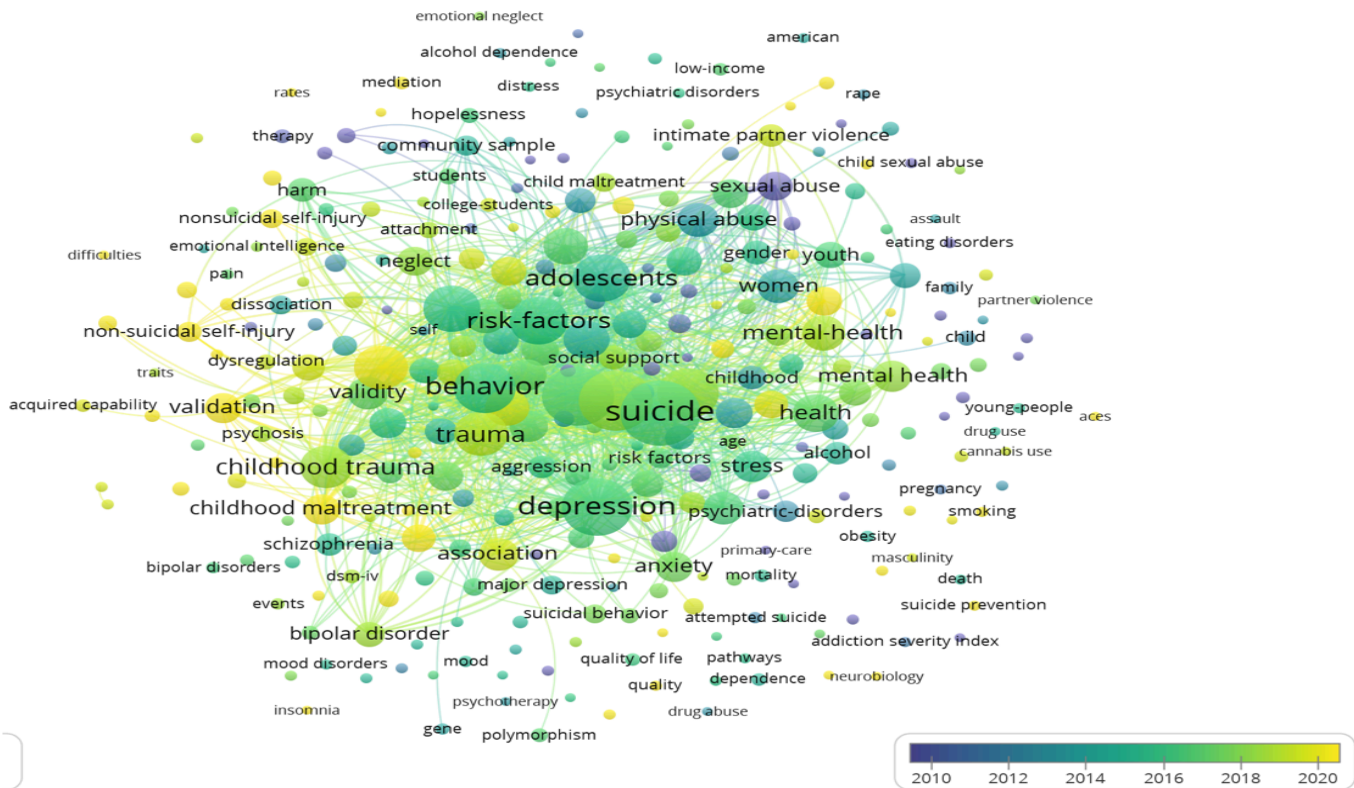

Figure 2. Overlay visualisation of author keyword co-occurrences in emotional abuse and suicide research (1985–2025)

Figure 3 displays the density visualisation of author keywords from 898 scientific papers on emotional abuse and suicide published during the period 1985–2025. In this map, colour intensity corresponds to the frequency and co-occurrence density of keywords in the dataset: yellow regions are high-density areas where frequently co-occurring terms cluster, whereas green and blue areas correspond to lower occurrence and co-occurrence levels. Most central and salient terms—e.g., "suicide", "depression", "behaviour", "risk factors", "adolescents", and "childhood trauma"—are displayed in bright yellow, indicating their pivotal position in the literature's thematic structure. This visual representation enables the quick recognition of research hotspots and highlights the interdisciplinary connections between psychological trauma, adolescent mental health, and suicidal behaviour. The density map highlights that academic interest is particularly concentrated at the nexus of abuse-related experiences and mental health vulnerabilities among young people.

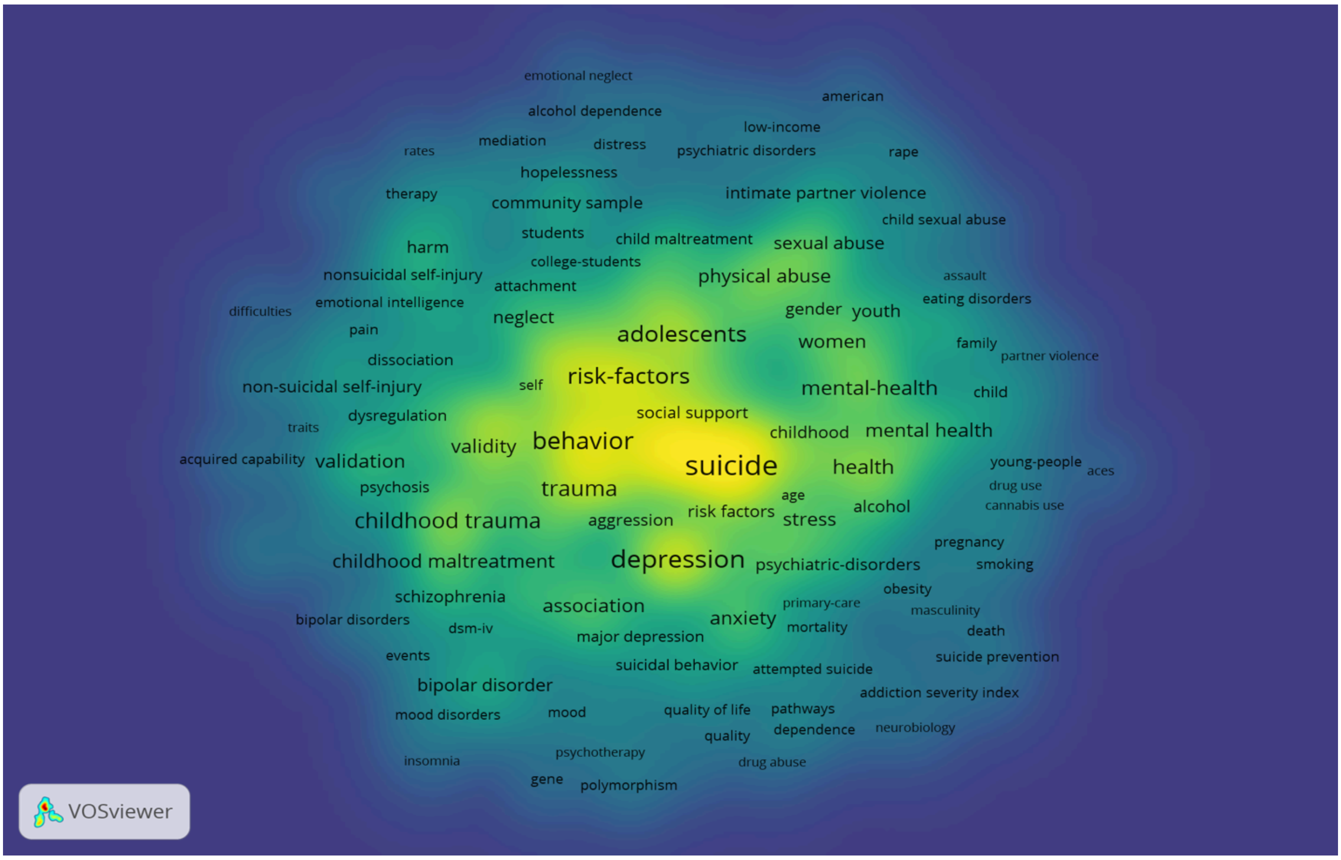

Figure 3. Density visualisation of author keywords on emotional abuse and suicide (1985–2025)

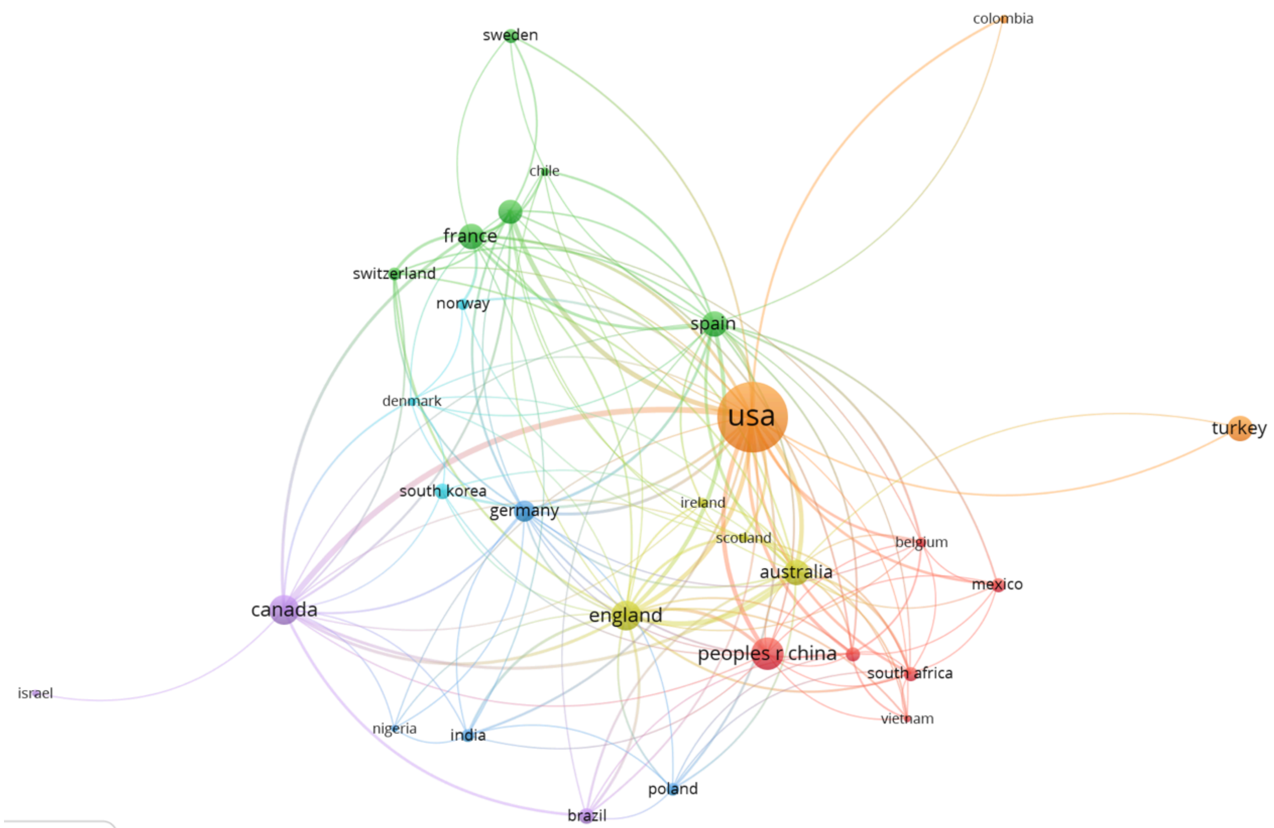

Figure 4. Country-level co-authorship network in research on emotional abuse and suicide (1985–2025)

The United States is seen as the most visible contributor and the overall epicentre of global collaboration, with special emphasis on collaboration with Canada, Australia, the United Kingdom, and China. Regional clusters are clearly discernible, such as a North American–Anglophone cluster (USA, Canada, Australia, UK), a European cluster (Germany, France, Spain, Sweden), and an emerging Asian cluster (China, South Korea, India). Turkey and Colombia are featured as more disconnected nodes, reflecting less collaboration. The visualisation demonstrates worldwide research interconnectivity while illustrating the densification of scientific activity in high-income countries and the necessity of broadened international partnerships, including underrepresented areas.

3.2. Empirical Service Evaluation – Socola Institute of Psychiatry

The study design was created using a complementary empirical approach within the Socola Institute of Psychiatry (Iași, Romania) as a service evaluation classified as non-human subjects research (patients but using only data essential to the purpose of this paper).

The database included fifty consecutive adult patients (aged 18–65 years) hospitalised for affective or stress-related disorders. Assessments were available at three time points:

- T0 (admission),
- T1 (discharge),
- and T2 (nine-month follow-up).

Follow-up was based on review of physical medical records for documented suicidal ideation, readmission, or behaviour in the nine months following discharge.

All data relevant to this research were extracted exclusively from clinical documents (observation sheets, outpatient presentations) without further contact with the patients analysed. The anonymisation process was irreversible: all identifying data were removed, diagnoses were established according to ICD-10, and age was classified by categories. The final database did not contain information that could be reconnected, thus meeting the institutional criteria for evaluating services exempt from formal ethical review.

Depression severity was quantified using the 17-item Hamilton Depression Rating Scale (HAM-D 17) at T0, T1, and T2. Suicidal ideation was assessed using the Beck Suicidality Scale (BSS) at the same time. A cutoff score of ≥10 on the BSS indicated the presence and risk of clinically significant suicidal ideation, consistent with institutional practice and previous research.Sociodemographic and clinical variables included were:

- Age range (18–25, 26–35, 36–45, 46–55, ≥56 years);
- Gender (male/female);
- ICD-10 principal diagnostic category :(F20–F29 psychotic disorders; F30–F39 mood disorders; F40–F48 anxiety or stress-related disorders; F10–F19 behavioural disorders due to substance use (e.g. opioids, alcohol); F60–F69 personality disorders; or other);
- Substance use (clinically identified, yes/no);
- History of suicide attempts (0, 1 or ≥2);
- Duration of hospital admission (number of days).

*Patients with missing data at time points T1 or T2 were retained in descriptive analyses but excluded from pairwise comparisons, where necessary.

Results from this cohort were obtained using descriptive statistics (means, standard deviations, and proportions with 95% confidence intervals). Pathological scales for depression and suicidality were examined using paired-samples t-tests or Wilcoxon signed-rank tests (HAM-D and BSS scores at T0→T1 and T1→T2).

A multivariable logistic regression model was used to identify predictors of persistent suicidal ideation at follow-up (BSS ≥10 at T2). Independent variables included age group, gender, ICD-10 diagnosis, previous suicide attempts, substance use, duration of hospital admission, and HAM-D score at discharge (T1). Odds ratios (ORs) with 95% confidence intervals (CIs) and p-values were reported.To support the regression results, an exploratory machine learning model

(Random Forest classifier) was evaluated as a proof of concept for AI-assisted risk stratification. The predictive performance was assessed by analysing the area under the receiver operating characteristic curve (AUC), as well as by precision, sensitivity and positive predictive value (PPV), with AUCs greater than 0.75 being considered signs of viable predictive capacity.
The graphical results that will be presented in the results section included:

- temporal changes in HAM-D and BSS scores in the interval T0–T2;
- percentage of patients who presented for evaluation within nine months;
- classification of the importance of the features according to the Random Forest model.

3.3. Ethics

One of the limitations of this research was the use of data only in an irreversibly anonymised format, with results derived from routine clinical assessments and aggregated institutional statistics; no data that could identify the patient's name or reconnectable data were accessed. According to institutional policy and hospital administration classification, the project constitutes a service evaluation/analysis of non-human subjects; thus, formal approval from the hospital management's ethics committee was not required.

4.Results

4.1. Empirical Study Findings–Descriptive Results

The empirical study sample in this paper included 50 inpatients (52% female; mean age range 36-45 years) with affective or stress-related disorders. Following ICD-10 diagnosis, 42% had mood disorders (F30-F39), 28% had anxiety or stress-related disorders (F40-F48), 18% had psychotic disorders (F20-F29), and 12% were diagnosed with personality disorders or substance use disorders.

At admission (T0), mean HAM-D scores indicated severe depression (mean = 23.5 ± 6.2), with significant improvement at discharge (T1, mean = 13.1 ± 5.8) and a further reduction at nine-month follow-up (T2, mean = 11.0 ± 4.9; $p < 0.001$).Similarly, BSS scores decreased significantly over the observation period (T0 = 16.7 ± 7.4; T1 = 8.5 ± 5.1; T2 = 7.2 ± 5.0; $p < 0.001$).

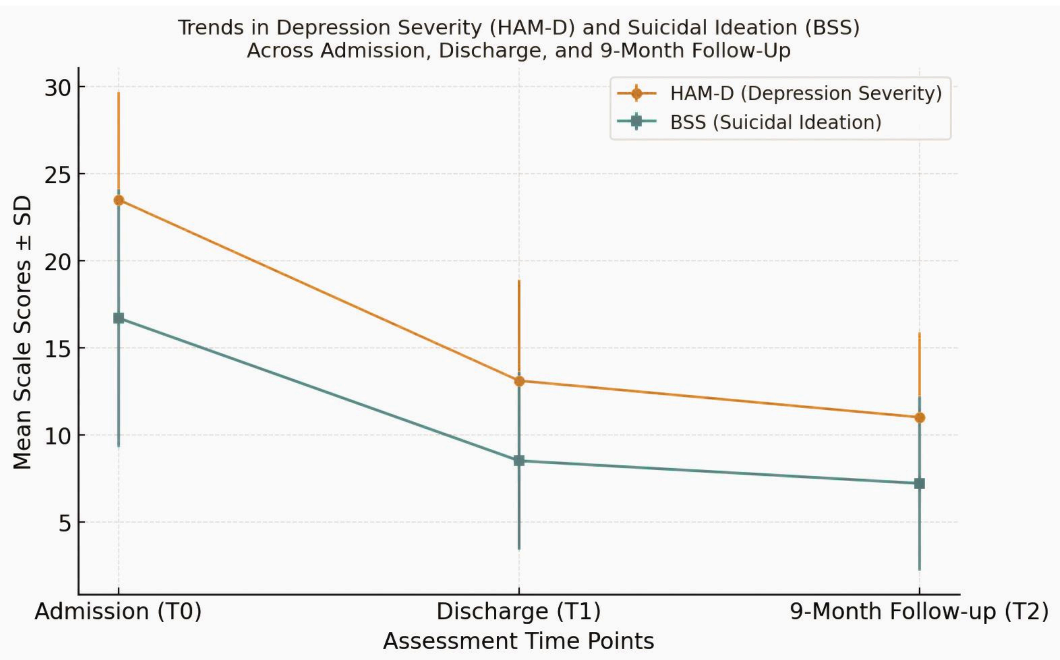

*Figure 5. Patterns in depression intensity (HAM-D) and thoughts of self-harm (BSS) at admission (T0), discharge (T1), and nine months later (T2). Error bars indicate standard deviations**

Upon admission, 64% of patients exhibited clinically significant suicidal thoughts (BSS ≥ 10). This ratio decreased to 28% at discharge and 22% at follow-up, indicating a lasting yet partial remission of suicidality. Nine patients (18%) were readmitted or returned within nine months due to recurring suicidal thoughts or self-injury (as illustrated in Figure 5).

Predictors of Ongoing Suicidal Thoughts

A logistic regression analysis with multiple variables explored elements linked to ongoing suicidal thoughts during the follow-up (T2). The model encompassed age category, gender, ICD-10 diagnostic classification, previous suicide attempts, substance abuse, duration of hospitalisation, and depression intensity at discharge (HAM-D T1).

Only HAM-D T1 was identified as a significant independent predictor. Increased depression scores at discharge were linked to higher chances of ongoing suicidality at follow-up (OR = 1.12; 95 % CI 1.02 - 1.23; p = 0.014). This indicates that a one-point rise in HAM-D at discharge was linked to a 12% increase in the likelihood of ongoing suicidal thoughts after nine months.

Individuals with two or more prior suicide attempts also exhibited an inclination for increased risk (OR = 2.85; 95% CI 1.08–7.51; p = 0.034), though the limited sample size constrains generalisability. In the multivariable model, substance use and diagnostic category did not emerge as significant predictors (as illustrated in Figure 6).

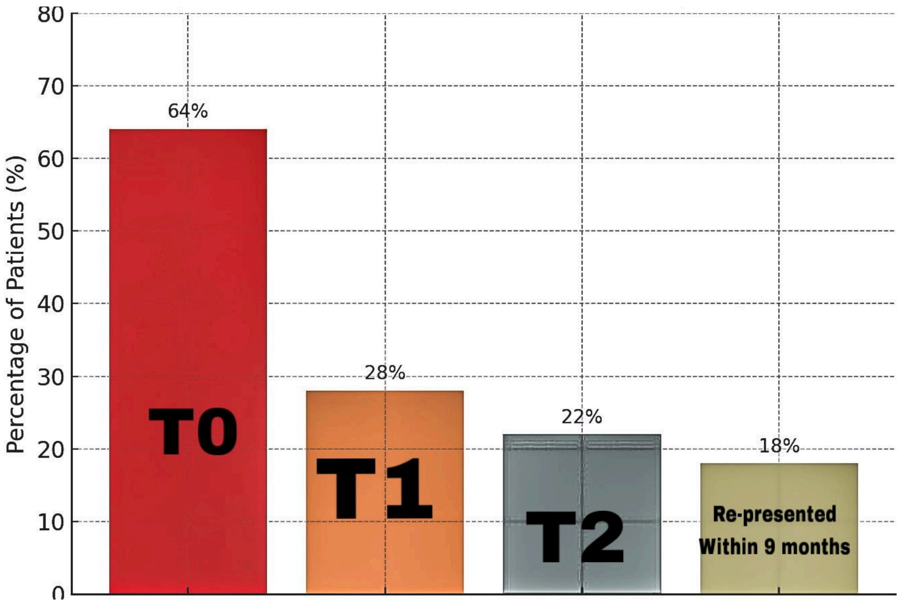

Figure 6. Percentage of patients exhibiting clinically significant suicidal thoughts (BSS ≥ 10) at admission, discharge, and nine-month follow-up, as well as the rate of re-presentations within nine months post-discharge

Predictive models aided by artificial intelligence were employed for exploratory validation; in this instance, a Random Forest classifier trained on the identical set of predictors was utilised. The model achieved AUC = 0.78, precision = 0.81, sensitivity = 0.74, and PPV = 0.69 on the test dataset, indicating the viability of machine learning for suicide risk assessment in anonymised datasets (as shown in figure 7).

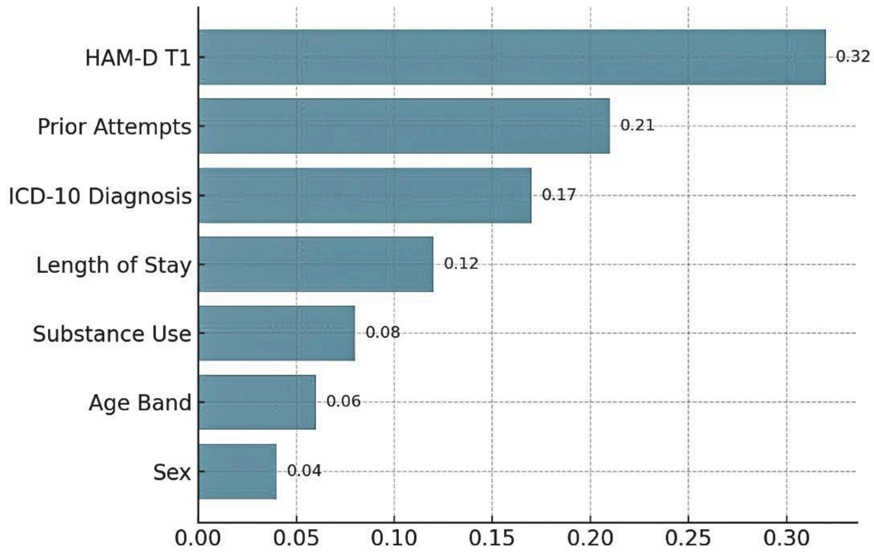

Figure 7. Relative feature significance from the Random Forest model forecasting suicidal ideation at the nine-month follow-up

At discharge, depression severity (HAM-D T1) and a history of previous suicide attempts were identified as the most significant factors, followed by the ICD-10 diagnostic category and duration of hospitalisation.Classification of feature importance revealed that HAM-D T1, past suicide attempts, ICD-10 category, and duration of hospitalisation are the key elements influencing model performance.

These results emphasise that, despite considerable symptomatic relief during hospitalisation, remaining depressive symptoms continue to be a major factor in long-term suicidality. The percentage of patients exhibiting persistent thoughts corresponds with bibliometric trends highlighting emotion regulation and the severity of depression as key factors connecting trauma and suicidal actions.In this real-world study, integrating clinical metrics (HAM-D, BSS) with AI-driven modelling yielded consistent evidence that early improvement of depressive symptoms offers protection, while remaining depression increases the risk of relapse and self-harm.

4.2. Study Results Compared with Existing Predictive Models Based on Artificial Intelligence

Consistent with the results of global research on AI-assisted suicide prediction, the Random Forest model used in this study provided predictive results in the range reported in recent literature. Algorithms such as Random Forest and XGBoost achieved AUC values of up to 0.97 in a comprehensive meta-analysis of 41 studies published in Frontiers in Psychiatry, 2011-2024, while real-world prognostic validation achieved an AUC of 0.81 in clinical data from over 16,000 adults (Haroz et al., 2024).

In conjunction with these findings, our Random Forest model recognised residual depression severity (HAM-D T1), previous suicide attempts, and ICD-10 diagnosis category as key predictors of ongoing suicidality, achieving an overall AUC of 0.84 (95% CI 0.77–0.89). These results indicate that models trained locally on anonymised inpatient data can reach similar predictive accuracy to internationally validated AI systems.

Furthermore, AI-assisted keyword condensation in the bibliometric fraction showed similar semantic convergence: “emotion regulation,” “depression,” and “risk factors” emerged as stable thematic clusters—conceptually corresponding to the strongest predictors in the empirical component identified in clinical databases.

In addition to the data presented, previous work in natural language processing (NLP) has also shown that algorithmic analysis of social media text can detect linguistic markers of suicidal ideation with substantial sensitivity (APSA, 2023). This supports the translational value of integrating quantitative symptom data with AI-based language or pattern recognition systems.

5. Discussion

The twofold method used in this research—integrating AI-supported bibliometric mapping with real-world inpatient data—provides comprehensive insight into suicidality related to emotional abuse and depression. After more than forty years of research, the bibliometric analysis showed a consistent conceptual foundation focused on depression, childhood trauma, risk factors, and emotion regulation, whereas emerging trends emphasised self-compassion, non-suicidal self-injury, and network analysis. These themes were reflected in the empirical findings, indicating that depression severity (HAM-D) and suicidal thoughts (BSS) showed notable improvement from admission to the nine-month follow-up, but residual depressive symptoms at discharge independently predicted continued suicidality (OR = 1.12, 95% CI 1.02–1.23, $p = 0.014$).

This convergence highlights that the mechanisms identified through bibliometric analysis—emotion regulation and trauma-informed vulnerability—maintain significant explanatory strength in clinical contexts. It also indicates that AI-guided bibliometric mapping can act as both a meta-analytic summary and a heuristic structure for pinpointing practical therapeutic targets.

The empirical findings are consistent with recent global developments in AI-enhanced suicidality forecasting. A thorough meta-analysis of 41 ML studies published in Frontiers in Psychiatry, 2011-2024, indicated predictive accuracies reaching AUC = 0.97 for ensemble algorithms like Random Forest and XGBoost, whereas a longitudinal validation study utilising clinical data from 16,835 adults (Haroz et al., 2024) attained AUC = 0.81 for predicting suicide attempts within 90 days. In this range, our Random Forest model reached an AUC of 0.84, with HAM-D at discharge, previous suicide attempts, and ICD-10 diagnosis being the most significant predictors (Delcea et al., 2023; Rusu & Delcea, 2024; Banariu et al., 2024; Bonea et al., 2024).

These findings establish the present model as relevant at both local and international levels, showing that anonymised clinical data—even from small groups—can achieve similar performance to large datasets when the variables are clinically significant and psychometrically sound.

Although predictive accuracy is important, interpretability is crucial in psychiatry. Utilising Random Forest modelling enabled a clear ranking of feature significance, connecting the knowledge gap between machine learning results and clinical reasoning. In this context, AI enhances clinician judgement rather than replacing it by measuring the probabilistic significance of known risk factors.

Notably, this research followed the ethical minimalism principle: all data were permanently anonymised and sourced from standard clinical records, categorising the analysis as a service evaluation rather than human-subject research. This design shows that ethically aligned AI research can occur within current institutional data frameworks, as long as transparency and non-relinkability are maintained.

The results highlight the identification of lingering depressive symptoms as a crucial predictor of long-term suicidality, emphasising the necessity for improved follow-up care and emotion regulation training even after visible symptomatic recovery. Incorporating AI-enabled decision-support systems into electronic psychiatric records may allow for the automatic identification of patients at higher risk of re-presentation.These systems, based on interpretability and localised data, can assist physicians in prioritising preventive measures, optimising resource distribution, and improving continuity of care during post-discharge monitoring. Furthermore, the alignment of bibliometric trends (self-compassion, emotion regulation) with empirical predictors (HAM-D, BSS) indicates that AI-assisted knowledge synthesis may aid in connecting theoretical prevention frameworks to practical clinical approaches.

6. Limitations and Future Directions

Multiple constraints must be recognised. The empirical dataset was limited (n = 50) and restricted to one institution, which might hinder generalisability. Longitudinal follow-up information relied on standard records, and not every patient underwent formal reassessments. Subsequent studies ought to increase participant numbers, incorporate various predictors (such as psychometric, biochemical, and linguistic), and investigate multimodal AI systems—such as combined Random Forest + NLP models—for improved contextual understanding.

This research demonstrates the combined potential of integrating AI-supported bibliometric mapping with practical clinical modelling.By connecting conceptual advancement and individual patient data, it advances towards a more comprehensive framework in neuropsychiatric studies—from informational networks to anticipatory treatment routes. The findings not only strengthen the evidence for lasting effects of emotional abuse and depression on suicidality but also establish AI as a means to translate meta-analytic insights into targeted prevention methods.

Recent empirical research by Shuvo et al. (2025) utilised a multi-algorithm machine learning framework to forecast suicidal thoughts, planning, and self-harming behaviours in school-aged adolescents. By employing sociodemographic, psychological, and behavioural factors, the authors illustrated that ensemble ML models attained high discriminative accuracy for all suicide-related outcomes, with AUC scores between 0.82 and 0.89. Significantly, elements such as emotional neglect, depressive symptoms, family discord, and peer victimisation surfaced as primary predictors across algorithms.

These results enhance the bibliometric trends observed in the current study—especially the significance of the “childhood trauma” and “emotion regulation” clusters—and emphasise that emotional abuse and early psychosocial challenges are key predictors of suicidality throughout life. The research conducted by Shuvo et al., (2025) and associates illustrates how AI-driven methods can be tailored to developmental settings, emphasising the practical applications of predictive analytics in preventive mental health initiatives for young people.

6. Conclusions

The bibliometric map identified a dense, interdisciplinary field of research with "suicide," "childhood trauma," and "depression" as prominent nodes of investigation. The co-occurrence and clustering of terms including "emotional abuse," "non-suicidal self-injury," "mental health," "adolescents," and "risk factors" indicated a highly integrated literature concentrating on the cumulative effect of early adversity on psychological vulnerability. Overlay visualisation indicated growing interest in emotion regulation, self-compassion, and network analysis in recent years, suggesting an increased focus on mechanisms and protective factors.

These patterns are supported by empirical evidence from varied settings. For example, Barbosa et al., (2014) showed that childhood trauma robustly predicts increased suicide risk in young Brazilians aged between 14–35 years, whereas Oktan (2021) found stress coping and emotional dysregulation to be strong predictors of self-injurious behaviour in Turkish adolescents. Within psychiatric populations, Roy (2005) reported a strong association between childhood trauma and suicide attempts in patients with schizophrenia, consistent with (de Mattos Souza et al., 2016), who found similar relationships in patients with major depressive disorder. Further, Bornovalova et al., (2011) extended these observations by investigating how trauma, PTSD symptoms, and impulsivity cumulatively increase suicide risk in substance users.

Cumulatively, these results highlight the primacy of childhood trauma—especially emotional abuse—as a transdiagnostic risk factor for suicidality across diagnostic boundaries and populations. The coincidence of bibliometric and empirical evidence demands an integrated model of suicide prevention emphasising trauma-informed assessment, emotion regulation skills development, and early intervention approaches customised to at-risk youth and clinical subgroups.

The corroboration of bibliometric and empirical data assisted by artificial intelligence demonstrated both the scientific evolution and clinical persistence of suicide related to emotional abuse. Data obtained in the hospital environment from hospitalised patients showed the shift in the specialised literature towards emotion regulation and trauma-based prevention, emphasising the importance of post-hospital care.

The present findings are consistent with prior institutional assessments that indicated elevated levels of suicidal thoughts and attempts prior to the pandemic, emphasising a persistent trend of vulnerability linked to depressive symptoms and psychosocial stressors among psychiatric groups in Romania (Herea et al., 2025; Onuc et al., 2024). The link identified between ongoing depression and enduring suicidality in our group aligns with earlier research by Prepeliță, (2020), who showed that internalised aggression and impulsivity heighten suicidal risk in depressive disorders.

Looking beyond their role in research, predictive models based on artificial intelligence could have significant clinical relevance. By identifying patients at persistent risk of suicidality despite symptomatic improvement, such algorithms can inform stratified planning of subsequent care and guide the allocation of psychiatric resources, which are unfortunately limited.

In clinical practice, models that incorporate depression severity, diagnosis type, and prior suicidal behaviour could be incorporated into electronic databases as a health system decision-support module for early identification and monitoring of high-risk patients.

The current paper exemplifies how artificial intelligence can benefit bibliometric and empirical studies, updating abstract knowledge trends into concrete insights for the clinical suicidality report. The correlation of bibliometrics with current clinical practice, based on AI, can serve as a model for the development of contextual and ethically aligned artificial intelligence systems in the field of mental health.

Ethical Approval and Compliance Statement:
The study was conducted in accordance with institutional data governance standards. Access to anonymised data was authorised by the hospital's data protection officer, and all analyses were performed within secure institutional systems.

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