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Original

Modeling recurrent suicide attempts using probabilistic Hawkes processes

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ABSTRACT

Background: Assessing the risk of suicide attempt recurrence requires integrating multiple clinical factors, including suicidal ideation and intent. Although clinical evaluation remains the most reliable method for estimating risk, few longitudinal mathematical models exist that leverage routine clinical data to predict recurrence dynamically. This gap limits the use of predictive analytics in suicide prevention.
Methods: We analyzed data from 1112 individuals from the MCOSUL Cohort (Lleida, Spain), who were treated for a suicide attempt, with a minimum 5-year follow-up or until death. Baseline sociodemographic and clinical variables were collected during structured assessment, and follow-up data were extracted from electronic health records. For each participant, Hawkes process parameters (μ, α, δ) were estimated using maximum likelihood and conditioned via a neural network. A Gaussian Mixture Model was applied to identify temporal risk profiles.
Results: Recurrence showed a temporal clustering pattern: 61.1% of repeat attempts occurred within 1 month of a previous event, and nearly all within 12 months. The model captured self-exciting dynamics and generated individualized survival and intensity curves. Five clusters emerged: a large low-risk heterogeneous group; a moderate-risk group; a predominantly male group with infrequent and less severe attempts; a high-risk group with multiple previous attempts; and a small but extreme group with severe and chronic recurrences.
Conclusions: Suicide attempt repetition in this cohort demonstrates self-exciting temporal behavior. Hawkes-based modeling enables dynamic, time-varying risk estimation and may offer advantages over traditional static prediction tools. Prospective validation should assess clinical integration, scalability, and utility for personalized suicide prevention.

Introduction

Suicide attempts are 10–30 times more common than suicide-related deaths,[1] and have a significant impact on the lives of

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patients and their relatives. Although a prior attempt is the most robust predictor of future attempts, specific probabilistic models to assess the risk of suicide attempt repetition are lacking. Suicide risk estimation has traditionally relied on static variables, such as demographic and clinical factors, which offer limited predictive capacity.[2] To address the complexity of factors influencing suicidal behavior, numerous studies have used machine learning methods to predict the likelihood of future attempts, but these models face significant challenges in effectively balancing sensitivity and specificity, limiting their accuracy.[3,4]

Of note, research has primarily focused on identifying the mechanisms necessary for suicide attempts, with less attention on the temporal fluctuations of suicide risk. However, temporal processes are needed to explain upsurges in suicidal risk when self-regulation fails, and positive feedback loops are engaged, destabilizing the individual and increasing vulnerability.[5] Supporting this view, larger fluctuations in suicidal ideation, especially before a suicide-related event, have been noted in those with repeated attempts.[6] Recent models have started to focus on estimating time-framed probabilities for each patient individually, and they have shown promising results. For instance, the Oxford Mental Illness and Suicide tool (OxMIS) evaluates the 12-month suicide risk in individuals with severe mental illness.[7] This tool is It was presented as a standardized, scalable, and transparent model that relies on only 17 variables for prediction. The model was externally validated in a large population, achieving an area under the curve (AUC) of 0.708, and subsequently validated in general psychiatric clinics in Spain and China.[8] In addition, another study validated a risk calculator for predicting suicide attempts in youth with bipolar disorder, demonstrating acceptable accuracy (AUC, 0.78) over a 1-year follow-up.[9] Our group, along with others, has demonstrated the value of time-stamped data sources derived from ecological assessments to improve risk prediction in populations of suicide ideators and attempters.[10] Altogether, these findings indicate the importance of examining temporal patterns to better understand and predict suicide risk.

Although they may initially appear as isolated events, clinical data indicates that suicide attempts frequently occur in clusters during periods of crisis.[11] Individuals who have attempted suicide are at significantly higher risk of attempting again, often within a short period, due to a heightened vulnerability.[12] Suicide attempters often endure ongoing emotional distress and psychological pain,[13] such as shame or guilt related to their actions, and may face additional stressors like stigma, strained relationships, or inadequate support,[14] all of which can intensify feelings of isolation. An initial attempt may serve as a behavioral rehearsal, lowering mental resistance to future self-harm, while recurrent attempts can act as experiential avoidance strategies aimed at reducing suffering.[15] Suicide attempts can thus exhibit a self-reinforcing or self-exciting pattern, where one attempt increases the likelihood of subsequent attempts in a relatively short period of time. Hawkes processes have been used for statistical modeling of such self-exciting events in various fields, from earthquakes to finance and social behavior.[16] These processes are particularly useful for understanding and predicting patterns where an initial random event increases the likelihood of subsequent events, effectively capturing the self-exciting nature of suicide attempts.

In this study, we have used comprehensive data from a large clinical cohort in Spain to model the repetition of suicide attempts using Hawkes processes. We aimed to create a personalized function that could provide accurate estimates of future suicidal behavior for an individual using basic demographic data and details of past suicidal behavior (eg, somatic lethality and dates of any former suicide attempts). Furthermore, we will explore to what extent suicide attempts align with the concept of self-exciting events.

Methods

Sample and setting

This cohort study used data from the MCOSUL Cohort, which has been described in detail elsewhere[17] and has been previously used in other clinical studies.[18,19] Briefly, the MCOSUL Cohort includes individuals who attempted suicide and received care at either the Liaison and Consultation Psychiatry Unit of *Hospital Universitario Arnau de Vilanova* or the Psychiatric Emergency Service of *Hospital Universitario Santa Maria*, both located in Lleida, Spain. These two hospitals provide psychiatric emergency coverage for the entire population of the province, totaling 459,723 inhabitants as of July 1st, 2025.

Ethical considerations

All procedures were conducted in accordance with national and institutional ethical standards for human research and with the principles of the Declaration of Helsinki (1975), as revised in 2008. The study was approved by the Ethics Committee of *Hospital Universitario Arnau de Vilanova* (CEIC-1540) and was reported in accordance with the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidelines for observational studies (Supplementary data).

Participants

This present study includes individuals treated for a suicide attempt from January 2009 through December 2022, with a minimum 5-year follow-up from the index episode or until death.

Variables and data collection

Sociodemographic and clinical variables were collected at the time of the index episode, defined as the first suicide attempt documented in the cohort. A suicide attempt was defined according to Silverman et al. as a self-inflicted, potentially harmful behavior with a non-fatal outcome and evidence of intent to die.[20] Suicidal intent at the index episode was assessed face-to-face using a structured documentation protocol completed by psychiatrists trained in the MCOSUL Cohort procedures, including mandatory categorical fields regarding intent to die.

Variables included demographic characteristics recorded at the index episode: sex (man or woman), age (years), nativity status (native or foreign-born), marital status (single, married, divorced, or widowed), and employment status (employed or unemployed). The number of prior suicide attempts was also recorded when applicable. Follow-up outcomes captured both the occurrence and timing of subsequent suicide attempts, as well as their somatic lethality – operationalized as the duration of required inpatient treatment (days), modelled as a continuous measure.

Baseline clinical information was recorded during the structured face-to-face assessment described above. Follow-up data were extracted from the regional integrated electronic health record (EHR) system, which consolidates health care encounters across primary care, psychiatric and general emergency departments, hospital admissions, and official mortality registries. Suicide attempts identified through the EHR were documented by the same psychiatry teams working in emergency and liaison services, ensuring consistent application of diagnostic and documentation criteria across baseline and follow-up episodes.

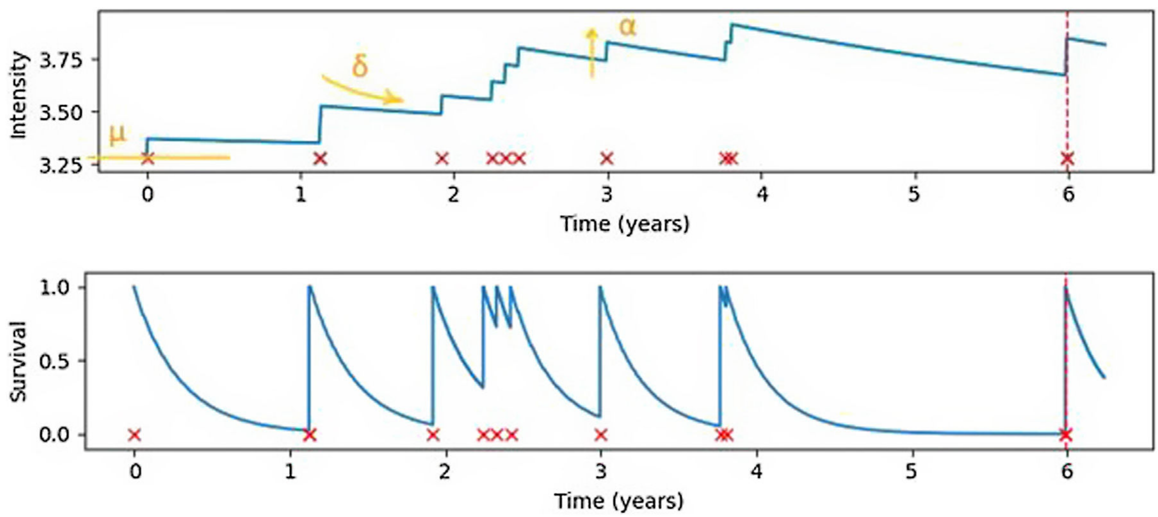

Fig. 1. Example intensity curve of a patient and its corresponding survival curve. Parameters μ, α, and δ are marked on the picture; μ indicates the baseline intensity, which occurs at time step zero. The intensity decays over time toward baseline μ. The rate of this decay is controlled by the parameter δ. The parameter α controls how much the intensity increases immediately after observing a new event.

Hawkes process model

The model used a total of seven variables as inputs: sex, age, nativity status, marital status, employment status, the number of prior suicide attempts and somatic lethality. These features were used as inputs to the neural network to condition the individual Hawkes process parameters.

The Hawkes process is a mathematical model used to describe a self-exciting process, where each event increases the likelihood of subsequent events occurring. This model is particularly suitable for analyzing phenomena that exhibit clustering behavior, such as the repetition of suicide attempts.

A Hawkes process is characterized by its intensity function $\lambda(t)$, which describes the rate at which events are expected to occur at time t. The intensity function for a Hawkes process can be expressed as:

$$\lambda(t) = \mu + \sum\nolimits_{t_i<t} \alpha \cdot \exp(-\delta(t - t_i)) \tag{1}$$

where:

- μ is the base intensity, representing the baseline rate of events.
- α is the excitation parameter, indicating the increase in intensity following an event.
- δ is the decay parameter, describing how quickly the increased intensity diminishes over time.
- t_i represents the times of former events.

In the context of suicide attempts, Hawkes process parameters can be interpreted as follows:

- μ: The baseline risk of a suicide attempt occurring at any given time.
- α: The increase in risk immediately following a suicide attempt, capturing the self-exciting nature of such events. The higher the alpha, the more the intensity increases when a new event is observed.
- δ: The rate at which the elevated risk decays back to the baseline level after an attempt. The higher the delta, the faster the intensity decays.

The intensity function $\lambda(t)$ described in Eq. (1) above captures the dynamic risk of a reattempt over time. By converting this intensity function into a survival curve (Fig. 1), clinicians can estimate the probability that a patient will not experience another suicide attempt within a given time frame. Given the intensity function, computing the survival can be done in close form, as shown in Eq. (2).

$$\begin{aligned} S(t) &= \exp\left(-\int_0^t \lambda(s)ds\right) \\ S(t) &= \exp\left(-\mu t - \sum\nolimits_{t_i<t} a/\delta(1 - \exp(-\delta(t - t_i)))\right) \end{aligned} \tag{2}$$

Using the historical data of suicide attempts, we estimated the parameters μ, α, and δ for each patient.[21,22] This was done through maximum likelihood estimation, which fits the model to the observed data by maximizing the likelihood of the observed event times (Fig. 2). These parameters are conditioned to the cross-sectional data of each patient by means of a neural network.

Clustering analysis

To further analyze temporal patterns, we applied a Gaussian Mixture Model (GMM) to cluster patients based on their fitted Hawkes parameters (μ, α, δ). Since these parameters are individual-level and time-invariant, each patient was assigned to a single cluster. The GMM assumes that the data arise from a mixture of Gaussian distributions with unknown parameters and enables probabilistic classification into latent risk profiles.

Model selection criteria, including the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to determine the optimal number of clusters. Cluster characteristics were then examined to assess alignment with known demographic and clinical risk groups.

Results

Sample characteristics

The study sample included a total of 1112 individuals, predominantly women (61.9%), with a mean age of 42.5 years (SD, 15.88 years). Nearly half were married (47.8%), and most were employed (76.4%). Full demographic details are presented in Table 1.

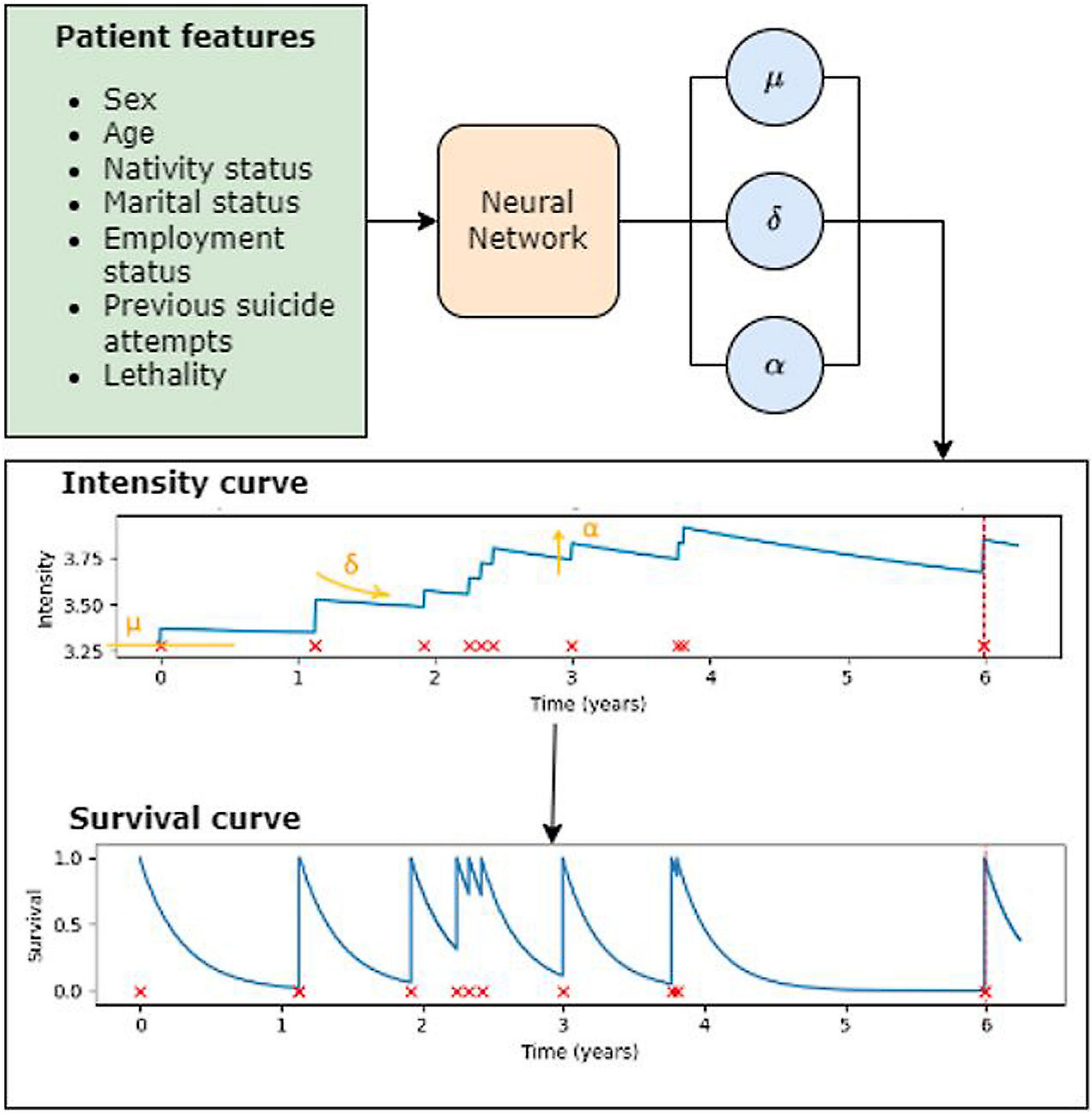

Fig. 2. Schematic representation of the process. The input features of each patient are fed into the trained neural network. The network outputs the parameters for that patient that characterize the patient's intensity curve. The intensity curve can be easily transformed to a more interpretable representation, the survival curve.

Suicide attempt repetition

We observed a pattern in the timing of subsequent suicide attempts that aligns with self-exciting behavior in this sample. Specifically, 61.12% of suicide attempts occurred within 1 month of the previous attempt, 83.48% within 3 months, 95.79% within 6 months, and 99.89% within 12 months. Fig. 3 illustrates the time distribution of recurrent attempts.

Hawkes processes modeling

The models represent the trajectory of suicidal behavior for any given patient. The examples in Fig. 4 show the excitation patterns that the suicide attempts present and the decay of the risk as time advances. The blue line indicates the intensity (left column) or survival (right column) at any time point.

Clustering

Five clusters were identified, including 1 small outlier group. The clusters differed meaningfully in their Hawkes parameters and clinical patterns, reflecting varying trajectories of recurrence risk.

- Cluster #1 (45.38% of patients), a heterogeneous and large cluster carrying the lowest risk of a new attempt.
  - Largest group, majority of women, one-third employed, 56% in a relationship, 22% foreigners (vs 10% in other clusters).
  - Mean parameters: $\mu = 3$; $\delta = 0.30$, $\alpha = 0.07$.
  - Tendency to make less lethal attempts (mean length of stay of 0.5 days).
  - Less than half attempted suicide during follow-up (172 out of 472).
  - Median survival time: 47 days.

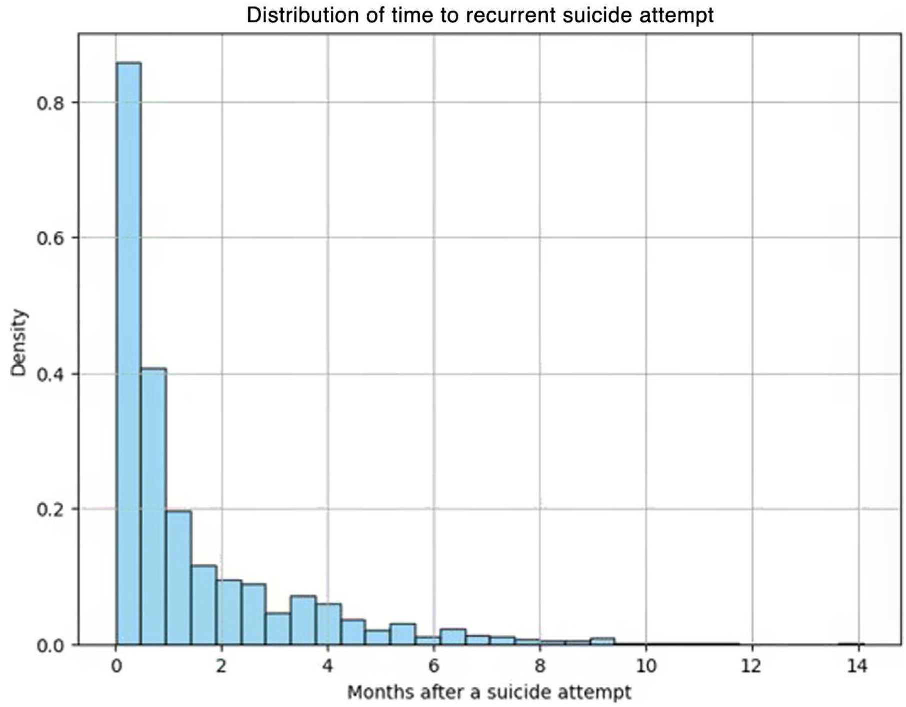

Fig. 3. Probability distribution of all recurrent attempts in the sample by months.

Table 1
Sample characteristics.

Variables	Total sample ($n = 1112$)
Sex, n (%)	
Female	689 (61.9)
Male	423 (38.1)
Age, years (SD)	42.5 (15.8)
Nativity status, n (%)	
Native-born	940 (84.5)
Foreign-born	172 (15.5)
Marital status, n (%)	
Single	257 (23.1)
Married	532 (47.8)
Divorced	262 (23.6)
Widowed	61 (5.5)
Employment status, n (%)	
Employed	850 (76.4)
Unemployed	262 (23.6)
Former suicide attempts, n (%)	
None	378 (34)
1	390 (35)
2	162 (14.6)
≥3	182 (16.4)
Somatic lethality of suicide attempts: mean length of stay (days, SD)	0.9 (5.85)

- Cluster #2 (34.42% of patients), a relatively steady pattern of moderate risk.
  - Mostly men, 27% single, 44% in a relationship, and 22% employed.
  - $\alpha = 0.14$; $\delta = 0.35$.
  - Tendency to make less lethal attempts (mean length of stay of 0.5 days).
  - One-third attempted suicide at the follow-up (115 out of 358).
  - Median survival time: 36 days.
- Cluster #3 (11.35% of patients), male attempters characterized by making few attempts, isolation, and short lengths of stay.
  - All men, 40% single, one-third separated, less than 20% in a relationship, nearly none employed, very few foreigners.
  - Fewest former attempts (mean, 0.44).
  - Highest α and δ (0.23 and 0.37).
  - Tendency to make less lethal attempts (mean length of stay <1 day).
  - One-third attempted suicide during follow-up (36 out of 118).
  - Median survival time: 31 days.
- Cluster #4 (7.7% of patients), characterized by a persistent high risk of a new attempt.
  - Mostly women, 56% in a relationship, 25% separated, and 22% employed.
  - High mean number of former attempts = 5.
  - Second-highest μ (5) and second-lowest α (0.02).
  - Tendency to make more lethal attempts vs the overall mean (1.5 days within the cluster vs 0.9 days overall).
  - More than half attempted suicide at the follow-up (58 out of 80).
  - Median survival time: 32 days.
- Cluster #5 (1.15% of patients), a small group with severe and chronic risk.
  - Mostly women, one-third separated, with the oldest mean age (around 47 years), a very small group ($n = 12$). Statistically, these patients can be considered outliers.
  - Many former attempts (average of 12).
  - Highest μ (12), lowest α (0.0001) and δ (0.035).
  - Multi-recidivists with severe attempts (average inpatient stay per attempt: 15 days).
  - Nearly all attempted suicide during follow-up (10 out of 12).
  - Median survival time: 21 days (the shortest).

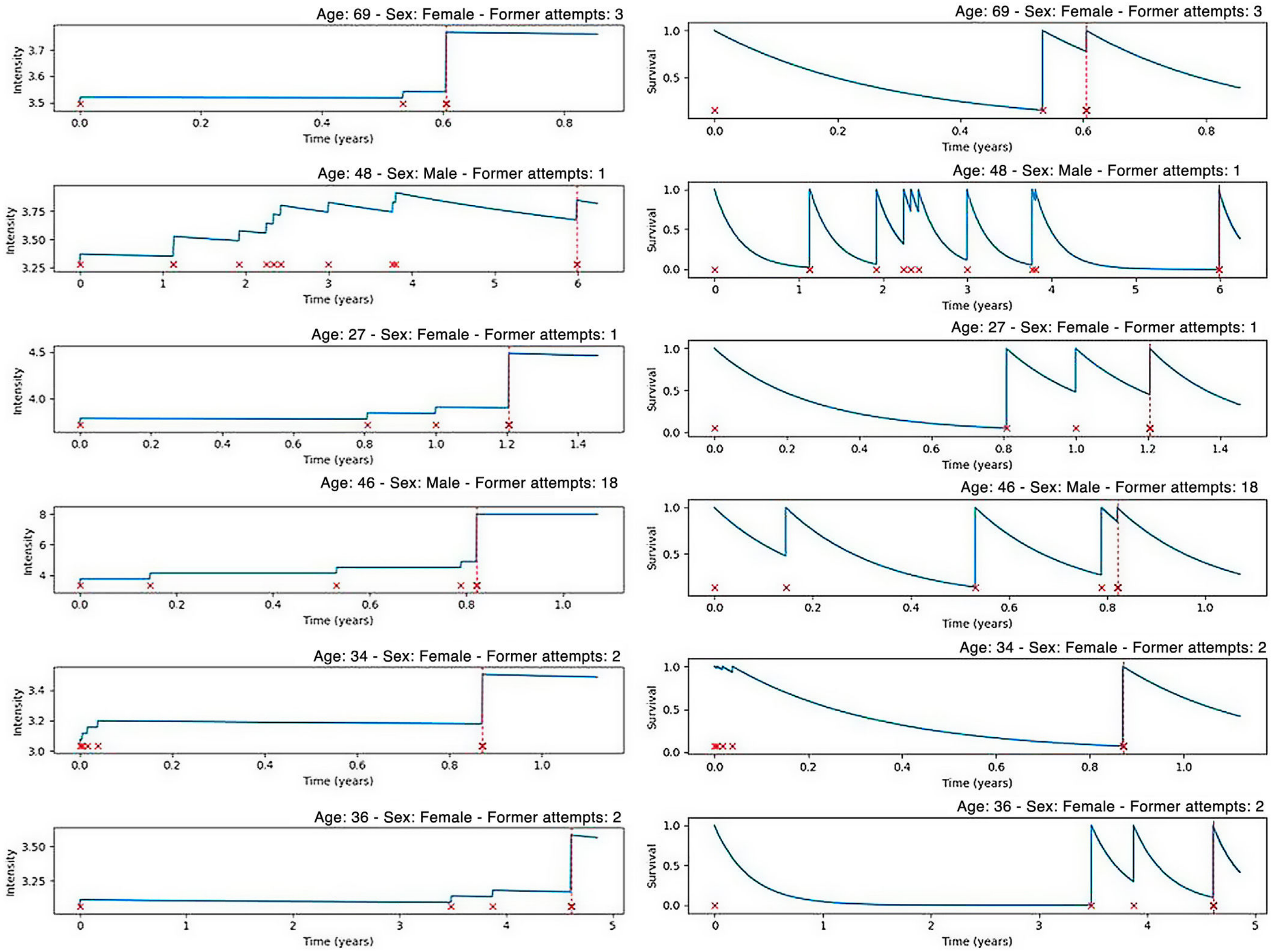

Fig. 4. Intensity curves for a random sample of 6 patients (left column) and their corresponding survival curves in between events (right column). The red crosses on the *x*-axis indicate when a suicide attempt happened, and the blue line the intensity or survival at any time point. These examples show the excitation patterns that the suicide attempts present and the decay of the risk as time advances. When an event happens very far away from the previous one, the Hawkes model considers that this event is no longer explained by the history of events, but rather by external factors (eg, the patient's cross-sectional data).

Discussion

Suicide attempts often lead to multiple hospitalizations, long-term psychiatric care, and, in many cases, eventual death by suicide or early mortality.[23] These events are associated with substantial health care costs, place significant strain on health care systems, and impose profound emotional and financial burdens on families and communities.[24] Therefore, accurate prediction models could help mitigate these impacts by enabling more targeted interventions. The ability to predict the risk of a new suicide attempt is crucial for early intervention and prevention efforts.[1] While prior suicide prediction models demonstrate good overall classification accuracy, their positive predictive value for future suicide events remains extremely low, raising concerns about their readiness for widespread clinical use.[25] In this context, we present a new probabilistic model, based on Hawkes processes, that offers a promising approach as an adjunctive source of information for clinicians in assessing the risk of subsequent suicide attempts. Hawkes processes are particularly well-suited for modeling events that are self-exciting, meaning that each event (such as a suicide attempt) increases the likelihood of subsequent events. These models are dynamic, adapting as new data is added, which makes them highly applicable in real-world scenarios where patient data is continuously updated. By estimating the baseline intensity (μ), the triggering effect (α), and the decay rate of influence (δ), the model provides individualized risk predictions that can inform clinical decision-making. Of note, we identified one unpublished study that applied Hawkes processes to suicidal behavior, specifically focusing on suicide contagion, which differs from our approach, using epidemiological data from England and Wales (United Kingdom).[26]

Our probability model builds on previous efforts to estimate suicide risk within a specified time frame.[9,27] Rather than providing a single probability estimate of suicide risk over a specified period, we developed individualized graphical models for each patient. These models can be easily generated and integrated into EHRs or monitoring systems, providing clinicians with a quick visualization of the temporal decline in suicide risk, facilitating more informed decision-making and prioritization of high-risk patients. Clinical decision support systems are being developed to enhance the management of self-harm and could benefit from these visualizations.[28] This is particularly relevant in the initial months following a suicide attempt, when the risk is highest, and other estimation tools, such as the OxMIS tool,[7] fall short as they only provide a 1-year risk assessment.

Our results suggest that suicide attempts satisfy the mathematical criteria for self-exciting behaviors. A recent meta-analysis indicates that at least one in five individuals who attempt suicide make a second attempt, with the risk of this repetition increasing linearly over time. However, the included studies examined only the period after the index attempt and had a relatively short median 15-month follow-up.[29] Our results reveal a time-dependent decline in the risk of subsequent attempts following each new incident (Fig. 3). Self-exciting behaviors, often modeled by Hawkes processes, are characterized by a conditional intensity function that increases after an event (e.g., a suicide attempt), causing events to cluster throughout time. The intensity of events is highest immediately following the initial event and gradually decreases as time passes. Moreover, each event has a lasting influence on future occurrences, increasing the likelihood of subsequent attempts soon after. If suicide attempts occurred randomly and independently of each other, a Poisson Process would suffice, as it models independent events over time without any memory of previous events. However, our model offers greater flexibility: when alpha = 0, it behaves like a Poisson Process, with no dependence on prior events, but when alpha $\neq$ 0, it operates as a Hawkes process, accounting for the influence of past events.

Although the current model demonstrates promise, it can be further refined by incorporating additional variables that are typically available in EHRs. In this study, we only used a limited set of parameters, which are widely accessible in many healthcare systems. Expanding the model to include other clinically relevant factors, such as psychiatric diagnoses, social and environmental factors, or biomarkers, could significantly enhance its predictive accuracy and adaptability to individual patients.[30,31] Previous research has shown that combining EHR data with clinical assessments and patient self-reports increases the ability to identify patients at high risk of suicide attempt.[32] Also, our estimates can help identify high-risk individuals for personalized treatment, but they do not capture acute suicide risk factors that may precipitate an attempt.

Of note, while the model parameters are individualized and based on retrospective data, prospective validation is essential for evaluating its precision and ensuring better calibration. Our model may be more useful for individuals with multiple attempts rather than those with only a few attempts. Future studies should focus on gathering prospective data to test and refine the model in real-world settings, which will allow for continuous improvement in its ability to forecast suicidal behavior and provide clinicians with reliable, data-driven tools for suicide prevention.

Conclusion

Our results indicate that suicide attempts follow a self-exciting temporal pattern, and Hawkes models can generate individualized, time-varying risk estimates. This dynamic approach reflects the sharp increase in risk shortly after an attempt and its gradual decline, offering advantages over traditional static prediction tools. While further prospective validation and integration of additional clinical variables are needed, this method represents a promising step toward more precise and actionable suicide risk assessment.

CRediT authorship contribution statement

JLC and PMO conceived the idea. JLC and DCL performed the literature search, drafted the manuscript and added suggestions from the other authors. DCL and PMO conducted the analyses and developed the probabilistic models. All the authors critically revised the manuscript.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version available at https://doi.org/10.1016/j.sjpmh.2026.01.003.

Declaration of competing interest

None declared.

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