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Subgrouping suicidal ideations: an ecological momentary assessment study in psychiatric inpatients

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Abstract

Background Suicidal ideation (SI) is one of the strongest predictors of suicide attempts, yet reliable prediction models for suicide risk remain scarce. A key challenge is that SI can fluctuate over time, potentially reflecting different subgroups that may offer important insights for suicide risk prediction. This study aims to build upon previous approaches that averaged SI trajectories by adopting a method that respects the temporal nature of SI.

Methods First, we applied longitudinal clustering to ecological momentary assessment (EMA) data on SI, with five daily assessments over 28 days from 51 psychiatric patients (61% female, mean age = 35.26, SD = 12.54). We used the KmlShape algorithm, which takes raw SI scores and the measurement occasion index as input. Second, we regressed each identified subgroup against established clinical risk factors for SI, including a history of suicidal thoughts and behaviors, hopelessness, depression diagnosis, anxiety disorder diagnosis, and history of abuse.

Results Four distinct subgroups with unique SI patterns were identified: (1) "High SI, moderate variability" (high mean, medium variability, high maximum); (2) "Lowest SI, lowest variability" (lowest mean, lowest variability, lowest maximum); (3) "Low SI, moderate variability" (low mean, medium variability, high maximum); and (4) "Highest SI, highest variability" (highest mean, highest variability, highest maximum). Furthermore, these subgroups were significantly associated with clinical characteristics. For instance, the subgroup with the least severe SI ("lowest SI, lowest variability") showed the lowest levels of hopelessness (beta = -0.95, 95% CI = -1.04, -0.86), whereas the subgroup with the most severe SI ("highest SI, highest variability") exhibited the highest levels of hopelessness (beta = 0.84, 95% CI = 0.72, 0.95).

Conclusion Applying longitudinal clustering to EMA data from patients with SI enables the identification of well-defined and distinct SI subgroups with clearer clinical characteristics. This approach is a crucial step toward a deeper understanding of SI and serves as a foundation for enhancing prediction and prevention efforts.

Trial registration 10DL12_183251.

Keywords Suicidal ideation, Subgroups, Suicide risk, Longitudinal clustering analysis, Risk factors

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Introduction

Every 40 s, someone takes their life. Globally, this amounts to more than 700,000 deaths by suicide every year [1]. This number might be even higher considering stigma, taboos, poor data quality of reporting, and the illegality of suicidal behavior in some countries [1]. Indeed, more than 9% of adults across the world have suicidal ideations (SI) at least once in their lives [2]. Even though the majority will not act upon them, a concerning one-tenth will [3]. Elaborate psychological ideation-to-action theories offer explanation models for this transition from thinking about taking own's life to acting upon those thoughts [4–8]. Yet, the prediction of suicidal thoughts and behaviors (STBs) remains challenging. The term STBs in suicide research entails suicide ideations, suicide plans, and suicide attempts but excludes non-suicidal self-injury (e.g., self-harm by cutting) because the self-injury happens without the intent to die [2]. Although the incidence of suicide has declined in most countries worldwide, certain populations have experienced an increase in suicide deaths [9]. Furthermore, despite over 50 years of research on risk factors, each demonstrating only weak predictive power [10], clinical efforts have yet to enhance the efficacy of STB interventions [11]. Thus, there is a growing call for a more thorough investigation of SI to improve prevention and intervention strategies [12].

Traditional clinical tools for assessing SI, such as retrospective self-report questionnaires and semi-structured or structured interviews, often offer limited predictive accuracy due to their cross-sectional design and the gaps in time between assessments, which can range from days to months. To capture the dynamic nature of SI more effectively, higher temporal resolution is needed, which can be achieved in real-time through methods like ecological momentary assessment (EMA) [13–16]. EMA allows for the fine-grained collection of data [17], allowing the identification of instances of SI that might otherwise go unnoticed by retrospective self-report measures [18]. Contrary to previous assumptions that combining subjective EMA data with objective digital markers (e.g., passive sensor data) would enhance prediction models, recent research indicates that EMA data alone is a strong predictor of next-day SI, while passive sensing data did not improve predictive accuracy [19]. Another factor that could help improve prediction models might be to reduce complexity. Suicidal ideations are a heterogeneous phenomenon, and the processes leading up to both suicidal thoughts and suicidal behaviors are the result of a highly complex dynamic interplay of various factors. Thus, reducing complexity and heterogeneity by subtyping at-risk individuals is recommended [20–22]. Being able to categorize at-risk individuals into meaningful clinical risk groups will give guidance on the next steps for research, prevention, and intervention.

Different approaches to subtyping SI have been proposed. One of the earliest frameworks [20] identified two subgroups based on stress responsiveness: [1] a stress-responsive subtype, characterized by a history of childhood trauma, fluctuating SI, and transient increases in SI following stressful events. This subtype is also associated with impulsive behaviors and unplanned suicide attempts. In contrast, [2] the non-stress-responsive subtype is linked to depression, persistent SI, a stronger intent to die, and carefully planned, potentially more lethal suicidal behaviors. Building upon this framework, subsequent studies have introduced subtyping based on other characteristics. Longitudinal studies [23–26] examining SI trajectories or repeated measures [26] have revealed that individuals with chronic, stable SI are more likely to experience depression [24], impulsivity, and perfectionism [26]. This subgroup also faces higher odds of repeat suicide attempts [23, 26], re-hospitalization [23], and increased suicide attempts and hospitalizations within six months following discharge [25]. Additionally, they demonstrate greater difficulty in accepting emotional responses and fewer emotion regulation strategies [25]. More recent EMA studies [27–29] have focused on SI variability, identifying distinct subgroups. One subgroup, characterized by high mean SI with low variability, was associated with prior suicide attempts in the preceding month [27]. Another subgroup, marked by high SI variability, had no history of prior suicide attempts [27] but exhibited greater SI increases in response to stressful events [28] and the highest levels of SI and depression [29]. Taken together, these findings underscore two key insights: [1] examining the temporal dynamics of SI can reveal distinct subgroups with unique patterns, and [2] the number and characteristics of these subgroups vary across studies, highlighting the need for further investigation.

To optimally subtype SI, it is crucial to use EMA data, as it allows for the accurate capture of dynamic changes in SI through frequent assessments over time. This enables the application of statistical models that leverage the rich, intensive longitudinal data. While previous research has contributed to our understanding of SI subgroups, conclusions may be limited when longitudinal EMA data are summarized into person-level means and variances for analysis. Such summary estimates of temporal data can obscure valuable information, leading to models that may inappropriately classify cases based on mean and variance alone. For instance, an individual who reports a stable level of SI followed by a period of high variability could be grouped the same as someone with a similar mean but a consistently low variance over time

(Supplementary Fig. 1). This distinction between the two cases is crucial for predicting future SI and determining the most appropriate treatment approach [8]. We propose an alternative approach, longitudinal clustering, which takes raw temporal trajectories into account and better discriminates between these types of cases.

We aimed to use EMA data collected from a high-risk psychiatric inpatient sample with STBs and apply longitudinal clustering to identify potential subgroups of SI. First, we sought to determine whether distinct subgroups differed in terms of SI characteristics, specifically the mean level of SI and its volatility. This research question was informed by one of the earliest studies on SI characteristics [27], and we hypothesized the presence of five distinct subgroups. Second, we aimed to examine the relationship between the identified subgroups and known clinical risk factors for SI [10] hypothesizing that the subgroups would exhibit distinct clinical profiles. This hypothesis was exploratory, as the mixed results from prior research made it difficult to draw definitive conclusions regarding the specific clinical characteristics of the subgroups.

Methods

This study is part of the larger Suicidal Ideation Monitoring (SIMon) study [30], a feasibility study designed to assess [1] the feasibility and acceptability of implementing a digital mental health protocol using self-reports and behavioral measures via smartphone applications and [2] whether SI and psychiatric hospital readmission can be predicted from app-derived variables. In the SIMon study, inpatient recruitment at the Psychiatric University Hospital Zurich, Switzerland, began in July 2019 and concluded in November 2020. Assessments commenced simultaneously in July 2019 and continued until the final follow-up in February 2021. The ethics proposal of the SIMon study was reviewed and approved by the Ethics Committee of the Faculty of Arts and Social Sciences (IRB) of the University of Zurich, Switzerland (approval number 19.2.1). For structured and transparent reporting, we followed the STROBE guidelines for observational studies (Supplementary STROBE Checklist; [31].

Participants

We screened for the following inclusion criteria: [1] SI or suicide attempts as the reason for hospital admission independent of the psychiatric diagnosis, [2] sufficient fluency in German, [3] older than 18 years of age, and [4] owner of a smartphone. We defined SI as thoughts to end one's life with or without explicit intent [32], and suicide attempts as an act in which a person harms themselves with the intention to die [32]. Suicidal ideation at admission and a history of suicide attempts were assessed through discussions with the treatment team and review of the electronic patient health records. Exclusion criteria were the following: (1) plans to leave the greater Zurich area during the study, (2) sharing a smartphone with another person, (3) active military personnel (as passive sensing and EMA assessments would be challenging in active duty), and (4) current psychotic episode. Before data collection in the SIMon study, a power analysis was conducted to determine the necessary sample size for detecting a medium effect (Cohen's $d = 0.5$) in the outcome of suicidal ideation, as measured via EMA (5 prompts per day for 28 days). The power analysis indicated that achieving 80% power at a significance level of 0.05 required a conservative sample size of $N= 80$ [30]. To account for potential dropouts, we aimed to recruit 100 participants.

We screened 1,095 patients, the majority of whom were excluded due to ineligibility or lack of interest in participating ($n = 1{,}007$). Of the remaining 88 patients who provided written informed consent, 16 dropped out before or during the baseline assessment, resulting in 72 participants who completed this phase. During the EMA phase, 58 participants successfully completed the assessment, while 14 did not. By the follow-up assessment, a total of 22 participants were lost to follow-up, leaving 46 who completed this final phase (see Supplementary Fig. 2). For the analysis, we included the 58 participants who completed the EMA phase.

Procedures

Patients who met the inclusion criteria were informed about the study with the approval of the treating clinician. Once patients agreed to participate in the study and gave written informed consent, they were enrolled.

Baseline assessment

Participants completed a baseline assessment during their hospital stay, which included self-report questionnaires (non-mandatory responses) to evaluate suicidal thoughts, behaviors, and related psychological variables. The assessment also involved a brief videotaped semi-structured qualitative interview to capture linguistic and acoustic features, a diagnostic interview, and the installation of the mobile application SIMON.

App data collection

The SIMON app was developed specifically for this study to facilitate the collection of EMA and passive sensing data. It was built on the open-source MobileCoach software platform (www.mobile-coach.eu) and integrated the Aware framework (https://awareframework.com/) [30]. For 28 days, participants received prompts to answer questions about social interactions (SI) and their well-being five times daily. The 28-day duration was selected as it represents a critical period following discharge [33]. Prompts were sent in a predefined 12-h time frame according to a stratified random interval scheme with the time frame divided into five equal intervals, allowing for some individualization (e.g., from 9 AM to 9 PM, from 10 AM to 10 PM) [30]. EMA and passive mobile data collection started once participants left the hospital. Compliance with the protocol was promoted through multiple strategies (see the protocol paper for a full list, [30]). For example, participants received text message reminders when their EMA response rate dropped below 60% update. Also, in terms of positive reinforcement, participants received weekly messages from the chatbot thanking them for their valuable contribution to suicide prevention research. Finally, in addition to being reimbursed for taking part in the study (CHF 30 for each part of the study), participants can earn another CHF 30 if their EMA response rate is above 60%, resulting in a total of CHF 120 for the whole study.

Follow-up assessment

The study was completed with a follow-up assessment one month after the baseline assessment and entailed self-rating questionnaires about suicidal thoughts and behaviors and user experience with the app (for the study design, see Supplementary Fig. 3).

Assessments

In this study, several questionnaires and assessments were conducted. Here, only the questionnaires and assessments relevant to these analyses are being described.

Baseline assessment

At baseline, we assessed demographic and clinical variables using a variety of self-rating questionnaires. Prior suicidal ideation was measured with the Beck Scale for Suicide Ideation (BSS; German validated version; [34], which can range from 0 to 38, with higher values indicating greater suicide risk. A history of abuse was assessed with the Childhood Trauma Questionnaire (CTQ; [35], which can range from 5 to 25, with higher values indicating more extreme experiences of childhood maltreatment. A history of stressful live events was assessed with the Life Events Checklist (LEC; [36]), where events were rated based on whether one experienced them oneself, witnessed them, heard about them, was confronted with them because of one's job, or is unsure. The clinical diagnosis was assessed by trained research staff (i.e., psychology students at least Master level) with the Mini International Neuropsychiatric Interview (MINI; [37]). For an overview of all questionnaires administered in the SIMon study, see Supplementary Table 2.

Ecological momentary assessment

We used EMA to assess SI fluctuations over time. Consistent with methodologies employed in previous studies [38, 39] and incorporating a validated EMA item scale, we evaluated the severity of suicidal ideation using four specific items. Two items measured active suicidal ideation ('At the moment, I want to die by suicide.' and 'At the moment, I think about taking my life.'), while two items assessed passive suicidal ideation ('At the moment, I feel that life is not worth living.' and 'At the moment, I have more reasons to die than to live.'). The items were rated on a slider scale from '0' to '100' ("not at all" to "very much"), adding up to a total score that ranged from 0 to 400 (adapt from [29, 38, 39]). The scores from these items were combined to calculate a total score for suicidal ideation. For an overview of all EMA items of the SIMon study, see Supplementary Table 3.

Statistical analyses

For the descriptive statistics, we computed means (M) with standard deviations (SD) or standard error (SE) for all measures of interest. We excluded participants with four or fewer EMA data points (n =7, 12%), resulting in a final dataset of N= 51 for the main analysis. We selected four as the threshold because exploratory analyses revealed that a single case with four data points was disproportionately influencing the results. This cutoff balances data quality and sample retention, ensuring meaningful contributions to the analysis.

First, we employed a longitudinal clustering approach that groups cases based on their raw SI trajectories. We had pre-registered the use of a Dynamic Latent Class Structural Equation Model (DLC-SEM; [40]) for analyzing the SI EMA data, as it does not require data aggregation and preserves the temporal characteristics of the data. However, due to the small sample size (N =51), the DLC-SEM failed to converge. Several alternative methods exist for estimating between-subject clusters from intensive longitudinal data [41]. One such method, KmlShape, is a k-Means longitudinal shape-respecting, distance-based clustering algorithm [33], which takes raw scores and the measurement occasion index as inputs. This algorithm estimates k groups by maximizing homogeneity within each group regarding the temporal trajectories of a variable and assesses similarity between time series by calculating discrete Fréchet distances [42, 43] between the nearest measurement occasions. Additionally, KmlShape incorporates case-level mean information to account for similarities among cases with similar trends, even if they occur at different times (Supplementary

Fig. 5). A key advantage of this longitudinal classification approach, particularly for EMA data, is its natural handling of missing data. The algorithm creates a continuous average trajectory between cases, extending this logic to groups by linking the nearest available observations using discrete Fréchet distances. For our analysis, we estimated classes using a four-cluster solution, based on our replication of previous work [27] and for comparison with cross-sectional latent profile analysis (Supplementary Analysis, Supplementary Figs. 6–8, and Supplementary Table 1).

Second, we used linear and logistic regression analyses to examine the relationship between the latent subgroups and established risk factors for SI [10]. The risk factors considered included prior STBs, such as a history of suicide attempts [44] and prior SI, as assessed by the BSS; hopelessness, measured via EMA; depression diagnosis, assessed using the MINI; history of abuse, including childhood trauma, evaluated with the CTQ total score and subscales [20, 28]; other stressful life events, as measured by the standard total score of the LEC, following Weis et al.'s recommendations [45]; and anxiety disorder diagnosis, assessed using the MINI. To control for multiple comparisons and minimize the risk of Type I errors, we applied the Holm-Bonferroni correction method.

Data and code availability

This paper was written in R (version 3.6.2) with the R packages rmarkdown (version r 2.29); represearch (version r 0.0.0.9000; https://github.com/philipphoman/represearch.git); knitr (version r 1.49); and papaja (version r 0.1.3). We computed longitudinal clustering using kmlShape (version r 0.9.5) [33]. Data and code are available online to ensure reproducibility at https://osf.io/xtreu/ and study preregistration at https://osf.io/epav6.

Results

Descriptive statistics

Considering the initial data set of 58 participants, the EMA with five prompts per day for 28 days would have allowed to collect 8,120 data points in this sample. However, 7 participants (12%) responded to four or fewer prompts and were therefore excluded from the analysis.

The remaining 51 participants (33 female, 65%, age M = 35.14, SD = 12.30) provided 2,435 valid EMA responses, with an average of 47.75 per participant (SD = 36.31), corresponding to an overall response rate of 34%. Response rates were highest during the first week, with 806 responses (33% of the total), but declined steadily over the subsequent weeks: 27% in week 2, 23% in week 3, and 17% in week 4 (see Supplementary Fig. 4).

All participants fulfilled the inclusion criteria and had been admitted to the hospital for either suicidal ideation or after a suicide attempt. At baseline, 23 participants (45%) reported experiencing moderate to severe suicidal ideation in the last seven days, as indicated by a mean BSS total score of 17.61 (SD =7.88); data was not available from 28 participants. A history of suicide attempts (BSS item 20) was reported by 19 participants, 14 [27] of whom reported two or more attempts; data was not available from 20 participants. Among the participants with prior suicidal ideation, 17 out of 23 (74%) also had a history of suicide attempts. Additionally, 20 participants (39%) reported a history of non-suicidal self-injury; data was not available from 20 participants. Among the participants with prior suicidal ideation, 16 (70%) also had a history of non-suicidal self-injury. Regarding the most frequent diagnoses, 35 (69%) had a diagnosis of major depression (live time) and 29 (57%) of an anxiety disorder.

Throughout the study, 10 participants had to be readmitted. Of those, more than half were readmitted once (6, 60%). For most participants (9, 90%), this fell within the EMA phase, which could have contributed to the low EMA response rate considering the emotional distress of participants. Only a fraction of readmissions was during the follow-up phase (1, 10%). For participants in the EMA phase, the first readmission happened on average 45.14 days after hospital discharge (SD = 62.43, range: 8, 182), for participants in the follow-up phase, the readmission was after 294 days. More details on the sample are summarized in Table 1.

Longitudinal clustering

The four-cluster solution exhibited high stability given the modest sample size showing consistent class membership during repeated runs for the four extracted subgroups (Table 2). The subgroups were defined based on SI mean and volatility as follows (Fig. 1): (1) high mean, medium variability, and high maximum ("High SI, moderate variability" subgroup containing 14 patients (27%)), (2) lowest mean, lowest variability, and lowest maximum ("Lowest SI, lowest variability" subgroup containing 14 patients (27%)), (3) low mean, medium variability, and high maximum ("Low SI, moderate variability" subgroup containing 13 patients (25%)), and (4) highest mean, highest variability, and highest maximum ("Highest SI, highest variability" subgroup containing 10 patients (20%)).

Clinical characteristics of subgroups

We identified several significant associations between the risk factors and the subgroups (Fig. 2). Subgroup 1 ("High SI, moderate variability") comprised mildly hopeless individuals (EMA 'hopelessness' item: beta =0.29, 95% CI =0.21, 0.37, P< 0.001, corrected P< 0.001) but was not characterized by other clinical risk factors. Subgroup

Table 1 Descriptive statistics

Variable	*N*	*N* = 51[1]
Age	50	35.14 (12.30)
NA		1
Sex	50	
female		33/50 (66%)
male		17/50 (34%)
NA		1
Nationality	32	
Other European countries		4/32 (13%)
Swiss		25/32 (78%)
Swiss, double citizenship		3/32 (9.4%)
NA		19
Living situation	31	
Alone		14/31 (45%)
Shared		6/31 (19%)
Assisted living		1/31 (3.2%)
With parents		1/31 (3.2%)
With partner		4/31 (13%)
Other		5/31 (16%)
NA		20
Education level	30	
Apprenticeship		11/30 (37%)
College		5/30 (17%)
Highschool		3/30 (10%)
Junior high school		5/30 (17%)
University		6/30 (20%)
NA		21
Rehospitalized	29	
Yes		10/29 (34%)
No		19/29 (66%)
NA		22
Number of rehospitalizations	10	
1		6/10 (60%)
2		3/10 (30%)
3		1/10 (10%)
NA		41
Severity of suicidal ideation (BSS total score)	23	17.61 (7.88)
NA		28
History of suicide attempts (BSS item 20)	31	
Never		12/31 (39%)
Once		5/31 (16%)
Twice or more than twice		14/31 (45%)
NA		20
History of non-suicidal self-injury	31	
Yes		20/31 (65%)
No		11/31 (35%)
NA		20
Life Events Checklist (LEC standard total score)	30	6.47 (4.55)
NA		21
History of childhood trauma (CTQ total score)	31	65.13 (18.62)
NA		20
Emotional abuse (CTQ subscale score)	31	14.00 (6.61)
NA		20
Physical abuse (CTQ subscale score)	31	9.87 (6.25)
NA		20
Sexual abuse (CTQ subscale score)	31	9.39 (6.05)
NA		20
Emotional neglect (CTQ subscale score)	31	14.87 (5.84)
NA		20
Physical neglect (CTQ subscale score)	31	10.13 (3.91)
NA		20

BSS, Beck Scale for Suicide Ideation; CTQ, Childhood Trauma Questionnaire; Note that baseline data were not available for all patients

[1] Mean (SD); n/N (%)

2 ("Lowest SI, lowest variability") comprised individuals who were the least hopeless (EMA 'hopelessness' item: beta = − 0.8, 95% CI = − 0.9, − 0.7, $P < 0.001$, corrected $P < 0.001$) compared with the other subgroups but was not associated with other clinical risk factors. Subgroup 3 ("Low SI, moderate variability") comprised individuals who were slightly below average hopeless (EMA 'hopelessness' item: beta = − 0.39, 95% CI = − 0.5, − 0.29, $P < 0.001$, corrected $P < 0.001$) and who had fewer stressful life events (LEC standard total score: beta = − 1.05, 95% CI = − 2, − 0.1, $P < 0.001$, corrected $P < 0.001$) compared with the other subgroups. Finally, subgroup 4 ("Highest SI, highest variability") comprised the most hopeless individuals (EMA 'hopelessness' item: beta = 0.48, 95% CI = 0.36, 0.6, $P < 0.001$, corrected $P < 0.001$) , who had a history of childhood trauma, including a history of sexual and emotional abuse (CTQ total score: beta = 1.02, 95% CI = 0.02, 2.03, $P = 0.047$, corrected $P = 1$; CTQ SA subscale: beta = 1.09, 95% CI = 0.1, 2.08, $P = 0.032$, corrected $P = 1$; CTQ EA subscale: beta = 1.03, 95% CI = 0.04, 2.02, $P = 0.042$, corrected $P = 1$), and prior suicidal ideation (BSS total score: beta = 1.12, 95% CI = 0.03, 2.21, $P = 0.045$, corrected $P = 1$) compared with the other subgroups. Note that only a subset of participants had baseline pathology scale data available for the analysis (see Table 1). For the summary of the regression results, see Supplementary Fig. 9. The subgroups were not associated with the other risk factors (i.e., prior suicide attempts, diagnosis of depression, and diagnosis of an anxiety disorder; see also Supplementary Tables 4–10).

Table 2 Summary of analysis results for longitudinal clustering

Estimated class	N	SI mean	SI SD	SI RMSSD	Maximum SI	Response %
Subgroup 1	14	132.90	60.83	61.14	218.79	26.17
Subgroup 2	14	21.29	18.84	23.46	82.36	40.41
Subgroup 3	13	74.22	55.83	61.64	258.54	38.96
Subgroup 4	10	240.65	80.85	94.46	353.30	30.07

N, number of subjects; Response %, percent of prompts for which a nonzero score on SI was reported; RMSSD, root mean square of successive differences; SD, standard deviation; SI, suicidal ideation

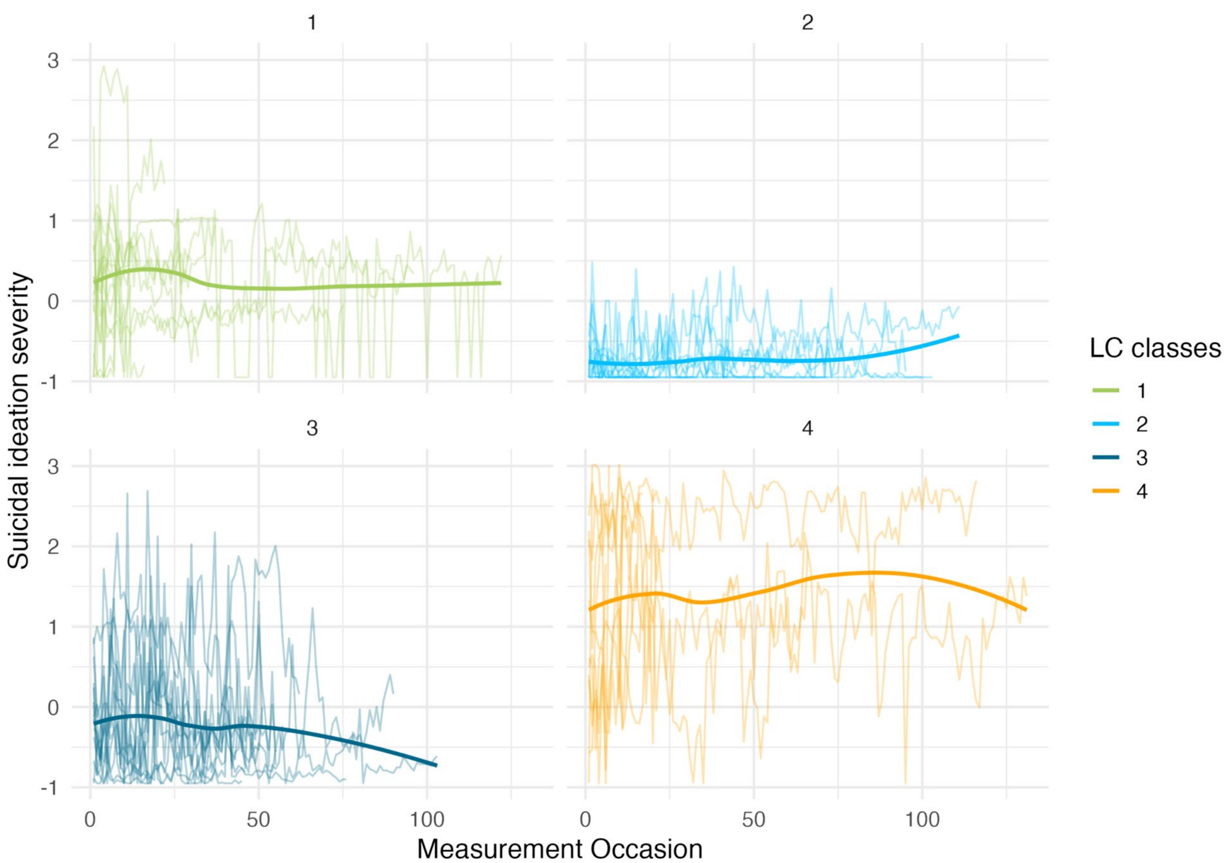

Fig. 1 Suicidal ideation subgroups. The line plot depicts the suicidal ideation (SI) trajectories by estimated class: (1) "High SI, moderate variability" subgroup, (2) "Lowest SI, lowest variability" subgroup, (3) "Low SI, moderate variability" subgroup, and (4) "Highest SI, highest variability" subgroup. A LOESS line is fitted to the trajectories of each subgroup to depict the average trend. The mean of the overall sample is zero, and this transformation was applied prior to the analysis. If the LOESS line dips below zero, it indicates that the fitted SI for that subgroup has fallen below the mean of the overall sample. On the x-axis, measurement occasions are depicted with zero, representing the day post-discharge from acute psychiatry and the start of EMA, and 140 is the maximum of possible data points (5 prompts per day for 28 days)

Discussion

Our ecological momentary assessments (EMA) found four distinct suicidal ideation (SI) subgroups that differed in SI mean and volatility. We used EMA since SI fluctuations might be crucial for suicide risk prediction. Yet, the heterogeneity between individuals in these fluctuations is challenging, and one explanation for the previously found heterogeneity might be underlying subgroups. Regarding our candidate risk factors, subgroups 2 ("Lowest SI, lowest variability") and 3 ("Low SI, moderate variability") presented clinically with the least burdened profiles, subgroup 1 ("High SI, moderate variability") with slightly elevated hopelessness levels, while, in comparison, subgroup 4 ("Highest SI, highest variability") was presenting a highly burdened profile with high levels of hopelessness, a history of abuse

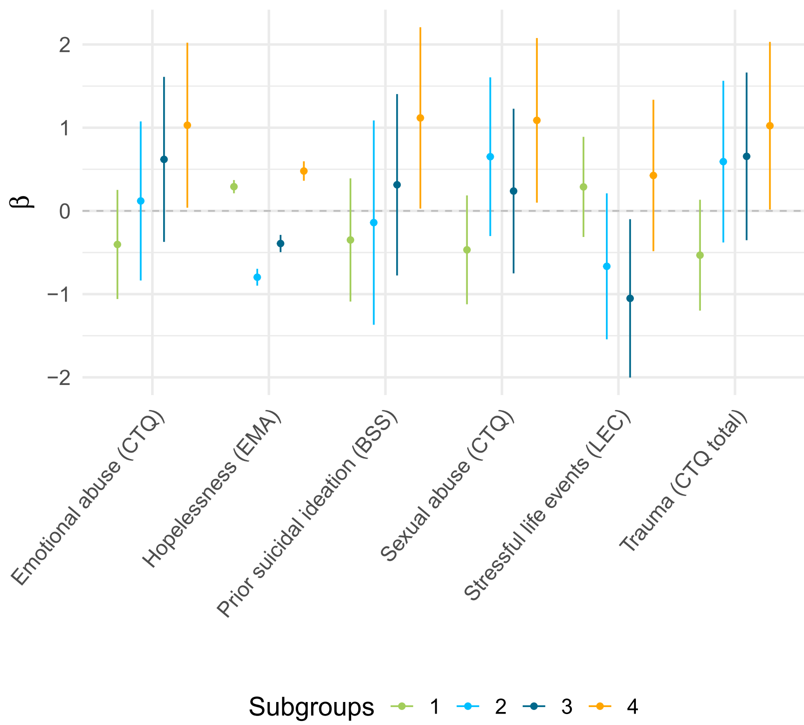

Fig. 2 Association of suicidal ideation subgroups with common correlates. The dot plot presents a selection of significant predictors from the regression analysis, revealing that all significant associations emerged exclusively from the continuous risk factors across the analyzed subgroups as measured with self-rating scales including the Childhood Trauma Questionnaire (CTQ), the Beck Suicide Ideation Scale (BSS), and the Life Events Checklist (LEC), and ecological momentary assessments (EMA). These results, represented as beta coefficients with their 95% confidence intervals, stem from regression analyses examining the associations between suicidal ideation subgroups and common correlates [10]

(sexual and emotional), and prior SI. In contrast to the other subgroups, subgroup 4 had a high mean SI that fluctuated over time, highlighting the importance of identifying subgroups of suicidal ideation based on distinct fluctuation patterns and clinical characteristics to develop personalized, effective suicide prevention strategies and advance consistent, reliable research.

Using the information on SI temporal characteristics (i.e., differences in mean and volatility) for subgrouping builds on prior work [27–29]. So far, the number of subgroups suggested has differed between studies. In our study, the four-subgroup solution best represented the data. Only one other study also suggested four subgroups [29], while the others suggested five [27] and two [28]. Of those, two studies [27, 29] were similar in design, approach, and study population, thus comparable to this study. Therefore, the findings of this study regarding the SI and clinical characterization of the subgroups are being discussed in comparison to those two studies in the following. One possible explanation for differences in the retrieved subgroups is the specific items used to assess suicidal ideation [46]. The wording of the self-report item, particularly the suggestion that suicidal ideation was “serious”, influenced participants’ response behavior [46]. To improve consistency, more clearly defined constructs are needed to facilitate unified, brief self-report assessments.

In terms of SI characterization, the high-risk subgroup in our study (subgroup 4, “Highest SI, highest variability”) is comparable with the high-risk subgroup (subtype 2) in Spangenberg and colleagues’ [29] study that showed the same SI characterization of high mean and high variability and was clinically also the most burdened subgroup as it presented with the most severe prior SI and depression levels. In contrast, in Kleiman and colleagues’ [27] study, the high-risk subgroup (subgroup 5) was characterized by high mean and low variability. This subgroup presented clinically as the subgroup with a considerably higher proportion of individuals who had made a suicide attempt in the month before the study and even the week before the study. Taken together, our study shows that the chronic profile (i.e., high mean and high variability SI) from previous cross-sectional studies [47] is also apparent in longitudinal trajectories and that this subgroup is clinically highly burdened. Future research is needed to examine this subgroup in greater depth, including a larger sample and focusing on the most compelling risk factors.

Hopelessness emerged as the one meaningful risk factor for each of the subgroups in our study, showing a unique manifestation in the four subgroups, with the most severe form in the high-risk subgroup (subgroup 4, "Highest SI, highest variability") and the least severe form in the subgroup with the lowest mean and lowest volatility (subgroup 2, "Lowest SI, lowest variability"). This is in line with previous findings that considered hopelessness an important SI predictor (odds ratio = 3.28) [48], a relationship already recognized early [49]. Given that hopelessness can be effectively targeted and reduced through psychotherapy [50], which may, in turn, help lower suicidal ideation risk, this becomes a critical focus area. Consequently, at-risk individuals showing a high mean and high volatility pattern should be considered more vulnerable. They would benefit from close monitoring and potentially just-in-time adaptive interventions [51]. In addition to hopelessness, a history of trauma, particularly sexual and emotional abuse, and prior suicidal ideation were clinically significant in distinguishing the subgroups. This supports the hypothesis that the subgroup characterized by more fluctuating suicidal ideation (subgroup 4) represents a stress-responsive subtype [20] associated with childhood trauma. Both trauma and prior suicidal ideation are highly relevant clinical risk factors, as they can and should be addressed in therapy. For adult survivors of childhood abuse, trauma-focused treatments are significantly more effective than non-trauma-focused approaches [52]. Meanwhile, interventions targeting suicidal ideation, whether direct or indirect, have demonstrated positive outcomes [53].

Interestingly, we found no evidence that the subgroups differed in terms of other expected predictors, such as a history of suicide attempts or a diagnosis of depression or anxiety disorders. This is surprising, given prior research suggesting a relationship between suicidal ideation and these risk factors [10], as well as their significance as distinctive features for subgroups of suicidal ideation [27, 29]. The non-significant predictors in our study were categorical, unlike the continuous ones examined. A possible explanation for this result is that the study may not have been sufficiently powered to detect these effects in the logistic regression analyses. Larger studies are needed to investigate the clinical characterization of the subgroups further. Future studies should focus on examining subgroups with a history of both suicide attempts and non-suicidal self-harm, as well as those with a history of only suicide attempts or only non-suicidal self-harm. Our sample size was too small to explore these differences effectively. What is more, further research is required to examine suicidal ideation over an extended period, allowing for a more comprehensive assessment of the stability of class membership. To date, this remains an open question [22], along with whether changes in class membership reflect shifts in the suicidal state or signify a critical period during which suicidal thoughts or behaviors are more likely to emerge.

Limitations and Strengths

Some limitations merit comment. First, while retaining pre-registered research questions (see Supplementary Analysis) regarding replication and extensions, we changed the statistical approach because of the small sample size. Longitudinal clustering with *k*-means is considered appropriate for intensive longitudinal data, even with small samples [41]. It is non-parametric, making it most suited for our goal of exploring SI profiles. Further, an unavoidable issue with clustering approaches regards stochastic starting points, which leads to differences in clustering solutions across repeated runs. To provide some certainty in our solution, we compared class membership across repeated runs revealing acceptable stability. Second, we lacked an independent sample to attempt a direct replication of our findings. However, our primary objective was to replicate previous findings [27] using the same statistical approach (see the latent profile analysis results in the Supplementary Material) and to extend this replication with a more advanced method, namely longitudinal clustering. Nonetheless, future studies should aim to replicate our longitudinal clustering findings in independent, larger samples. Third, albeit large for a clinical inpatient sample, our sample size was still small considering the complex analyses and had considerable missing data points (response rate = 34%). Recruitment and study adherence were challenging because of the focus on high-risk psychiatric inpatients and the critical four-week period after hospital discharge, which is typically associated with high rates of STBs, mood deterioration, and readmission [54]. Further, the COVID- 19 pandemic constituted another challenge with fewer admissions because of SI despite more admissions because of a first suicide attempt [55] and an impact on psychological well-being that might have influenced SI severity [56]. Yet, we did not observe a statistically significant difference in SI severity between individuals recruited before and during the pandemic ($t([49]) = -0.29$, $P = 0.78$; see Supplementary Fig. 10). Fourth, there were many missing values in the baseline data set (i.e., for BSS total score $n = 28$, CTQ total score = 20). The missing values arose from the non-mandatory response settings of the online survey used for the baseline questionnaires. Nonetheless, the subjects were included because of their EMA data ($n = 51$ complete data sets), which formed the basis of the primary analysis. For the secondary analysis, we acknowledged the limitation of the results due to missing values. Fifth, we did not assess gender identification, which might be a risk factor and potential characterization trait. Sixth, we did not assess racial/ethnic identification as a sociodemographic characteristic, but only asked participants to report on their country of origin. Last, the response rate of 34% was low, which posed a limitation for data analysis. A potential explanation for the limited data could be that participants were less likely to respond to prompts during periods of crisis or heightened alertness. This is particularly relevant given that the post-hospital discharge period is associated with an increased risk of suicide [54]. One way to test this hypothesis would be through retrospective assessments of these states or by incorporating an additional, objective measure, such as data from passive mobile sensors. Another possible explanation is that the number of daily prompts was too high or that the EMA phase was too lengthy. The observation that week four had the lowest response rate (17% compared to 33% in week one) supports the latter explanation.

An important strength of our study was that we used a relatively novel statistical approach. In comparison to previous studies that relied on latent profile analysis (e.g., [27, 29], we used longitudinal clustering. Longitudinal clustering is an advanced statistical approach that considers the raw temporal trajectories and the whole richness of information of the longitudinal, dynamic EMA data. This is not the case for latent profile analysis, a cross-sectional approach that requires EMA data to be summarized into person-level means and variances. The consequence is losing valuable information and a model that can only improperly discriminate cases based on a mean and variance. Cases with the same summary statistics but different time courses with dynamically different unfolding over time cannot be distinguished (see Supplementary Fig. 1 for an illustration). Latent profile classification has contributed to SI research; however, caution should be taken with cross-sectional summaries of temporal phenomena that might fail to represent potentially meaningful differences in the original trajectories.

Conclusions

Suicidal ideation is a temporal phenomenon, and subgroups should be established with this dimension intact. The aim is to find clinically meaningful subgroups that represent patterns of the interplay between fluctuation and persistence that predict the worsening of the suicidal state. The longitudinal approach used in this study successfully identified subgroups with clinically relevant characteristics, but further replication in larger samples using equivalent statistical methods is necessary to confirm their validity. Understanding these subgroups and their associated clinical features can enhance suicide prevention by enabling more precise and personalized interventions. Rather than applying uniform treatment strategies to all at-risk individuals, subgroup-based approaches can uncover unique risk factors and clinical needs, allowing for more tailored interventions. For example, high-risk groups such as subgroup 4, characterized by high and fluctuating SI, may benefit from targeted treatment focusing on hopelessness [50], trauma [52], and suicidal ideation [53]). A subgroup-specific therapeutic approach can optimize treatment precision, address individual risk factors more effectively, and ultimately contribute to reducing suicide risk.

Abbreviations

BSS	Beck Scale for Suicide Ideation
CTQ	Child Trauma Questionnaire
EMA	Ecological momentary assessments
MINI	Mini International Neuropsychiatric Interview
NSSI	Non-suicidal self-injury
LEC	Life Events Checklist
SI	Suicidal ideation
STB	Suicidal thoughts and behaviors

Supplementary Information

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Supplementary Material 1.

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Authors' contributions

Conceptualization: BK, AR, SH, IG-L, TK, PS; Software: PS, TK; Methodology: SH, ZR, BK, US, PH; Investigation: SH, SM, A-MB, NK, CB, SB, MG; Ressources: HS, MC, SV, SO, PH, ES, SM, A-MB, NK, CB, SB, MG; Writing – Original Draft Preparation: SH, ZR, BK; Writing – Review & Editing: TK, US, PH, SO, SB, AR, PS, SM, A-MB, NK, CB, MG, HS, MC, SV, ES, IG-L; Supervision: BK; Project Administration: BK.

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Data availability

Data and code are available online to ensure reproducibility at https://osf.io/xtreu/and study preregistration at https://osf.io/epav6.

Declarations

Ethics approval and consent to participate

The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008. All procedures were approved by the Ethics Committee of the Faculty of Arts and Social Sciences (IRB) of the University of Zurich, Switzerland (approval number 19.2.1). All participants provided written informed consent to participate in this study.

Consent for publication

Not applicable.

Competing interests
The authors declare no competing interests.

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References
1. WHO. Suicide worldwide in 2019: Global health estimates. 2021.
2. Nock MK, Borges G, Bromet EJ, Alonso J, Angermeyer M, Beautrais A, et al. Cross-national prevalence and risk factors for suicidal ideation, plans and attempts. Br J Psychiatry. 2008;192(2):98–105.
3. Ivey-Stephenson AZ, Crosby AE, Hoenig JM, Gyawali S, Park-Lee E, Hedden SL. Suicidal thoughts and behaviors among adults aged 18 years and older. MMWR Surveill Summ. 2022;71(1):1.
4. O'Connor RC, et al. Towards an integrated motivational–volitional model of suicidal behaviour. International handbook of suicide prevention: Research, policy and practice. 2011;1:181–98.
5. O'Connor RC, Kirtley OJ. The integrated motivational–volitional model of suicidal behaviour. Philosophical Transactions of the Royal Society B: Biological Sciences. 2018;373(1754):20170268.
6. Van Orden KA, Witte TK, Cukrowicz KC, Braithwaite SR, Selby EA, Joiner TE Jr. The interpersonal theory of suicide. Psychol Rev. 2010;117(2):575.
7. Klonsky ED, May AM. The three-step theory (3ST): A new theory of suicide rooted in the "ideation-to-action" framework. Int J Cogn Ther. 2015;8(2):114–29.
8. Rudd MD. Fluid vulnerability theory: A cognitive approach to understanding the process of acute and chronic suicide risk. 2006.
9. Ilic M, Ilic I. Worldwide suicide mortality trends (2000–2019): A joinpoint regression analysis. World Journal of Psychiatry. 2022;12(8):1044.
10. Franklin JC, Fox KR, Franklin CR, Kleiman EM, Ribeiro JD, Jaroszewski AC, et al. A brief mobile app reduces nonsuicidal and suicidal self-injury: Evidence from three randomized controlled trials. J Consult Clin Psychol. 2016;84(6):544.
11. Fox KR, Huang X, Guzmán EM, Funsch KM, Cha CB, Ribeiro JD, et al. Interventions for suicide and self-injury: A meta-analysis of randomized controlled trials across nearly 50 years of research. Psychol Bull. 2020;146(12):1117.
12. Jobes DA, Mandel AA, Kleiman EM, Bryan CJ, Johnson SL, Joiner TE. Facets of suicidal ideation. Archives of suicide research. 2024;28(4):1–16.
13. Bryan CJ, Rudd MD. The importance of temporal dynamics in the transition from suicidal thought to behavior. Clin Psychol Sci Pract. 2016;23(1):21–5.
14. Kleiman EM, Turner BJ, Fedor S, Beale EE, Huffman JC, Nock MK. Examination of real-time fluctuations in suicidal ideation and its risk factors: Results from two ecological momentary assessment studies. J Abnorm Psychol. 2017;126(6):726.
15. Hallensleben N, Spangenberg L, Forkmann T, Rath D, Hegerl U, Kersting A, et al. Investigating the dynamics of suicidal ideation. Crisis. 2017.
16. Wang C, Pan R, Wan X, Tan Y, Xu L, Ho CS, et al. Immediate psychological responses and associated factors during the initial stage of the 2019 coronavirus disease (COVID-19) epidemic among the general population in china. Int J Environ Res Public Health. 2020;17(5):1729.
17. Ballard ED, Gilbert JR, Wusinich C, Zarate CA Jr. New methods for assessing rapid changes in suicide risk. Front Psych. 2021;12:598434.
18. Gratch I, Choo TH, Galfalvy H, Keilp JG, Itzhaky L, Mann JJ, et al. Detecting suicidal thoughts: The power of ecological momentary assessment. Depress Anxiety. 2021;38(1):8–16.
19. Czyz EK, King CA, Al-Dajani N, Zimmermann L, Hong V, Nahum-Shani I. Ecological momentary assessments and passive sensing in the prediction of short-term suicidal ideation in young adults. JAMA Netw Open. 2023;6(8):e2328005–15.
20. Bernanke J, Stanley B, Oquendo M. Toward fine-grained phenotyping of suicidal behavior: The role of suicidal subtypes. Mol Psychiatry. 2017;22(8):1080–1.
21. Mou D, Kleiman EM, Nock MK. Proposed directions for suicide research: Incorporating successful approaches from other disciplines. Br J Psychiatry. 2020;217(6):659–60.
22. Kleiman EM, Glenn CR, Liu RT. The use of advanced technology and statistical methods to predict and prevent suicide. Nature Reviews Psychology. 2023;2(6):347–59.
23. Czyz EK, King CA. Longitudinal trajectories of suicidal ideation and subsequent suicide attempts among adolescent inpatients. J Clin Child Adolesc Psychol. 2015;44(1):181–93.
24. Köhler-Forsberg O, Madsen T, Behrendt-Møller I, Sylvia L, Bowden CL, Gao K, et al. Trajectories of suicidal ideation over 6 months among 482 outpatients with bipolar disorder. J Affect Disord. 2017;223:146–52.
25. Wolff JC, Davis S, Liu RT, Cha CB, Cheek SM, Nestor BA, et al. Trajectories of suicidal ideation among adolescents following psychiatric hospitalization. J Abnorm Child Psychol. 2018;46:355–63.
26. van Eijk NL, Wetherall K, Ferguson E, O'Connor DB, O'Connor RC. A latent class analysis using the integrated motivational-volitional model of suicidal behaviour: Understanding suicide risk over 36 months. J Affect Disord. 2023;336:9–14.
27. Kleiman EM, Turner BJ, Fedor S, Beale EE, Picard RW, Huffman JC, et al. Digital phenotyping of suicidal thoughts. Depress Anxiety. 2018;35(7):601–8.
28. Oquendo MA, Galfalvy HC, Choo TH, Kandlur R, Burke AK, Sublette ME, et al. Highly variable suicidal ideation: A phenotypic marker for stress induced suicide risk. Mol Psychiatry. 2021;26(9):5079–86.
29. Spangenberg L, Friedrich M, Forkmann T, Hallensleben N, Schönfelder A, Rath D, et al. Phenotyping suicidal ideation and behavior: Comparing clinical characteristics and future suicide attempts between suicidal subtypes in two clinical samples. Int J Methods Psychiatr Res. 2023;32(1):e1940.
30. Sels L, Homan S, Ries A, Santhanam P, Scheerer H, Colla M, et al. SIMON: A digital protocol to monitor and predict suicidal ideation. Front Psych. 2021;12:890.
31. Von Elm E, Altman DG, Egger M, Pocock SJ, Gøtzsche PC, Vandenbroucke JP. The strengthening the reporting of observational studies in epidemiology (STROBE) statement: Guidelines for reporting observational studies. The Lancet. 2007;370(9596):1453–7.
32. De Leo D, Goodfellow B, Silverman M, Berman A, Mann J, Arensman E, et al. International study of definitions of english-language terms for suicidal behaviours: A survey exploring preferred terminology. BMJ Open. 2021;11(2):e043409.
33. Genolini C, Ecochard R, Benghezal M, Driss T, Andrieu S, Subtil F. kmlShape: An efficient method to cluster longitudinal data (time-series) according to their shapes. PLoS ONE. 2016;11(6):e0150738.
34. Kliem S, Lohmann A, Mößle T, Brähler E. German beck scale for suicide ideation (BSS): Psychometric properties from a representative population survey. BMC Psychiatry. 2017;17(1):1–8.
35. Bernstein DP, Fink L, Handelsman L, Foote J. Childhood trauma questionnaire. Assessment of family violence: A handbook for researchers and practitioners. 1998.
36. Weathers F, Blake D, Schnurr P, Kaloupek D, Marx B, Keane T. The life events checklist for DSM-5 (LEC-5). 2013.
37. Sheehan DV, Lecrubier Y, Sheehan KH, Amorim P, Janavs J, Weiller E, et al. The mini-international neuropsychiatric interview (MINI): The development and validation of a structured diagnostic psychiatric interview for DSM-IV and ICD-10. J Clin Psychiatry. 1998;59(20):22–33.
38. Hallensleben N, Glaesmer H, Forkmann T, Rath D, Strauss M, Kersting A, et al. Predicting suicidal ideation by interpersonal variables, hopelessness and depression in real-time. An ecological momentary assessment

study in psychiatric inpatients with depression. European psychiatry. 2019;56(1):43–50.
39. Forkmann T, Spangenberg L, Rath D, Hallensleben N, Hegerl U, Kersting A, et al. Assessing suicidality in real time: A psychometric evaluation of self-report items for the assessment of suicidal ideation and its proximal risk factors using ecological momentary assessments. J Abnorm Psychol. 2018;127(8):758.
40. Kelava A, Brandt H. A nonlinear dynamic latent class structural equation model. Struct Equ Modeling. 2019;26(4):509–28.
41. Den Teuling N, Pauws S, Heuvel E van den. A comparison of methods for clustering longitudinal data with slowly changing trends. Communications in Statistics-Simulation and Computation. 2020;1–28.
42. Fréchet MM. Sur quelques points du calcul fonctionnel. Rendiconti del Circolo Matematico di Palermo (1884–1940). 1906;22(1):1–72.
43. Eiter T, Mannila H. Computing discrete fréchet distance. 1994.
44. Chu C, Buchman-Schmitt JM, Stanley IH, Hom MA, Tucker RP, Hagan CR, et al. The interpersonal theory of suicide: A systematic review and meta-analysis of a decade of cross-national research. Psychol Bull. 2017;143(12):1313.
45. Weis CN, Webb EK, Stevens SK, Larson CL, deRoon-Cassini TA. Scoring the life events checklist: Comparison of three scoring methods. Psychol Trauma Theory Res Pract Policy. 2022;14(4):714.
46. Ammerman BA, Burke TA, Jacobucci R, McClure K. How we ask matters: The impact of question wording in single-item measurement of suicidal thoughts and behaviors. Prev Med. 2021;152:106472.
47. Reeves KW, Vasconez G, Weiss SJ. Characteristics of suicidal ideation: A systematic review. Arch Suicide Res. 2022;26(4):1736–56.
48. Franklin JC, Ribeiro JD, Fox KR, Bentley KH, Kleiman EM, Huang X, et al. Risk factors for suicidal thoughts and behaviors: A meta-analysis of 50 years of research. Psychol Bull. 2017;143(2):187.
49. Beck AT, Brown G, Steer RA. Prediction of eventual suicide in psychiatric inpatients by clinical ratings of hopelessness. J Consult Clin Psychol. 1989;57(2):309.
50. Handley TE, Kay-Lambkin FJ, Baker AL, Lewin TJ, Kelly BJ, Inder KJ, et al. Incidental treatment effects of CBT on suicidal ideation and hopelessness. J Affect Disord. 2013;151(1):275–83.
51. Bernstein EE, Bentley KH, Nock MK, Stein MB, Beck S, Kleiman EM. An ecological momentary intervention study of emotional responses to smartphone-prompted CBT skills practice and the relationship to clinical outcomes. Behav Ther. 2022;53(2):267–80.
52. Ehring T, Welboren R, Morina N, Wicherts JM, Freitag J, Emmelkamp PM. Meta-analysis of psychological treatments for posttraumatic stress disorder in adult survivors of childhood abuse. Clin Psychol Rev. 2014;34(8):645–57.
53. van Ballegooijen W, Rawee J, Palantza C, et al. Suicidal Ideation and Suicide Attempts After Direct or Indirect Psychotherapy: A Systematic Review and Meta-Analysis. JAMA Psychiatry. 2025;82(1):31–7. https://doi.org/10.1001/jamapsychiatry.2024.2854.
54. Chung DT, Ryan CJ, Hadzi-Pavlovic D, Singh SP, Stanton C, Large MM. Suicide rates after discharge from psychiatric facilities: A systematic review and meta-analysis. JAMA Psychiat. 2017;74(7):694–702.
55. Hörmann C, Bandli A, Bankwitz A, et al. Suicidal ideations and suicide attempts prior to admission to a psychiatric hospital in the first six months of the COVID-19 pandemic: interrupted time-series analysis to estimate the impact of the lockdown and comparison of 2020 with 2019. BJPsych Open. 2022;8(1):e24. https://doi.org/10.1192/bjo.2021.1072.
56. Fortgang RG, Wang SB, Millner AJ, Reid-Russell A, Beukenhorst AL, Kleiman EM, et al. Increase in suicidal thinking during COVID-19. Clinical Psychological Science. 2021;9(3):482–8.

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