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Modeling the Dynamics of Perceived Burdensomeness, Thwarted Belongingness, and Suicidal Ideation in Continuous Time

Miguel Blacutt[1], Ross Jacobucci[2], and Brooke A. Ammerman[3]

1: Department of Psychology, University of Notre Dame
2: Center for Healthy Minds, University of Wisconsin – Madison
3: Department of Psychology, University of Wisconsin - Madison

Corresponding Author:
Miguel Blacutt
mblacutt@nd.edu

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Abstract

The Interpersonal Theory of Suicide (ITS) posits that perceived burdensomeness (PB) and thwarted belongingness (TB) are central to suicidal ideation (SI), where either one is sufficient for passive SI but both required for active SI. This study used continuous time modeling to examine the relationship between PB, TB, and passive and active SI. Three independent samples (N = 141) of participants with recent suicidal thoughts and behaviors completed 3-15 surveys per day for 28-30 days; each survey assessed PB, TB, passive SI, and active SI. Continuous time residual dynamic structural equation models estimated auto- and cross-drift effects (instantaneous rate of change) between PB, TB, and their interaction on passive and active SI. Negative drift rates indicate resistance to shifts away from equilibrium. Both passive and active SI had negative auto-drift effects. There were significant negative cross-drift effects of PB, TB, and their interaction on both active and passive SI. The effects of PB, TB, and their interaction lasted 5-5.5 and 4.5-5 hours on passive SI and active SI, respectively. Auto-drift effects were significantly larger than cross-drift effects, which did not differ from each other. Both passive and active SI reduce their own rates of change, resisting shifts away from their equilibrium. Contrary to the ITS, these findings suggest that rather than precipitating SI, PB, TB, and their interaction resist shifts away from a person's typical levels of passive and active SI.

Keywords: Interpersonal Theory; suicide; suicidal ideation; continuous time; momentary assessment; EMA

General Scientific Summary

It has been proposed that feeling like a burden and like one does not belong causes thoughts of suicide. This study suggests instead of causing suicidal thoughts, these two feelings might make it more difficult for these thoughts to change.

Introduction

Suicide stands as a leading cause of death globally, resulting in approximately 800,000 lives lost every year, and ranking as both the second and fifth leading cause of death among individuals aged 10–34 and 35–54 in the United States, respectively (CDC, 2023). In 2022, an estimated 13.2 million adults over the age of 18 had serious thoughts of suicide, while 3.8 million made suicide plans, and 1.6 million made suicide attempts (SAMHSA, 2023). Rates of suicide have been increasing since 1999 and currently generate a national annual cost of approximately $100 billion (Martinez-Ales et al., 2020). Despite the critical need, our ability to predict suicide remains low (Franklin et al., 2017). To address this public health crisis and improve suicide prevention techniques, we need to enhance our ability to model and predict time periods when individuals are at high risk for suicide.

Interpersonal Theory of Suicide

To better understand, prevent, and treat suicidal thoughts and behaviors (STBs), it is essential to delve into the theoretical frameworks that elucidate their underpinnings. One such framework is the Interpersonal Theory of Suicide (ITS; Joiner, 2005; Van Orden et al., 2010), which posits that two constructs are central and causal for STBs: perceived burdensomeness (PB) and thwarted belongingness (TB). The Theory proposes that both PB and TB are two-dimensional, time-varying, dynamic cognitive-affective states (Van Orden et al., 2010). PB consists of a belief that the self is so flawed that it causes a liability on others and an affectively-charged self-hatred; TB consists of loneliness and lack of reciprocally caring relationships (Joiner, 2005; Van Orden et al., 2010).

Thoughts of engaging in suicidal behavior, known as suicidal ideation (SI), stand as the third strongest predictor of eventual death by suicide (Franklin et al., 2017) and are associated with elevated negative affect and psychological distress, even when they do not lead to suicidal behavior (Coppersmith et al., 2023; Lucht et al., 2022). Therefore, developing our understanding of SI is essential for intervention and prevention of suicide (Jobes & Joiner, 2019). The ITS proposes that either PB or TB alone are sufficient to cause passive SI, broadly defined as an acquiescent desire for death (e.g., "I wish I was dead"). However, most individuals do not transition from passive SI to experiencing active SI (Thomas et al., 2002), which is characterized by the intention to end own's life (e.g., "I want to kill myself"). The ITS states that active SI requires the presence of PB *and* TB coupled with hopelessness regarding their improvement. This theoretical framework has spurred numerous empirical studies aimed at deepening our comprehension of these complex interactions and their implications for the prediction and prevention of STBs.

Examining the Evidence: Thwarted Belongingness and Perceived Burdensomeness

Cross-Sectional Insights

Cross-sectional investigations have consistently found a relationship between PB, TB, and SI in several demographic groups, including a general sample of undergraduates (Lockman & Servaty-Seib, 2016), those with adverse childhood experience (Bhargav & Swords, 2022), those with alcohol use disorder (Cole et al., 2020), sexual minorities (Hill & Pettit, 2012), prison inmates (Mandracchia & Smith, 2015), and military service members (Silva et al., 2017), to name a few. A seminal meta-analysis of 130 investigations that explored ITS revealed a consistent association between PB and SI ($r = .48$) and TB and SI ($r = .37$) (Chu et al., 2017).

Weekly and Daily Patterns

While the studies discussed above provide valuable insights, a limitation is that they are cross-sectional while PB and TB are purported to be dynamic cognitive-affective states (Kleiman et al., 2017; Van Orden et al., 2010), thus should be examined longitudinally. Ambulatory assessments have found an association between PB and both same-week and next-week active SI (Bodell et al., 2021). A pattern of findings has emerged in these studies – cross sectional effects of PB and TB on SI are observed, however, initially-observed longitudinal effects (e.g., next day) become negligible after models account for the autoregressive effect of SI. Such findings have been reported in daily diary studies in adult inpatient psychiatric settings (Kyron et al., 2019, 2022), adults who recently attempted suicide (Coppersmith et al., 2019), and adolescents recently discharge from psychiatric hospitalization (Czyz et al., 2019). Notably, in the last sample, authors found that the *interaction* of PB and TB was a significant predictor of SI – even in models that accounted for the autoregressive effect of SI, and when both predictors were non-significant. Other research in adolescents has explored the effects of PB and TB, but not their interaction, on SI. For example, Al-Dajani et al. (2024) found that PB and TB were associated with same-day suicidal urges (SU), however only PB was associated with next-day SU – though these models did not account for SU autoregression. Overall, studies that use weekly- and daily-level sampling show a consistent association between concurrent PB, TB, and SI but fail to find a consistent prospective effect when accounting for the autoregressive effects of SI. Uncovering if PB or TB are uniquely associated with upcoming SI has important implications for risk prediction and development of targeted interventions.

Momentary Dynamics

Perhaps more temporally fine-grained approaches, such as ecological momentary assessment (EMA), are needed to capture the prospective relationship between PB, TB, and SI. To our knowledge, four studies have leveraged EMA to explore the momentary relationship between TB, PB, and SI as per the ITS. Kleiman et al. (2017) used EMA to assess active SI, PB, and TB four times daily for 28-days and used multilevel modeling to examine the relationship between PB and TB with concurrent and prospective SI in two samples; individuals with past year suicide attempters and the other among those hospitalized due to suicide risk. Consistent with evidence at the daily- and weekly-level (Coppersmith et al., 2019; Czyz et al., 2019; Kyron et al., 2022), PB and TB were associated with concurrent SI, but had no effect on SI in prospective models that accounted for SI autoregression. These authors hypothesized that the effects of PB and TB on SI may manifest within a shorter time-frame than previously assessed. As such, Hallensleben et al. (2019) used an even more fine-grained EMA schedule (i.e., 10 daily surveys) to attempt to effectively capture these transient dynamics in an inpatient sample of adults with depression and current SI. These authors found that PB and TB were concurrently associated with active SI while only PB was associated with next-moment active SI when accounting for autoregression – partially supporting that previous research may have missed effects due to long sampling time frames (i.e., weekly, daily). Alternative analyses of these data (i.e., multilevel vector autoregression) demonstrated similar findings concurrently and prospectively (Rath et al., 2019). Glenn et al. (2017) found that TB was associated with next-moment SI in an adolescent sample recently discharged from psychiatric hospitalization – although models included neither PB nor SI autoregression. To date, only one EMA study has shown a prospective relationship between PB, TB, and active SI as per the ITS, where Jacobucci et al. (2023) used EMA, and a Bayesian mixed-effects model that accounted for SI autoregression and found that both PB and TB were significant predictors of next-moment active SI. Effects of PB and TB were both smaller compared to the autoregressive effect of SI, but not meaningfully different from each other.

Harnessing Continuous Time Modelling

With the exception of one study (Jacobucci et al., 2023), extant literature has not consistently captured the prospective relationship between PB, TB, and SI hypothesized as per the ITS (Hallensleben et al., 2019; Kleiman et al., 2017; Rath et al., 2019). A limitation across prior studies is their reliance on discrete time modeling, which models time implicitly (by the order of observations as opposed to actual time elapsed) and is typically used to analyze concurrent or prospective relationships at fixed intervals (e.g., within the same or lagged EMA prompts). This problem persists when measurement intervals are segmented into more precise bins (e.g., TINTERVAL command for DSEM in Mplus; Asparouhov et al., 2018; McNeish & Hamaker, 2020)), as time bins are still treated discretely without considering elapsed time. This segmentation overlooks the fluid continuity of time and potentially causes researchers to miss nuanced dynamics that unfold within and across these artificially bounded intervals.

In contrast, continuous time models assume that values exist at any moment and aim to estimate changes among variables over any time interval. The relationship between PB, TB, and SI may unfold over temporal scales too brief (e.g., <1 hour) or too extended (e.g., > 4-8 hours) to be captured by discrete time models using data collected every 3-5 hours (Hallensleben et al., 2019; Kleiman et al., 2017; Rath et al., 2019). By directly modelling the continuous data generating process through stochastic differential equations (SDEs), continuous time models estimate both instantaneous rates of change and the effect that variables have on these rates of change through the *drift rate* (Asparouhov & Muthén, 2024a; Driver et al., 2017) – an estimate that will be discussed in depth during the Analysis section. Auto- and cross-drift effects represent the influence of a variable on its own or another variable's rate of change, *explicitly* accounting for elapsed time. Aside from allowing estimation of how variables fluidly affect each other, continuous time models do not assume equal spacing between measurements, and produce more robust parameter estimates when handling unequally spaced measurements and missing data (de Haan-Rietdijk et al., 2017; McNeish & Hamaker, 2020).

Current Study

As discussed thus far, the ITS proposes that both PB and TB are time-varying dynamic states where either one is sufficient to lead to passive SI but both are needed for active SI (Van Orden et al., 2010). However, high-frequency sampling studies have not consistently found evidence for the purported relationship, especially with regards to active SI (Hallensleben et al., 2019; Kleiman et al., 2017; Kyron et al., 2022; Rath et al., 2019) – with some suggesting that the effects of PB and TB on SI could both occur and dissipate between sampling intervals and therefore, be missed by current sampling schemes and modelling approaches (Hallensleben et al., 2019; Kleiman et al., 2017). Some even propose that suicide risk itself is a time-limited episode, even among those with chronically elevated SI (Rudd, 2000).

The current study aims uses continuous time modelling to examine the relationship between PB, TB, and both passive and active SI, as per the ITS – aiming to use this novel modelling technique to potentially overcome some of the temporal challenges faced in this literature. Given that both theory and evidence suggest that PB and TB have relatively short-lived effect on SI, which potentially dissipates prior to typical EMA assessment windows, and is often obscured by the autoregressive effect of SI we hypothesized that modelling the relationship with continuous time will display that (1) PB and TB will exhibit a small, consistent relationship with passive SI throughout the study period, indicated by a modest positive cross-drift effect. This is expected to reflect a slight influence of PB and TB on elevated rate of change in passive SI. Further, we hypothesize that (2) PB, TB, and their interaction will demonstrate a short-term risk window for active SI, evidenced by a positive auto- drift effect and a transient peak in their autoregressive curves on active SI. Such findings would suggest that there exists a moment where PB,TB, and their interaction cause a rapid change in active SI away from a person's equilibrium. This finding would align with theory and evidence to date, indicating that the effects of PB and TB on active SI are dynamic, short-lived, and potentially dissipate between EMA prompts (Hallensleben et al., 2019; Kleiman et al., 2017; Rudd, 2000). Lastly, we hypothesize that although PB and TB will have cross-drift effects with passive and active SI, (3) the cross-drift effect of PB on both passive and active SI will be greater than the effect of TB, and (4) the auto-drift effect of both passive active SI on themselves will be larger than the cross-effects of PB and TB. Hypotheses 3 and 4 would align with both the ITS and evidence to date, which suggests that PB has a greater effect on SI than TB (Chu et al., 2017; Hallensleben et al., 2019; Van Orden et al., 2010), and that the auto-regressive effect of SI commonly overshadows the effects of PB and TB in temporal models (Hallensleben et al., 2019; Kleiman et al., 2017).

Methods

Participants and Procedures

Sample 1

We recruited 78 participants from the local community who experienced past-month STB, defined as repeated (i.e., at least two occurrences) or chronic (i.e., also occurring outside the past-month) past-month active SI, or prior month suicide plan or attempt. Additionally, participants were required to be in the United States, be 18 years or older, have an Android-based smartphone (based on the aims of the larger study, which used software only available on Android devices), and be English-speaking. Participants with zero variability in passive or active SI responses were removed as their inclusion caused convergence issues with continuous time models, likely because these data are not reliably decomposed into within- and between-person levels, especially for time series analysis. As per Asparouhov & Muthen et al. (2024c) participants with no variability provide little information to the model, and their removal can help convergence without meaningfully affecting the overall analysis. The final sample from this study included 49 participants (Age = 36.8 ±10.1, 67.3% female, 46.9% non-straight, and 22.4% non-White, 8.2% Hispanic; see Table 1 for full demographic characteristics). Following an in-person diagnostic assessment session in South Bend, IN, participants completed a 28-day EMA period using the LifeData smartphone application, receiving 6 survey prompts per day (each 2-3 minutes) at semi-randomized blocks within a 12-hours window. The mean time elapsed between prompts was 4.4 hours and the average compliance rate, defined as the percent of completed surveys across the total study period, was 61.1%.

Sample 2

We recruited 40 participants from online social media platforms (i.e., Reddit, Facebook) with a past-year history of STBs. To participate in this study, participants were required to be 18 years or older, have an iOS 12 operating system or newer (based on the aims of the larger study, which required access to Apple Screen Time), and live in the United States. After applying the same participant exclusion criteria as Sample 1, the final sample included 35 participants (Age = 27.3 ±7.0, 65.7% female, 11.4% other sex, 54.3% non-straight, and 28.6% non-White, 8.6% Hispanic; see Table 1 for full demographic characteristics). Following a phone session and self-report measures, participants completed a 30-day EMA period using the ilumivu mEMA smartphone application, receiving 4 survey prompts per day (each 2-3 minutes) at semi-randomized blocks within a 12-hour window. The mean time elapsed between prompts was 4.5 hours, and the average compliance rate was 61.2%.

Sample 3

We recruited 66 participants from online social media platforms (i.e., Craigslist) with past-month STBs, defined as repeated (i.e., at least two occurrences) or chronic (i.e., also occurring outside the past-month) past-month active SI, or prior month suicide plan or attempt. After applying the same participant exclusion criteria as Sample 1 and 2, the final sample from this study included 57 participants (Age = 33.5 ±11.9, 61.4% female, 33.3% non-straight, and 40.4% non-White, 8.8% Hispanic; see Table 1 for full demographic characteristics). Participants were required to be 18 years or old, have a smartphone (no restriction on device type), regular access to the internet, be English-speaking, and live in the United States. Following a virtual laboratory session, participants completed a 28-day EMA period, where they received either: 1) 4 surveys per day (each 2-3 minutes) with a randomly assigned one-week period during which the frequency increased to 10 surveys per day, or 2) 3-15 surveys per day, where the number of surveys varied randomly per day. Surveys were received within 12-hour window. The mean time elapsed between prompts was 3.4 hours, and the average compliance rate was 68.8%. Further, the average number of daily surveys for the first group was 5.3 and the 8.3 for the second group.

General Measures

The following measures were assessed during each EMA prompt across all studies, with identical language in the prompt and response choices.

Suicidal Ideation. Each EMA prompt asked participants to rate the extent to which they experienced SI (i.e., "Indicate to what extent you feel this way, in the moment."). Two items assessed passive SI: "Life is not worth living for me"; and "There are more reason to die than to live for me". Two items assessed active SI: "I want to die"; and "I think about taking my life". Participants responded to each item on a 5-point Likert scale (1 = *very slightly or not at all*; 5 = *extremely*). These items have been validated to assess passive and active SI in EMA contexts in high-risk samples (Forkmann et al., 2018). Items were separately summed to create a separate compositive score for active and passive SI, which has been validated for use in people with SI (Ammerman & Jacobucci, 2023). These items demonstrated appropriate multilevel reliability for passive (ω_{within} = .83, $\omega_{between}$ = .98) and active SI (ω_{within} = .76, $\omega_{between}$ = .88; see Yang et al. (2022) for interpretations of multi-level omega estimates)

Thwarted Belongingness and Perceived Burdensomeness. Two items assessed PB and TB at each EMA prompt. Participants were asked to rate the extent to which they felt "Like a Burden" and "Useless" for PB, and "Like I Do Not Belong" and " Alone" for TB, in the moment (i.e., "Indicate to what extent you feel this way *in this moment*."). Participants responded on a 5-point Likert Scale (1 = *Very slightly or not at all;* 5 = *Extremely).* PB and TB items were summed to generate a composite score for each variable, which has validated for use in high-risk samples (Forkmann et al., 2018). These items demonstrated appropriate multilevel reliability for PB (ω_{within} = .71, $\omega_{between}$ = .96) and TB (ω_{within} = .67, $\omega_{between}$ = .91) as per Yang et al. (2022).

Analysis

Given identical EMA items across the three samples, data integration did not require data harmonization techniques (e.g., moderated nonlinear factor analysis). Continuous time modeling was used to estimate drift rates, which represent the instantaneous rate of change in a variable and are estimated using first-order SDEs that assume the rate of change in a system has a deterministic and stochastic component.

Auto- and cross-drift effects for PB, TB, and their interaction, on both passive and active SI were estimated using continuous time residual dynamic structural equation modeling (CT-RDSEM; Asparouhov & Muthen, 2024) in Mplus 8.11 (Muthén & Muthén, 2017). Unlike the interpretation of coefficients in discrete time models (e.g., 1-unit change in PB leads to β change in SI), drift effects estimate the influence of a variable on the *instantaneous rate of change* of another variable (e.g., 1-unit change in PB leads SI to change at *D* faster rate), where D is the drift rate. Positive drift effects increase the rate of change and shift a person away from their equilibrium in a variable (e.g., usual SI levels). Negative drift effects decrease the rate of change and resist shifts away from equilibrium.

Residual dynamic structural equation models (RDSEM) decompose observed variables for individual *i* at time *j* into within and between-person components, and the within-person component is further decomposed into structural and autoregressive components. (Asparouhov & and Muthén, 2023; Asparouhov & Muthen, 2024a). The structural component models the relationships through contemporaneous regressions, yielding residuals (ε_{ij}), upon which assume that the autoregressive structure is contained and allowing us to include continuous time parameters as such:

$$\varepsilon_{ij} = R_{ij}\varepsilon_{ij-1} + \zeta_{ij} \tag{1}$$

Where R_{ij} is the individual-specific autoregressive coefficient of the residual, e_{ij}, and is obtained by exponentiating a person-specific drift matrix, D_i, at a time interval, Δt, between t and t-1, which allow us to treat time continuously, as follows:

$$R_{ij} = Exp(D_i|t_j - t_{j-1}|) \tag{2}$$

The drift matrix, D_i, is estimated based on first-order stochastic differential equations, known as the Ornstein-Uhlenbeck process, as follows:

$$\frac{d\boldsymbol{Y}(t)}{dt} = \boldsymbol{DY}(t) + \boldsymbol{W}(t)$$

(3)

Where $\frac{dY(t)}{dt}$ represents the first derivative of variables $\boldsymbol{Y}$ (e.g., SI) with respect to an infinitesimally small time interval. $\boldsymbol{D}$ represents the drift rate matrix, where diagonal elements represent auto-drift effects and off-diagonal elements represent cross-drift effects, and $\boldsymbol{W}$(t) represents the Wiener process which can be conceptualized as a white-noise residual term (e.g., random shocks). Bayesian Markov Chain Monte Carlo (MCMC) estimation aligning with RDSEM methodology as per Asparouhov & Muthen was used (2020), although drift and covariances matrices required estimation via the Metropolis-Hasting algorithm with a random walk process due to their lack of explicit conditional distributions (Asparouhov & Muthén, 2024a). Additionally, block updating was used for the drift matrix, the covariance matrix, and their random effects to improve MCMC chain convergence. For more details regarding CT-RDSEM, please see Asparouhov and Muthén (2024a).

We estimated the cross-drift effects of PB, TB, and their interaction, on both passive and active SI (e.g., how PB levels influence the rate of change in active SI) while accounting for the auto-drift effect of each outcome (e.g., how active SI levels influence its own rate of change). The within-person interaction term was computed as per Speyer et al. (2024). Subject-specific random effects for intercepts and drift effects were included. As per Equation 2, the product of the drift matrix and a time interval can be exponentiated to obtain autoregressive coefficients (which share interpretation with coefficients in discrete time models). We computed autoregressive coefficients at 0.5-hour time intervals in line with examples provided by Asparouhov and Muthén (2024a), which we used to report autoregressive curves. All fixed effects were allowed to covary at the between-person level – this covariance structure was chosen to reduce bias due to researcher degrees of freedom in multilevel modelling as per

Asparouhov & Muthen (2024b). An example of the CT-RDSEM model with active SI as the outcome can be seen in Figure 1.

Given differences in the severity of SI in the samples, sample membership was used as a time-invariant covariate. Statistical significance was determined if 95% credible intervals of the estimate did not include 0. Demographic differences between the full sample and the final analytic sample (after excluding participants with no variability in passive and active SI) were examined.

To evaluate hypothesis 1, we examined the cross-drift effects and autoregressive curves characterizing the relationship between PB, TB, and their interaction with passive SI. Similarly, for hypothesis 2, we examined cross-drift effects and autoregressive curves characterizing the relationship between PB,TB, and their interaction, with active SI. To address hypothesis 3, we computed difference parameters that directly compared the posterior distributions of the fixed cross-drift effects of PB and TB on active SI. A similar approach was used for hypothesis 4, which compared the auto-drift effect of active SI with the cross-drift effects of PB and TB.

Transparency and Openness

We report all samples and data exclusions, all manipulations, and all measures in the study. All data, analysis code, and research materials are publicly available on Open Science Framework and can be found at: https://osf.io/7p5em/?view_only=2c7d018a299b4a81b967936d724a6ff3. Data were analyzed using Mplus version 8.11 (Muthén & Muthén, 2017). This study's design and its analysis were not pre-registered.

Results

We observed 1672 (22.9%), 686 (14.9%), and 1955 (17.5%) non-zero active SI responses in the Samples 1, 2, and 3, respectively. A chi-square test for equality of proportions revealed a significant difference in the proportion of non-zero responses among the datasets ($\chi^2(2) = 45.7$, $p < .001$), indicating differences in clinical severity amongst the sample. As such, dataset was used as a time invariant covariate in analyses. Additionally, we did not find any significant differences in age, gender, race, and sexual orientation between the sample prior to exclusion of those with no SI variability and the final sample (after exclusion of those with no SI variability). Full model input and output for analyses are available in the author's linked OSF.

Passive SI

We found significant negative auto-drift effects on passive SI, PB, TB, and their interaction. We also found significant negative cross-drift effects of PB, TB, and their interaction on passive SI (Table 2)[1]. Sample membership did not have a significant on cross-drift effects for passive SI. Exponentiating the drift matrix revealed the autoregressive coefficients at 0.5hour time intervals (Figure 2), where we observed that the effects of passive SI, PB, TB, and their interaction on passive SI peaked at 0.5, 1.0, 1.0, 1.0 hours, decayed over time, and became non-significant after 6.5, 5.5, 5.0, and 5.5 hours, respectively (Table 3). This model displayed good convergence (Rhat < 1.05) and appropriate chain mixing in trace plots.

Active SI

We found significant auto-drift negative effects on active SI, PB, TB, and their interaction. We also found significant negative cross-drift effects of PB, TB, and their interaction on active SI (Table 4)[1]. Sample membership did not have a significant on cross-drift effects for

[1] We remind the reader than negative drift effects resist rate of change away from equilibrium

active SI. Further, we found that the auto-drift effect of active SI was greater than the cross-drift effects of PB and TB (differences = -0.97 [-1.04, -0.91] and -0.99 [-1.05, -0.92], respectively), and the two cross-drift effects did not differ from each other. Exponentiating the drift matrix revealed the autoregressive and cross-lagged coefficients at 0.5hour time intervals (Figure 3), where we observed that the effects of active SI, PB, TB, and their interaction on active SI peaked at 0.5, 1.0, 1.0, 1.0 hours, decayed over time, and became non-significant after 6.5, 5.0, 5.0, and 4.5 hours, respectively (Table 5). This model displayed good convergence (Rhat < 1.05) and appropriate chain mixing in trace plots.

Discussion

The current study aimed to examine the relationship between PB, TB, and their interaction on passive and active SI using continuous time modeling. The first hypothesis that PB,TB, and their interaction would exhibit a small consistent relationship with passive SI throughout the study period was somewhat supported, however, in the unexpected direction. We found small, negative cross-drift effects, indicating that these variables have a small, steady relationship with passive SI where they reduce the rate of change in passive SI, maintaining it at person-specific equilibrium points rather than driving increases. Similarly, our second hypothesis regarding short-term risk windows for active SI was not supported; the ITS variables stabilized active SI rather than precipitating acute episodes. Contrary to our third hypothesis, we did not observe significant difference between the cross-drift effects of PB and TB, however, the auto-drift effect of SI was significantly greater than both cross-drift effects – supporting our fourth hypothesis.

The findings from this study provide important insight into the ITS. According to the ITS, PB and TB are central factors causing SI (Van Orden et al., 2010). The Theory proposes that either PB or TB alone are sufficient to cause passive SI, but both are necessary for active SI. Our results suggest different mechanisms. Counter to the ITS and our first two hypotheses, the small negative cross-drift effects of PB, TB, and their interactions on both passive and active SI suggest that rather than driving increases in SI, or its onset, these variables maintain SI levels at a person's typical level and reduce rates of change away from this level. The autoregressive curves for these effects, obtained by exponentiating the cross-drift effects as per equation 2, reveal that PB, TB, and their interaction have a relatively small, negative effect on passive and active SI, which last up to 5.0-5.5 and 4.5-5.0 hours, respectively. The small magnitude and short duration of these effects further supports the notion that they may not be main drivers of either passive or active SI.

The discrepancy between our findings and those from previous EMA studies is potentially explained by two main factors. First, and briefly as this been extensively discussed in the present manuscript, the use of a continuous time framework may yield different results due to the estimation of a continuous data generation process, where we examine how variables affect instantaneous rates of change. Second, the magnitude and shorter duration of the effects of PB, TB, and their interaction on active SI observed in this study may further explain the difficulty in detecting these relationships in previous studies. These effects are relatively small, peak at the 1-hour mark, decay rapidly, and decrease to non-significant levels by the 5.0, 5.0, and 4.5 hour marks, while the autoregressive effect of active SI is substantially larger and remains significant until the 6-hour mark. The precise nature of these effects should be interpreted with caution as the choice to extract coefficients at 0.5-hour intervals may not match their true dynamics. Be that as it may, these findings align well with the results of Kleiman et al. (2017) who employed 4-8 hour EMA intervals and found a concurrent relationship between PB, TB, and active SI, and a prospective effect of past PB on current active SI that became non-significant after accounting for autoregression. Our continuous time results provide an explanation for this, as the relationship between PB, TB, and active SI is strongest when the time difference between them is relatively short (i.e., <1 hour) and substantially weakens as the time difference increases. The larger and longer-lasting autoregressive effect of active SI likely overshadows the smaller, short-lived effects of PB and TB in studies with longer time intervals between assessments.

The difference in clinical severity between our sample and those from previous studies may further contribute to the discrepancy in study findings. Hallensleben et al. (2019) recruited participants from three inpatient psychiatric hospitals in Germany, while our samples consisted of individuals with either a past-month or pasty-year history of STBs. Perhaps individuals with higher clinical severity stronger autoregression of active SI, which may overshadow the relatively smaller effects of PB and TB, whereas, our sample may have had relatively weaker autoregression, allowing these effects to emerge. Individuals in inpatient psychiatric care may experience greater PB (Siegmann et al., 2019), social rejection (Brown et al., 2019), and loneliness (Lindgren et al., 2019), resulting in chronically high PB and TB with less variability compared to the current study, making it more difficult to detect their effects on active SI.

These findings have important implications for clinical practice, which suggest that elevated levels of PB, TB, and prior SI create inertia that dampens responsiveness to change in both passive and active SI. In other words: traditionally positive experiences may have a diminished impact on SI reduction when PB and TB are high, especially when these are concurrently elevated given their negative interaction. For example, individuals with high PB and TB may experience diminished benefit from supportive interactions or therapeutic interventions that would typically reduce SI, as these variables resist change in SI. Although substantially more research is needed, these findings suggest that it may be prudent for clinicians to target PB and TB to reduce SI's inertia, allowing coping skills and risk reduction strategies to be more effective at changing SI.

Constraints on Generality

The current study had several limitations that constrain generalizability of these findings. First, the study solely included participants who already had a history of STBs. PB and TB could have been driving factors for the onset SI, or during the early stages of developing suicidal thinking; however, as time progressed, their role may have shifted towards maintaining SI as opposed to continuing to drive changes in it. Second, most participants across the three samples identified as White, non-Hispanic, females and all participants were adults from the United States limiting generalizability of results to individuals of different races, ethnicities, genders, and in different developmental stages. Third, we did not collect socioeconomic status (SES) for participants in Sample 2, limiting our ability to adequately describe our sample and examine whether SES differences were present. Fourth, inclusion criteria required owning a smartphone device, and the both the first and second samples were required to own a device with a specific operating system, both reducing the generalizability for those who have different operating systems or no smartphone.

Strengths and Additional Limitations

The current study has several notable strengths. First, the use of continuous time modeling allowed us to examine the relationships between PB, TB, and SI under a continuous data generating process – likely providing more realistic representation of these variables' dynamics. Second, the estimation auto- and cross-drift effects is relatively novel and yields new insight into SI and ITS dynamics. Third, the study leveraged data from three independent EMA studies with people who have a history of STBs – each with a different momentary sampling scheme – likely providing sufficient variation obtain robust estimates for continuous time parameters. Finally, the use of identical EMA items across all three studies allowed merging of datasets without data harmonization, which can otherwise introduce risks such as loss of information, greater researcher degrees of freedom, and potentially ambiguous measurement validity (Cheng et al., 2024; Rolland et al., 2015). Despite these strengths, the study had several additional limitations. First, we did not measure hopelessness about PB and TB, which the ITS requires for active SI, potentially missing indirect effects and limiting our ability to comprehensively test the theory. Second, each construct was assessed using only two items, which were validated for this context (Forkmann et al., 2018), however, more comprehensive measures may have provided a more nuanced information. Third, while compliance rates (~60%) were comparable to other EMA studies with this population (Ammerman & Law, 2022; Kivelä et al., 2022), it is unlikely that we captured all instances of passive and active SI. Fourth, given the 12-hour window in which participants received surveys, we likely missed overnight instances of SI. The lack of observed data during this time may bias parameter estimates, especially if the true data generating process behaves differently during nighttime compared to daytime. Since nighttime wakefulness and sleep disturbances are associated with increased SI (Hamilton et al., 2023; Tubbs et al., 2020), future investigations should incorporate event-contingent surveys for participants to report SI outside of scheduled assessment windows.

Conclusion

Our findings suggest that, contrary to the ITS, PB, TB, and their interaction may not be driving factors for passive or active SI. The small negative cross-drift effects estimated with CT-RDSEM suggest that the primary role of PB, TB, and their interaction may be to shift away from a person's typical level of passive and active SI. Autoregressive curves indicated that the effects of ITS variables on both passive and active SI are relatively small and short-lived. Clinically, these findings suggest that individuals with SI who have higher PB and TB may be more resistant to changes in SI, even when experiencing events or engaging in skills that should theoretically alter SI. This study highlights the value of continuous time modeling for capturing nuanced temporal dynamics that traditional discrete time models may miss. Future research should continue to leverage continuous time approaches to refine our understanding of how risk factors interact to influence suicidal thoughts over time. Such work should include individuals at risk for developing SI, so that investigators can explore whether PB and TB drive changes away from equilibrium in folks who previously have not experienced SI.

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Tables

Table 1. Participant characteristics for the three final samples used for analysis

	Sample 1 (*n* = 49)	Sample 2 (*n* = 35)	Sample 3 (*n* = 57)
Age (Mean (SD))	36.84 (10.09)	27.29 (7.02)	33.47 (11.90)
Sex (*n* (%))			
Male	16 (32.7)	8 (22.9)	22 (38.6)
Female	33 (67.3)	23 (65.7)	35 (61.4)
Other	0 (0.0)	4 (11.4)	0 (0.0)
Sexual Orientation (*n* (%))			
Lesbian or gay	4 (8.2)	6 (17.1)	3 (5.3)
Bisexual	10 (20.4)	9 (25.7)	9 (15.8)
Pansexual	6 (12.2)	0 (0.0)	3 (5.3)
Asexual	1 (2.0)	0 (0.0)	1 (1.8)
Straight	26 (53.1)	16 (45.7)	38 (66.7)
Other	2 (4.1)	4 (11.4)	3 (5.3)
Race (*n* (%))			
White	38 (77.6)	25 (71.4)	34 (59.6)
Black or African American	5 (10.2)	2 (5.7)	15 (26.3)
Asian	0 (0.0)	3 (8.6)	3 (5.3)
American Indian or Alaskan Native	5 (10.2)	1 (2.9)	1 (1.8)
Native Hawaiian or Pacific Islander	0 (0.0)	0 (0.0)	0 (0.0)
More than one	1 (2.0)	2 (5.7)	4 (7.0)
Other	0 (0.0)	2 (5.7)	0 (0.0)
Hispanic (*n* (%))	4 (8.2)	3(8.6)	5 (8.8)
Income (*n* (%))			
$0 - 29,999	21 (42.9)	-	17 (29.8)
$30,000 - 59,999	20 (40.8)	-	19 (33.3)
$60,000 - 99,999	7 (14.3)	-	10 (17.5)
$100,000 or more	1 (2.0)	-	11 (19.3)

Note. SD = Standard deviation; Income = Total yearly household income, not collected in Sample 2; Sex indicates sex-assigned-at-birth.

Table 2. Estimates and 95% credible intervals for two-level continuous time residual dynamic structural equation models examining the effects of PB, TB, and their interaction on passive suicidal ideation

Parameter	Notation	Estimate	95% CI
PassiveSI$_{(t)}$ → PassiveSI$_{(t+1)}$	**γ_{13}**	**-1.027**	**[-1.125, -0.944]**
PB$_{(t)}$ → PB$_{(t+1)}$	**γ_{14}**	**-1.007**	**[-1.043, -0.922]**
TB$_{(t)}$ → TB$_{(t+1)}$	**γ_{15}**	**-0.995**	**[-1.039, -0.960]**
Interaction$_{(t)}$ → Interaction$_{(t+1)}$	**γ_{16}**	**-1.02**	**[-1.076, -0.890]**
PB$_{(t)}$ → PassiveSI$_{(t+1)}$	**γ_{80}**	**-0.06**	**[-0.126, -0.030]**
TB $_{(t)}$ → PassiveSI$_{(t+1)}$	**γ_{90}**	**-0.051**	**[-0.101, -0.019]**
Interaction $_{(t)}$ → PassiveSI$_{(t+1)}$	**γ_{19}**	**-0.063**	**[-0.095, -0.026]**
Cov(PB, TB)	**-**	**3.623**	**[2.799, 4.755]**
Study2 on PB$_{(t)}$ → PassiveSI$_{(t+1)}$	γ_{04}	0.01	[-0.033, 0.051]
Study1 on PB$_{(t)}$ → PassiveSI$_{(t+1)}$	γ_{13}	0.012	[-0.028, 0.066]
Study1 on TB$_{(t)}$ → PassiveSI$_{(t+1)}$	γ_{05}	-0.022	[-0.096, 0.017]
Study2 on TB$_{(t)}$ → PassiveSI$_{(t+1)}$	γ_{14}	0.018	[-0.028, 0.064]

Note: CI = Credible Interval. PB = Perceived Burdensomeness, TB = Thwarted Belongingness. Notation as per Figure 1. Bolded font denotes statistical significance.

Table 3. Autoregressive and cross-lagged coefficients across 0.5-hour time intervals in the relationship between passive suicidal ideation (SI), perceived burdensomeness (PB), thwarted belongingness (TB), and the interaction of PB and TB on passive SI

	Passive SI		**PB**		**TB**		**Interaction**	
Time	**Est.**	**95% CI**	**Est.**	**95% CI**	**Est.**	**95% CI**	**Est.**	**95% CI**
0.5	0.6	[0.57, 0.62]	-0.018	[-0.037, -0.009]	-0.015	[-0.030, -0.006]	-0.019	[-0.028, -0.008]
1.0	0.36	[0.33, 0.39]	-0.022	[-0.044, -0.011]	-0.019	[-0.036, -0.007]	-0.023	[-0.034, -0.009]
1.5	0.21	[0.19, 0.24]	-0.02	[-0.040, -0.010]	-0.017	[-0.032, -0.006]	-0.021	[-0.030, -0.009]
2.0	0.13	[0.11, 0.15]	-0.016	[-0.031, -0.008]	-0.014	[-0.025, -0.005]	-0.016	[-0.024, -0.007]
2.5	0.077	[0.060, 0.094]	-0.012	[-0.023, -0.006]	-0.01	[-0.019, -0.004]	-0.012	[-0.018, -0.005]
3.0	0.046	[0.034, 0.059]	-0.009	[-0.017, -0.004]	-0.008	[-0.013, -0.003]	-0.009	[-0.013, -0.004]
3.5	0.027	[0.020, 0.037]	-0.006	[-0.012, -0.003]	-0.005	[-0.009, -0.002]	-0.006	[-0.009, -0.003]
4.0	0.016	[0.011, 0.023]	-0.004	[-0.008, -0.002]	-0.004	[-0.006, -0.001]	-0.004	[-0.006, -0.002]
4.5	0.01	[0.006, 0.014]	-0.003	[-0.005, -0.001]	-0.002	[-0.004, -0.001]	-0.003	[-0.004, -0.001]
5.0	0.006	[0.004, 0.009]	-0.002	[-0.003, -0.001]	-0.002	[-0.003, -0.001]	-0.002	[-0.003, -0.001]
5.5	0.004	[0.002, 0.006]	-0.001	[-0.002, -0.001]	-0.001	[-0.002, 0.00]	-0.001	[-0.002, -0.001]
6.0	0.002	[0.001, 0.003]	-0.001	[-0.001, 0.00]	-0.001	[-0.001, 0.00]	-0.001	[-0.001, 0.00]
6.5	0.001	[0.001, 0.002]	-0.001	[-0.001, 0.00]	0	[-0.001, 0.00]	-0.001	[-0.001, 0.00]
7.0	0.001	[0.00, 0.001]	0	[-0.001, 0.00]	0	[-0.001, 0.00]	0	[-0.001, 0.00]
7.5	0	[0.00, 0.001]	0	[0.00, 0.00]	0	[0.00, 0.00]	0	[0.00, 0.00]
8.0	0	[0.00, 0.001]	0	[0.00, 0.00]	0	[0.00, 0.00]	0	[0.00, 0.00]

Notes. Est = Estimate for the coefficient; CI = Credible Interval

Table 4. Estimates and 95% credible intervals for two-level continuous time residual dynamic structural equation models examining the effects of PB, TB, and their interaction on active suicidal ideation

Parameter	Notation	Estimate	95% CI
ActiveSI$_{(t)}$ → ActiveSI$_{(t+1)}$	$\boldsymbol{\gamma_{13}}$	**-1.034**	**[-1.106, -0.977]**
PB$_{(t)}$ → PB$_{(t+1)}$	$\boldsymbol{\gamma_{14}}$	**-1.006**	**[-1.055, -0.965]**
TB$_{(t)}$ → TB$_{(t+1)}$	$\boldsymbol{\gamma_{15}}$	**-0.978**	**[-1.039, -0.911]**
Interaction$_{(t)}$ → Interaction$_{(t+1)}$	$\boldsymbol{\gamma_{16}}$	**-1.003**	**[-1.112, -0.966]**
PB$_{(t)}$ → ActiveSI$_{(t+1)}$	$\boldsymbol{\gamma_{80}}$	**-0.057**	**[-0.086, -0.026]**
TB $_{(t)}$ → ActiveSI$_{(t+1)}$	$\boldsymbol{\gamma_{90}}$	**-0.051**	**[-0.074, -0.019]**
Interaction $_{(t)}$ → ActiveSI$_{(t+1)}$	$\boldsymbol{\gamma_{19}}$	**-0.052**	**[-0.094, -0.019]**
Cov(PB, TB)	**-**	**3.623**	**[2.804, 4.758]**
Study2 on PB$_{(t)}$ → ActiveSI$_{(t+1)}$	γ_{04}	-0.022	[-0.058, 0.017]
Study1 on PB$_{(t)}$ → ActiveSI$_{(t+1)}$	γ_{13}	-0.004	[-0.090, 0.046]
Study1 on TB$_{(t)}$ → ActiveSI$_{(t+1)}$	γ_{05}	-0.026	[-0.081, 0.015]
Study2 on TB$_{(t)}$ → ActiveSI$_{(t+1)}$	γ_{14}	0.005	[-0.031, 0.037]

Note: CI = Credible Interval. PB = Perceived Burdensomeness, TB = Thwarted Belongingness. Notation as per Figure 1. Bolded font denotes statistical significance.

Table 5. Autoregressive and cross-lagged coefficients across 0.5-hour time intervals in the relationship between active suicidal ideation (SI), perceived burdensomeness (PB), thwarted belongingness (TB), and the interaction of PB and TB on active SI

	Active SI		PB		TB		Interaction	
Time	**Est.**	**95% CI**	**Est.**	**95% CI**	**Est.**	**95% CI**	**Est.**	**95% CI**
0.5	0.6	[0.58, 0.61]	-0.017	[-0.026, -0.008]	-0.015	[-0.023, -0.006]	-0.015	[-0.028, -0.005]
1.0	0.36	[0.33, 0.38]	-0.021	[-0.031, -0.009]	-0.018	[-0.027, -0.007]	-0.019	[-0.034, -0.006]
1.5	0.21	[0.19, 0.23]	-0.018	[-0.028, -0.008]	-0.016	[-0.025, -0.007]	-0.017	[-0.031, -0.006]
2.0	0.13	[0.11, 0.14]	-0.015	[-0.022, -0.007]	-0.013	[-0.020, -0.005]	-0.013	[-0.025, -0.004]
2.5	0.075	[0.063, 0.087]	-0.011	[-0.017, -0.005]	-0.01	[-0.015, -0.004]	-0.01	[-0.019, -0.003]
3.0	0.045	[0.036, 0.053]	-0.008	[-0.012, -0.004]	-0.007	[-0.011, -0.003]	-0.007	[-0.014, -0.002]
3.5	0.027	[0.021, 0.033]	-0.006	[-0.009, -0.002]	-0.005	[-0.008, -0.002]	-0.005	[-0.010, -0.002]
4.0	0.016	[0.012, 0.020]	-0.004	[-0.006, -0.002]	-0.003	[-0.006, -0.001]	-0.003	[-0.007, -0.001]
4.5	0.01	[0.007, 0.012]	-0.003	[-0.004, -0.001]	-0.002	[-0.004, -0.001]	-0.002	[-0.005, -0.001]
5.0	0.006	[0.004, 0.008]	-0.002	[-0.003, -0.001]	-0.002	[-0.003, -0.001]	-0.002	[-0.003, 0.00]
5.5	0.003	[0.002, 0.005]	-0.001	[-0.002, 0.00]	-0.001	[-0.002, 0.00]	-0.001	[-0.002, 0.00]
6.0	0.002	[0.001, 0.003]	-0.001	[-0.001, 0.00]	-0.001	[-0.001, 0.00]	-0.001	[-0.001, 0.00]
6.5	0.001	[0.001, 0.002]	-0.001	[-0.001, 0.00]	0	[-0.001, 0.00]	0	[-0.001, 0.00]
7.0	0.001	[0.00, 0.001]	0	[-0.001, 0.00]	0	[-0.001, 0.00]	0	[-0.001, 0.00]
7.5	0	[0.00, 0.001]	0	[0.00, 0.00]	0	[0.00, 0.00]	0	[0.00, 0.00]
8.0	0	[0.00, 0.00]	0	[0.00, 0.00]	0	[0.00, 0.00]	0	[0.00, 0.00]

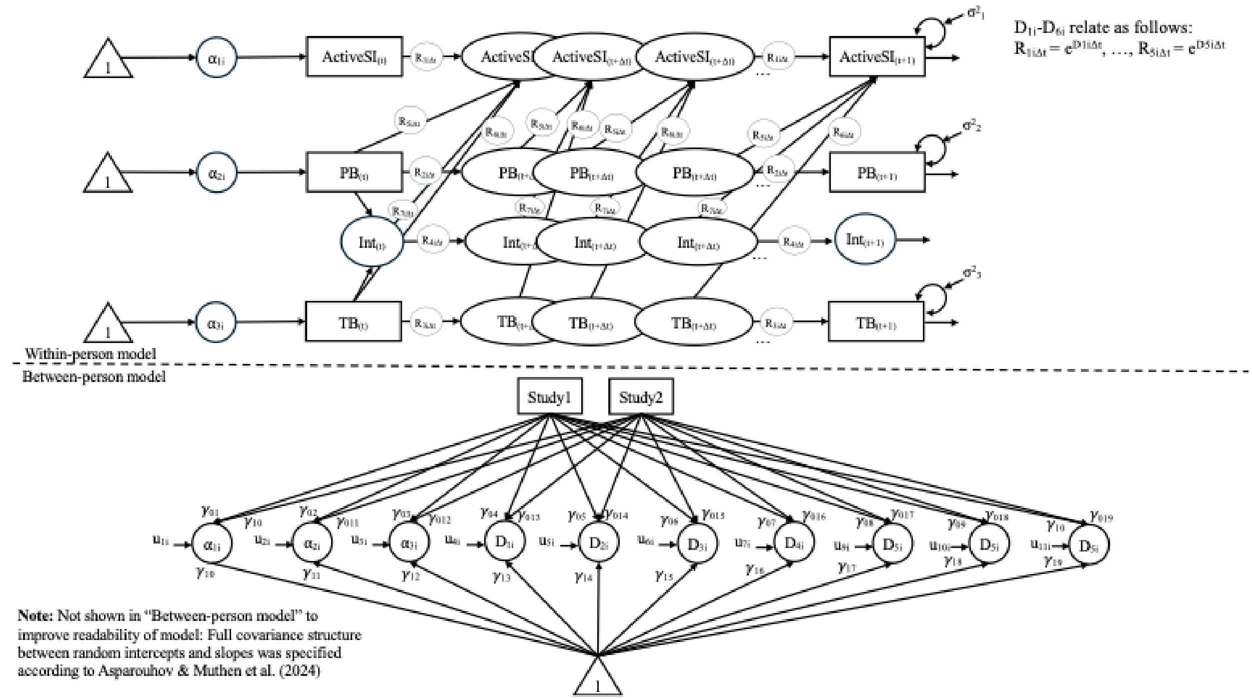

Figure 1. Path diagram depicting two-level continuous time residual dynamic structural equation model examining the relationship between perceived burdensomeness (PB), thwarted belongingness (TB), and their interaction, on active suicidal ideation (SI). Effect of study sample membership was examined at the between-person level, with sample 1 as the reference group

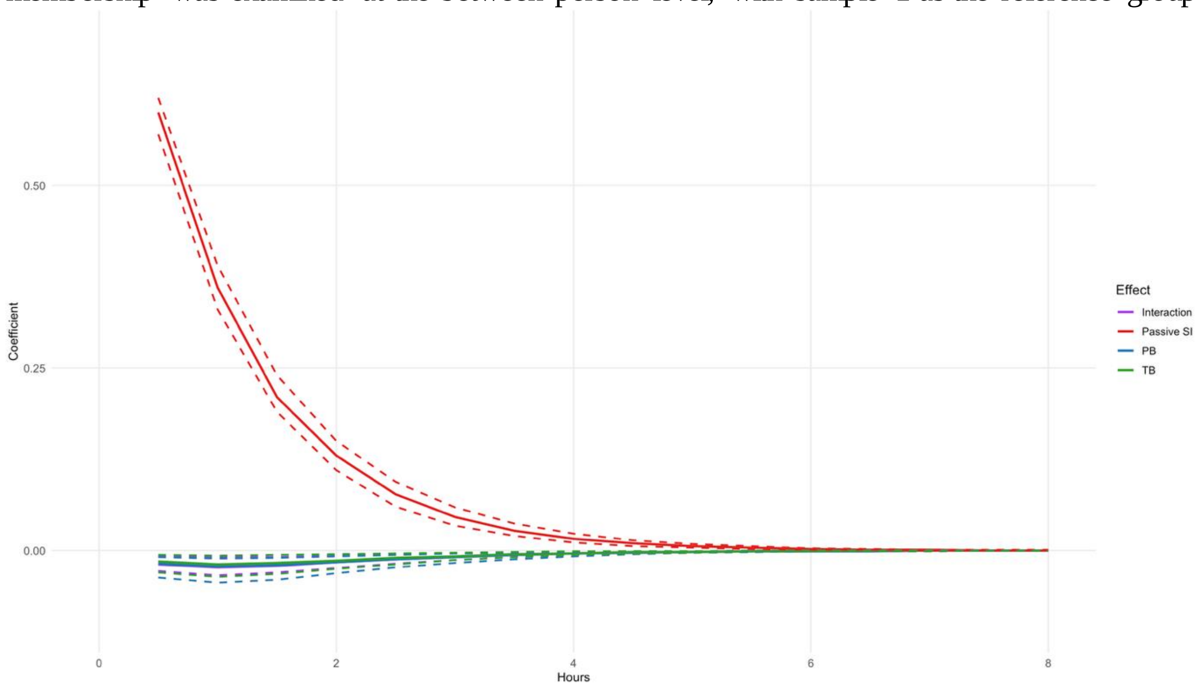

Figure 2. Effects of passive suicidal ideation (SI), perceived burdensomeness (PB), thwarted belongingness (TB), and the interaction of PB and TB on passive SI in continuous time. Solid lines represent the median of the posterior distribution of the effect and dashed lines represent the 95% credible intervals.

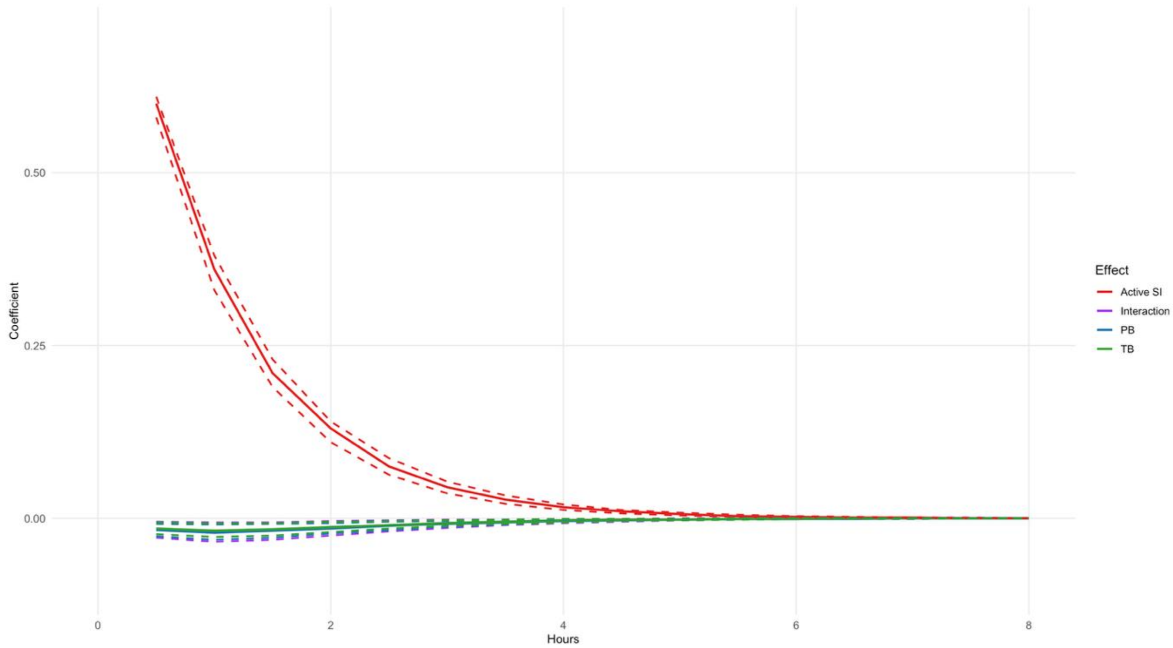

Figure 3. Effects of active suicidal ideation (SI), perceived burdensomeness (PB), and thwarted belongingness (TB), and the interaction of PB and on active SI in continuous time. Solid lines represent the median of the posterior distribution of the effect and dashed lines represent the 95% credible intervals.