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Suicide and Life-Threatening BEHAVIOR

ORIGINAL ARTICLE

Do people know how suicidal they will be? Understanding suicidal prospection

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Abstract

Introduction: Little research has been done on how people mentally simulate future suicidal thoughts and urges, a process we term *suicidal prospection*.

Methods: Participants were 94 adults with recent suicidal thoughts. Participants completed a 42-day real-time monitoring study and then a follow-up survey 28 days later. Each night, participants provided predictions for the severity of their suicidal thoughts the next day and ratings of the severity of suicidal thoughts over the past day. We measured three aspects of suicidal prospection: predicted levels of desire to kill self, urge to kill self, and intent to kill self. We generated prediction errors by subtracting participants' predictions of the severity of their suicidal thoughts from their experienced severity.

Results: Participants tended to overestimate (although the average magnitude was small and the modal error was zero) the severity of their future suicidal thoughts. The best fitting models suggested that participants used both their current suicidal thinking and previous predictions of their suicidal thinking to generate predictions of their future suicidal thinking. Finally, the average severity of predicted future suicidal thoughts predicted the number of days participants thought about suicide during the follow-up period.

Conclusions: This study highlights prospection as a psychological process to better understand suicidal thoughts and behaviors.

KEYWORDS
prospection, suicidal ideation, suicide

INTRODUCTION

The way that people think about the future influences what they decide to do today (Gilbert et al., 2002). One way that people think about the future is by making predictions about how they will feel, a process known as affective forecasting (Wilson & Gilbert, 2005). Prior work has shown that people often make inaccurate affective forecasts. Interestingly, people with certain psychiatric conditions have been shown to be even less accurate in forecasting some future states as compared with healthy control participants (Marroquín & Nolen-Hoeksema, 2015;

Mathersul & Ruscio, 2020). For example, in one study, people with clinical depression predicted that they would be significantly sadder in the future than they actually turned out to be (Zetsche et al., 2019). In this example, the difference between people's predicted sadness and their experienced sadness represents a "prediction error" (Niv & Schoenbaum, 2008). Given that future-oriented thinking, such as predictions about whether aversive emotions and circumstances will become more manageable, is thought to play an important role in decisions to attempt suicide (Baumeister, 1990; Dombrovski & Hallquist, 2022), differences in future-oriented thinking may be especially prevalent among people with suicidal thoughts and play an important role in maintaining them.

Affective forecasting and other forms of future-oriented thinking requires one to mentally represent future events and states (Szpunar et al., 2014), a process known as prospection. Research indicates that aspects of prospection are associated with both past and future suicidal thoughts (Cha et al., 2019; MacLeod et al., 2005; O'Connor et al., 2008, 2015; O'Connor & Williams, 2014; Pollak et al., 2021). For example, less positive future thinking has been associated with greater risk of future suicidal thinking (O'Connor et al., 2008). However, limited research to date has examined prospection of suicidal thoughts per se (Janis & Nock, 2008), for example by asking people to predict their own future suicidal thoughts. Suicidal thoughts include multiple related constructs (House et al., 2020; Jobes & Joiner, 2019). In the current paper, we focus on suicide thought-related motivational states, such as the desire and urge to kill oneself (Beck et al., 1979).

Prospection about suicidal desire and related motivational states may be associated with risk for suicidal thoughts and behaviors in numerous ways. Consider how predictions about future desire to kill oneself could affect suicidal thoughts and behavior (STB) risk factors, such as hopelessness and perceived entrapment. If a person predicts that their desire to kill themself tomorrow will increase relative to their desire today, this could produce/increase feelings of hopelessness and entrapment, thus increasing the likelihood of attempting suicide today (e.g., "if I'm going to want to kill myself even more tomorrow then maybe I should just get it over with now"). On the other hand, if a person predicts that their suicidal desire will decrease tomorrow, they may be more willing to tolerate current distress today, thus decreasing their risk of attempting suicide. Relatedly, one's accuracy in predicting suicide motivational states may be associated with STB risk. For instance, if a person predicts that their desire to kill themself will decrease tomorrow and then it actually does decrease, this accuracy could be a marker of a risk-buffering process as well as increase self-efficacy and the willingness to tolerate distress, thus reducing STB risk. Currently, we know of little research that has examined whether these predictions and their accuracy are related to STB risk.

New technologies, such as smartphones, have made it possible to collect the data required to examine such possibilities. With ecological momentary assessment (EMA; Shiffman et al., 2008), where participants complete real-time smartphone questionnaires for several days (Kleiman et al., 2023; Kleiman & Nock, 2018), researchers can now collect both participants predicted and actually experienced suicidal thoughts and motivational states. Such data allow researchers to examine participants' predictive accuracy and how this relates to risk of STB. In the current study, we used EMA to investigate how well people simulate future suicidal thoughts, a process we refer to as "suicidal prospection."

Here we explored three foundational questions about suicidal prospection. First, how accurate are people in predicting their next-day suicidal thinking? Second, what constructs predict participants' predictions of future suicidal thinking? Third, do predictions of future suicidal thoughts contribute to risk for continued suicidal thinking? Together, these questions have the potential to improve our understanding of suicide prospection and its potential role in STB.

METHODS

Participants

Participants were 94 adults with past week suicidal thoughts recruited through online advertisements. The demographics of the participants included in this analysis are provided in Table 1.

Procedure

The study procedure consisted of a baseline survey, 6-week real-time monitoring period, and a follow-up survey 4 weeks later (Coppersmith et al., 2023). For the real-time monitoring period, participants downloaded a smartphone-based survey app (MetricWire) that sent them three types of surveys over a 6-week period: daily surveys (1 time per day), momentary surveys (5 times per day), and burst surveys (6 times/h, 2 per day, 4 days/week). The present paper only used the daily surveys.

The daily survey was sent each day 1 h before participant's self-reported bedtime. The daily survey stayed open for 6 h. Participants were paid $0.25 for each completed survey and a $1 bonus for any day where they completed at least five surveys. The maximum amount participants

TABLE 1 Demographics.

Characteristic	
Age	
Mean (SD)	29.51 (9.33)
Sex assigned at birth	
Female	62
Male	31
Did not report	1
Gender identity	
Female	51
Male	33
Transgender	1
Genderqueer/non-binary/gender fluid	4
Did not report	1
Race	
White	60
Black/African-American	8
Asian	5
Native American	1
Middle Eastern or North African	1
Multiracial	20
Ethnicity	
Hispanic/Latino	13

could earn in the study was $190. In each momentary survey in the study, participants were provided with resources for treatment and safety (e.g., suicide prevention hotlines).

The follow-up survey was sent 28 days after participants completed the real-time monitoring period. The follow-up survey was sent 28 days after participants completed the real-time monitoring period. The purpose of this survey was to examine if data from the real-time monitoring period predicted later STBs.

All study procedures were approved by the Harvard University-Area. Institutional Review Board (IRB# 19–1819; "High-Resolution Real-Time Capture of Suicidal Thoughts and Urges"). Informed consent was obtained from all participants.

Daily measures

In the daily survey, various aspects of suicidal thinking were measured. The severity of suicidal thoughts was measured with items assessing the desire, urge, and intent to kill oneself. Each item was rated on a 0 (not at all) to 10 (very much) scale. Desire was defined for participants as "how much do you want to kill yourself." Urge was defined for participants "how much do you feel like actually killing yourself." Intent was defined for participants as "to what extent are you actually going to kill yourself." These items have been used in prior research (Bentley et al., 2021; Kleiman et al., 2017) and shown predictive validity of suicidal behavior (Wang et al., 2021).

We chose to focus on forecasts of these specific aspects of suicidal thinking rather than global predictions of suicidal thoughts for several reasons. First, past research suggests that participants can interpret single items of suicidal thinking in different ways (Gratch et al., 2022; Hom et al., 2016; Millner et al., 2015). The ambiguity of single items can increase measurement error and interfere with valid inference. Second, we wanted the measures to be consistent with a growing conceptualization of suicidal thinking as a multifaceted phenomenon (Jobes et al., 2024). Third, past research suggests that different aspects of suicidal thinking have different within-person frequencies and variability (Kleiman et al., 2017). Given all these factors, we chose to measure and model multiple aspects of suicidal thinking.

Participants were also asked to generate predictions about their expected levels of desire, urge, and intent to kill themselves the next day. For example, participants were asked, "Tomorrow, how strong do you think your desire to kill yourself will be?" Each item was rated on a 0 (not at all) to 10 (very much) scale.

Follow-up measures

In the follow-up survey participants were asked about suicidal thoughts and behaviors. Suicidal thinking was assessed with the item, "How many days in the past 28 days did you have suicidal thoughts?". Participants provided a numeric value ranging from 0 to 28. This type of item is consistent with measures used by our group in past research (Bentley et al., 2021) and similar to items used in some clinical risk assessment measures (Posner et al., 2011).

Analysis

How accurate are people in predicting their next-day suicidal thinking?

We computed a difference score between participant's prediction from the prior day and their current day suicidal thinking score (i.e., prediction error). We computed prediction errors for each of the three types of suicidal thoughts (desire, urge, and intent). We calculated descriptive statistics and generated graphs of the prediction errors. We also categorized the prediction errors into three categories: overestimation (i.e., positive prediction error), underestimation (i.e., negative prediction error), and no error (i.e., prediction error equals zero). We calculated percentages for the three categories.

What constructs predict participants' predictions of future suicidal thinking?

To better understand how people generate predictions of their suicidal thoughts, we drew from the prediction error literature (Den Ouden et al., 2012; Friston, 2005; Niv & Schoenbaum, 2008; Rescorla & Wagner, 1972). Formally, we define $y(t)$, current day rating and $p(t)$, previous day prediction. A simple error-driven updating rule moves the prediction in the direction towards the experienced rating:

$$p(t+1) = p(t) + w\left[y(t) - p(t)\right] \tag{1}$$

where, w is a learning rate parameter and $y(t)-p(t)$ is the prediction error. This is mathematically equivalent to the following linear regression model:

$$p(t+1) = \mathrm{b1} \times p(\mathrm{t}) + \mathrm{b2} \times y(t) \tag{2}$$

where, $\mathrm{b1} = 1 - \mathrm{b2}$. This formulation allows us to empirically test the hypothesis that people use prediction errors to update their predictions during suicidal prospection. Specifically, we compare this regression model (the prediction error model) to sub-models that include only $p(t)$ or $y(t)$. The second model uses just $y(t)$, participants' severity of suicidal thinking that day. This model is testing if participants use just their current suicidal thinking to generate predictions of their future suicidal thinking. We term this model the state model:

$$p(t+1) = w1 \times y(t) \tag{3}$$

In the third model, the predictor was just $p(t)$, participants' prediction of their suicidal thinking from the prior day. This model is testing if participants use their previous predictions of their suicidal thinking to generate predictions of their future suicidal thinking. We term this model the history model:

$$p(t+1) = w1 \times p(t) \tag{4}$$

All models were set up as mixed effects models and were run with the *brms* package (Bürkner, 2018). We specifically fit a Bayesian model with the *brms* package (Bürkner, 2018) because Bayesian models provide improved model convergence, more intuitive person specific parameters, and better accommodate the heterogeneous within-person variance (Williams et al., 2021). All models were estimated using Markov Chain Monte Carlo simulation, with four chains per model and 5000 iterations per chain, and non-informative prior distributions. The distribution of the model was ordinal with a flexible threshold (Bürkner & Vuorre, 2019) due to the nature of the suicidal thinking variables. We compared the models with the model performance metrics of Bayesian leave-one-out cross-validation (LOO) and widely applicable information criterion (WAIC), which are widely used in Bayesian statistics (Vehtari et al., 2017). Lower LOO and WAIC values correspond to better model performance. We used the R package performance (Lüdecke et al., 2021) to compute LOO and WAIC.

In addition to fit statistics, we also generated a predictive check plot for each type of suicidal thinking. For the plots, we visualized prediction errors on the x-axis and predictions for the severity of suicidal thinking on the y-axis. We categorized prediction errors into three categories: −5 to −1, 0, 1 to 5. The categories were generated based on the frequency of the prediction errors. For example, we did not include predictions errors greater than −5 or 5 due to the low frequency of these errors. We also categorized severity of suicidal thinking that day (11-point scale) into high and low based on the overall distribution of responses in the following way: low was a rating of 0, 1, 2, and 3 and high was a rating of 4 or higher. We then plotted the means and standard errors within each combination of prediction error category and prediction severity category by category of suicidal thinking that day (low and high). To provide support for the prediction error model, we would expect that the relationship between prediction error and predictions of future suicidal thinking should be offset by category of suicidal thinking that day. In Figure 1 we visualize what support for the prediction error mode would look like.

Do predictions of future suicidal thoughts contribute to risk for continued suicidal thinking?

We sought to understand the relationship between predictions of suicidal thinking and future suicidal thoughts over longer timescales. We specifically sought to predict the number of days with suicidal thoughts in the 4-week follow-up period. We conceptualized this analysis as an approach to predictive validity of the real-time data. Suicidal thoughts in a 4-week period was selected because we viewed it as short-term clinical outcome of interest that it is used in suicide risk assessments (e.g., Posner et al., 2011). While retrospective reports of suicidal thoughts over weeks have significant limitations (Gratch et al., 2021) especially for single items (Gratch et al., 2022),

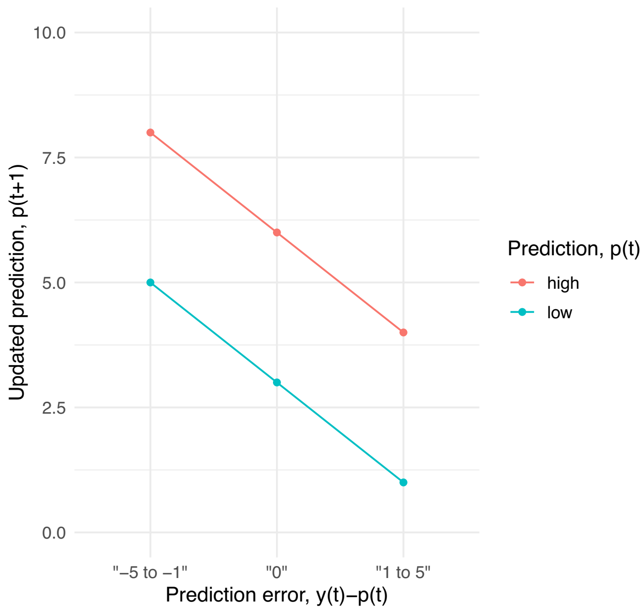

FIGURE 1 Hypothesized association between prediction error, updated predictions, and current predictions.

they are still often used in risk assessments (Rudd, 2023), and clinical research (Batterham et al., 2015).

We tested three types of predictors of future suicidal thoughts: mean severity, mean accuracy, and mean absolute value accuracy. For the mean severity models, we computed mean predictions for suicidal desire, urge, and intent for each participant. For the mean accuracy models, we computed mean difference scores between participants' prediction from the prior day and experienced severity for suicidal desire, urge, and intent for each participant (i.e., prediction errors). For the absolute value models, we computed the absolute value of mean accuracy for each type of suicidal thinking. For all models, we then tested how these mean forecasts predicted suicidal thoughts in the follow-up period. We specifically fit a Bayesian regression model with a beta distribution where the number of days with suicidal thoughts in the follow-up period (a proportion variable) was the outcome. Results were interpreted by summarizing the 95% highest density interval (HDI) around the median beta values. To aid in interpretation of the models, we generated marginal effects plots using the *ggeffects* package (Lüdecke, 2018).

RESULTS

The total number of daily surveys submitted in the study was 2304. The number of daily surveys with consecutive surveys to compute prediction errors was 1822. The average number of daily surveys per participant was 19 ($SD=14$). The number of participants with both daily data and follow-up data was 53.

How accurate are people in predicting their next-day suicidal thinking?

The distributions of prediction error for the three types of suicidal thinking are shown in Figure 2. For all three types of suicidal thinking, the mean prediction error was positive (Table 2). This suggests that on average, participants overestimated the severity of their future suicidal thinking, although the average magnitude of error was small. More specifically, the percentage of days on which participants overestimated their future suicidal thinking was 37.3% (desire), 33.9% (urge), and 27.7% (intent). The percentage of days on which participants underestimated their suicidal thinking was 27.3% (desire), 24.2% (urge), and 15.2% (intent), and the percentage of days when participants were accurate in their predictions was 35.4% (desire), 41.9% (urge), and 57.1% (intent). To test if the number of days between error categories were distinct from one another, we ran a series of chi-square tests to compare overestimation, underestimation, and accurate predictions across desire, urge, and intent. We specifically ran three chi-square tests (one for each type of suicidal thought) to test if the proportion of error categories were distinct. For desire, we found that the proportions of the types of error were significantly different from even proportions (X^2 (2, $N=1822$) $=30.96$, $p<0.001$). The biggest difference between the expected (33.3%) and observed proportions was underestimation (27.3%). For urge, we found that the proportions of the types of error were significantly different from even proportions (X^2 (2, $N=1820$) $=85.18$, $p<0.001$). The biggest difference between the expected (33.3%) and observed proportions was underestimation (24.2%). For intent, we found that the proportions of the types of error were significantly different from even proportions (X^2 (2, $N=1822$) $=506.91$, $p<0.001$). The biggest difference between the expected (33.3%) and observed proportions was accurate predictions (57.1%).

What constructs predict participants' predictions of future suicidal thinking?

Across all three types of suicidal thinking, the model that included the severity of suicidal thinking that day and participants' prediction of their suicidal thinking from the prior day (prediction error model) had the best model performance. Specifically, the LOOIC and WAIC were lowest for all three outcome measures (Table 3). The predictive check plots (Figure 3) also provided qualitative support for the prediction error models. This suggests that people may use prediction errors to update their predictions of suicidal thinking.

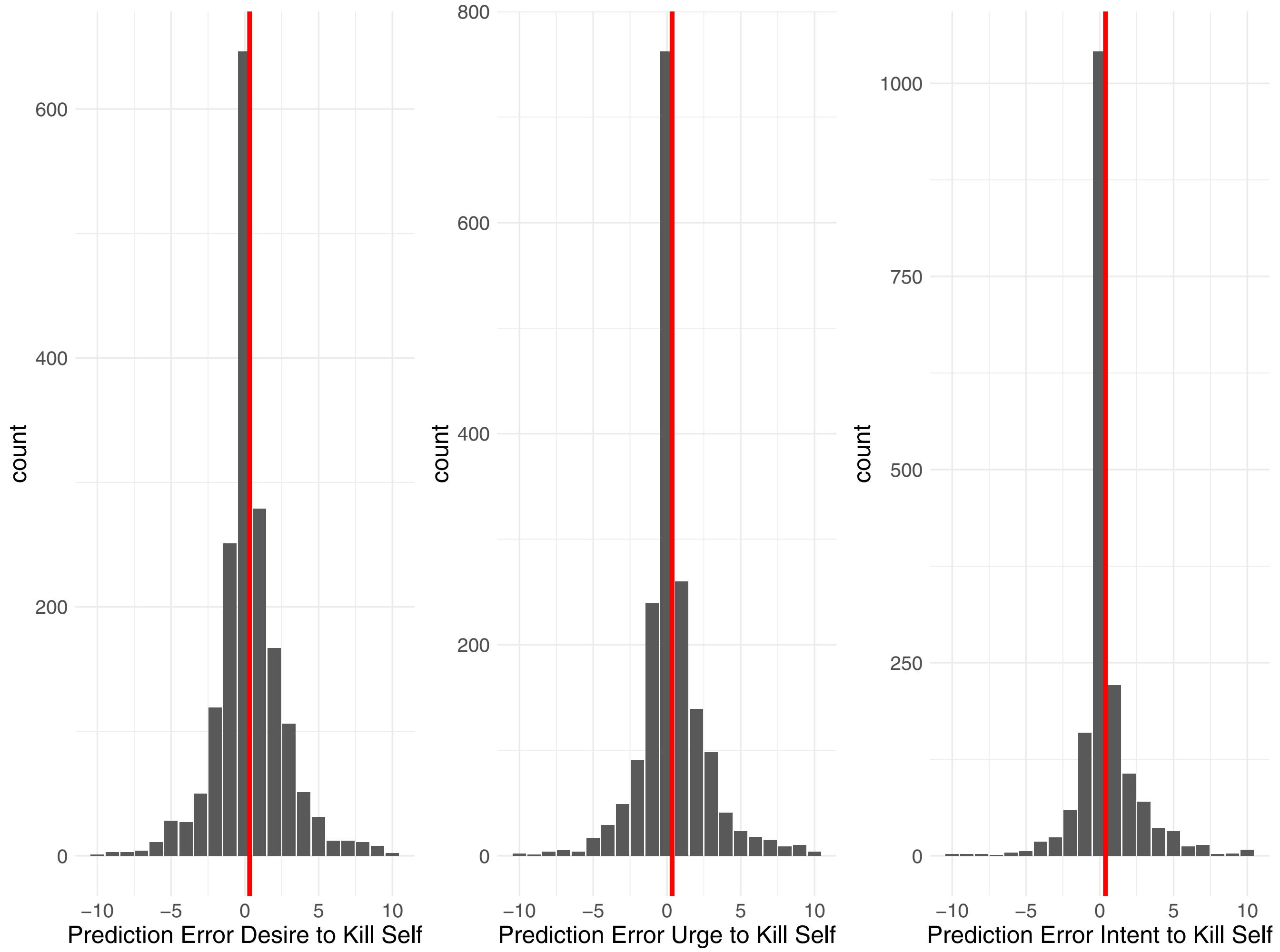

FIGURE 2 The distributions of prediction errors of three different types of suicidal thinking. Red vertical line represents the mean of the prediction errors.

TABLE 2 Descriptive statistics of suicidal thinking prediction errors.

Population and individual means and standard deviations					
Variable	**M**	**SD**	**iM (range)**	**iSD (range)**	**ICC**
Desire PE	0.32	2.26	0.31 (−7.0 to 4.7)	1.87 (0–4.2)	0.16
Urge PE	0.35	2.19	0.34 (−8.0 to 4.3)	1.61 (0–8.5)	0.17
Intent PE	0.39	1.87	0.33 (−4.0 to 3)	1.2 (0–4.9)	0.12

Note: ICC was computed from a null random intercept mixed-effects model.

Abbreviations: ICC, intraclass correlation; iM, mean of individual level means; iSD, standard deviation of individual level standard deviation; M, population mean of raw data; PE, prediction errors; SD, population standard deviation of raw data.

Do predictions of future suicidal thoughts contribute to risk for continued suicidal thinking?

Mean severity of predictions for desire (median = 0.36, 95% HDI = 0.22–0.48) and urge (median = 0.22, 95% HDI = 0.09–0.34) predicted the number of days with suicidal thinking in the month after the real-time monitoring period. More severe predictions of future desires and urges were associated with more days of suicidal thinking (Figure 4). Mean severity of predictions for intent (median = 0.13, 95% HDI = −0.02 to 0.27) did not predict the number of days with suicidal thinking.

Mean accuracy of prediction errors for desire (median = 0.11, 95% HDI = −0.21 to 0.45), urge (median = 0.16, 95% HDI = −0.17 to 0.49), and intent (median = 0.05, 95% HDI = −0.35 to 0.49) did not predict the number of days with suicidal thinking. Mean absolute value of accuracy for prediction errors for desire (median = 0.27, 95% HDI = −0.11 to 0.69), urge (median = 0.38, 95% HDI = −0.01 to 0.82), and intent (median = 0.46, 95% HDI = −0.05 to 0.98) did not predict the number of days with suicidal thinking.

TABLE 3 Model performance across three different types of models for three different types of suicidal thinking.

Model	LOO	WAIC
Desire State Model	5466.671	5463.670
Desire History Model	5746.550	5743.440
Desire Prediction Error Model	5442.315	5440.574
Urge State Model	5015.573	5013.004
Urge History Model	5270.609	5267.046
Urge Prediction Error Model	4998.609	4996.912
Intent State Model	4070.436	4068.453
Intent History Model	4239.534	4234.255
Intent Prediction Error Model	4052.009	4050.638

Abbreviations: LOO, Bayesian leave-one-out cross-validation; WAIC, widely applicable information criterion.

DISCUSSION

The current study sought to explore foundational questions about suicidal prospection. There were three key findings. First, on average people overestimated the severity of future suicidal thinking, although the magnitude of error was small and the modal error was zero. Second, when generating predictions of future suicidal thinking, the best fitting statistical models suggest that people used both their current suicidal thinking and past predictions. Third, the severity of predictions of future suicidal thinking was associated with the frequency of future suicidal thinking. Each of these findings warrants further comment.

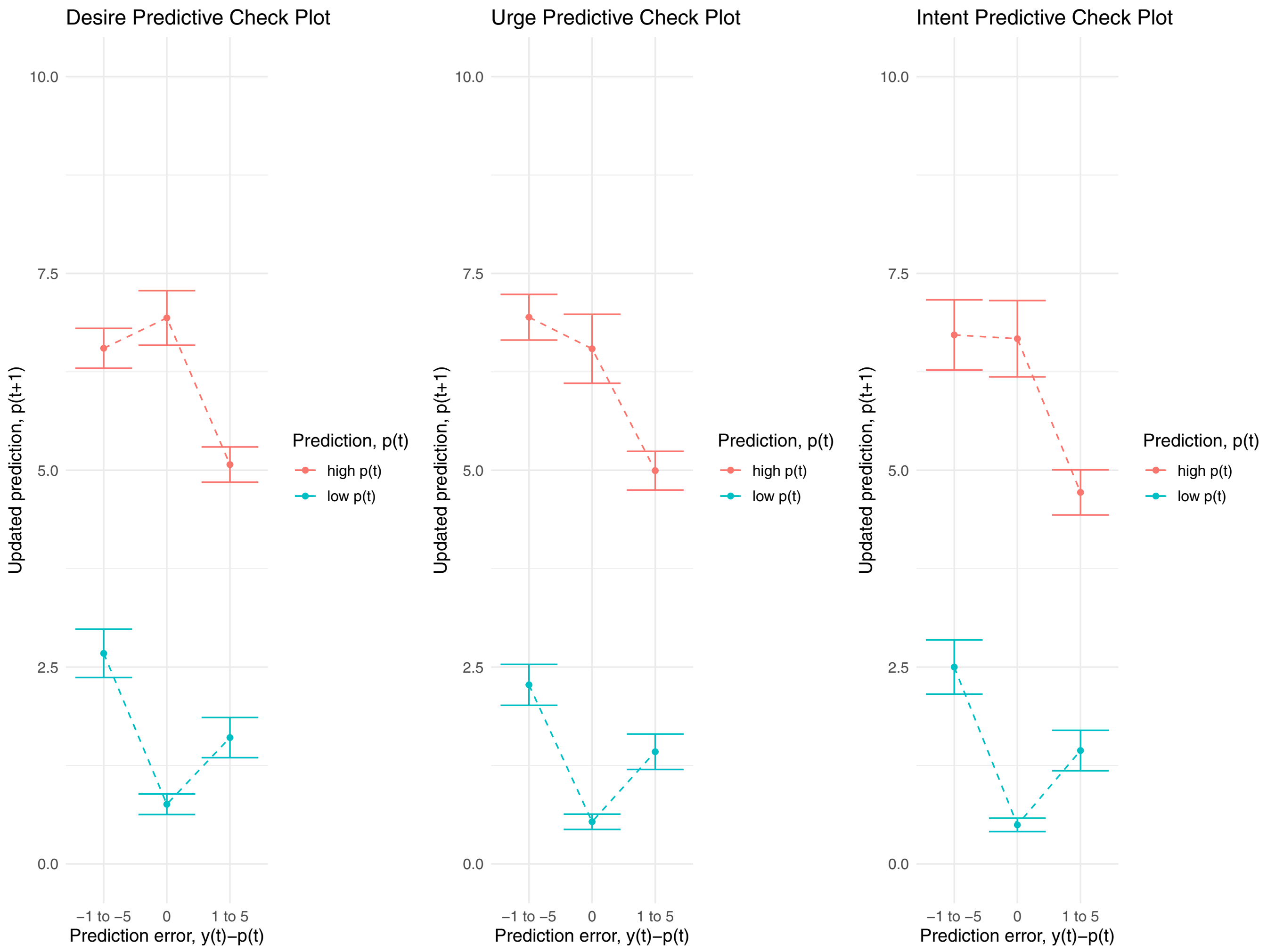

FIGURE 3 Association between prediction error and updated prediction by level of current prediction of three different types of suicidal thinking. The error bars are bootstrapped 95% confidence intervals around the mean.

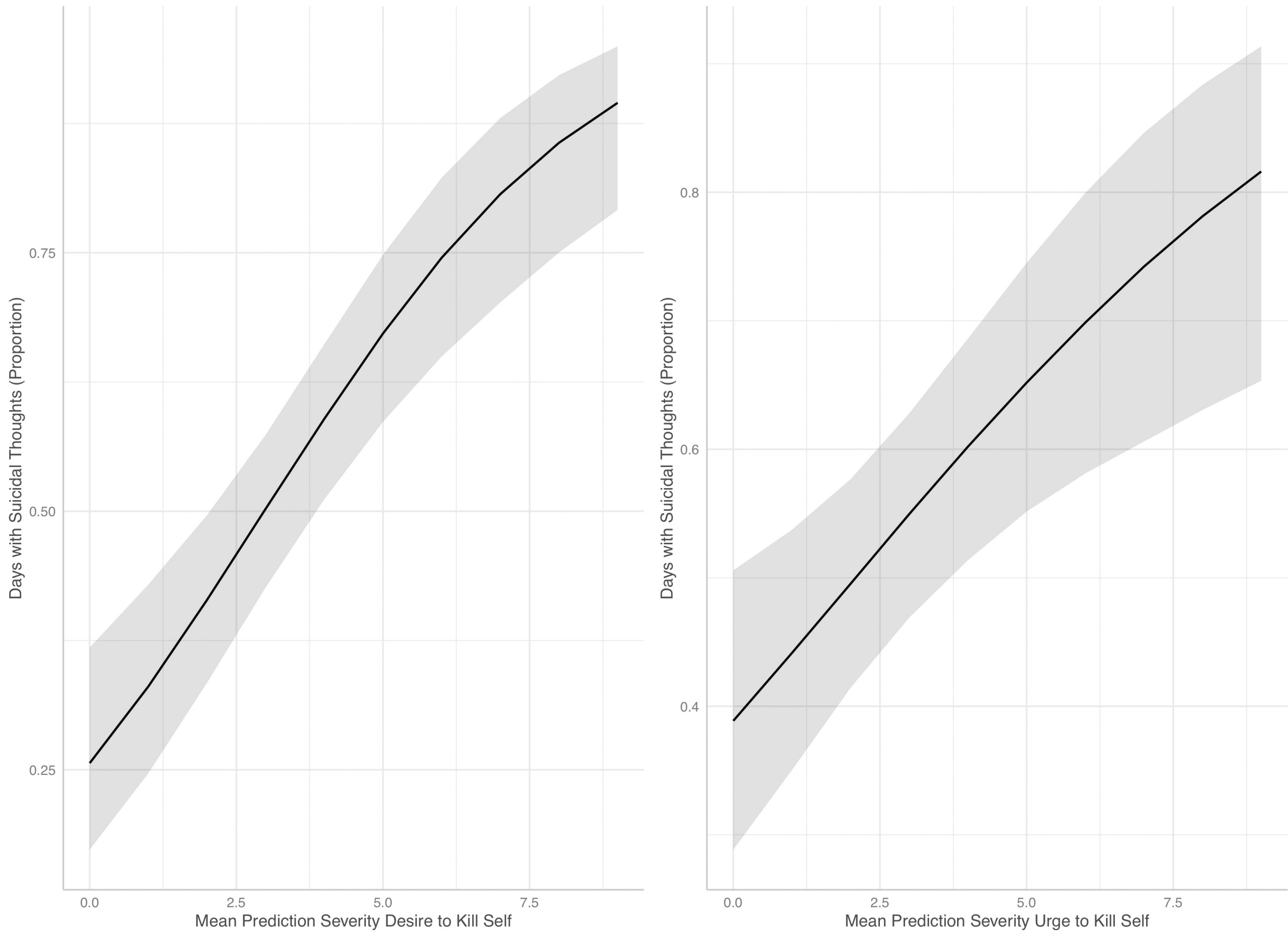

FIGURE 4 Association between mean severity of predictions of suicidal thinking and number of days with suicidal thoughts in the follow-up survey.

People's predictions of their own suicidal thoughts are included in numerous clinical assessments (Fox et al., 2020) and could be key in people's own decision making around suicidal behavior, but almost no prior work has examined the actual accuracy of these predictions. In this study, we found that when viewing error dimensionally on average people overestimated the severity of their suicidal thoughts. These findings align with previous research among people with clinical depression that found that people expected to be sadder than they actually experienced (Zetsche et al., 2019). There is important nuance in the findings of the current study. The modal error for three types of suicidal thoughts was zero and when viewing error categorically, the most common category for two of the three types of suicidal thinking was accurate prediction. This could be somewhat driven by consecutive days with no suicidal thoughts. Our sample and other real-time monitoring of suicidal thoughts show zero inflation of suicidal thinking (Ammerman & Law, 2022). One implication; however, of the high prevalence of no error would be that people are updating their predictions of suicidal thinking correctly. Another important nuance in accuracy is that the level of error varied by type of suicidal thinking. Average error was highest for desire to kill self and lowest for intent to kill self. The prevalence of the no error category was especially high for intent to kill self. This suggests it may be harder for people to predict how much they will want to kill themselves than their intent to kill themselves.

Better understanding how people generate predictions of suicidal thinking may provide both new insights into the suicidal mind and the identification of treatment targets for suicidal thoughts. In this study, we specifically found that people use both their current suicidal thinking and past predictions. These findings suggest people may use prediction errors to update their predictions of suicidal thinking. Prediction errors have been implicated in different types of psychopathology (Paulus et al., 2019; Yaple et al., 2021; Zald & Treadway, 2017) related to suicidal thoughts and behaviors. Less work has directly examined prediction errors and their role in learning among individuals with suicidal thoughts and behaviors (Dombrovski et al., 2013; Dombrovski & Hallquist, 2017). Our findings suggest that a prediction error framework may be especially helpful for understanding suicidal thinking and possibly suicidal behavior. More broadly, our findings suggest that people may be systematic rather than random in how they generate future predictions of their own suicidal thoughts. This finding is especially striking in our study because people were not provided with feedback about their prior predictions and the delay between prediction and rating of experience was rather long (i.e., 1 day). These findings are promising for building more complex computational models (Daw, 2011) of this psychological process.

A key step in identifying a psychological process involved in suicidal thoughts and behaviors is testing if that process predicts future suicidal thoughts and behaviors. We found that the average severity of predictions of future suicidal thinking was associated with the frequency of future suicidal thinking 1 month later. Average error in predictions; however, was not associated with the frequency of future suicidal thinking. These results suggest that the extent to which people believe they will think about suicide is more associated with risk than the accuracy of those beliefs. This finding on the importance of beliefs of future suicidal thinking is consistent with prior research on hopelessness and STBs (Ribeiro et al., 2018). These findings also align with prior work showing less positive future thinking is associated with greater risk of future suicidal thinking (O'Connor et al., 2008). However, an important possibility is that this finding is driven by a bias to overestimate. The accuracy of participants' retrospective reports of suicidal thoughts is not known (Gratch et al., 2021). It is therefore possible that the association between predictions of next day suicidal thoughts and the frequency of suicidal thoughts in the past 4 weeks could be driven by a general overestimation bias. That is, that individuals more likely to overestimate that they will experience future suicidal thoughts may also be more likely to overestimate that they have experience more suicidal thoughts when retrospecting. Combining momentary data with retrospective data over shorter timescales (e.g., daily, weekly) may be one path towards better addressing this measurement issue.

The present study represents a significant advancement in describing and understanding suicidal prospection, but still has notable limitations. First, the study only examined predictions about suicide thought-related motivational states. It is unknown to what extent predictions about suicidal thoughts provide unique information beyond general predictions of negative affect. Comparing future thinking about suicide with global future thinking would be useful in the future. Another limitation is that depressive symptoms were not assessed. Given prior research on negative affective forecasting and depression (Rizeq, 2024; Wenze et al., 2012), this information could be useful in future work for discerning the contributions of depression to inaccuracies in suicidal prospection. Another limitation is that participants were not provided with any direct feedback and there was a relatively long time lag between prediction and re-rating of experiences. Providing direct feedback to participants about past predictions in the future may be one way to better understand if people update predictions. Finally, the follow-up assessment used a single item and could be affected by retrospective bias.

There are several important future directions that could build on this work. First, one could examine the metacognition of predictions (Hoven et al., 2019; Rouault et al., 2018). Confidence of predictions of future suicidal thoughts could be an important parameter for better understanding individual differences in suicidal prospection. Second, the current study only examined how suicidal prospection was associated with future suicidal thoughts, but clinicians are often most concerned about risk of future suicidal behavior. Future work with larger samples could examine if individual differences in suicidal prospection are associated with risk of suicidal behavior. Finally, future work could systematically show participants previous predictions to promote learning. Given a core aspect of cognitive behavioral therapy is testing expectations against experiences, it's possible that this type of feedback could be therapeutic. For example, if a person is consistently overestimating their future suicidal thoughts, providing that feedback could be helpful. Testing the effects of providing feedback on both learning and overall symptoms could be a useful future direction.

The decision to end one's own life is one of the most consequential decisions a human can make. The current paper sought to describe what could be a core psychological process in this decision, suicidal prospection. Better measuring and understanding this process could 1 day help advance the prevention of suicidal behaviors.

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CONFLICT OF INTEREST STATEMENT

Dr. Nock receives publication royalties from Macmillan, Pearson, and UpToDate. He has been a paid consultant in the past 3 years for Apple, Microsoft Corporation, and COMPASS Pathways, and for legal cases regarding deaths by suicide. He has stock options in Cerebral Inc. and is an unpaid scientific advisor for Empatica, Koko, and TalkLife. Dr. Kleiman has been a paid consultant in the past 3 years for Boehringer Ingelheim Pharmaceuticals.

DATA AVAILABILITY STATEMENT

Data is available from the corresponding author upon request.

ETHICS STATEMENT

All study procedures were approved by the Harvard University-Area Institutional Review Board. Informed consent was obtained from all participants.

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