Title
Idiographic prediction of short-term suicidal ideation

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Publication Date
2021

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by

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A dissertation submitted in partial satisfaction of the requirements for the degree of

Doctor of Philosophy

in

Psychology

in the

Graduate Division

of the

University of California, Berkeley

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Summer 2021

Abstract

Despite decades-long efforts devoted to enhancing the understanding, prediction, and prevention of death by suicide, suicide rates have continued to rise both in the United States specifically and in many countries worldwide. Although the advent of machine learning techniques has improved our ability to predict suicidal thoughts and behaviors (STBs), few studies have focused on the short-term prediction of these phenomena. Furthermore, the increasing recognition of the individual- and time-varying nature of STBs necessitates the use of individualized predictive models to detect short-term STBs person-by-person with greater precision. In the present study, I used ecological momentary assessment (EMA) data collection methods with idiographic analytic approaches to better describe and predict short-term suicidal ideation and its risk factors on a person-by-person basis. Key factors measured via these EMA methods included variables related to several prominent theories of suicidal behavior, including the interpersonal, hopelessness, and three-step theories of suicide, and key emotions previously demonstrated to predict suicidal thinking. I also employed a series of machine learning techniques to examine whether these approaches could enhance individualized prediction models for short-term suicidal ideation. With a largely female sample of ten (N = 10) individuals that reported at least one suicide attempt in the past year or reported intense ideation for more days than not over the past month. These individuals were also largely Caucasian and identified as sexual minorities. Results demonstrated that short-term suicidal ideation and its risk factors displayed considerable variability over time. Further, results also indicate that individualized models can produce reliable predictions of short-term suicidal ideation—and that these predictions could be further improved by employing machine learning techniques. Furthermore, both auto-regressive and machine learning-based models, on average, outperformed individualized models derived from the interpersonal, hopelessness, and three-step theory of suicide. Taken together, the present findings may represent a first step toward developing a more precise and individualized approach for understanding and preventing death by suicide through better modeling and predicting short-term suicidal ideation and its risk factors. Specifically, these findings suggest that the combination of EMA methodology, idiographic modeling, and machine learning can be used to effectively identify sets of risk factors related to promiment theories of suicide and past research to predict short-term suicidal ideation person-by-person with high precision.

Dedication

First and foremost, I would like to dedicate this dissertation to my mother and father, Carrie and Wendall Reeves. Thank you for your endless support and love over the years as I pursued my wildest dreams, even when you couldn't quite understand what they were and why. I am grateful and so very proud to be your son. I would also like to dedicate this dissertation to those that came before me who fought tirelessly against racism and inequity so that I could have this opportunity – it has been one the greatest privileges of my life to do what so many Black and brown folk before me have been denied by a racist and white supremacist society. I am grateful to be a smart part of this legacy of resistance and pursuit of justice at any cost. It is my deepest hope that my contributions, as yours did, help pave the road for those who come after. Finally, last, but not least, I would also like to dedicate this dissertation to Dr. Bryan Karazsia. Your encouragement helped me believe in myself and gave me my first true sense of belonging in this field. It helped propel me to heights I never imagined I would reach and, for that, I am forever grateful.

Preventing death by suicide is a top public health priority worldwide (World Health Organization, 2014). In the United States alone, suicide is a leading cause of death across all age groups (Centers for Disease Control and Prevention, 2016). Furthermore, despite a brief period of decline, the age-adjusted US suicide rate has increased by 24% over the past two decades (Curtin, Warner, & Hedegaard, 2016). To make matters worse, this rate has nearly tripled among adolescents and young adults (Curtin & Heron, 2019). Taken together, these trends have added further urgency to decades-long efforts to improve our understanding, prediction, and prevention of suicide (Nock, 2016). To curb these trends, the Research Prioritization Task Force, a public-private partnership between the National Institute of Mental Health and the National Action Alliance for Suicide Prevention, identified several research gaps that must be prioritized to reverse these rising rates (National Alliance for Suicide Prevention: Research Prioritzation Task Force, 2014).

The Research Prioritization Task Force strategic plan identifies improving our understanding and prediction of short-term, or imminent, risk for suicide as a critical area for advancement (National Alliance for Suicide Prevention: Research Prioritzation Task Force, 2014). Short-term risk for suicide refers to risk for suicidal thoughts or behaviors (STBs) over the span of several minutes, hours, or days rather than over traditionally longer time periods. To date, an overwhelming majority of research has focused on factors that confer 12-month and lifetime risk for suicide (Franklin et al., 2017), resulting in a relative dearth of knowledge about factors that confer increased suicide risk over far shorter periods of time (termed "short-term risk factors"). This knowledge gap is problematic for two major reasons. First, previous research suggests that there may be important differences in risk conferred by long- versus short-term risk factors (Glenn & Nock, 2014). Whereas long-term risk factors may indicate *who* is at risk for suicide in their lifetime or the next year, short-term risk factors may instead indicate *when* a given individual is likely to engage in suicidal behavior in the near future. Thus, although data on long-term risk factors for suicide are critical for guiding primary prevention efforts, this knowledge has limited utility for clinical decisions on whether an at-risk individual is at imminent risk for suicide (Glenn & Nock, 2014; Rudd et al., 2006).

Second, precisely *how* long-term risk factors confer risk for future suicidal behavior is unclear. The reason is that long-term risk factors are by nature distal from the associated outcome of interest and generally static over time (e.g., biological sex; history of trauma). Given the historical emphasis on long-term risk factors in extant suicide research noted above (Franklin et al., 2017), there is little information on intermediary mechanisms that link the occurrence of these risk factors to future suicidal behavior. This problem is compounded by evidence that even widely known long-term risk factors for suicide only weakly predict future suicidal behavior (Nock, 2016). For instance, although past suicide attempts have reliably been shown to confer risk for future suicide behavior (Joiner et al., 2005), an estimated 60% of previous attempters will not make another attempt in their lifetime (Nock, Borges, & Ono, 2012).

One possibility is that long-term risk factors for suicide exert their effects *through* short-term risk factors for suicide. That is, it may be that an initial suicide attempt triggers several intermediary mechanisms that increase the likelihood individuals will make a future attempt. If true, then the identification of these intermediary mechanisms could potentially help clinicians target these processes with prevention strategies to reduce suicide risk. Thus, taken together, improving our understanding of short-term risk for suicide is critical. Closing this gap may both (a) provide clinicians with actionable information to better assist at-risk patients and (b) highlight proximal mechanisms that lead to increased risk for future suicidal behavior.

To date, advancements in our understanding of short-term suicide risk have largely been made by describing the basic properties of suicidal ideation and its risk factors as these occur naturally over brief periods. These basic properties refer to how suicidal ideation and its risk factors occur, vary, and persist over these brief time periods. These studies are an important starting point, given that suicidal ideation is a putative precondition for other suicidal behaviors and may therefore serve as a key early intervention target (Bagge, Littlefield, Conner, Schumacher, & Lee, 2014; Husky et al., 2017; Kessler et al., 1999; Nock et al., 2008). Further, through the increased accessibility of mobile technology, the few studies in this area have revealed novel information about the dynamic properties short-term suicidal ideation and its risk factors display over short periods of time (Kleiman & Nock, 2018).

For instance, previous research has demonstrated that, rather than being a relatively stable process, suicidal ideation tends to vary considerably over short periods of time, changing drastically in its severity from hour to hour (Hallensleben et al., 2018; Kleiman et al., 2017). This finding corroborates previous research from studies using coarser retrospective designs and once-per-day ratings to examine the dynamics of suicidal ideation in at-risk individuals (Bagge et al., 2014; Ben-Zeev, Young, & Depp, 2012; Witte, Fitzpatrick, Joiner, & Schmidt, 2005; Witte, Fitzpatrick, Warren, Schatschneider, & Schmidt, 2006). Furthermore, suicidal ideation also tends to be episodic, with almost half of real-time assessments of suicidal ideation sampled on an hourly basis having a zero response, indicating the absence of suicidal ideation at the precise moment of assessment—but its subsequent return quite soon (Ben-Zeev et al., 2012; Kleiman et al., 2017). Importantly, these studies have also provided evidence for the acceptability, feasibility, and validity of using real-time monitoring methods to assess suicidal behaviors, such as suicidal ideation, in high-risk populations (Husky et al., 2014; Kleiman & Nock, 2018; Kleiman et al., 2017)

These studies have also revealed important information about the short-term properties of well-known risk factors for suicide—including those risk factors from prominent theories of suicide, including the interpersonal (Van Orden et al., 2010) and hopelessness (Beck, Kovacs, & Weissman, 1975) theories of suicide. Briefly, the interpersonal theory of suicide proposes that suicide ideation is caused by relatively stable perceptions of burdensomeness and thwarted belongingness (Van Orden et al., 2010). The hopelessness theory of suicide instead argues that suicidal ideation is caused by fairly stable feelings of hopelessness about one's future (Beck et al., 1975). Similar to suicidal ideation, previous research has found that even putatively stable phenomena, such as loneliness, burdensomeness, and hopelessness, instead exhibit considerable hourly variability (Kleiman et al., 2017). Further, while this has not been formally studied using EMA methods, the three-step theory of suicide makes similar assumptions about risk factors for suicide ideation. Specifically, the three-step theory of suicide assumes that stable feelings of psychological pain and hopelessness cause suicide ideation, which is then further escalated in the presence of stable feelings of lack of connectedness to life (Klonsky & May, 2015). Thus, though we lack empirical data on these how processes unfold over brief periods of time, past research on other risk factors suggests these may similarly be highly variable from hour to hour (Kleiman et al., 2017).

In addition, previous studies have also demonstrated that these risk factors may differentially relate to specific aspects of suicidal ideation. For instance, whereas Kleiman et al. (2017) found that hopelessness and loneliness were each correlated with suicidal ideation and predicted future episodes, these experiences did not predict time-lagged changes in suicidal ideation. Instead, other affective states, such as sadness and anxiousness, have been shown to predict these changes (Husky et al., 2017). This distinction may be especially important to highlight, as the factors that predict changes in short-term suicidal ideation may be key drivers of change to be targeted in real-time intervention applications. Moreover, this distinction highlights that short-term risk factors for suicidal ideation may be non-trivially specific to the particular feature of suicidal ideation of interest.

There are several key extensions of extant research that are likely to improve our understanding of short-term suicidal ideation and its risk factors. First, in recent years, researchers have become increasingly concerned about the low rates of replicability of even well-known findings in psychological science. In a landmark attempt at reproducing results from one-hundred experiments in the psychological literature, researchers from the Open Science Collaboration (2015) found that only about one-third to one-half of original findings were successfully replicated. To make matters worse, even those with evidence for replication typically revealed smaller effect sizes than the original reports. This lack of reproducibility calls into question the validity of findings across psychological science and may have dire consequences in the context of research on STBs. Thus, in line with larger efforts to address this problem (Open Science Collaboration, 2015), the importance of engaging in replication efforts within suicide research specifically and psychological science generally cannot be overstated.

As well, these efforts may be particularly relevant for recent research on the basic properties of short-term suicidal ideation and its risk factors. Specifically, Kagan (2007) suggested that the slow progress of psychological science relative to other sciences is partly because psychological scientists have historically lacked the ability to intensively study psychological phenomena as these occur in their natural environment. This issue has been particularly challenging for suicide research due to the low base-rate of STBs. Although the rise of mobile technology and ecological momentary assessment (EMA) designs has begun to remedy this issue (Kleiman & Nock, 2018), the historical absence of these approaches has led to a proliferation of extant theories on suicide supported by rarely examined assumptions about the basic nature of STBs and their associated risk factors (Beck et al., 1975; Van Orden et al., 2010). As such, especially in this burgeoning period of research on short-term suicidal ideation, replicating recent findings on the basic properties of short-term suicidal ideation and its risk factors over short spans of time is of vital importance.

Second, in addition to reinforcing findings describing the basic properities of short-term suicidal ideation and its risk factors, a renewed focus on idiographic approaches should further improve our understanding and ability to predict STBs (Barlow & Nock, 2009; Fisher, 2015; Wright & Woods, 2020). The idiographic approach comprises a range of individualized assessment and statistical analysis techniques united by the intensive study of a single individual over time. Over the past decade, the highly heterogenous and idiosyncratic nature of psychological phenomena has been increasingly recognized (Fisher, Medaglia, & Jeronimus, 2018; Wright & Woods, 2019). In response, researchers and clinicians have called for a renewed focus on idiographic approaches in clinical psychological science (Barlow & Nock, 2009; Piccirillo & Rodebaugh, 2019).

There are several reasons this approach may be especially beneficial for the study of short-term suicidal ideation. For one thing, from a conceptual standpoint, it is worth noting that STBs are hypothesized to result from processes unfolding over time *within an individual*. In fact, existing theories of suicide typically describe a set of processes developing over time within an individual, leading that individual to contemplate and eventually attempt suicide (Beck et al., 1975; Klonsky & May, 2015; Van Orden et al., 2010). As such, to evaluate these theories, it follows that idiographic methods should be used to match the individually- and time-varying nature of these processes. This proposition is underscored by evidence that nearly half of the short-term variability in short-term suicidal ideation is attributed to intraindividual variation (Hallensleben et al., 2018; Kleiman et al., 2017). Furthermore, findings based on interindividual variability have limited generalizability to those based on intraindividual variability (Fisher et al., 2018; Molenaar, 2004, 2007; Wright & Woods, 2019). The idiographic approach is therefore likely to be necessary for acquiring precise and individaulized information that clinicians can readily use to determine whether an individaul is at imminent risk for suicide.

A third extension of past research on short-term suicidal ideation relates to the accurate prediction of future STBs. To understand why decades of suicide prevention efforts have not translated to a decline in suicides, Franklin and colleagues (2017) recently conducted a meta-analysis of longitudinal studies from the past five decades that aimed to predict STBs. In addition to reporting that the field's ability to predict STBs was at near-chance levels for the past 50 years, these authors also identified methodological limitations that impede our ability to accurately predict STBs. In addition to highlighting the distinction between long- and short-term risk factors, these authors highlighted that most studies either examined a single risk factor in isolation or interactions among a small set of putative risk factors described by extant theories of suicide. Ribeiro et al. (2016) corroborated this finding by demonstrating that examining prior engagement in STBs as a sole risk factor – widely accepted as a robust risk factor of future suicidal behavior – only marginally improved predictive accuracy above chance.

Instead, Franklin and colleagues (2017) suggest that accurate STB prediction requires developing machine learning-based algorithms that can examine complex relationships among many possible risk factors and select those most useful for predicting a given STB outcome (Kessler et al., 2015; Ribeiro et al., 2016). Doing so in the study of short-term suicidal ideation will help us better identify and understand proximal predictors of suicidal ideation. Further, when used alongside the idiographic approach, this procedure can allow for the construction of *individualized* suicide risk algorithms, which assist in the accurate prediction of STBs on a person-by-person basis. Additionally, this approach provides the unique opportunity to compare these algorithmically derived predictions of future STBs with those drawn from widely known extant theories of suicide (Beck et al., 1975; Klonsky & May, 2015; Van Orden et al., 2010). Beyond comparing the predictive accuracy of each approach on an individual level, this process allows us to examine, person-by-person, which approach is best fit to each individual.

In summary, past research on short-term suicidal ideation and its risk factors can be usefully extended in three key ways. First, given the larger replication crisis across psychological science as a whole (Open Science Collaboration, 2015) and its consequences for research on STBs specifically, future studies should aim to replicate recent findings on the basic properties of short-term suicidal ideation and its risk factors. This will allow us to either reinforce or further clarify our emerging knowledge about the basic properties of these short-term processes and form hypotheses that accurately reflect these properties. Second, as the processes underlying STBs are likely highly individually- and time-varying (Hallensleben et al., 2018; Kleiman et al., 2017), an idiographic approach is necessary for acquiring precise and individaulized information on how short-term suicidal ideation and its risk factors operate for each individaul. This actionable information could then be used by clinicians to determine whether an individaul is at imminent risk for suicide. Third, given that machine learning approaches have recently been shown to outperform traditional approaches to prediction when examining STBs (Franklin et al., 2017), these should be used alongside idiographic data to construct individualized suicide risk algorithms that will assist with the accurate prediction of short-term suicidal ideation person by person. In addition to optimizing our ability to accurately predict short-term suicidal ideation for each individual, this approach can also be compared with more traditional approaches to suicide prediction to identify the approach best fit to each individual.

Thus, the present study had four aims. For the first aim, I attempted to replicate past findings on the basic properties of short-term suicidal ideation and its risk factors. I was specifically interested in examining whether short-term suicidal ideation was both highly variable over time and episodic in nature (Ben-Zeev et al., 2012; Hallensleben et al., 2018; Kleiman et al., 2017). I was similarly interested in whether risk factors for suicidal ideation were similarly highly variable over time (Kleiman et al., 2017). I chose not to examine the duration of suicidal ideation in our present study as the study design was not appropriate for accurately assessing the length of reported suicidal thoughts over short periods of time. Based on past research (Ben-Zeev et al., 2012; Hallensleben et al., 2018; Kleiman et al., 2017), I hypothesized that short-term suicidal ideation and its risk factors would both be variable over time. I also hypothesized that short-term suicidal ideation would be episodic, with nearly half of observations indicating an absence of suicidal ideation (Kleiman et al., 2017).

Second, I aimed to examine whether an idiographic approach could be used to construct individualized models that predict future short-term suicidal ideation on a person-by-person basis. I hypothesized that idiographic models of short-term suicidal ideation could be estimated and would predict future short-term suicidal ideation with at least fair predictive accuracy. Given evidence that short-term risk factors are non-trivially specific to each feature of suicidal ideation (Kleiman et al., 2017), I constructed a series of models per individual predicting different versions of suicidal ideation, including the absolute level of suicidal ideation over time and the presence of *intense* suicidal ideation over time. These were chosen to reflect two clinically significant targets, including the general intensity of short-term suicidal ideation over time and the presence of suicidal ideation that more closely reflects heightened risk for imminent harm. Further, for each individual, I evaluated predictive accuracy by training a model on a randomly partitioned portion of a given individual's data and then testing predictions made by this model on a holdout sample of the same individual's data. That is, for each individual, I randomly partitioned their data into a training and testing set. Predictive accuracy was assessed for each individual via out-of-sample R^2 for continuous models and the area-under-the-curve (AUC) metric with sensitivity, specificity, and Brier scores for dichotomous models.

Third, I aimed to examine whether machine learning algorithms could be used to improve the ability to predict short-term suicidal ideation on a person-by-person basis. I hypothesized that these algorithmically-derived models would improve upon idiographic models using more traditional approaches to prediction (both those based on continuous and dichotomous variables; Franklin et al., 2017).

Fourth, I aimed to compare the accuracy of algorithmically driven idiographic models to that of theoretically driven models predicting short-term suicidal ideation. Across all models, I compared the accuracy of predictions from a small set of machine learning approaches to those generated by the hopelessness theory of suicide (Beck et al., 1975), the interpersonal theory of suicide (Van Orden et al., 2010), and the three-step theory of suicide (Klonsky & May, 2015). Given past research demonstrating the limited utility of individual or small sets of traditional risk factors for predicting STBs (Franklin et al., 2017; Ribeiro et al., 2016), I hypothesized that, across individuals, algorithmically derived models would uniformly outperform theoretically driven models when predicting short-term suicidal ideation.

To address these aims, we used an EMA design to intensively assess short-term suicidal ideation and its risk factors person-by-person over a 15-day period. I then used this data to estimate idiographic predictive models aimed at accurately predicting short-term suicidal ideation.

Method

Participants

Ten (*N* = 10) participants were included in the present study (see recruitment and screening procedures below). The included participants largely identified as White/Caucasian (*n* = 7; 70%) and female (*n* = 9; 90%) with an average age of 24.25 years old (*SD* = 3.85). Most of these participants identified as bisexual (*n* = 4; 40%), followed by three that identified as homosexual (*n* = 3; 30%), two that identified as heterosexual (*n* = 2; 20%), and one that identified as asexual (*n* = 1; 10%). Participants reported an average of 2.5 (*median* = 2.5) lifetime suicide attempts. Lastly, the most frequently reported annual income brackets reported in the current sample were $20,000 - $29,999 and $30,000 - $39,999. Table 1 displays demographic characteristics for each included participant.

Procedure

All study procedures were approved by the University of California, Berkeley Committee for the Protection of Human Subjects. The study included two phases: (a) recruitment and screening and (b) a 15-day EMA sampling period. Participants were compensated $50 for completion of all study procedures.

Recruitment and screening. Inclusion criteria were (a) being between the ages of 18-65, (b) having daily access to a web-enabled smartphone, (c) willingness to access and regularly use the LifeData phone application, (d) willingness to agree to a suicide safety plan for the duration of the study, and (e) either reporting suicidal ideation more days than not over the past month or reporting having made at least one suicide attempt in the past 12 months. Adapting the recruitment approach from Kleiman et al. (2017), all participants were recruited using moderator approved posts from individual forums hosted on Reddit (www.reddit.com). Participants were specifically recruited from the individual forums r/SuicideWatch (www.reddit.com/r/SuicideWatch). Each post contained a hyperlink to a brief screener that assessed past suicidal ideation and attempt history. This brief screening interview was adapted from the short-form of the Self-Injurious Thoughts and Behaviors Interview (SITBI; Nock, Holmberg, Photos, & Michel, 2007). Qualifying participants were then contacted directly by study staff and asked if they wished to participate.

After providing informed consent, participants who agreed to the study completed a baseline survey assessing demographic characteristics, psychiatric history, and history of suicidal thoughts and behaviors. Prior to completing this baseline assessment, participants were recruited to complete a brief comprehension quiz and agree to a suicide safety plan in order to continue study participation. Following completion of this survey, participants were then given instructions to download the LifeData web application and received instructions on completing the 15-day EMA sampling period.

Ecological momentary assessment paradigm. The LifeData Experience Sampling app was used to collect data during the 15-day EMA sampling period. After enrollment and completing the baseline assessment, each participant downloaded the LifeData Experience Sampling application onto their personal phone and joined a secure web-based survey system.

This system sent notifications to each participant's phone 10 times per day for a minimum of 15 days. Each message was tied with a time stamp recording the time the notification was received and an indicator displaying whether the patient completed the survey. For each survey, participants rated how strongly they were experiencing a given item on a 0 (*absent*) to 9 (*as strong as possible)* scale. Survey items included three items for assessing different aspects of suicidal ideation, including (1) intensity of desire to die by suicide ("how strong is your desire to kill yourself right now?"), (2) intention to die by suicide ("How strong is your intention to kill yourself right now?"), and (3) ability to resist the urge to die by suicide ("How strong is your ability to resist the urge to kill yourself right now?").

In addition, I also used several items that were previously used to assess risk factors for suicidal ideation (Forkmann et al., 2018). I specifically selected items reflecting the interpersonal theory of suicide (perceived burdensomeness, loneliness, lack of belongingness, and uselessness; Van Orden et al., 2010), hopelessness theory of suicide (hopelessness; Beck et al., 1975), and the three-step theory of suicide (pain and connectedness; Klonsky & May, 2015). We also selected items representing several emotions that have been previously shown to correlate suicidal ideation over brief periods of time, including happiness, anxiety, sadness, anger, being full of energy, shame, guilt, impulsivity, and negative urgency (Bagge et al., 2014; Ben-Zeev et al., 2012; Hallensleben et al., 2018; Kleiman et al., 2017; Witte et al., 2006). Finally, we also selected items representing the acquired capability for suicide (fearlessness of death, ability to overcome pain, and urges to engage in self-harm; Ribeiro et al., 2014). For each survey for each individual across the 15-day sampling period, each of the above EMA were presented and rated by the participant in terms of the degree to which they were currently experiencing each item.

Data preparation

There were several data preparation steps taken prior to conducting our analyses to address the main hypotheses of the study. First, a composite variable representing the level of suicidal ideation at each survey was created for each individual. Adapting previously published methods by Kleiman and colleagues (2017), this was calculated by summing the items for (1) intensity of desire to die by suicide, (2) intention to die by suicide, and (3) the reverse-scored version of the ability to resist the urge to die by suicide. The internal consistency of this sum score was acceptable across individuals (α = .72, range = .42 – .91). This operationalization was selected for two reasons. First, consistent with our first aim to replicate past research, this operationalization was used in previously published research using an EMA approach to assess short-term suicidal ideation and its risk factors (Kleiman et al., 2017). Second, each feature of this composite variable mirrors decision rules employed by clinicians when determining imminent suicide risk. Specifically, just as intensity of ideation, intention to die by suicide, and protective factors are assessed and linearly combined to determine level of risk at a given time (DeCou & Schumann, 2018), this variable represents a linear combination of these variables to similarly assess risk at each observation (with higher levels representing higher relative risk).

Second, for each individual separately, we then used this composite variable to create a binary variable representing the presence/absence of intense suicidal ideation at each observation. The presence of intense suicidal ideation was operationalized as any observation that fell in the uppermost tertile of a given individual's composite suicidal ideation ratings. Third, for each individual, I then calculated a series of time variables to detect trends and cycles in ratings of short-term suicidal ideation and its risk factors over time. The time stamps accompanying each set of ratings were used to calculate a cumulative time elapsed over the 15-

day sampling period. I then created linear transformations of this cumulative time variable (representing linear time) to calculate quadratic and cubic time variables. Afterward, I used sine and cosine terms with our cumulative time variable to calculate daily cycles in these ratings, consistent with methods provided by Flury and Levri (1990).

Fourth, I then created lagged versions of each variable to examine the degree to which we are able to accurately predict suicide ideation in the future (at time $t + 1$) using preceding levels of its risk factors (at time t). Finally, to examine the ability to predict short-term suicidal ideation "out of sample" for each individual, I randomly partitioned each individual's data into a training and testing set of equivalent size. All models were initially fit to each individual's training data and then evaluated using that same individual's testing data.

Approach to constructing and evaluating prediction models

To address study aims related to predicting short-term suicidal ideation, predictive models were constructed for each individual with respect to two versions of suicidal ideation. First, I constructed models aiming to predict the level of short-term suicidal ideation over time using the continuous composite variable for suicidal ideation described above. Second, I constructed models aiming to predict the presence of *intense* short-term suicidal ideation over time using the dichotomized version of the composite suicidal ideation variable described above. These two sets of models correspond to predicting the level of suicidal ideation over time and predicting intense suicidal ideation, respectively. These were selected because each are clinically relevant features of suicidal ideation that clinicians routinely assess to determine an individual's level of risk for future suicidal behavior.

For each set of models, I then constructed a series of predictive models aimed at predicting short-term suicidal ideation. These included a simple autoregressive model, three different models each corresponding to a specific theory of suicide (Beck et al., 1975; Klonsky & May, 2015; Van Orden et al., 2010), and a series of models corresponding to a series of machine learning algorithms described in more detail below. This approach was selected to evaluate the degree to which we can accurately predict short-term suicidal ideation using traditional approaches to prediction. I also selected this approach to examine whether machine learning algorithms improve the ability to predict short-term suicidal ideation beyond traditional approaches to prediction and variable interactions described by extant theories of suicide (Franklin et al., 2017). For continuous models, predictive accuracy was determined by out-of-sample R^2 values. This ranges from 0 to 1 and reflects the proportion of variance in short-term suicidal ideation from the out-of-sample set explained by the set of variables used as predictors in each individual model. For dichotomous models, predictive accuracy was determined by area-under-the-curve (AUC) metrics, sensitivity, specificity, and Brier scores. AUC is a metric that ranges from .5 to 1 and describes how well a given classification model performed (with values closer to .5 reflecting poorer performance and values closer to 1 reflecting better performance). Sensitivity reflects how well each model predicted the outcome of interest for a given model, whereas specificity reflects how well each model correctly predicted the *lack* of our outcome of interest. Brier scores ranges from 0 (representing perfect accuracy) to 1 (representing perfect inaccuracy) and similarly measures the overall accuracy of binary predictions for a given model.

For continuous models, I provided the number of observations present in both training and testing sets. For dichotomous models, I provided the number of events (presence of intense suicidal ideation) and non-events (absence of intense suicidal ideation) in all training and testing sets. Table 3a and Table 4a display these values, respectively.

Autoregressive model. For each individual, two autoregressive models were initially estimated predicting suicidal ideation at time *t* +1 with suicidal ideation at time *t* only. For each individual's continuous model, I used a simple linear regression approach. For each individual's dichotomous model, I used a logistic regression approach.

Theoretical models. For each individual, I then estimated a series of models pertaining to extant theories of suicidal behavior. Specifically, I constructed these models based on the hopelessness model for suicide (Beck et al., 1975), the interpersonal theory of suicide (Van Orden et al., 2010), and the three-step theory of suicide (Klonsky & May, 2015). For each model, predictors pertaining to that respective theory of suicide at time *t* were the only variables included to predict short-term suicidal ideation at time *t* + 1. For all continuous models, I used a multiple linear regression approach. For all dichotomous models, I used a multiple logistic regression approach.

Machine learning algorithms. For each individual, I next estimated a series of models using a series of machine learning algorithms that selected a series of predictors at time *t* specific to each individual model to predict suicidal ideation at time *t* + 1. For each approach, models were fit for either continuous or dichotomous outcomes.

***Elastic net regularization*.** Elastic net regularization (Zou & Hastie, 2005) is a regularized regression approach that estimates sparse models through penalizing coefficients. Elastic net is a useful tool for regularization and variable selection due to its use of L_1 and L_2 penalization. Whereas both L_1 and L_2 guard against overfitting by shrinking model coefficients and standard errors, the scaling of the L_1 penalty provided by the least absolute shrinkage and selection operator (LASSO) results in coefficients being shrunk to zero and omitted from the model. Thus, the use of LASSO in regularization and prediction modeling provides the added benefit of variable selection. The elastic net blends LASSO and ridge regression via the alpha hyper-parameter, which can be set by the user. An alpha value of 0 provides pure ridge regression, and a value of 1 provides pure LASSO regression. I constructed all predictive models with alpha = 0.50, representing an equal blend of the two approaches. A k-fold cross-validation with 10 folds was used to select the optimal model. Consistent with best-practice standards for this approach, the lambda value with the minimum mean cross-validated error was used to select the final model.

Minimax concave penalty (MCP). The minimax concave penalty (MCP) was also used for model estimation. Similar to elastic net, MCP is a regularization approach that estimates sparse models via penalization of coefficients and can similarly be used for variable selection. MCP was selected as techniques that rely on LASSO can produce biased parameters (particularly for large coefficients) by linearly applying its penalization and can produce inconsistency in variable selection (Zhang, 2010). MCP guards against this bias by reducing the penalization rate of parameters, resulting in less biased parameters while still obtaining sparse models.

***Smoothly clipped absolute deviation (SCAD) penalty*.** The smoothly clipped absolute deviation (SCAD) penalty was also used for model estimation. Similar to MCP, SCAD is another regularization approach to estimates sparse models and apply penalization of coefficients to addresses shortcomings of LASSO. SCAD similarly guards against biases in parameter estimation produced by LASSO, but specific to large coefficients. SCAD accomplishes this by retaining the penalization rate applied by LASSO for small coefficients, but continuously relaxes this rate of penalization as the value of the coefficient increases (Fan & Li, 2001).

Random forest. Random forests were the final approach used for model estimation. Random forest decision trees are an ensemble method for classification and variable selection that estimate a series of individual decision trees. This approach guards against overfitting by averaging or combining the results of the series of individual trees initially estimated.

Results

Group-level descriptive and variability statistics

Participants completed an average of 110 surveys (*SD* = 13), with a minimum of 93 and a maximum of 134 surveys across the 15-day EMA sampling period. Descriptive (mean, SD, % zero) and variability statistics (range and root mean square successive difference; RMSSD) were calculated. These were used to examine the basic properties of short-term suicidal ideation and its risk factors. I was specifically interested in whether short-term suicidal ideation and its risk factors were variable over short periods of time and episodic. The mean, standard deviations, percentage of zeros, ranges, average RMMSD, and standard deviation of RMSSD for each item are displayed in Table 2. Results indicate that, on average across participants, short-term suicidal ideation tended to be of moderate intensity (*M* = 10.99, range = 0 – 29), was highly variable (RMSSD = 3.64, range = 2.06 – 5.75), and generally not episodic (% zero = 2.37%).
Further, these results similarly suggest that risk factors for short-term suicidal were highly variable (RMSSDs ranging from 1.21 to 2.06). Furthermore, whereas most risk factors were non-episodic (% zero ranging from 1.36% to 16.49%), urges to self-harm (% zero = 20.52%), happiness (% zero = 30.12%), and feeling full of energy (% zero = 31.75%) were relatively more episodic in nature.

Predictive accuracy of idiographic models predicting levels of short-term suicidal ideation

Autoregressive models. For each individual, an autoregressive model was constructed predicting suicidal ideation at time $t + 1$ with suicidal ideation at time t as the sole predictor. Table 3a displays the predictive accuracy of these models for each individual determined by out-of-sample R^2. The mean out-of-sample R^2 for these models was .34 (*SD* = .25) with a range of .05 to .76.

Hopelessness theory of suicide. For each individual, a linear regression model was constructed predicting suicidal ideation at time $t + 1$ with hopelessness at time t as the sole predictor. Table 3a displays the predictive accuracy of these models for each individual determined by out-of-sample R^2. The mean out-of-sample R^2 for these models was .23 (*SD* = .17) with a range of .02 to .55.

Interpersonal theory of suicide. For each individual, a multiple regression model was constructed predicting suicidal ideation at time $t + 1$ with perceived burdensomeness and thwarted belongingness at time t as the sole predictors. Table 3a displays the predictive accuracy of these models for each individual determined by out-of-sample R^2. The mean out-of-sample R^2 for these models was .20 (*SD* = .16) with a range of .02 to .57.

3-Step theory of suicide. For each individual, a multiple regression model was constructed predicting suicidal ideation at time $t + 1$ pain and hopelessness at time t as the sole predictors. Table 3a displays the predictive accuracy of these models for each individual determined by out-of-sample R^2. The mean out-of-sample R^2 for these models was .27 (*SD* = .18) with a range of .01 to .57.

Elastic net. For each individual, elastic net regularization was used to select a set of predictors at time *t* to predict suicidal ideation at time *t* + 1. Table 3b displays the predictive accuracy of these models for each individual determined by out-of-sample R^2. The mean out-of-sample R^2 for these models was .60 (*SD* = .16) with a range of .21 to .76.

MCP. For each individual, the MCP was used to select a set of predictors at time *t* to predict suicidal ideation at time *t* + 1. Table 3b displays the predictive accuracy of these models for each individual determined by out-of-sample R^2. The mean out-of-sample R^2 for these models was .34 (*SD* = .27) with a range of .01 to .76.

SCAD. For each individual, the SCAD penalty was used to select a set of predictors at time *t* to predict suicidal ideation at time *t* + 1. Table 3b displays the predictive accuracy of these models for each individual determined by out-of-sample R^2. The mean out-of-sample R^2 for these models was .34 (*SD* = .27) with a range of .01 to .76.

Random forest. For each individual, the random forest approach was used to select a set of predictors at time *t* to predict suicidal ideation at time *t* + 1. Table 3b displays the predictive accuracy of these models for each individual determined by out-of-sample R^2. The mean out-of-sample R^2 for these models was .64 (*SD* = .17) with a range of .26 to .86.

Predictive accuracy of idiographic models predicting intense short-term suicidal ideation

Autoregressive models. For each individual, an autoregressive logistic regression model was constructed predicting the presence of intense suicidal ideation at time *t* + 1 with the presence of intense suicidal ideation at time *t* as the sole predictor. Table 4a displays the predictive accuracy of these models for each individual determined AUC, sensitivity, specificity, and Brier scores. The mean AUC for these models was .72 (*SD* = .08) with a range of .60 to .81. The mean sensitivity of these models was .63 (*SD* = .12) with a range of .42 to .76. The mean specificity of these models was .80 (*SD* = .07) with a range of .67 to .87. Lastly, the mean Brier score of these models was .19 (*SD* = 0.14) with a range of .14 to .25.

Hopelessness theory of suicide. For each individual, logistic regression model was constructed predicting the presence of intense suicidal ideation at time *t* + 1 with the presence of hopelessness at time *t* as the sole predictor. Table 4a displays the predictive accuracy of these models for each individual determined AUC, sensitivity, specificity, and Brier scores. The mean AUC for these models was .70 (*SD* = .10) with a range of .58 to .88. The mean sensitivity of these models was .64 (*SD* = .26) with a range of .08 to .94. The mean specificity of these models was .72 (*SD* = .21) with a range of .42 to 1.00. Lastly, the mean Brier score of these models was .21 (*SD* = .03) with a range of .14 to .25.

Interpersonal theory of suicide. For each individual, a multiple logistic regression model was constructed predicting the presence of intense suicidal ideation at time *t* + 1 with perceived burdensomeness and thwarted belongingness at time *t* as the sole predictors. Table 4a displays the predictive accuracy of these models for each individual determined AUC, sensitivity, specificity, and Brier scores. The mean AUC for these models was .72 (*SD* = .06) with a range of .61 to .81. The mean sensitivity of these models was .81 (*SD* = .13) with a range of .58 to 1.00. The mean specificity of these models was .63 (*SD* = .09) with a range of .44 to .77. Lastly, the mean Brier score of these models was .22 (*SD* = .03) with a range of .19 to .28.

3-Step theory of suicide. For each individual, a multiple logistic regression model was constructed predicting the presence of intense suicidal ideation at time *t* + 1 with pain and hopelessness at time *t* as the sole predictors. Table 4a displays the predictive accuracy of these models for each individual determined AUC, sensitivity, specificity, and Brier scores. The mean

AUC for these models was .69 (*SD* = .12) with a range of .46 to .86. The mean sensitivity of these models was .66 (*SD* = .26) with a range of .17 to 1.00. The mean specificity of these models was .74 (*SD* = .15) with a range of .39 to .90. Lastly, the mean Brier score of these models was .21 (*SD* = .03) with a range of .15 to .24.

Elastic net. For each individual, elastic net regularization was used to select a set of predictors at time *t* to predict the presence of intense suicidal ideation at time *t* + 1. Table 4b displays the predictive accuracy of these models for each individual determined AUC, sensitivity, specificity, and Brier scores. The mean AUC for these models was .73 (*SD* = .12) with a range of .50 to .91. The mean sensitivity of these models was .64 (*SD* = .25) with a range of 0 to .89. The mean specificity of these models was .70 (*SD* = .27) with a range of 0 to .98. Lastly, the mean Brier score of these models was .19 (*SD* = .04) with a range of .13 to .25.

MCP. For each individual, the MCP was used to select a set of predictors at time *t* to predict the presence of intense suicidal ideation at time *t* + 1. Table 4b displays the predictive accuracy of these models for each individual determined AUC, sensitivity, specificity, and Brier scores. The mean AUC for these models was .71 (*SD* = .13) with a range of .50 to .86. The mean sensitivity of these models was .68 (*SD* = .26) with a range of 0 to 1.00. The mean specificity of these models was .70 (*SD* = .27) with a range of 0 to 1.00. Lastly, the mean Brier score of these models was .20 (*SD* = .03) with a range of .14 to .26.

SCAD. For each individual, the SCAD penalty was used to select a set of predictors at time *t* to predict the presence of intense suicidal ideation at time *t* + 1. Table 4b displays the predictive accuracy of these models for each individual determined AUC, sensitivity, specificity, and Brier scores. The mean AUC for these models was .72 (*SD* = .12) with a range of .50 to .90. The mean sensitivity of these models was .65 (*SD* = .25) with a range of 0 to .89. The mean specificity of these models was .68 (*SD* = .27) with a range of 0 to .98. Lastly, the mean Brier score of these models was .20 (*SD* = .04) with a range of .13 to .27.

Random forest. For each individual, the random forest approach was used to select a set of predictors at time *t* to predict the presence of intense suicidal ideation at time *t* + 1. Table 4b displays the predictive accuracy of these models for each individual determined AUC, sensitivity, specificity, and Brier scores. The mean AUC for these models was .99 (*SD* = .02) with a range of .93 to 1.00. The mean sensitivity of these models was .98 (*SD* = .02) with a range of .94 to 1.00. The mean specificity of these models was .98 (*SD* = .05) with a range of .82 to 1.00. Lastly, the mean Brier score of these models was .06 (*SD* = .02) with a range of .04 to .10.

Discussion

In the present study, I focused on advancing our understanding of short-term suicidal ideation and its risk factors through several aims. First, consistent with recent efforts to examine the reproducibility of findings across psychological science (Open Science Collaboration, 2015), I aimed to replicate recent findings on the basic nature of short-term suicidal ideation and its risk factors (Ben-Zeev et al., 2012; Hallensleben et al., 2018; Kleiman et al., 2017). Specifically, I was interested in examining whether short-term suicidal ideation and its risk factors were highly variable over short periods of time rather than being relatively stable. I was also interested in ascertaining whether short-term suicidal ideation was episodic in nature. Second, given increasing evidence of the individually and time-varying nature of psychopathology (Wright & Woods, 2019), I aimed to explore whether idiographic prediction models could be estimated and used to accurately predict short-term suicidal ideation on a person-by-person basis. I hypothesized that idiographic models of short-term suicidal ideation could be estimated and would predict short-term suicidal ideation with at least fair predictive accuracy (across both continuous and dichotomous models). Next, I aimed to examine whether employing machine learning techniques would improve our ability to predict short-term suicidal ideation on a person-by-person basis. Based on recent evidence that machine learning approaches can guard against methodological limitations tied with traditional approaches to prediction (Franklin et al., 2017), I hypothesized that employing these techniques would improve individualized prediction of short-term suicidal ideation. Finally, I aimed to compare the predictive accuracy of these algorithmically-derived models to models representing three existing theories of suicide, including the hopelessness theory of suicide (Beck et al., 1975), the interpersonal theory of suicide (Van Orden et al., 2010), and the three-step theory of suicide (Klonsky & May, 2015) to determine which approach was best fit to each individual. Given past research demonstrating the limited utility of individual or small sets of traditional risk factors for predicting STBs (Franklin et al., 2017; Ribeiro et al., 2016), I hypothesized that, across individuals, algorithmically-derived models would uniformly outperform theoretically-driven models when predicting short-term suicidal ideation.

Regarding the first aim, results both reinforce and provide novel information about the basic properties of short-term suicidal ideation and its risk factors. Specifically, whereas both suicidal ideation and its risk factors have been theorized to be relatively stable over time in extant theories of suicide (Beck et al., 1975; Kleiman et al., 2017; Van Orden et al., 2010), these results reinforce empirical findings that each of these phenomena are highly variable over short periods of time (Ben-Zeev et al., 2012; Hallensleben et al., 2018; Kleiman et al., 2017). However, findings also suggest that short-term suicidal ideation may not be as episodic as previously reported. Whereas Ben-Zeev et al. (2012) initially suggested that suicidal ideation may be episodic based on retrospective data, Kleiman et al. (2017) examined this hypothesis prospectively using an EMA design. Although they reported that suicidal ideation was relatively episodic from observation to observation, a limitation described was that the rating scale for suicidal ideation did not differentiate between the absence of suicidal ideation and low suicidal ideation. In the present study, however, the use of a finer-grained rating scale allowed differentiation between these two levels. Results indicated that only a small percentage of ratings of short-term suicidal ideation were rated at zero (ranging from 0.37% to 14.50% for components of short-term suicidal ideation; % zero = 2.37% for the composite of these components of suicidal ideation). Taken together, rather than being episodic, these findings suggest that short-term suicidal ideation varies considerably over short periods of time and may fluctuate from low to high levels from hour to hour while only occasionally being absent in at-risk individauls.

As for my second aim, results also provide evidence that idiographic models predicting short-term suicidal ideation can produce reliable predictions with at least fair accuracy. Specifically, idiographic autoregressive continuous models predicting short-term suicidal ideation yielded an average out-of-sample R^2 in the large range (medium = 0.13; large = 0.26; Cohen, 2013), suggesting that these models were generally able to explain a considerable amount of variability in out-of-sample data (M_{auto} = 0.34, *SD* = 0.25, range = 0.05 - 0.76). Further, idiographic autoregressive dichotomous models predicting presence of intense suicidal ideation similarly yielded an average out-of-sample of AUC in the acceptable range (no discrimination = 0.50, acceptable = 0.70 - 0.80, excellent = 0.80 - 0.90, outstanding = 0.90 – 1.00; Mandrekar, 2010), suggesting these models were generally able to accurately discern the presence/absence of short-term suicidal ideation in out-of-sample data (AUC = 0.72, *SD* = 0.08, range = 0.60 - 0.81).

Thus, results from these initial models suggest that the individually and time-varying nature of short-term suicidal ideation can be adequately modeled and predicted using idiographic assessment and analysis methods (Fisher, 2015; Hallensleben et al., 2018; Kleiman et al., 2017; Wright & Woods, 2019).

With respect to the third aim, results partially demonstrate that employing machine learning techniques can improve our ability to predict short-term suicidal ideation on a person-by-person basis. Specifically, with respect to continuous models, employing a series of machine learning approaches to predicting short-term suicidal ideation out-of-sample yielded R^2 values of equivalent or larger size than simple autoregressive models ($M_{elastic}$ = .60, $SD_{elastic}$ = .16, range = .21 - .76; M_{MCP} = .34, SD_{MCP} = .27; range = .01 - .78; M_{SCAD} = .34, SD_{SCAD} = .27; range = .01 - .78; M_{random} = .64, SD_{random} = .17, range = .26 - .86). However, with respect to dichotomous models, while elastic net regularization and random forest models yielded average AUCs larger than simple autoregressive models within the acceptable to outstanding range ($AUC_{elastic}$ = .73, *SD* = .12, range = .50 - .91; AUC_{random} = .99, *SD* = .02, range = .93 – 1.00), both MCP and SCAD penalty approaches yielded AUCs of equivalent or smaller size within the acceptable range (AUC_{MCP} = .71, *SD* = .13, range = .50 - .86; AUC_{SCAD} = .72, *SD* = .12, range = .50 - .90).

Taken together, this pattern of findings suggests that machine learning techniques can be used to improve idiographic prediction of short-term suicidal ideation. Additionally, penalizations provided by MCP and SCAD may not be the preferred methods for the nature of the present data; instead elastic net and random forest approaches may be more appropriate. Further, given that elastic net only marginally outperformed simple autoregressive models predicting intense short-term suicidal ideation, random forest may be *most* appropriate for the present data. A partial reason is that, unlike random forest, elastic net regularization, MCP, and SCAD perform variable selection and classification via a form of LASSO penalization. Although this approach guards against overfitting that commonly occurs with more traditional approaches to prediction and is attenuated by MCP and SCAD modifications to penalization, this penalization can still result in biased parameters, particularly in the case of multicollinearity of predictor varibales (Fan & Li, 2001; Zhang, 2010).

On the contrary, random forest instead represents an ensemble approach to prediction that achieves improved prediction by averaging across an series of weaker decisions rather than penalization of parameters. This approach may be particularly beneficial for idiographic data with multicollinear relationships between predictors mutually interacting over time to predict an outcome of interest. Future studies should further examine which features of idiographic data determine which machine learning technique is best fit for accurate prediction of a given outcome of interest. This will facilitate standardization of the idiographic approach to technique selection and model construction when predicting important outcomes on a person-by-person basis.

With respect to my fourth aim, results also provide partial evidence that algorithmically-derived models predicting short-term suicidal ideation outperform those representing exisiting theories of suicide (Beck et al., 1975; Kleiman et al., 2017; Van Orden et al., 2010). Specifically, for continuous models, models representing the hopelessness theory of suicide (*M* = .23, *SD* = .17, range = .02 - .55), the interpersonal theory of suicide (*M* = .20, *SD* = .16, range = .02 - .57), and three-step theory of suicide (*M* = .27, *SD* = .18, range = .01 - .57) uniformly underperformed relative to algorithmically-derived predictive models. However, parallel to above-noted findings, dichotomous models provided more mixed results. Whereas the models representing the hopelessness theory of suicide ($AUC_{hopeless}$ = .70, *SD* = .10, range = .58 - .88), interpersonal theory of suicide ($AUC_{interpersonal}$ = .72, *SD* = .06, range = .61 - .81), and three-step theory of suicide ($AUC_{three\text{-}step}$ = .69, *SD* = .12, range = .54 - .86) yielded average AUCs comparable to those from models using the MCP, the SCAD penalty, and elastic net regularization, these uniformly underperformed relative to random forest models (AUC_{random} = .99, *SD* = .02, range = .93 – 1.00).

Thus, although existing theories of suicidal ideation may uniformly underperform relative to machine learning techniques when predicting levels of suicidal ideation over time, these perform relatively better when identifying the presence of intense suicidal ideation (while still underperforming relative to specific machine learning techniques). It is important to examine the context in which these existing theories of suicide were developed. Specifically, whereas intensive study of STBs (as they occur naturally in their environment) has only recently become possible through mobile technology (Kleiman and Nock, 2018), the theories in question predated such methods, dervied largely via intensive clinical observation of patients. Given that determining whether an individual is at imminent risk for suicide has historically been a critical issue that has received considerable attention over the years (Nock, 2016), the impetus for developing these theories was likely to better identify suicidal thought with a high likelihood to transition into potentially lethal suicidal behavior rather than suicidal thought alone. Although spectulative, this hypothesis may partly explain the improved performance of these models relative to algorithmically-derived models in the case of predicting intense suicidal ideation specifically.

There are several important contributions and implications of findings for the extant literature. First, as noted above, these findings both reinforce and provide novel information about the properties of short-term suicidal ideation and its risk factors. Specifically, the results corroborate past research demonstrating the high variablity of short-term suicidal ideation and its risk factors while also demonstrating that suicidal ideation is less episodic that previously reported (Kleiman et al., 2017). These findings thus reinforce both our current understanding of short-term suicidal ideation and its risk factors and the importance of intensively studying psychological phenomena as these naturally occur in their environment. Adopting this approach may allow us to acquire a better understanding of the basic nature of these phenomena, identify methods likely to best capture these properites, and develop more ecologically-valid hypotheses about how these phenomena function and change in response to intervention. These aims are particularly important given the urgent need to better detect imminent suicide risk and reverse rising suicide rates in the United States specifically (National Alliance for Suicide Prevention: Research Prioritzation Task Force, 2014) and worldwide (World Health Organization, 2014).

Second, these results provide evidence that individualized models predicting short-term suicidal ideation can produce reliable, weakly stationary results. That is, because the models were trained on one set of person-specific data and then evaluated on a holdout sample from that same individual, the reliability of both the underlying constructs and statistical properties derived from these constructs over time (a condition known as stationarity) could be determined. This fact further reinforces the individually- and time-varying nature of STBs while providing an example of how to leverage EMA paradigms and idiographic analysis methods to develop individualized prediction of short-term suicide risk (Fisher, 2015; Hallensleben et al., 2018; Kleiman et al., 2017; Wright & Woods, 2019). Inappropriately modeling these features of suicidal ideation may directly hamper our ability to determine when an at-risk individual may be at imminent risk for suicide, particularly as extant research has largely focused on interindividaul variation—such findings do not reliably generalize to inferences related to intraindividaul variation. As such, the development of these individualized models represents an initial step toward providing clinicians with precise and real-time information about imminent risk for suicide that can be readily implemented in standard evidence-based practice.

Further, these results also reinforce that machine learning techniques can help optimize our ability to predict short-term suicidal ideation by selecting a set of person-specific predictors from a larger set of risk factors. This is critical because this both reinforces burgeoning evidence that machine learning techniques are critical for enhancing the prediction of STBs (Kessler et al., 2015; Ribeiro et al., 2019; Walsh et al., 2017, 2018) while also providing a pathway to assist clinicians with the functional assessment of STBs for each individual. Further, these results provide evidence that these techniques can outperform existing theories of suicide used to identify “warning signs” of imminent suicidal behavior (Rudd et al., 2006). Such detection is crucial, as it may indicate a pathway for evaluating our existing gold-standard rules for assessing suicidality and developing new evidence-based standards for detecting imminent suicide risk. Further, it also encourages the use of a more flexible approach to detecting heightened risk that is less biased by clinician perceptions of the utility of a given theory of suicide and instead allows for synchronized examination of features drawn from multiple theories of suicide that may be uniquely relevant for a given individual. These results may represent an initial step toward the development and use of technological schemes that can accomplish these parallel goals and prevent the dire consequences of STBs.

Additionally, these findings also highlight a pathway by which research on STBs can become more practically useful for clinicians. As noted above, the lack of equivalence between intra- and inter-individaul variabilty limit the generalizability of findings drawn from one type of variablility to the other (Fisher, Medaglia, & Jeronimus, 2018; Wright & Woods, 2019). For research on STBs, this translates to research on predicting STBs largely based on group-level data having limited applicability to our ability to accurately predict the occurrence of STBs for a single individual. This tension results in the *therapist’s dilemma*, in which clinicians face the challenge of determining what is best for a single individaul using empirical research based solely on groups (Piccirillo & Rodebaugh, 2019). These results highlight an alternative approach that can be used to circumvent this delimma. Specifically, as noted above, these results demonstrate that data can be intensively collected from each individual and modeled to meaningfully predict clinically significant short-term suicidal ideation for each individual. As such, rather than relying on group-level research, clinicians can instead use this idiographic approach to routinely assess each individual’s experience and identify antecedents to relevant therapuetic targets. While this approach is not new (Persons, 2008), these results reinforce this individualized approach used by clinicians and highlight a standardized framework using digitized tools that supplement clinican judgment when assessing STBs in this way.

Finally, these results further reinforce the individaully-varying nature of psychopathology (Fisher et al., 2018; Molenaar, 2004, 2007; Wright & Woods, 2019), particularly STBs (Hallensleben et al., 2018; Kleiman et al., 2017). This variation is represented most clearly in the range of predictive power across each individual’s predictive model for short-term suicidal ideation. For instance, out-of-sample R^2 values for autoregressive models predicting levels of short-term suicidal ideation ranged from .05 to .76. This varying predictive power reflects that, whereas considering preceding levels of suicidal ideation is helpful for predicting future ideation for some individuals, there are also those for whom this monitoring approach would not usefully predict future ideation. Instead, achieving acceptable prediction of short-term suicidal ideation for this individual (Participant 008) required the use of an algorithmically-derived set of risk factors fit for that individual (Franklin et al., 2017). Given that the auto-regressive and theoretically-driven models more closely reflect how clinicians might currently use standard evidence-based practices and extant theory to guide suicide risk assessment (DeCou & Schumann, 2018), this result underscores the utility of applying machine learning to idiographic data to identify complex patterns of risk not readily identifiable by clinicians.

However, this also indicates that there are individuals for whom the machine learning approaches employed in the current study were largely not useful for improving the prediction of suicidal ideation (Participant 004). With respect to predicting intense suicidal ideation for this individual specifically, while employing a random forest approach yielded predictive power in the outstanding range, use of elastic net regularization, the MCAP, and SCAD penalty yielded no discernment between the presence and absence of intense suicidal ideation for this individual. Further, autoregressive and theoretically-driven models instead yielded marginally better predictive power approaching the acceptable range. Given that multicollinearity is likely common at the individual-level and biases parameters from these machine learning approaches (Fan & Li, 2001; Zhang, 2010), this highlights that there will be individuals for whom using a more traditional approach to prediction may be preferable than certain machine learning techniques. This may indicate to us that assumptions tied to specific techniques that did not achieve acceptable prediction may not hold for a given individual's data (e.g., multicollinearity) and that therefore other approaches may be preferrable. Further, in cases where no machine learning approaches meaningfully improve prediction, this may indicate that the set of risk factors selected may not meaningfully relate to that individaul's experience of suicidal ideation. As such, in addition to further reinforcing the individually-varying nature of STBs (Hallensleben et al., 2018; Kleiman et al., 2017), these results also further underscore the importance of developing a standardized approach to idiographic assessment, model construction, and prediction. This approach will facilitate (a) the selection of predictors likely to be most relevant to each individual, (2) the identification of assumptions best fit to each individual's data, and (3) the prediction approach that optimizes our ability to predict STBs for each individual.

There are several limitations of the present findings that are important to discuss. First, although this study emphasizes properties of short-term suicidal ideation, the small sample size ($N = 10$) limits the generalizability of these results. Further, although recruitment was based on the presence of current suicidal ideation and/or past suicide attempts, the present sample consisted of young adults who largely identified as white, female, and sexual minorities. Given evidence for elevated rates of suicidal thoughts and behaviors among this population (Curtin & Heron, 2019), this sample may represent an extreme end of the suicide risk continuum and may have skewed descriptive and variability statistics on short-term suicidal ideation and its risk factors. As such, future studies should aim to replicate these results with larger sample sizes and more diverse samples.

Second, on a related note, the present study used an EMA paradigm to intensively study short-term suicidal ideation and its risk factors over a 15-day period. Although our sampling frequency was high (10 times per day), the properties of short-term suicidal ideation and its risk factors may have been influenced by this relatively brief sampling period. In fact, other studies examining short-term suicidal ideation have examined longer periods of 28-days to a month (Kleiman et al., 2017). Similar to our small sample size across individuals, this small sample size of days within individuals may represent a more limited sample of the experience of suicidal ideation and its risk factors for each individaul over time. On the other hand, it may also be the case that suicidal ideation fluctuates more quickly over briefer periods of time, implying that our within-day sampling frequency, while the more frequently used in extant research (Kleiman & Nock, 2018), may still be relatively coarse compared with the true nature of the phenomena. As such, future studies should also endeavor to replicate these results at varying within-day sampling frequencies over long periods of time in order to better understand the basic properites of these phenomena.

Third, on a related note, all models were evaluated by training a model on one randomly partitioned portion of an individual's data and testing predictions on a remaining holdout sample. Although this procedure allowed me to assess predictive accuracy based on data to which each model had previously lacked exposure, these data were collected within the same data collection period. The result may be an artificially inflated estimate of the accuracy of the models due to similarity in trends occurring across the data collection period. As such, future studies should endeavor to further evaluate predictive accuracy by using out-of-sample data drawn from periods with a greater distance in time from the initial data collection period. Whereas this point is more generally relevant for research on idiographic predictions of behavior, it may be particularly relevant for suicide research as past research has identified clinically meaningful events associated with increased imminent suicide risk (e.g., post-hospital discharge; Forte, Buscajoni, Fiorillo, Pompili, & Baldessarini, 2019).

A fourth limitation of this study is that these models only partially modeled how variability in the predictors of interest may relate to our outcomes of interest. Specifically, while time and daily cycle variables were used to examine how each risk factors may non-linerally relate to short-term suicidal ideation, arguably instability in these risk factors may also relate both linearlly and non-linearlly to short-term sucidial ideation (Schipek et al., 2011). For instance, above and beyond the completion of a particular daily cycle in a given risk factor relating to short-term suicidal ideation, it is also possible that specific points of extreme lability in a given risk factor relate to short-term suicidal ideation at a given time. While beyond the scope of the present study, future research should further expand the possible risk factors selected in the present study to include varying transformations of these risk factors that reflect different aspects of lability. This will allow us to determine, for each individual separately, the degree and complex patterns by which these risk factors predict short-term suicidal ideation.

Despite these limitations, the present study represents an important extension of reseach on short-term suicidal ideation and its risk factors. Specifically, findings further reinforce the highly variable nature of short-term suicidal ideation and its risk factors while also clarifying that suicidal ideation may be less episodic than previously reported. Further, results also provide evidence that individualized prediction models for short-term suicidal ideation can be produce reliable results and can be further improved by machine learning techniques. Taken together, these results may represent an initial step toward developing a more precise and individualized approach for understanding and preventing death by suicide through better modeling and predicting short-term suicidal ideation and its risk factors. Given the marked increase in suicidal behavior in the U.S. and many other nations in recent years, the stakes are high.

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Table 1. Participants characteristics by ID

ID	Age	Gender	Race/Ethnicity	Sexual Identity	Income	Past attempts
001	22	Female	Hispanic/Latino	Heterosexual	Less than $20,000	3
002	27	Female	White/Caucasian	Bisexual	$20,000 - $29,999	4
003	-	Female	White/Caucasian	Heterosexual	$20,000 - $29,999	1
004	32	Female	White/Caucasian	Bisexual	$30,000 - $39,999	-
005	-	Female	White/Caucasian	Asexual	$50,000 - $59,999	2
006	26	Gender Queer	American Indian	Homosexual	Less than $20,000	3
007	21	Female	White/Caucasian	Homosexual	$20,000 - $29,999	0
008	23	Female	White/Caucasian	Homosexual	$40,000 - $49,999	0
009	22	Female	Asian/Pacific Islander	Bisexual	$30,000 - $39,999	10 or more
010	21	Female	White/Caucasian	Bisexual	$30,000 - $39,999	-

Note. ID = Participant identification number; “-“ = Prefer not to answer; Past attempts = number of previous suicide attempts reported

Table 2. Group-level descriptive and variability statistics for suicidal ideation and its risk factors

	Group-level descriptive and variability statistics						
Variable	***M***	***SD***	**Range**	**Cronbach's α**	**% zero**	***M* RMSSD**	**RMSSD *SD***
Suicidal Ideation (composite)	10.99	3.84	0-27	.72	2.37%	3.64	1.08
Desire to kill self	4.25	1.92	0-9		11.33%	1.61	0.45
Intention to kill self	3.04	1.49	0-9		14.50%	1.19	0.38
Ability to resist the urge to kill self	5.30	1.44	0-9		0.37%	1.46	0.38
Useless	6.25	1.68	0-9		2.08%	1.64	0.52
Burden	6.53	1.49	0-9		1.52%	1.38	0.48
Lonely	6.52	1.65	0-9		1.36%	1.62	0.62
Not belong	6.51	1.60	0-9		1.66%	1.57	0.47
Hopeless	6.42	1.68	0-9		2.84%	1.47	0.51
Pain	4.43	1.76	0-9		2.28%	1.63	0.49
Connected	2.38	1.37	0-9		16.49%	1.37	0.47
Unafraid of death	4.36	1.19	0-9		1.55%	1.21	0.64
Overcome pain	3.66	1.54	0-9		2.68%	1.57	0.29
Happy	2.01	1.40	0-9		30.12%	1.35	0.59
Anxious	6.04	1.59	0-9		1.68%	1.67	0.61
Sad	6.09	1.52	0-9		1.71%	1.50	0.52
Angry	4.21	2.06	0-9		8.65%	2.06	0.61
Full of energy	2.02	1.33	0-9		31.75%	1.39	0.74
Ashamed	5.17	1.75	0-9		10.41%	1.78	0.54
Guilty	5.10	1.73	0-9		8.43%	1.70	0.62
Impulsive	3.65	2.00	0-9		8.85%	1.94	0.60
Urgency	4.07	1.79	0-9		6.23%	1.77	0.46
Self-harm Urge	3.39	2.06	0-9		20.52%	1.84	0.63

Note. RMSSD = root mean square of successive differences

Table 3a. Predictive accuracy of idiographic models predicting levels of suicidal ideation over time

	Training	Testing		Autoregressive	Hopelessness	Interpersonal	3-Step
PID	***n***	***n***	***N***	out-of-sample R^2			
P001	67	67	134	.56	.38	.34	.32
P002	59	60	119	.68	.55	.57	.57
P003	55	56	111	.36	.22	.12	.23
P004	63	64	127	.14	.02	.07	.01
P005	46	47	93	.07	.07	.09	.20
P006	47	48	95	.44	.42	.18	.45
P007	50	51	101	.06	.18	.19	.01
P008	56	57	113	.05	.14	.07	.16
P009	48	48	96	.30	.04	.02	.31
P010	53	54	107	.76	.23	.35	.44
M	54	55	109	.34	.23	.20	.27
SD	7	7	13	.25	.17	.16	.18

Note. PID = Participant ID; Hopeless = hopelessness theory of suicide; Interpersonal = interpersonal theory of suicide; 3-Step = three-step theory of suicide.

Table 3b. Predictive accuracy of idiographic machine learning models predicting levels of suicidal ideation over time

	Training	**Testing**		**Elastic Net**	**MCP**	**SCAD**	**Random Forest**
PID	***n***	***n***	***N***		*out-of-sample R^2*		
P001	67	67	134	.72	.58	.59	.78
P002	59	60	119	.73	.67	.69	.84
P003	55	56	111	.64	.39	.41	.65
P004	63	64	127	.21	.06	.10	.70
P005	46	47	93	.49	.01	.02	.26
P006	47	48	95	.63	.50	.50	.61
P007	50	51	101	.48	.01	.01	.51
P008	56	57	113	.57	.14	.14	.53
P009	48	48	96	.75	.23	.21	.69
P010	53	54	107	.76	.78	.78	.86
M	54	55	109	.60	.34	.34	.64
SD	7	7	13	.16	.27	.27	.17

Note. PID = Participant ID; MCP = minimax concave penalty; SCAD = smoothly clipped absolute deviation.

Table 4a. Predictive accuracy of idiographic models predicting presence of intense suicidal ideation over time

	Training		Testing			Autoregressive				Hopeless				Interpersonal				3-Step			
PID	**Yes**	**No**	**Yes**	**No**	***N***	**AUC**	**Sens**	**Spec**	**Brier**	**AUC**	**Sen**	**Spec**	**Brier**	**AUC**	**Sens**	**Spec**	**Brier**	**AUC**	**Sens**	**Spec**	**Brier**
P001	25	42	45	22	134	.80	.73	.87	.14	.70	.91	.47	.20	.76	.91	.62	.19	.68	.45	.87	.87
P002	23	36	18	42	119	.81	.75	.86	.15	.80	.63	.89	.19	.76	.88	.66	.23	.79	.88	.64	.64
P003	16	39	22	34	111	.76	.74	.78	.18	.73	.53	.89	.21	.65	.58	.70	.22	.61	.47	.81	.81
P004	24	39	26	38	127	.66	.60	.72	.22	.60	.72	.46	.23	.61	.60	.64	.23	.58	.36	.90	.90
P005	8	38	10	37	93	.64	.42	.86	.18	.58	.08	1.00	.25	.70	.83	.60	.19	.54	.17	.89	.89
P006	19	28	19	29	95	.79	.76	.81	.16	.88	.88	.81	.14	.81	.82	.77	.19	.86	.82	.87	.87
P007	26	24	22	29	101	.60	.54	.67	.24	.58	.33	.78	.25	.75	1.00	.44	.20	.69	.75	.67	.67
P008	20	36	21	36	113	.63	.52	.74	.25	.69	.83	.59	.23	.74	.74	.74	.22	.69	.83	.62	.62
P009	19	29	13	35	96	.70	.53	.87	.19	.69	.94	.42	.22	.64	.82	.55	.28	.67	1.00	.39	.39
P010	18	35	22	32	107	.79	.72	.86	.17	.79	.52	.93	.19	.79	.92	.55	.20	.86	.92	.72	.72
M	20	35	22	33	110	.72	.63	.80	.19	.72	.64	.72	.21	.72	.81	.63	.22	.70	.66	.74	.21
SD	5	5	9	5	13	.08	.12	.07	.04	.10	.26	.21	.03	.06	.13	.09	.03	.10	.26	.15	.08

Note. PID = Participant ID; AUC = area-under-the-curve; Sens = sensitivity; Spec = specificity; Brier = Brier score; Hopeless = hopelessness theory of suicide; Interpersonal = interpersonal theory of suicide; 3-Step = three-step theory of suicide.

Table 4b. Predictive accuracy of idiographic machine learning models predicting presence of intense suicidal ideation over time

	Training		Testing			Elastic Net				MCP				SCAD				Random Forest			
PID	**Yes**	**No**	**Yes**	**No**	***N***	**AUC**	**Sens**	**Spec**	**Brier**	**AUC**	**Sens**	**Spec**	**Brier**	**AUC**	**Sens**	**Spec**	**Brier**	**AUC**	**Sens**	**Spec**	**Brier**
P001	25	42	45	22	134	.78	.55	.89	.18	.76	.64	.84	.18	.73	.50	.96	.19	1.00	1.00	.98	.05
P002	23	36	18	42	119	.86	.69	.98	.13	.84	.69	.98	.14	.85	.69	.98	.13	1.00	1.00	1.00	.04
P003	16	39	22	34	111	.82	.89	.81	.17	.79	.84	.73	.18	.79	.89	.73	.18	1.00	1.00	1.00	.05
P004	24	39	26	38	127	.50	.00	.00	.24	.50	0	0	.24	.50	0	0	.24	1.00	1.00	1.00	.05
P005	8	38	10	37	93	.65	.83	.49	.19	.50	1.00	1.00	.20	.65	.83	.46	.19	1.00	1.00	1.00	.07
P006	19	28	19	29	95	.83	.88	.68	.17	.82	.82	.74	.19	.82	.88	.74	.18	.99	.94	.97	.05
P007	26	24	22	29	101	.59	.54	.67	.24	.59	.54	.67	.25	.59	.54	.67	.24	1.00	1.00	1.00	.05
P008	20	36	21	36	113	.69	.70	.71	.25	.69	.78	.62	.26	.68	.70	.68	.27	.93	.96	.82	.10
P009	19	29	13	35	96	.71	.59	.81	.20	.71	.71	.61	.20	.69	.65	.71	.20	1.00	.94	1.00	.07
P010	18	35	22	32	107	.91	.72	.93	.15	.86	.80	.83	.17	.90	.80	.86	.16	1.00	1.00	1.00	.04
M	20	35	22	33	110	.73	.64	.70	.19	.71	.68	.70	.20	.72	.65	.68	.20	.99	.98	.98	.06
SD	5	5	9	5	13	.12	.25	.27	.04	.13	.26	.27	.03	.12	.25	.27	.04	.02	.02	.05	.02

Note. PID = Participant ID; AUC = area-under-the-curve; Sens = sensitivity; Spec = specificity; Brier = Brier score.