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A Machine Learning Approach to Predicting Different Trajectories of Suicidal Behavior: A Longitudinal Study from Adolescence to Middle Adulthood

By

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Abstract

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The importance of studying suicidal behavior cannot be overstated given the concerning prevalence. Despite a wide range of studies on suicidal behaviors, three major limitations remain. First, most studies are cross-sectional. Second, most studies examined risk factors of suicidal ideation in isolation. A meta-analysis covering the past 50 years of suicidal research found that prediction was only slightly better than chance because researchers rarely tested the combined effect of multiple risk factors. Researchers recommended utilizing machine learning (ML) approaches to study suicidal ideation instead because ML can address complex classification problems. Third, many studies have ignored the possibility that suicidal ideation can shift throughout different developmental stages. Disregarding the fact that there are different trajectories of suicidal ideation can lead to biased results. In this paper, I addressed the limitations of past research by first investigating different trajectories of suicidal ideation using Latent Class Growth Analysis on a large, nationally representative longitudinal dataset (n = 7,295). I then used two ML approaches, classification trees and random forests, to examine which risk factors are predictive of the identified trajectories. Two hundred and eighty-one predictors were included in the ML models, spanning demographic, psychological, behavioral, economic, social, and environmental variables linked to suicidal behaviors, such as mental health, violence exposure, family, peer, and school functioning, neighborhood characteristics, community engagement, negative life events, expectations for the future, risky behaviors, self-esteem, and substance use. The Latent Class Growth Analysis identified three distinct trajectories: (a) Resilient Class, (b) Declining Class, and (c) Escalating Class. When comparing the predictive performance, machine learning models, specifically classification tree (AUC = 0.73) and random forest (AUC = 0.79), outperformed the traditional multinomial logistic regression (AUC = 0.64). Variable importance analysis from the random forest model revealed prior suicidal behaviors, psychological distress, and school belonging to be one of the most important predictors across all three classes. The findings of this study provide insight into the utility of these advanced computational approaches for predicting suicidal outcomes and inform future intervention efforts to support those struggling with suicidal ideation. Limitations and future directions are discussed.

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A Machine Learning Approach to Predicting Different Trajectories of Suicidal Behavior: A Longitudinal Study from Adolescence to Middle Adulthood

Suicide is a major public health concern. Globally, more than 700,000 people die by suicide every year; that is, one person dies every 40 seconds (World Health Organization [WHO], 2021). Suicide accounts for an estimated 8.5% of all deaths among young people aged 15–29 and 4.1% of all deaths among adults aged 30–49. For young people aged 15 to 29 years old, suicide is currently the third leading cause of mortality among females and the fourth among males. In the United States in 2020 alone, 12.2 million adults seriously thought about suicide, 3.2 million adults made a suicide plan, 1.2 million adults attempted suicide, and more than 45,000 people died by suicide (Centers for Disease Control and Prevention [CDC], 2022). There is also a large financial toll associated with suicidal behavior. In 2019, the economic impact of suicide and nonfatal self-harm in the U.S. was approximately $490 billion in medical care, work loss costs, and quality of life costs (Peterson et al., 2021). Given the concerning prevalence of suicide, it is important to study factors that predict suicidal behaviors with the goal of identifying persons for targeted interventions, treatment, and support.

Suicidal behaviors often progress through a series of stages (Bolognini et al., 2003, Kessler et al., 1999). For example, in an Australian sample of 11,572 participants responding to a telephone survey, 99.2% reported suicidal ideation prior to their attempt (de Leo et al., 2005). In another study, Nock et al. (2013) reported that within the first year of the onset of suicidal ideation, 63.1% of sampled adolescents transitioned from ideation to planning and 86.1% transitioned from ideation to attempts. Likewise, individuals with a clear intention to die reported suicidal ideation lasting weeks to months prior to their suicide attempt (Anestis et al., 2014).

Suicidal behaviors are complex phenomena. No single cause or stressor can sufficiently explain the emergence of suicidal thoughts and behaviors. Instead, multiple risk factors act together to influence an individual’s susceptibility to suicidal behaviors. Among these risk factors, researchers have suggested that past suicide attempts (Li et al., 2022; Seo et al., 2015), mental disorders (Nock et al., 2013), substance use (Holma et al., 2010), familial and social relationships (Fergusson et al., 2003), economic distress (Austin & Shanahan, 2020; Jeong, 2021), physical health and sleep habits (Harris et al., 2020; Recklitis et al., 2014), weight control and body image (Daly, 2020; Kim & Kim, 2009), involvement with the criminal justice system (Mitchell et al., 2021), and personality factors (Handley et al., 2018; McCallum et al., 2022; Millner et al., 2020) are associated with suicidal behaviors. Despite a wide range of studies on suicidal behaviors, three major limitations remain.

First, most studies are cross-sectional, which limits inferences of causality. In addition, suicidal behaviors measured at a single time point cannot establish a temporal relationship between the predictor and the outcome. It is possible that the variables used to predict suicidal behaviors occurred after the behavior took place (Kivela et al., 2019). To overcome this limitation, longitudinal studies are recommended to better identify predictors that impact the course of suicidal behaviors over time (Girard et al., 2020).

Second, most studies examined risk factors for suicidal behaviors in isolation. Individual risk factors have limited ability to predict suicide outcomes accurately and sufficiently (LeFevre, 2014). A meta-analysis of the past 50 years of research on suicidal ideation and behavior covering 365 studies and 3,428 risk factors found that prediction was only slightly better than chance for all outcomes (Franklin et al., 2017). A reason for this disappointing discovery is that researchers rarely tested the combined effect of multiple risk factors. As stated earlier, suicidal behaviors are a result of a constellation of factors. Nevertheless, accurate prediction may require algorithms that model complex relationships among hundreds of predictors and their interactions. However, most studies have utilized traditional statistical techniques, such as linear or logistic regression, which are only helpful for examining relatively simple hypotheses about suicidal behaviors. To overcome this limitation, Ribeiro et al. (2016) recommended utilizing machine learning approaches to study suicidal behaviors because machine learning techniques are ideal to address complex classification problems. For example, Kessler et al. (2015) applied machine learning techniques to predict suicide after psychiatric hospitalization among a large sample of U.S. army soldiers. The results yielded an area under the receiver operating characteristic curve (AUC) of 0.84, which is a substantially stronger prediction than what the literature in the past 50 years has been able to produce (AUC of 0.56; Franklin et al., 2017).

Third, little is known about the different developmental trajectories of suicidal behaviors (Whalen et al., 2022). The majority of studies have ignored the possibility that suicidal behaviors can shift from childhood to adolescence to adulthood (Nkansah-Amankra, 2013). Emotional and behavioral problems can arise as individuals enter different developmental stages with evolving life roles, social relationships, and career responsibilities (Arnett, 2000; Rudolph et al., 2001). To address this issue, researchers have suggested investigating trajectories of suicidal behaviors instead (Kivela et al., 2019; Nkansah-Amankra, 2013; Salagre et al., 2020; Whalen et al., 2022) by categorizing individuals with similar trajectories of suicidal behaviors into the same group. This approach, which is possible through latent class growth analysis (LCGA), allows researchers to capture the complexity and heterogeneity of suicidal behaviors. LCGA is a person-centered analytic method that can be used to identify unobserved underlying groups of individuals with suicidal behaviors (Jung & Wickrama, 2008; Nylund-Gibson & Choi, 2018).

To this end, the present study addressed the previously mentioned research gaps by first identifying trajectories of suicidal behaviors from a longitudinal dataset using LCGA and then applying two machine learning methods, classification trees and random forest, to examine novel predictors of the identified trajectories. To date, no study in the literature on suicide has employed both LCGA and machine learning methods on a longitudinal dataset.

In the following literature review, I first addressed issues regarding the definitions of suicide and suicidal behaviors. Second, I reviewed leading theories as well as risk factors for suicide and suicidal behaviors. Reviewing theories and risk factors would set the stage for the selected predictors included in the machine learning model. Finally, I discussed studies that have used machine learning methods to predict suicidal outcomes and studies that have used LCGA to identify trajectories of suicidal behaviors.

Suicidal Behaviors and Suicidal Ideation

In the academic literature, suicide is defined as a deliberate act to end one's life (Nock et al., 2013). However, the definition of suicidal behavior is not as clear-cut and varies in degree and specificity. Suicidal behaviors refer to suicidal ideation or suicide attempts. Suicidal ideation occurs along a spectrum ranging from fleeting thoughts about killing oneself to formulating a specific plan to execute a suicidal act (Bolognini et al., 2003). For example, ideation can include expressing the intent to hurt or kill oneself, actively searching for ways to kill oneself, or openly talking about suicide. A suicide attempt is a self-directed injurious behavior intended to cause death but that does not result in death (Kaslow, n.d). Suicide typically begins with suicidal ideation and then suicide attempts and often ends with the act of killing oneself (Nock et al., 2013).

It is important to note that suicidal behavior is distinct from non-suicidal self-injury (NSSI). NSSI is operationalized as "the intentional destruction of one's own body tissues without suicidal intent and for purposes not socially sanctioned" (Klonsky et al., 2013, p. 231). In other words, NSSI refers to self-harming behaviors that lack the intent to end one's life. For example, individuals who engage in NSSI utilize nonlethal methods that may cause physical damage, such as cutting, burning, and excessive rubbing, to cope with strong and unpleasant experiences. Common and trivial behaviors such as nail biting and socially sanctioned practices such as body piercing and tattooing are not considered NSSIs. Although both NSSIs and suicidal behaviors involve harming oneself and often co-occur, NSSIs are distinct from suicidal behaviors. Persons who exhibit suicidal behaviors perceive life as unbearable and thus not worth living, whereas persons who exhibit NSSIs are primarily concerned with relief from painful and overwhelming emotional stimuli *without* the intention to die (Guan et al., 2012).

Leading Theories of Suicidal Behaviors

Sociologists were among the first to systematically study suicide. In particular, the French sociologist Emile Durkheim's work, *Suicide: A Study in Sociology* (Durkheim, 1897), was pivotal to the growth and development of suicidology. According to Durkheim (1897), suicide is the result of societal influences rather than an individual's psychological state. He argued that there are four forms of suicide that reflect the individual's relationship to society: (a) altruistic, (b) anomic, (c) egoistic, and (d) fatalistic. Altruistic suicide occurs when the individual is in a state of excessive social integration so that sacrificing oneself is for the good of the larger group. Terrorist suicide bombers or the Japanese kamikaze pilots in World War II are examples of altruistic suicide. Anomic suicide occurs when the individual cannot rationally deal with a disruption in society, such as an economic depression or a natural disaster. Suicide rates increased drastically during the 2008–2009 U.S. mortgage crisis (Kerr et al., 2017) as well as the COVID-19 pandemic outbreak (Pathirathna et al., 2022). Egoistic suicide occurs when the individual is not attached to society and therefore feels meaningless, indifferent, and depressed. Fatalistic suicide occurs when the individual feels hopeless about an overregulated society that restricts freedom.

Durkheim's (1897) work laid the foundation for the field of suicidology, and many scholars have extended his theoretical tradition from a purely sociological approach to an integrative-psychological approach (Berman et al., 2006). One notable contribution is Shneidman's (1993) theory of suicide as psychache. Shneidman, a clinical psychologist, defined psychache as an acute state of immense psychological pain associated with feelings of anguish, despair, fear, humiliation, hurt, loneliness, and shame. According to Shneidman, psychache leads to suicide once the psychological pain becomes unbearable to the point where death is the only means of escape. In this framework, suicide is seen as a problem-solving behavior rather than the result of psychopathology. Shneidman (1993) described the progression to suicide in five steps: (a) the individual is exposed to triggering life events, (b) these triggering life events are perceived as negative and painful, (c) the perception of pain becomes unbearable, (d) the individual believes that the termination of consciousness may be a potential solution to this pain, and finally, (e) suicide occurs when the individual can no longer tolerate the level of pain.

Another integrative approach to understanding suicide is the diathesis-stress model of suicidal behavior (Schotte & Clum, 1987). The term *diathesis* originates from the Greek word for predisposition, and the term now refers to biological, cognitive, psychological, situational, environmental, or social predisposed vulnerability (Zuckerman, 1999). The diathesis-stress model proposes that suicidal behavior is the result of an interaction between predisposed factors and stressful life events (Mann et al., 1999; O'Connor, 2011). For example, O'Connor et al. (2007) found that distinct components of perfectionism, a cognitive factor acting as a diathesis, were linked to suicidal ideation in the presence of stress. To conceptualize this theory, consider the "cup analogy." Imagine several cups, each filled with different numbers of marbles. The same amount of water is poured into each of the cups. The cups with more marbles will overflow, whereas the cups with fewer marbles will not. In this analogy, the marbles represent diathesis and the water represents stress. The greater the diathesis, the less stress needed to trigger the risk for suicide (Theodore, 2022).

One of the fastest-growing areas of research in suicidology falls under Thomas Joiner's interpersonal-psychological theory of suicidal behavior (IPTSB; Joiner, 2005). Joiner argued that serious suicidal behavior requires each of three specific interpersonal-psychological precursors: (a) perceived burdensomeness, (b) a sense of low belongingness or social alienation, and (c) the acquired ability to enact lethal self-injury. Perceived burdensomeness is the view that one's existence burdens family, friends, or society. A sense of low belonginess refers to the experience of feeling alienated from others and not an integral part of family, friends, or community. The acquired ability to enact lethal self-injury alludes to a force powerful enough to overcome self-preservation instincts (Joiner et al., 2009). The self-preservation instinct refers to human beings' innate tendency to fear cues that signal threats to survival. The ability to enact lethal self-injury—in other words, the capability to be fearless of death—is acquired over time through repeated exposure to painful and otherwise provocative events. These distressing experiences, such as previous self-injury, physical fights, or exposure to combat in war, result in higher tolerance for pain and numbness toward death. There is considerable empirical support for the interpersonal-psychological theory of suicidal behavior. For example, Bryan et al. (2010) found that active-duty members of the United States Air Force who had repeatedly witnessed violence and injuries had higher levels of acquired capability for suicide than a nonmilitary clinical sample. Likewise, perceived burdensomeness was a significant predictor of suicidal ideation and attempts among a sample of adults recruited from an outpatient clinic (Van Orden et al., 2006). In another study that tested the IPTSB, Van Order et al. (2008) found that levels of suicidal ideation varied across semesters among college students, with peak levels in summer compared to both fall and spring. This peak was explained by the fact that campuses were generally less active during summer and thus levels of social belonging were at their lowest.

The four theories introduced above provide a framework for understanding suicidal behaviors and their related characteristics. From these theories, researchers have identified a set of variables that are associated with suicidal behaviors. In the following section, I reviewed studies that examine these variables in the form of risk factors, thus setting the stage for the selected variables that were included in my machine learning model.

Risk Factors

Risk factors are traits or characteristics that may predict the likelihood of suicide or suicidal behaviors (Sharaf et al., 2010). In this section, I detailed research addressing risk factors for adolescent suicide and suicidal behaviors. In particular, I organized the risk factors based on the four theories introduced above. It is important to note that multiple theories may share similar components and therefore can generate the same risk factors. For example, the sociological theory of suicide (STS; Durkheim, 1897) and the diathesis-stress model of suicidal behavior (DSMSB; Mann et al., 1999) both suggest an association between neighborhood effects and the risk of suicide (Fedina et al., 2019; Hagedoorn & Helbich, 2021). From the perspective of STS, living in a socially disconnected neighborhood is an illustration of egoistic suicide. Likewise, from the perspective of DSMSB, living in a neighborhood filled with violence acts as an environmental diathesis that escalates the risk of suicide.

To develop a well-ordered organization, the same risk factor identified from multiple theories will only appear under one theory.

Sociological Theory of Suicide (STS).

Economic Factors. STS proposes that the presence of economic instability or distress, a form of social disruption or anomie, impacts the risk of suicide (Pierce, 1967). For example, Dooley et al. (1989) interviewed 500 adults from 1978 to 1982 and found that those who were unemployed for six months or who were voluntarily without work had elevated levels of suicidal ideation during periods of economic contraction after accounting for symptoms of psychological disorder. Almost two decades later, Kerr et al. (2017) studied the impact of economic recession on suicide rates. The historically severe economic conditions from 2008 through 2011 were marked by high levels of income loss, unemployment, and foreclosure activity. As a result, poverty rates increased from 10.8% in 2006 (before the recession) to 15% in 2011 (after the recession began). The results indicated that poverty rates fully mediated the relationship between unemployment rates and suicide rates for those aged 45–64 years during the recession. In another study, Richardson et al. (2013) conducted a meta-analysis of 65 studies and found that personal unsecured debt, such as credit card debt, student loans, or being behind on payments to utility companies, was significantly related to suicide attempts or completed suicide (odds ratio [OR] = 5.76). Similarly, Austin and Shanahan (2020) found that experiencing material hardships was related to an increased likelihood of suicidal behavior compared to experiencing no material hardship in a nationally representative, longitudinal sample of 10,685 US adults. In this study, material hardship was defined as the lack of food, housing, utility, medical care, or financial security, and suicidal behavior was defined as the combination of suicidal ideation and suicide attempts in the previous 12 months. The authors noted that the relationship between material hardship and suicidal behavior remained significant after controlling for substance use disorders, depression, and prior suicidal behavior. Taken together, there is considerable evidence supporting the impact of harsh economic conditions on the risk of suicide.

Suicide as Psychache Theory (SPT). SPT proposes that suicidal behaviors occur when psychological pain becomes unbearable to the individual (Shneidman, 1993). In the following sections, I review the literature that examines the association between suicidal behaviors and psychological pain, namely, mood and affect disorders, and substance abuse.

Mood and Affect Disorders. Research has established an association between mood and affect disorders and suicidal behaviors (Brent, 1995; Comtois et al., 2004; Nock et al., 2013). A case–control, psychological autopsy study indicated that 90% of teens who completed suicide were diagnosed with one or more mental disorders. For males, 50% had mood disorder, 43% had conduct disorder, 38% had substance disorder, and 19% had anxiety disorder. Among females, 69% had mood disorder, 48% had anxiety disorder, 24% had conduct disorder, and 17% had substance disorder (Shaffer et al., 1996). Shortly thereafter, Mazza and Reynolds (1998) conducted a longitudinal study over a period of one year with 374 high school students. In the study, researchers collected data from the adolescents on suicidal ideation, depression, hopelessness, and social-environmental factors. The results indicated that changes in depression scores were associated with changes in suicidal ideation for both males and females after adjusting for social-environmental factors such as social support. When hopelessness was covaried, depression was related to suicidal ideation for both females and males. This finding suggests that depression may be the strongest driving force behind suicidal ideation. More recently, Liu et al. (2020) conducted a systematic review and meta-analysis of 86 studies that examined suicidal ideation and its psychiatric comorbidity, associated sociodemographic characteristics, and psychological and environmental correlates. The results suggested that the largest pooled effect sizes for suicidal ideation were clinical factors, such as depression, anxiety, and psychosis. In another study, Lucht et al. (2022) investigated the association of mood and affect and suicidal ideation among a sample of 74 psychiatric inpatients with unipolar depression. The authors employed an ecological momentary assessment design in which participants were provided with Android smartphones to collect real-time mood and affect data over six days. The smartphones randomly prompted the participants to answer questions about their current mood, affect, and suicidal ideation throughout the day. The results suggested that negative valence of mood and low positive affect predicted subsequent intensity as well as changes in suicidal ideation. In short, the literature posits that mood and affect factors are important risk factors for suicidal behaviors.

Substance Abuse. Substance abuse can be a maladaptive means to cope with psychological pain (Koob, 2015). As theorized by the SPT, individuals who struggle with suicidal behaviors may use substances to suppress their negative emotions (Mee et al., 2019). This line of reasoning is supported by the literature (Armoon et al., 2022; Rontziokos & Deane, 2019). For example, Brent (1995) conducted a psychological autopsy study and found that those who completed suicide were 12.7 times more likely to abuse substances than those who did not complete suicide. Adams and Overholser (1992) examined substance abuse among 716 psychiatric emergency room patients and found that suicidal patients, compared to nonsuicidal controls, were more likely to have a history of drug abuse and to report a family history of alcohol abuse. Afifi et al. (2007) examined the associations between health risk behaviors and suicidal ideation among 2,090 Canadian adolescents and found that substance use was significantly associated with suicidal ideation for males after controlling for depressive symptoms scores, emotional or anxiety symptom scores, and physical aggression scores. A relatively recent meta-analysis covering 31 studies and 420,732 participants indicated a significant association between alcohol use disorder and suicidal ideation (OR = 1.86), suicidal attempts (OR = 3.13), and completed suicides (OR = 2.59; Darvishi et al., 2015), with little concern for the presence of publication bias. Given the evidence documented in the literature, researchers and clinicians must consider substance use factors when examining suicidal behaviors.

Diathesis-Stress Model of Suicidal Behavior (DSMSB). The DSMSB proposes that predisposed factors and stressful life events can lead to suicidal behaviors (Mann et al., 1999; O'Connor, 2011). In the following sections, I review the literature that examines neighborhood effects as well as physical health conditions as forms of diathesis and stress that can increase the risk of suicidal behaviors.

Neighborhood Effects. The DSMSB provides theoretical support that suicidal behaviors may be influenced by the neighborhood environment (O'Connor, 2011). Living in an area marked by distress or social disconnectedness can act as a diathesis that, when combined with stress, may heighten an individual's risk of suicide (Hagedoorn & Helbich, 2021). Numerous studies that examine the association between neighborhood effects and suicidal behaviors lend support to this assertion (Cairns et al., 2017). A systematic review of the literature dating from 1897 to 2004 covering 86 publications with 221 separate analyses suggested that neighborhoods riddled with high poverty/deprivation, high unemployment, or low levels of education are associated with high suicidal mortality. The authors of the review noted that the significant association between SES and suicidal mortality depends on the size of the region investigated. Studies using smaller area units, such as neighborhood area levels rather than state levels, were more likely to report significant results (Rehkopf & Buka, 2005). In another study, Fedina et al. (2021) found evidence that neighborhood disconnectedness and compositional change increase the risk of psychological distress symptoms and suicidal ideation, with the effect being more pronounced for those suffering from intimate partner violence. Neighborhood disconnectedness was defined as one's feelings of recent disconnectedness from their neighborhood, and composition change was defined as changes in the area related to affluence/resources, crime, residential mobility, and infrastructure. These findings suggest that rapid changes in the neighborhood can disrupt social ties and the perception of neighborhood connectedness, which may impact mental health outcomes.

Physical Health Conditions. A convergence of evidence suggests that many poor physical health conditions, such as chronic pain, heart disease, stroke, cancer, perception of overweight, and asthma, are a diathesis for greater risk of suicide (Daly, 2020; Juurlink et al., 2004; Kuo et al., 2010; Recklitis et al., 2014; Webb et al., 2012). A meta-analysis that examined various correlates of suicidal ideation found that physical health problems had a pooled effect size of 0.50 (Liu et al., 2020). Fairweather et al. (2006) examined physical health problems and suicidal behaviors among a subsample of 522 suicide ideators and concluded that physical medical conditions, defined as the presence of heart trouble, cancer, arthritis, diabetes, or head injury, were significantly associated with an increased likelihood of suicidal attempts (OR = 1.95). The authors noted that the relationship between physical medical conditions and suicide attempts was stronger among older adults. Individuals between the ages of 40 and 44 had an odds ratio of 2.58, whereas those between the ages of 20 and 24 had an odds ratio of 1.70. More recently, Ahmedani et al. (2017) conducted a case–control study that compared the physical health records of 2,674 individuals who died by suicide and 267,400 controls between 2000 and 2013. The results indicated that 17 physical health conditions were significantly associated with an elevated risk of suicide after adjustment for age and sex. Nine of the 17 conditions remained significant after additional adjustment for mental health and substance use diagnoses. The top three conditions with the strongest effects were traumatic brain injury (OR = 8.80), HIV/AIDS (OR = 2.14), and sleep disorders (OR = 2.08). Additionally, multimorbidity was a factor; 38.2% of those who died by suicide had multiple physical health conditions compared to only 15.5% of the controls. Logistic regression analyses revealed that multimorbidity was associated with an increased risk of suicide (OR = 4.12) after controlling for age, sex, and any mental health variables.

Interpersonal-Psychological Theory of Suicide Behavior (IPTSB). The IPTSB proposes that suicidal behaviors stem from (a) perceived burdensomeness, (b) a sense of low belongingness or social alienation, and (c) the acquired ability to enact lethal self-injury (Joiner, 2005). In the following sections, I review the literature on three constructs that fall under the umbrella of each of the components of IPTSB: hopelessness, social support, and delinquency behaviors.

Hopelessness. Feelings of hopelessness can be conceptualized as having negative perceptions or expectations about the future (Horwitz et al., 2017; McCallum et al., 2022). Under the IPTSB, the pathway to suicidal behaviors involves the construct of hopelessness in which individuals believe that the sense of thwarted belongingness and perceived burdensomeness will never change (Chu et al., 2017). The literature supports this line of reasoning, and the link between hopelessness and suicidal behaviors is well established (Beck et al., 1985; Mazza & Reynolds, 1998; Rutter, 1998). Revisiting the meta-analysis introduced earlier that examined 86 studies, Liu et al. (2020) found that hopelessness had the third largest pooled effect size (d =.80) for suicidal ideation after depression (d =.96) and psychiatric problems (d =.81). In a cross-sectional study that examined the association between personality domains and suicidal behaviors among 1428 adolescents from Australia, McCallum et al. (2022) applied logistic regression and found that a one-unit increase in hopelessness was associated with twice the odds of suicidal ideation as well as having made a suicide plan after controlling for psychological distress, age, and gender. Using a community sample of 454 participants ranging from 18 to 73 years old, Holler et al. (2022) found that hopelessness was significantly correlated with suicidal ideation. In particular, hopelessness partially mediated the relationship between internal and external entrapment (i.e., feelings of being trapped or a lack of control due to internal or external circumstances) with suicidal ideation. In a longitudinal study of 59 adolescents over four years, Horwitz et al. (2017) examined the relationship between hopelessness and suicidal ideation by distinguishing between negative expectations and positive expectations within the construct of hopelessness. An example of a negative expectation is when individuals feel that they do not expect to get what they truly want, whereas an example of a positive expectation is when individuals can look forward to more good times than bad times. The results indicated that positive expectations were a significant predictor of suicidal behavior when controlling for baseline levels of depression, suicidal ideation, and negative expectations. In other words, the more positive expectations one has, the less likely the individual is to manifest suicidal behaviors. Conversely, the fewer positive expectations an individual has, the more likely he or she is to manifest suicidal behaviors. However, negative expectations were not significantly predictive of suicidal behaviors. These findings suggest that positive expectations may be a stronger driving force than negative expectations in the relationship between hopelessness and suicidal behavior among adolescents.

Social Support. A lack of social support from family or peers is known to be an important risk factor for suicidal behaviors (Bearman & Moody, 2004; Miller et al., 2007). According to the IPTSB, family and peer relationships marked by high levels of conflict, low levels of support or cohesion, and greater difficulty in communication can elevate thwarted belongingness and perceived burdensomeness, which in turn can lead to lethal acts (Hunt et al., 2021; Kerr et al., 2006; Ursoniu et al., 2009). For example, Cero and Sifers (2013) found that proxy measures of thwarted belongingness and perceived burdensomeness mediated the relationship between parental support and suicide attempts among adolescents. In another study, Nguyen et al. (2017) found that the frequency of contact with friends was negatively associated with suicidal ideation and attempts among a sample of 3,263 African Americans. In the following literature review, I will first discuss studies on social support from families and then studies on social support from peers.

Social Support from Families. Research has shown that impaired parent–child communication in combination with a low level of emotional support expressed by parents is associated with a risk of adolescent suicidal behavior (Miller et al., 2007). Family relationships have various forms. One aspect of family relationships is family cohesion, which is a sense of belongingness family members have toward one another. It can be characterized by fulfilling familial obligations, maintaining harmonious family relationships, and sharing a sense of loyalty with one’s family (Joel Wong et al., 2012). Research has documented that this strong emotional bond is negatively associated with suicidal ideation (Baumann et al., 2010; Czyz et al., 2012). For example, in a study of 236 adolescent psychiatric inpatients, researchers compared ratings of family cohesion between those who attempted suicide and those who did not. The findings indicated that nonattempters rated significantly higher family cohesion than attempters. In other words, adolescents who did not attempt suicide rated stronger emotional bonding of family members toward one another than those who attempted suicide (Sheftall et al., 2013).

Similar to family cohesion, research has found parent-family connectedness to be negatively associated with suicidal behaviors (Kidd et al., 2006). Analyzing data from the National Longitudinal Study of Adolescent Health, Resnick (1997) surveyed suicidal ideation and behaviors among 12,118 seventh- to twelfth-graders. The findings demonstrated that after controlling for key demographic variables and family structures, parent-family connectedness was the strongest protective factor against adolescent suicidal behaviors and ideation. In another study with a national sample of 11,666 American Indian and Alaska Native youth, Borowsky et al. (1999) discovered that male adolescents who reported higher family connectedness were 47% less likely to have made a past suicide attempt, whereas female adolescents were 56% less likely. In short, the role of family relationships in reducing the risk of suicidal behavior is powerful because family acts as individuals' primary source of security and support, both concurrently and prospectively.

Social Support from Peers. Research has linked strong peer support and friendships to a low frequency and severity of depressive symptoms, suicidal ideation, and suicide attempts among adolescents (Bearman & Moody, 2004). One aspect of peer relationships is peer connectedness, defined as the sense of closeness, belonging, satisfaction, and comfort with an individual or group of peers (Barber & Schluterman, 2008). Peer connectedness has been shown to act as a protective factor for suicidal adolescents. For example, Czyz et al. (2012) examined the relation between suicidal behaviors and peer connectedness in a sample of 338 adolescents who were hospitalized due to suicidal behaviors. The researchers assessed suicidal ideation, attempts, depressive symptoms, and peer connectedness among the adolescents at baseline and at three, six, and 12 months post-hospitalization. The findings suggested that during the 12-month period, adolescents who reported greater improvements in peer connectedness were half as likely to attempt suicide. In another study, Marver et al. (2017) explored the impact of friendship on suicide attempts among 132 adults with major depressive episodes. The results indicated that impaired friendship, or low frequency and poor quality of friendship, predicted a greater risk of suicide attempts. The effects of the quality of friendship contacts appeared to be stronger than the frequency. Interestingly, when depression severity was entered into the model, the effect of friendship on suicide attempts was mediated by depression severity. Individuals with poor-quality and low-frequency friendship contacts may be more likely to be depressed, which increases the risk of suicidal behaviors.

Delinquency, Crime, and Physical Violence There is emerging evidence that delinquency, crime, and physical violence, hereafter referred to as aggressive behaviors, are linked to the risk of suicide (Conner et al., 2003; Kafka et al., 2022; Mitchell et al., 2021). From the perspective of IPTSB, aggressive behaviors play an indirect role in suicide. Recall that one of the central components of IPTSB is the acquired ability to enact lethal self-injury (Joiner, 2005). This acquired ability is theorized to begin with exposure and habituation to frightening and painful experiences. Witnessing or engaging in aggressive behaviors exposes an individual to these painful and frightening experiences, which then desensitizes the individual to acquire the ability to self-harm. In turn, this acquired ability increases the likelihood that suicidal ideation will transition to suicidal attempts (Joiner et al., 2009). As a case in point, prison inmates are at greater risk of suicide than the general population (Hayes, 1995). Furthermore, inmates who died by suicide were more likely to be incarcerated for manslaughter than inmates who did not die by suicide (DuRand et al., 1995). Devries et al. (2013) conducted a systematic review and concluded that 11 out of 13 longitudinal studies showed a significant association between intimate partner violence (IPV) victimization and subsequent suicide attempts among women. Wolford-Clevenger et al. (2017) suggested that a high prevalence of IPV perpetrators (33%) experienced nonfatal suicidal ideation. In another study, Swogger et al. (2014) found outwardly directed aggression to be associated with suicidal attempts among a sample of criminal offenders as well as a sample of psychiatric inpatients after controlling for gender, substance use disorder, and depression. Based on these findings, accounting for aggressive behaviors is a fruitful avenue to advance our understanding of suicide.

Overview of Studies Using Machine Learning Methods to Predict Suicidal Behaviors

Despite the flourishing literature that has produced numerous studies on predictors of suicidal behaviors, the inherent limitation of these studies is that they only tested single risk factors. For example, studies have tested the relationship only between neighborhood effects and suicidal behaviors or only between hopelessness and suicidal behaviors. Very few studies have tested the combined predictive effects of multiple risk factors. Testing only single risk factors is problematic because the accurate prediction of suicidal behaviors may require the evaluation of a complex and large number of factors and their interactions (Kessler et al., 2015). As referenced earlier in this paper, a meta-analysis that reviewed studies in the suicidology literature from the past 50 years concluded that prediction was only slightly better than chance, with a weighted AUC for predicting suicide attempts of 0.58 and a weighted AUC for predicting completed suicide of 0.55 (Franklin et al., 2017). Consider the blind men and the elephant analogy. Three blind men discovered an elephant for the first time in their lives. These men decided to understand and explore the elephant by using their hands to feel it. The first man explored the trunk and concluded it was a snake. The second felt the legs and announced it was a tree. The third grabbed the tail and described it as a rope (Blind men and an elephant, 2022). Although not a perfect analogy, the blind men represent studies that tested single risk factors, none of which could accurately describe the entire elephant. To address this limitation, Franklin et al. (2017) recommended using machine learning approaches, which are capable of testing numerous risk factors and detecting complex patterns of suicidal behaviors.

The term machine learning was first coined by Arthur Samuel in 1959. Samuel, who was a computer scientist at IBM who specialized in artificial intelligence, programmed a computer to win against humans in a game of checkers using machine learning procedures, which involved developing mathematical models with the ability to learn from data iteratively to determine the best decisions and predictions (Samuel, 1959). The popularity of machine learning has skyrocketed in recent decades, and scientists have applied machine learning to many areas of research due to its advantages over traditional statistical methods (e.g., linear or logistic regression; Gardner et al., 1996; Steadman et al., 2000). The advantages include (a) the capability to efficiently process large datasets and model highly complex relationships among hundreds of predictors, (b) the ability to generate optimal algorithms from a set of predictors without the need to preset which variables to include in the model and what the relationships among the variables should be, and (c) the flexibility to relax statistical assumptions such as linear relationships, the normal distribution of residuals, or the presence of multicollinearity (Franklin et al., 2017).

Scientists who study suicide have recently begun to incorporate machine learning into their analyses because these sophisticated statistical methods can produce models that accurately reflect the complex nature of suicide among a large sample size. For example, Agnes et al. (2020) employed an elastic net model to predict the risk of suicidal attempts in 959 outpatients with obsessive-compulsive disorder (OCD). The model used clinical and sociodemographic variables as predictors and achieved an AUC of 0.95. The results suggested that previous suicide planning, previous suicidal ideation, lifetime depressive episodes, and intermittent explosive disorder were important predictors of suicidal outcomes. Likewise, Su et al. (2020) built machine learning models using deidentified electronic health records (EHRs) from a hospital covering the longitudinal clinical records of 41,721 young patients to predict suicidal behaviors among children and adolescents. The clinical records included patient demographic characteristics, mental health-related factors, routing tests, medications, and laboratory tests. The authors found that the models predicted suicidal behaviors with AUCs varying from 0.81 to 0.86 as well as positive predictive values ranging from 3 to 6% for 90% specificity and from 4 to 8% for 95% specificity. Overall, the machine learning models outperformed the baseline logistic regression models, providing evidence that using machine learning methods with clinical data can adequately predict the risk of suicide attempts.

In another study, Hill et al. (2020) applied classification tree analysis, a branch of machine learning, to prospectively identify suicide attempters using a large longitudinal dataset of 4,834 adolescents. The results indicated that physiological and depression symptoms, familial characteristics, propensity for risky behaviors, sex and sexually transmitted disease-related variables, and substance use were important predictors of individuals at risk of suicidal attempts. In addition, the flexibility of classification trees allowed researchers to adjust the number of true positives (sensitivity) or true negatives (specificity) of individuals at risk for suicide attempts that the model could identify. This flexibility, in turn, allowed clinical practitioners to tailor screening approaches that can be adapted to the goals of a particular organization. For example, high sensitivity should be considered if the organization provides low-cost services such as psychoeducation, whereas high specificity should be considered if the organization offers services with greater intensity, such as one-on-one therapy.

The number of studies that apply machine learning methods to predict suicidal outcomes is growing; however, no studies to date have examined different *trajectories* of suicidal behaviors. In the next session, I provided a brief overview of studies that have examined trajectories of suicidal behaviors identified through latent class growth analysis.

Latent Class Growth Analysis to Distinguish Trajectories of Suicidal Behaviors

The majority of studies conducted in the suicidology literature have measured suicidal outcomes at a specific point in time or the relatively few studies that measured suicidal outcomes repeatedly often aggregated the temporal levels of suicidal behaviors. These approaches do not account for the fact that developmental trajectories exist or the fact that there may be heterogeneity within these trajectories of suicidal behaviors. Collapsing unique trajectories can induce loss of information whereby combining individuals with positive changes and those with negative changes in a variable over time will cancel each other out. This process masks subgroup trends by producing population-level trajectories that appear stable or average (Population Health Methods, 2022; Wang et al., 2019). To address these issues, researchers recommend conducting longitudinal studies and using latent class growth analysis (LCGA) to better understand the temporal course of suicidal behavior (Jung & Wickrama, 2008).

Few studies have used LCGA to investigate the trajectories of suicidal behavior. For example, Prinstein et al. (2008) studied the trajectories of suicidal ideation among a sample of 143 adolescents who were assessed during psychiatric inpatient hospitalization. The adolescents were assessed again at 3, 6, 9, 15, and 18 months post discharge. LCGA revealed a substantial decline in suicidal ideation during the first 6 months posthospitalization as well as a period of re-emergence between 9 and 18 months following discharge. Several years later, Nkansah-Amankra (2013) used semiparametric growth mixture models (GMMs), a technique that is in the same statistical family as LCGA, to identify distinct clusters of suicidal ideation using a nationally representative longitudinal dataset of 9,421 participants. The longitudinal dataset tracked individuals from adolescence to adulthood in four waves of data. The results suggested a three-class model fit for suicidal ideation with the following breakdown: (a) *intensifiers* (31.3% of the sample), where individuals began with low levels of suicidal ideation in wave one of the data, but the levels slowly increased in wave two to wave four, (b) *decliners* (58% of the sample), where individuals began with high levels of suicidal ideation in wave one but declined in wave two to wave four, and (c) *re-emergers* (10.8% of the sample), where individuals began with high levels of suicidal ideation in wave one, levels declined slightly in waves two and three, and levels rebounded in wave four.

In a more recent study that examined the trajectories of suicidal ideation over nine months among homeless youth, Wu et al. (2022) used GMM and found three distinct trajectories: (a) fast declining (74.7% of the sample), where individuals showed lower levels of suicidal ideation at baseline, then a sharp decline over the next 3 months followed by a slow decline between 3 to 9 months; (b) chronic (19.3% of the sample), where individuals showed high levels of suicidal ideation at baseline, then declined slightly over the next 9 months but maintained elevated subclinical levels; and (c) steadily declining (6% of the sample), where individuals showed relatively high levels of suicidal ideation at baseline, then slowly and steadily declined over the course of 9 months. In another study, Hoffmire et al. (2022) used LCGA to study the trajectories of suicidal ideation among individuals who transitioned out of military service. The authors identified four trajectories: (a) resilient class (90.1% of the sample), characterized by minimum suicidal ideation over the study period of 27 months; (b) delayed onset class (5% of the sample), characterized by low levels of suicidal ideation at baseline that steadily increased with time; (c) remitting class (2.7% of the sample), characterized by moderate to high levels of suicidal ideation at baseline that decreased with time; and (d) chronic class (2.2% of the sample), characterized by moderate to high levels of suicidal ideation throughout the study period. The findings reported above highlight the methodological advantage of LCGA to identify the patterns and trajectories of suicidal behavior, thereby allowing researchers and practitioners to tailor preventative strategies to specific risk profiles.

The Present Study

To my knowledge, no research has used machine learning techniques to explore the impact of risk factors on different trajectories of suicidal behaviors. In the present study, I sought to overcome the limitations of past research by first investigating different trajectories of suicidal behaviors using LCGA on a large longitudinal dataset. This dataset contains survey data collected from individuals spanning adolescence to adulthood over a period of 24 years. I then used a machine learning approach, namely, classification trees and random forests, to examine which risk factors are predictive of the identified trajectories. The findings of this study provided insight into the utility of these advanced computational approaches for predicting suicidal outcomes and inform future prevention and intervention efforts to support those struggling with suicidal behaviors.

Research Questions

My first research question is, what are the different trajectories of suicidal behaviors. Consistent with previous studies (Hoffmire et al., 2022; Nkansah-Amankra, 2013; Prinstein et al., 2008; Wu et al., 2022), I hypothesized that my LCGA model will identify heterogenous groups of individuals with distinct trajectories of suicidal behaviors over the span of 24 years from adolescence to adulthood. My second research question asks whether a machine learning approach (classification trees and random forest) can improve model accuracy compared to traditional models (logistic regression) to predict trajectories of suicidal behaviors. Given that a number of machine learning studies have reported better prediction accuracy than simpler models (Agnes et al., 2020; Fox et al., 2019; Hill et al., 2020; Su et al., 2020), I hypothesized that machine learning models will improve the prediction of suicidal behaviors trajectories compared to traditional models. My third research question is, what are the prominent risk factors for each of the trajectories of suicidal behaviors. There was no hypothesis because this research question is exploratory and inductive in nature.

Method

Data and Participants

In the current study, I used data from the National Longitudinal Study of Adolescent to Adult Health, commonly known as Add Health. The data is obtained through the Carolina Population Center portal (CPC) after passing a set of data storage security procedures. Add Health is one of the most comprehensive surveys that measures features of the social environment, individual characteristics, and health risks and behaviors. Starting in 1994, the research team recruited a nationally representative sample of middle and high school students from 144 schools with a total sample size of 90,118. The group then pulled out a select sample for further in-home interviews in 1995 (Wave I, aged 11–19 years), 1996 (Wave II, aged 12–20 years), 2001 (Wave III, aged 18–26 years), 2007 (Wave IV, aged 24–32 years), and 2016 (Wave V, aged 32–42 years). At Wave I, 20,745 participants completed in-home surveys. For respondents who were eligible for follow-up since the conclusion of Wave I, 14,738 completed surveys at Wave II, 15,197 at Wave III, 15,701 at Wave IV, and 12,300 at Wave V (Harris et al., 2019). The final sample used in this study includes 7,295 participants as the Add Health user guide recommends dropping participants without sampling weights. The sampling weights are used to correct oversampling of certain population, such as youth who were disabled, Black youth from highly educated families, Chinese youth, and Puerto Rican youth. The average age of the participants is 15.7 years old (*SD* = 1.60). Males comprised 41.5% of the sample. Participants self-identified with the following ethnic-racial groups: White (*n* = 4426, 60.68%), Asian American/Pacific Islanders (*n* = 386, 5.29%), Black/African American (*n* = 1376, 18.86%), Hispanic/Latinx (*n* = 1019, 13.97%), Native American (*n* = 38, .52%), and other (*n* = 49, .68%). Approximately 9% of the sample qualified for public assistance or welfare. Further information on the demographics of the participants can be found in Table 1.

Measures

The Add Health study collected self-report data on psychological, behavioral, economic, social, and environmental variables linked to suicidal behaviors, such as mental health, violence exposure, family, peer, and school functioning, neighborhood characteristics, community engagement, negative life events, expectations for the future, risky behaviors, self-esteem, and substance use. To account for criterion contamination, I inspected each of the survey questions and removed duplicated items (Pincus & Callahan, 1993).

Suicidal Behaviors

Suicidal behaviors was operationalized as the combination of suicidal thoughts and attempts in the previous 12 months. These two constructs were measured in all five waves. For suicidal thoughts, respondents in each wave were asked, "*During the past 12 months, did you seriously think about committing suicide?*" Responses were dichotomized with "1" indicating yes and "0" indicating no suicidal ideation. For suicidal attempts, respondents in each wave were asked, "*During the past 12 months, how many times did you actually attempt suicide?*" Responses ranged from 0 to 4 with "0" representing *zero times* and "4" representing *six or more times*. Suicidal behavior scores ranged from 0 to 5 as a result of summing both suicidal thoughts and suicidal attempts.

Data Analyses

Data analyses were conducted using R software. Due to oversampling of underrepresented groups in the Add Health dataset, I conducted all analyses using the suggested sample weight for proper adjustment to ensure that the results are nationally representative with unbiased estimates (Chantala & Tabor, 2010).

Predictors and Missing Data

Initially there were 2,874 predictors. However, to ensure that the predictors used in the analysis were theoretically sound and to prevent issues with multicollinearity, certain predictors were removed from the dataset. Specifically, any predictors that were deemed to have no theoretical connection to suicidal behaviors, predictors with missing data of 10% or more, predictors with a variance inflation factor (VIF) of 10 or more, as well as predictors with near zero variance were removed. Following this process, a total of 281 predictors were deemed appropriate for use in the multinomial logistic, classification trees, and random forest models. The final list of the 281 predictors is presented in the appendices. Missing data of predictors were extremely limited (0.54%), and they were processed through single imputation of mean for continuous variables and mode for categorical variables.

Research Question 1

Research question one was, what are the different trajectories of suicidal behaviors? To answer research question one, I identified trajectories of suicidal behaviors using LCGA. LCGA is an analytic technique that identifies unobserved subgroups, or latent classes, within a population (Nylund-Gibson & Choi, 2018). This method utilizes responses to a chosen set of observed variables to establish groups that are similar to each other. The LCGA model in this study was built using respondents' self-reports of suicidal behaviors in four waves of the dataset. The enumeration process extracted several classes, and this process ended when the addition of a new class yielded little additional information. The decision regarding the number of classes was based on interpretability and goodness-of-fit statistics, such as the Akaike information criterion (AIC), the Bayesian information criterion (BIC), entropy, and the integrated completed likelihood criterion (ICL; Wang et al., 2019). All LCGA analyses were performed using the "lcmm" statistical package from R.

Research Question 2

Research question two was, does a machine learning approach (classification trees and random forest) improve model accuracy compared to traditional models (multinomial logistic regression) to predict trajectories of suicidal behaviors? To answer research question two, I compared model fit metrics between the three models on the identified trajectories from LCGA. In the following section, I provide an overview of classification trees and random forest models.

Overview of Classification Trees. Classification trees are a nonparametric method that takes continuous or categorical variables as input and predicts a categorical outcome. This method, in the form of a decision tree, begins with a root at the top that represents the space spanned by all predictor variables. The root then splits recursively into smaller partitions of the data, called nodes and leaves. The splitting process follows the impurity reduction principle that ends when the nodes are no longer impure (see Stroble et al., 2009 for further details on how classification trees work). In the context of this study, classification trees can create a structural mapping of binary decisions that classify risk factors into trajectories of suicidal behaviors identified from the LCGA. For instance, let us consider a hypothetical study where an LCGA model has identified three different trajectories of suicidal behaviors: (a) stable, (b) growing, or (c) declining. Classification trees would begin with the question, "What risk factors are predictive of the *growing* trajectory"? From this point, more questions are asked, such as "whether someone drinks alcohol" or "whether a friend has recently died by suicide." Answering "yes" to these questions will follow a particular branch to a node, and answering "no" will follow an alternative branch to another node. Figure 1 illustrates this hypothetical usage of a classification tree in which someone who drinks alcohol *and* had a friend who died by suicide are classified into the growing trajectory of suicidal behaviors.

Classification trees are a popular machine learning technique because they can process large-scale data efficiently, deliver nonlinear predictions, and provide a useful decision-making tool that is visually interpretable (Hill et al., 2020). However, this technique is not without flaws. The main disadvantage is that predictions of single classification trees show high variability due to their sensitivity to small changes in the training data. In recursive splitting, the decision about which variable to split follows the impurity reduction principle whereby the predictor with the lowest Gini impurity index becomes the root of the tree that marks the beginning of the tree model. The root then selects the next predictor, or node, with the lowest Gini impurity index to split, and the new node then splits continuously until a terminal node with no impurity is reached. The impurity of a variable is calculated based on the distribution of observations in the training data. As such, a slight change in the distribution of observations can alter the impurity of a variable. This changes the selection of the splitting variable (root and nodes), which can alter the entire tree completely, akin to a domino effect. To illustrate this disadvantage, Stroble et al. (2009) found that classification tree models built on four different bootstrap samples derived from the same original dataset all varied substantially from each other. The high variability in the predictions of single classification trees often leads to overfitting issues.

Overview of Random Forests. Ensemble-based methods such as random forests can mitigate the aforementioned concerns by combining the output of multiple classification trees to produce a single, more accurate estimate. The random forest model begins by creating a number of bootstrap samples. Bootstrap samples are obtained by randomly drawing from the training dataset with replacement, meaning certain observations may appear more than once, whereas others are omitted from the bootstrap sample (Stroble et al., 2009). Next, the random forest grows a diverse set of classification trees on each of the created bootstrap samples by randomly restricting the set of predictor variables to select from in each split. Finally, the random forest aggregates the results of all the trees with the idea that although each single classification tree is unstable, averaging the prediction of all the trees will produce the right prediction. Intuitively speaking, the random forest is based on the "wisdom-of-the-crowds" concept, where the aggregate predictions of a group often outperform individual predictions. For example, in the popular game show *Who Wants to Be a Millionaire*, contestants are asked a multiple-choice question and can either phone a friend or poll the audience as a lifeline. Polling the audience is correct 91% of the time, whereas phoning a friend is correct 66% of the time (Grigas, 2019). Although random forests often yield higher prediction accuracy and have a reduced risk of overfitting compared to single classification trees (Buhlmann & Yu, 2002), the ensemble method is not easy to interpret. Therefore, this study will use both classification trees and random forest to borrow strength from each machine learning technique.

Analyses for Research Question 2. All statistical analyses were performed using the "glm", "caret", "rpart", "randomForest", and "DMwR" packages from R. I randomly divided the entire dataset into 70% training and 30% testing sets. To build the multinomial logistic regression, I used age, age-squared, gender, race, and maternal educational level as covariates.

To build the classification tree model, I developed the tree model using the training set, setting the maximum tree depth to 5 and the minimum number of observations needed in a node to 10. Doing so reduced the risk of model overfitting and improve interpretability. I also performed a 10-fold cross-validation to obtain the best complexity parameter (cp) for the pruning process. The final model fitted on the training dataset was selected based on cp, which yielded the highest accuracy.

To build the random forest model, I generated 500 different bootstrapped samples and fit a classification tree on each of the bootstrapped samples. I then selected the *mtry* parameter, a value that controls the number of variables examined at each split of the fitted classification tree, via 10-fold cross-validation. The minimum number of observations in each classification tree terminal node was set to 5.

It is worth noting that studies that investigate suicidal behaviors may suffer from class imbalance issues; that is, one or more classes may have very low proportions in the training set compared to other classes (Wang, 2021). Interpreting a machine learning model based on an imbalanced dataset can lead to inaccurate conclusions because any patterns that were predictive of the outcome can be overwhelmed by the large percentage of non-cases. Indeed, suicidal behaviors in the current study are rare phenomena and there are significantly more non-cases than cases. To address this class imbalance issue, I applied the SMOTE method. SMOTE, which stands for the synthetic minority over-sampling technique, generates a balanced training set by simultaneously oversampling the minority class and under-sampling the majority class (Schubach et al., 2017). It is important to note that SMOTE was only applied to the training and not the testing data set to prevent biased measure of model performance.

Model Fit Indices. The metrics used to evaluate the performance of the final models included overall accuracy, sensitivity, specificity, positive predictive value, and area under the receiver operating characteristic curve (AUC). Accuracy is the proportion of correctly classified cases out of all cases, calculated as the sum of correctly classified cases for all classes divided by the total number of cases. Sensitivity is the proportion of true positives that are correctly identified by the model, obtained by dividing the true positives by the sum of true positives and false negatives. Specificity is the proportion of true negatives that are correctly identified by the model, computed by dividing the true negatives by the sum of the true negatives and false positives. Positive predictive value is the proportion of true positives among all positive predictions made by the model, calculated as the number of true positives divided by the sum of true positives and false positives (Wang, 2021).

Finally, AUC measures how well a classification model can distinguish between positive and negative classes and is a widely used measure of performance for supervised classification machine learning models. However, AUC is only applicable to binary classification in its simplest form. In cases where there are more than two classes, hereafter referred to as multi-class, Hand and Till (2001) recommended first calculating the pairwise AUCs for every class pair, and then averaging each pair over all pairs of classes. According to established guidelines, AUC values ranging from 0.50 to 0.59 indicate extremely poor classification, 0.60 to 0.69 indicate poor classification, 0.70 to 0.79 indicate fair classification, 0.80 to 0.89 indicate good classification, and values above 0.90 indicate excellent classification (Fox et al., 2019). The same guidelines were adopted for assessing the performance of sensitivity, specificity, and positive predicted value.

Research Question 3

Research question three was, what are the prominent risk factors for each of the trajectories of suicidal behaviors? To answer research question three, I performed variable importance analysis from the random forest model. Variable importance measures how much removing a variable decreases accuracy. The variable that has the highest mean decrease in accuracy can be interpreted as the most important predictor of the outcome.

Results

Descriptive Statistics of Suicidal Behaviors

Scores for suicidal behaviors initially ranged from 0 to 5 across all waves of data. However, the presence of extremely low frequencies in the upper end of the score spectrum resulted in unstable estimate of the latent classes. To address this issue, the scores were collapsed to a range of 0 to 3, with a score of 3 indicating a range of 3 to 5. In wave one, the distribution of scores was as follows: 85.98% had a score of 0, 10.14% had a score of 1, 2.41% had a score of 2, and 1.47% had a score of 3. In wave two, the distribution of scores was as follows: 88.37% had a score of 0, 7.91% had a score of 1, 2.38% had a score of 2, and 1.34% had a score of 3. In wave three, the distribution of scores was as follows: 93.37% had a score of 0, 4.88% had a score of 1, 1.11% had a score of 2, and .64% had a score of 3. In wave four, the distribution of scores was as follows: 92.90% had a score of 0, 6.19% had a score of 1, .67% had a score of 2, and .24% had a score of 3. In wave five, the distribution of scores was as follows: 92.83% had a score of 0, 6.03% had a score of 1, .71% had a score of 2, and .43% had a score of 3 (see Table 2 for further details).

Poisson regression analyses were also conducted to examine the association between suicidal behaviors and various demographic variables, including gender, age, maternal educational level, race, family structure, and public assistance/welfare status for each wave. Poisson regression analysis was chosen because suicidal behaviors followed a Poisson distribution. After controlling for all other variables at wave one, females reported approximately twice the frequency of suicidal behaviors compared to males, $\beta = .71$, $\exp(\beta) = 2.03$, $SE = .06$, $p < .05$. Participants who were older reported higher levels of suicidal behaviors, $\beta = .08$, $\exp(\beta) = 1.08$, $SE = .02$, $p < .05$. Participants who lived with both parents, as opposed to those who lived with one parent or no parents, reported fewer levels of suicidal behaviors, $\beta = -.21$, $\exp(\beta) = .81$, $SE = .06$, $p < .05$. Black participants compared to Asians reported 34% fewer levels of suicidal behaviors, $\beta = -.41$, $\exp(\beta) = .66$, $SE = .14$, $p < .05$. Participants whose family received public assistance or welfare reported 25% higher levels of suicidal behaviors than those who did not, $\beta = .22$, $\exp(\beta) = 1.25$, $SE = .09$, $p < .05$. Maternal education level was not found to be statistically significantly associated with suicidal behaviors, along with participants who self-reported as White, Latino, Native American, or other. The same analyses and results for wave two, three, four, and five can be found in Table 3.

Latent Class Growth Analysis: Classes of Suicidal Behaviors

Latent classes were identified using self-reported suicidal behaviors data collected at wave two, wave three, wave four, and wave five. To determine the optimal model fit, several statistical fit indices were considered (see Table 4), including lower Akaike information criterion (AIC), Bayesian information criterion

(BIC), and integrated completed likelihood criterion (ICL) values, along with a minimum entropy value of .8 and substantive interpretability, as recommended by Jung and Wickrama (2008) and Nylund-Gibson and Choi (2018). Based on these criteria, a three-class model was selected as the optimal model fit, which is graphically represented in Figure 2. The identified classes were labeled as (a) Resilient, (b) Declining, and (c) Escalating (see Figure 3). Class 1, labeled Resilient, accounted for 92.02% of the total sample. Respondents assigned to this class are characterized by minimal suicidal behaviors over the duration of the assessed time period. Class 2, labeled Declining, accounted for 3.59% of the total sample. Respondents assigned to this class exhibited moderate initial levels of suicidal behaviors that decreased with time. Class 3, labeled Escalating, accounted for 4.39% of the total sample. Respondents assigned to this class demonstrated low initial levels of suicidal behaviors that increased with time. Intercept, linear, and quadratic growth parameters for the 3-class models are displayed in Table 5. Due to the extremely imbalanced classes, I employed SMOTE to evenly balance the identified classes before fitting a multinomial logistic regression, classification trees, and random forest model. After SMOTE, Class 1 (Resilient) accounted for 33.33%, Class 2 (Declining) accounted for 33.33%, and Class 3 (Escalating) accounted for 33.33% of the total sample. The results of the LCGA provided supported for the first hypothesis that distinct groups of individuals with heterogeneous trajectories of suicidal behaviors exist.

Comparing Model Performance between Multinomial Logistic Regression, Classification Trees, and Random Forest

Multinomial logistic regression, classification trees, and random forest models were first fitted on the training dataset and then again on the testing dataset to assess the predictive performance of all study variables on the three identified classes. For multinomial logistic regression, the results yielded poor overall accuracy of .62. The sensitivity for Class 1 was calculated to be .64, for Class 2 it was .44, and for Class 3 it was .32. In terms of specificity, Class 1 exhibited a value of .65, Class 2 exhibited a value of .84, and Class 3 exhibited a value of .79. The positive predictive value for Class 1 was .95, for Class 2 it was .1, and for Class 3 it was .07. The no information rate was found to be .92. AUC was found to be .64. Overall, the multinomial logistic model performed poorly across all classes as there were numerous false positives and false negatives.

For classification trees, I applied a stacked approach in which I incorporated two tree models to determine the model performance metrics (see Figure 4 for further details on the stacked approach). The first tree model utilized a binary classification scheme in which I combined Class 2 and Class 3 into a single class. The outcome was categorized as either Class 1 or the combined Class of 2 and 3. I then applied a second classification tree model on the prediction generated from the first tree model, specifically targeting the combined class predictions. The second model then predicted the outcome as either Class 1, 2, or 3. These predictions from both tree models were combined and subsequently compared with the observed results from the testing dataset.

To determine the optimal complexity parameter (cp) value that would yield the highest accuracy score, I conducted a 10-fold cross validation. The cp value is a parameter that can prevent overfitting by removing splits that do not sufficiently improve the model fit (Grigas, 2019). The range of cp values considered was 0 to .1 with an increment of .002. The optimal cp value was found to be .018. Moreover, the model specified a minimum node size of 20, which meant that nodes containing fewer than 20 cases would not split to further branches. The model also implemented a weighted loss strategy, wherein a larger loss penalty was assigned to false negatives compared to false positives (LFN = 100 vs. LFP = 1). This decision was driven by the considerable cost associated with misclassifying individuals with escalating suicidal trajectories as having resilient trajectories, as opposed to misclassifying individuals with resilient trajectories as having escalating trajectories. From a practical standpoint, spending resources on individuals who are healthy is less detrimental compared to the potentially fatal outcome resulting from the failure to allocate resources to individuals in crisis.

The results from the stacked tree model yielded a fair accuracy of .70. The sensitivity for Class 1 was calculated to be .72, for Class 2 it was .51, and for Class 3 it was .58. In terms of specificity, Class 1 exhibited a value of .75, Class 2 exhibited a value of .93, and Class 3 exhibited a value of .78. The positive predictive value for Class 1 was .97, for Class 2 it was .22 and for Class 3 it was .1. The no information rate was found to be .92. AUC was found to be .73. These outcomes indicate that the classification trees model outperformed the multinomial logistic model.

For the random forests model, I employed the same stacked approach as outlined above. A 10-fold cross validation was performed to determine the optimal “mtry” value that would yield the highest accuracy score. “Mtry” represents the number of variables randomly sampled as candidate predictors at each split in the construction of decision trees within the random forest ensemble (Grigas, 2019). The range of mtry values considered was 1 to 20. The optimal mtry value was found to be 9. The random forest model also implemented the same weighted loss strategy outlined above (LFN = 10 vs. LFP = 1). The results from the stacked ensemble method yielded an excellent accuracy score of .96. The sensitivity for Class 1 was calculated to be .98, for Class 2 it was .82, and for Class 3 it was .66. In terms of specificity, Class 1 exhibited a value of .75, Class 2 exhibited a value of .99, and Class 3 exhibited a value of .99. The positive predictive value for Class 1 was .98, for Class 2 it was .73 and for Class 3 it was .9. The no information rate was found to be .92. AUC was found to be .79. Comparatively, the random forest model outperformed the multinomial logistic regression and classification tree model across all metrics. These findings provided support for the second hypothesis of the study. The performance metrics of each model can be found in Table 6.

Variable Importance

The random forest model estimated the variable importance for each class trajectory. For Class 1 (Resilient Trajectory), the top 10 most important predictors include existing suicidal behaviors, poor appetite, maternal presence at home, frequency of physical sickness, feelings of depression, feelings of emotional distress, self-acceptance, being in a non-judgmental school environment, a planful approach to problem solving, which refers to purposeful problem-focused strategies intended to actively alter the situation, and teacher-student rapport at school (see Table 7). For Class 2 (Declining Trajectory), the top 10 most important predictors include measures of sleep quality, existing suicidal behaviors, quality of home environment, frequency of crying, frequency of physical sickness, cost of living in the neighborhood, school enjoyment, self-perception of body image, and feelings of sadness (see Table 8). For Class 3 (Escalating Trajectory), the top 10 most important predictors include frequency of crying, frequency of physical sickness, existing suicidal behaviors, delinquent behaviors such as acting loud, rowdy, or unruly in a public place, measures of sleep quality, self-acceptance, maternal presence at home, school belonging, an argumentative personality, and measures of distress tolerance (see Table 9). It is important to acknowledge that the estimation of variable importance was solely conducted within the specific context of the random forest model in the present study. Caution should be exercised when generalizing the strength of these predictors beyond the scope of the present models.

Discussion

Despite decades of research that have deepened our understanding of suicidal behaviors, the field still faces several key challenges. These challenges include the need to address methodological limitations, such as cross-sectional designs and the focus on isolated risk factors, as well as the lack of comprehensive understanding of the developmental trajectories of suicidal behaviors. To address these challenges, the present study had three primary objectives. First, I investigated the distinct trajectories of suicidal behaviors by employing latent class growth analysis (LCGA) on a longitudinal dataset. Second, I tested whether the predictive performance of a machine learning approach (classification trees and random forest) would demonstrate improvement compared to a traditional approach (multinomial logistic regression) in predicting the identified suicidal trajectories. Third, I examined significant risk factors associated with each trajectory through variable importance analyses conducted on the random forest model.

Trajectories of Suicidal Behaviors

From the LCGA analysis, a solution of three latent growth classes yielded the best fit for the data in the study. The three latent growth classes identified include a (a) Resilient Class, (b) Declining Class, and (c) Escalating Class. As such, hypothesis one was supported. This finding was in line with number of previous studies that have also identified distinct trajectories of suicidal behaviors (Erausquin et al., 2019; Hoffmire et al., 2022; Nkansah-Amankra, 2013; Prinstein et al., 2008; Wu et al., 2022), with the slight difference being on the measurement period assessed and the population samples used.

To the best of my knowledge, this study is the first to investigate trajectories of suicidal behaviors across ages 12 to 43, spanning from adolescence to middle adulthood. Findings revealed that the Resilient Class accounted for 92.02% of the sample, indicating that the majority of the population did not exhibit substantial suicidal behavior. On the other hand, the Declining Class accounted for 3.59% and the Escalating Class accounted for 4.39% of the sample. These results underscore the importance of directing resources towards individuals in the minority who exhibit symptomatic trajectories, such as those in the Declining Class and Escalating Class. In addition, when researchers solely focus on the average experience, those with symptomatic trajectories who could benefit from specialized attention could be glossed over because of the dominant representation of the Resilient Class in the sample. Examining changes in suicidal behaviors offers a deeper understanding than only examining absolute levels of suicidality at a single time point.

Predictive Performance Comparison between Models

In the comparison of the predictive performance, machine learning models, specifically classification tree and random forest, outperformed the traditional multinomial logistic regression. This finding supports the second hypothesis. Among the selected performance metrics, including accuracy, sensitivity, specificity, positive predicted value, and AUC, the random forest model produced the best prediction across all metrics. This finding is consistent with previous studies that demonstrated the superior performance of machine learning methods compared to simpler models (Agnes et al., 2020; Hill et al., 2020; Su et al., 2020). Notably, the random forest stood out as the only model that demonstrated an accuracy higher than the no-information rate. The no-information rate, also referred to as the base rate, represents the accuracy that would be achieved if the model simply predicted the most prevalent class without any input variables or features (Grigas, 2019). When a model's accuracy falls below the no-information rate, it suggests that the model predictions are no better than random guessing. Alternatively, when a model's accuracy surpasses the no-information rate, it suggests that the model is providing meaningful predictions. In this study, the most prevalent class was the Resilient Class, and the no-information rate was calculated to be .92. The accuracy of the multinomial logistic regression model was .62 whereas the classification tree model had an accuracy of .70, suggesting the limited value of these two approaches. In contrast, the random forest model had an excellent accuracy score of .96.

The poor performance of the multinomial logistic regression emphasizes the highly multifaceted nature of suicidal behaviors (Franklin et al., 2017; Heckler et al., 2022; LeFevre, 2014). Suicidal thoughts and behaviors cannot be attributed to a single cause or stressor alone. Prior studies that found success using simpler models in predicting suicidal outcomes tended to focus on a relatively narrow set of risk factors, often fewer than six (Baumann et al., 2010; Cero & Sifers, 2013; Conner et al., 2003; Liu et al., 2020; Nkansah-Amankra, 2013; Wu et al., 2022). However, when a broader range of risk factors is considered, the performance of these simpler models may decline. As demonstrated in the present study, the multinomial logistic regression had an extremely poor accuracy when it incorporated a comprehensive dataset that contained 21 types of risk factors, including physical health, academics, mental health, parental relationships, delinquency, neighborhood variables, economic factors, and substance use, among others. This finding not only highlights the effectiveness of machine learning techniques in capturing multitude of risk factors, but also provides support for theories suggesting that suicidal behavior is highly complex and necessitates a comprehensive set of factors and sophisticated statistical modeling for accurate risk detection.

Variable Importance Analysis

The variable importance analysis conducted on the random forest model revealed key risk factors associated with each trajectory. For the Resilient Class, the top predictors were related to prior suicidal behaviors, parental presence, psychological distress, school belonging, and effective problem-solving skills. For the Declining Class, the top predictors included sleep quality, prior suicidal behaviors, quality of home environment, psychological distress, cost of living in the neighborhood, school enjoyment, and self-perception of body image. For the Escalating Class, the top predictors were psychological distress, physical health, prior suicidal behavior, delinquent behaviors, sleep quality, self-acceptance, parenting presence, and school belonging.

Notably, prior suicidal behaviors, psychological distress, and school belonging appeared as one of the most important predictors across all three classes. These findings are supported by existing research and theories discussed in the introduction. For example, the World Health Organization (2014) has identified previous suicide attempts as the single, strongest predictor of completed suicides. Psychological autopsy studies revealed that approximately 10% to 44% of the adolescents who had died by suicide had made at least one previous attempt (Miller et al., 2007). In another study following adolescents who were hospitalized due to a suicidal attempt, Kotila (1992) found that within five years, 8.7% of the males and 1.2% of the females killed themselves.

The association between psychological distress and suicidal behaviors aligns with the suicide as psychache theory propose by Shneidman (1993). Depression, in particular, has been consistently linked to suicidal behaviors and is a significant factor in all suicidal outcomes (Agne et al., 2020; Bertolote et al,, 2005; Scocco et al., 2008). Further, major depressive disorder (MDD) has been found to predict the development of a suicide plan, as well as the transition from suicidal ideation to an attempt (Nock et al., 2013).

The importance of school belonging is consistent with the Interpersonal-Psychological Theory of Suicide Behavior (IPTSB) proposed by Joiner (2005). This theory explains how a sense of low belongingness can increase the risk of suicide. Providing empirical support for the IPTSB, Zhou et al. (2022) found that school belonging was associated with reduced negative effects of suicidal behaviors among 393 college students from China. Similarly, Olcon et al.

(2017) analyzed the 2013 Texas Youth Risk Behavior Survey of 2,560 participants and suggested that feeling unsafe at school increased the odds of youth suicidal behaviors, whereas community belonging reduced the odds. The findings from this study, along with the results of previous research, adds to the growing body of evidence supporting the critical role of a sense of belonging within the school environment. By incorporating these important predictors identified from the random forest algorithm into preventive interventions at school, such as providing mental health resources to those that had exhibited prior suicidal behavior and psychological distress, as well as promoting school belongness, educators and mental health professionals can address the multifaceted nature of suicidal behaviors and work towards preventing youth from experiencing harmful trajectories.

Implications for Preventive Interventions

The findings of the current study have implications for preventive strategies that target at-risk individuals. First, the variable importance analysis offers valuable insights that can inform the development of screening tools. Researchers can consider incorporating every prominent predictor into the screener, thereby playing a crucial role in preventing suicidal behaviors among youth (Macalli et al., 2021). Previous research has suggested the use of screening tools to be promising. A systematic review highlighted the effectiveness of implementing screening within school settings, including enhanced treatment referrals and increased utilization of support services among high-risk adolescents (Gould et al., 2009). Screening tools can easily be adopted in schools. For example, stakeholders may consider integrating online questionnaires administered at the beginning of each semester, as online questionnaires are generally deemed acceptable by students, making the screening tool a viable and convenient option for mental health assessment (Zalsman et al., 2016).

Second, the current study advocates for a targeted approach to interventions rather than adopting a one-size-fits-all strategy. Understanding suicidal behavior trajectories and their predictors can provide critical information to tailor and identify optimal timing for interventions. A noteworthy finding from the variable importance analysis is that delinquent behaviors emerged as a prominent indicator associated exclusively with the Escalating Class, distinct from the other two classes. This highlights the potential effectiveness of interventions that target adolescents who exhibit high levels of delinquency, with the goal of redirecting their symptomatic trajectory towards a healthier one. For instance, practitioners can consider the Parent Management Training-Oregon Model that has demonstrated success in preventing delinquent behaviors. DeGarmo and Forgatch (2005) reported that through this intervention that teaches and encourages effective parenting strategies, reductions in affiliations with deviant peers mediated the relationship between parenting skills and reduced delinquency, with the effect persisting up to nine years post-intervention (Forgatch et al., 2009). Implementing such evidence-based interventions into targeted programs has the potential to mitigate the risk of suicidal behaviors among at-risk adolescents.

It is important to note that careful consideration must be given when implementing and utilizing the random forest algorithm generated from this study. Although machine learning/artificial intelligent tools offer fast assessment of suicide risk that can facilitate prevention efforts, researchers and practitioners must be mindful of false positives. Given that suicide and suicidal behaviors are relatively rare occurrences within the general population, even highly predictive variables can yield a substantial number of false positives. For instance, based on the research by Roy et al. (2020), assuming a suicide ideation population rate of 10%, and considering a classifier sensitivity of .8 and specificity of .78, there would be 2.4 false positive suicidal ideators for every true one. The false positive rate for suicidal attempters is even higher, with approximately 53 false positive attempters for each true positive attempter. As a result, the risk algorithm should be regarded as a decision aid rather than a diagnostic instrument.

Limitations and Future Directions

This study possesses several key strengths, namely the inclusion of a large sample of students and the longitudinal design. Given the complex nature of suicidal behaviors, accurate prediction necessitates the consideration of multiple factors. The ADD Health dataset utilized in this study includes a substantial number of variables, which enabled analyses of numerous potential predictors (279 in the present study) associated with suicidal behaviors. Nevertheless, the present study has several limitations that should be considered when interpreting my findings. First, this study relied solely on self-reported data regarding past year suicidal thoughts and attempts. Self-report data may be susceptible to memory biases, social stigma, or social desirability, potentially impacting the accuracy and reliability of the reported information (Clifasefi et al., 2011). Future studies should consider including other sources of data to triangulate the findings (Heckler et al., 2022; Roy et al., 2020). For example, Ji et al. (2018) demonstrated the feasibility and practicability of detecting suicidal ideation using posts from both Reddit, a popular online forum, and Twitter, a widely used online social networking platform. By employing machine learning and natural language processing methods, the authors analyzed and classified posts into those indicative of suicidal ideation and those considered normal. Findings yielded excellent levels of accuracy with an impressive AUC value of up to .96. Another promising avenue for the prediction of suicidal behaviors is through user-generated data from smartphones. Dogrucu et al. (2020) applied machine learning methods on voice samples, browser history, call logs, location, as well as social media data from 335 participants' smartphones. The results yielded a good accuracy score of .85, along with a sensitivity of .86 and specificity of .73, indicating the successful classification of suicidal ideation.

The second limitation of this study is the lack of interpretability inherent in complex models such as the random forest algorithm. Although machine learning techniques offer superior predictive performance, they often suffer from the black box paradox, wherein the internal workings of the model are not readily interpretable by the user (Bagchi, 2023). Researchers often face challenges in examining the model's inner code or logic that produce the output. Conversely, simpler models provide transparent and interpretable explanations of the relationship between predictors and the outcome, but at the cost of predictive performance. Reviewing previous studies that used machine learning to investigate suicidology, Cox et al. (2020) argued that the predictive performance gain through machine learning methods may not always justify the trade-off in interpretability, particularly when the goal of the suicidal risk algorithm is to inform practitioners or clinical services.

Third, the strength of the predictors is contingent upon the current random forest algorithm. Caution should be exercised when interpreting predictors that have been identified as "important" beyond the scope of the present model. Further, the variable importance analysis identifies only the most influential variables but does not explicitly provide information about the direction or causality of these variables. For instance, it is unclear whether better sleep quality is negatively or positively associated with the Declining Class if based solely on the output of the random forest model. That said, domain knowledge and theoretical foundations, as discussed in the introduction, are essential to determine the direction of variables.

Fourth and finally, researchers and practitioners must navigate the logistical challenges that may arise when implementing these models in educational settings. For example, the effectiveness of the current model is only maximized when schools administer surveys that precisely measure the variables used in this study. As detailed earlier in the method section, the survey encompassed a total of 279 variables, which can be time-consuming and overly burdening for participants when completing a survey of such length. Schools that plan to utilize the findings of this study to develop screening tools should consider administering shorter surveys. Instead of including the entire set of 279 variables, the focus could be placed on measuring only the most important predictors identified from this study's random forest algorithm. This approach ensures that the screening tools are effective, efficient, and can reduce the time and effort required from students.

Conclusion

This study adds to the existing literature suggesting that suicidal behaviors can be categorized into distinct trajectories using LCGA. Conducting an LCGA provides a more holistic picture by allowing researchers to develop models that are relevant for different groups within the same population (Erausquin et al., 2019; Hoffmire et al., 2022; Wu et al., 2022). Furthermore, this study provides evidence suggesting that machine learning methods are more ideal for testing numerous risk factors and detecting complex patterns of suicidal behaviors than traditional approaches, as the random forest model outperformed the multinomial logistic regression. The findings of this study can be used to inform the design of suicidal risk screening tools and more personalized prevention.

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Table 1

Demographic Characteristics of Respondents

Variables		N	%	Mean (SD)
Gender				
	Male	3024	41.5	
	Female	4271	58.5	
Age				15.7 (1.60)
Race				
	White	4426	60.68	
	Black	1376	18.86	
	Asians	386	5.29	
	Latinx	1019	13.97	
	Native American	38	.52	
	Other	49	.68	
Maternal Education Level				
	Eighth grade or less	304	4.54	
	More than eighth grade but did not graduate from high school	655	9.79	
	Trade school instead of high school	53	.79	
	High school graduate	2059	30.77	
	Completed a GED	235	3.51	
	Trade school after high school	446	6.66	
	Went to college but did not graduate	882	13.18	
	Graduated from university	1429	21.35	
	Graduate or professional university	629	9.39	
Family Structure	Orphan	298	4.08	
	Single Parent Household	2238	30.68	
	Two-Parent Household	4759	65.24	
Public Assistance/Welfare				
	Yes	633	9.15	
	No	6288	90.85	

Table 2

Descriptive Statistics of Suicidal Behaviors for Each Wave

		N	%	Mean (SD)
Wave 1				.20 (.54)
	0	6235	85.98	
	1	735	10.14	
	2	175	2.41	
	3	107	1.47	
Wave 2				.17 (.52)
	0	6423	88.37	
	1	575	7.91	
	2	173	2.38	
	3	97	1.34	
Wave 3				.09 (.38)
	0	6660	93.37	
	1	348	4.88	
	2	79	1.11	
	3	46	.64	
Wave 4				.08 (.32)
	0	6753	92.90	
	1	450	6.19	
	2	49	.67	
	3	17	.24	
Wave 5				.09 (.35)
	0	6632	92.83	
	1	431	6.03	
	2	51	.71	
	3	30	.43	

Table 3

Poisson Regression Analyses of Demographic Variables and Suicidal Behaviors for Each Wave

Wave	Variables		β	exp(β)	SE	p
1	Gender	Female	**.71**	**2.03**	**.06**	**< .05**
	Age		**.08**	**1.08**	**.02**	**< .05**
	Race	Black	**-.41**	**.66**	**.14**	**< .05**
		Latino	-.12	.89	.14	.37
		Native American	.27	1.31	.33	.42
		Other	.17	1.19	.32	.61
		White	-.15	.86	.12	.22
	Family Structure	Two-Parent Household	**-.21**	**.81**	**.06**	**< .05**
	Maternal Education		.01	1.01	.01	.22
	Public Assistance/Welfare	Yes	**.22**	**1.25**	**.09**	**< .05**
2	Gender	Female	**.59**	**1.80**	**.07**	**< .05**
	Age		**-.07**	**.93**	**.02**	**< .05**
	Race	Black	**-.66**	**.52**	**.16**	**< .05**
		Latino	-.11	.90	.38	.49
		Native American	.16	1.17	.38	.68
		Other	-.07	.93	-1.17	.85
		White	-.16	.85	.13	.24
	Family Structure	Two-Parent Household	**-.12**	**.89**	**.07**	**< .05**
	Maternal Education		-.02	.98	.01	.26
	Public Assistance/Welfare	Yes	**.29**	**1.34**	**.10**	**< .05**
3	Gender	Female	.15	1.17	.09	.08
	Age		**-.11**	**.90**	**.03**	**< .05**
	Race	Black	-.31	.74	.22	.17
		Latino	-.01	.99	.23	.95
		Native American	**.85**	**2.33**	**.42**	**< .05**
		Other	-1.35	.26	1.02	.19
		White	.03	1.03	.19	.89
	Family Structure	Two-Parent Household	-.02	.98	.10	.83
	Maternal Education		.03	1.03	.02	.11
	Public Assistance/Welfare	Yes	**.66**	**1.93**	**.13**	**< .05**
4	Gender	Female	**.28**	**1.32**	**.09**	**< .05**

	Age		.00	1.00	.03	.93
	Race	Black	.31	1.36	.25	.22
		Latino	.07	1.07	.26	.79
		Native American	**1.27**	**3.56**	**.42**	**< .05**
		Other	.11	1.12	.62	.86
		White	.23	1.26	.23	.32
	Family Structure	Two-Parent Household	-.01	.99	.10	.89
	Maternal Education		-.03	.97	.02	.09
	Public Assistance/Welfare	Yes	**.59**	**1.80**	**.13**	**< .05**
5	Gender	Female	-.04	.96	.09	.69
	Age		**-.11**	**.90**	**.03**	**< .05**
	Race	Black	.32	1.38	.25	.20
		Latino	.15	1.16	.26	.55
		Native American	**1.26**	**3.53**	**.42**	**< .05**
		Other	-1.00	.37	1.03	.33
		White	.23	1.26	.23	.32
	Family Structure	Two-Parent Household	-.15	.86	.01	.12
	Maternal Education		-.01	1.00	.02	.80
	Public Assistance/Welfare	Yes	**.58**	**1.79**	**.13**	**< .05**

Note. B = Beta, Exp(β) = Exponent of beta, SE = Standard Error, p = P-value.

Table 4

Goodness of Fit Statistics for the Number of Latent Growth Classes of Suicidal Behaviors

Models	NPM	AIC	BIC	Entropy	ICL
1-Class Model	4	28653.69	28681.27	1	28681.27
2-Class Model	8	2000000000	2000000000	1	2000000000
3-Class Model	12	16339.75	16422.49	0.99	1893.831
4-Class Model	16	16343.69	16454.01	0.65	4745.52

Note. NPM = Number of Parameters Estimated by Maximum Likelihood, AIC = Akaike Information Criteria, BIC = Bayesian Information Criteria, and ICL = Integrated Completed Likelihood Criteria.

Table 5

Intercept, Linear, and Quadratic Growth Parameters for the 3-Class Model

Classes		Estimate	Standard Error
Resilient			
	Intercept	0*	0
	Linear	-.15*	.02
	Quadratic	.04*	.01
Declining			
	Intercept	7.43*	.07
	Linear	-7.76*	.11
	Quadratic	1.86*	.03
Escalating			
	Intercept	.93*	.07
	Linear	2.98*	.11
	Quadratic	-.85*	.04

Note. *p < .05.

Table 6

Performance Metrics of Each Model Evaluated

Metrics	Random Forest	Classification Trees	Multinomial Logistic Regression
Accuracy	0.96	0.7	0.62
No Info Rate	0.92	0.92	0.92
Sensitivity (Class 1)	0.98	0.72	0.64
Sensitivity (Class 2)	0.82	0.51	0.44
Sensitivity (Class 3)	0.66	0.58	0.32
Specificity (Class 1)	0.75	0.75	0.65
Specificity (Class 2)	0.99	0.93	0.84
Specificity (Class 3)	0.99	0.78	0.79
Positive Predictive Value (Class 1)	0.98	0.97	0.95
Positive Predictive Value (Class 2)	0.73	0.22	0.1
Positive Predictive Value (Class 3)	0.9	0.1	0.07
AUC	0.79	0.73	0.64

Note. AUC = Area Under the Curve.

Table 7

The Top 10 Most Important Variables for the Resilient Class (Class 1) according to the Random Forest Model

Variables	Corresponding Survey Question
Prior suicidal behaviors	During the past 12 months, did you every seriously think about committing suicide/how many times did you actually attempt suicide?
Poor appetite	How often have you had poor appetite in the past 12 months?
Maternal presence at home	How often is mom at home when you return from school?
Frequency of physical sickness	You seldom get sick.
Feelings of depression	How often did you feel depressed during the last week?
Feelings of emotional distress	How often were you bothered by things that usually don't bother you during the last week?
Self-acceptance	You like yourself just the way you are.
Being in a non-judgmental school environment	Students at your school are prejudiced.
A planful approach to problem solving	You usually go out of your way to avoid having to deal with problems in your life.
Teacher-student rapport at school	How often did you have trouble getting along with your teachers in the past school year?

Table 8

The Top 10 Most Important Variables for the Declining Class (Class 2) according to the Random Forest Model

Variables	Corresponding Survey Question
Measures of sleep quality	How often have you had trouble falling asleep or staying asleep in the past 12 months?
Prior suicidal behaviors	During the past 12 months, did you every seriously think about committing suicide/how many times did you actually attempt suicide?
Quality of home environment	How much do you feel that you want to leave home?
Frequency of crying	How often did you cry in the past 12 months?
Frequency of physical sickness	How often have you had a headache in the past 12 months?
Cost of living in the neighborhood	Interaction of cost of living and consumer price index based on Zip code
Measures of sleep quality	How often have you woken up feeling tired in the past 12 months?
School enjoyment	You are happy to be at your school.
Self-perception of body image	How do you think of yourself in terms of weight?
Feelings of sadness	How often did you feel sad during the last week?

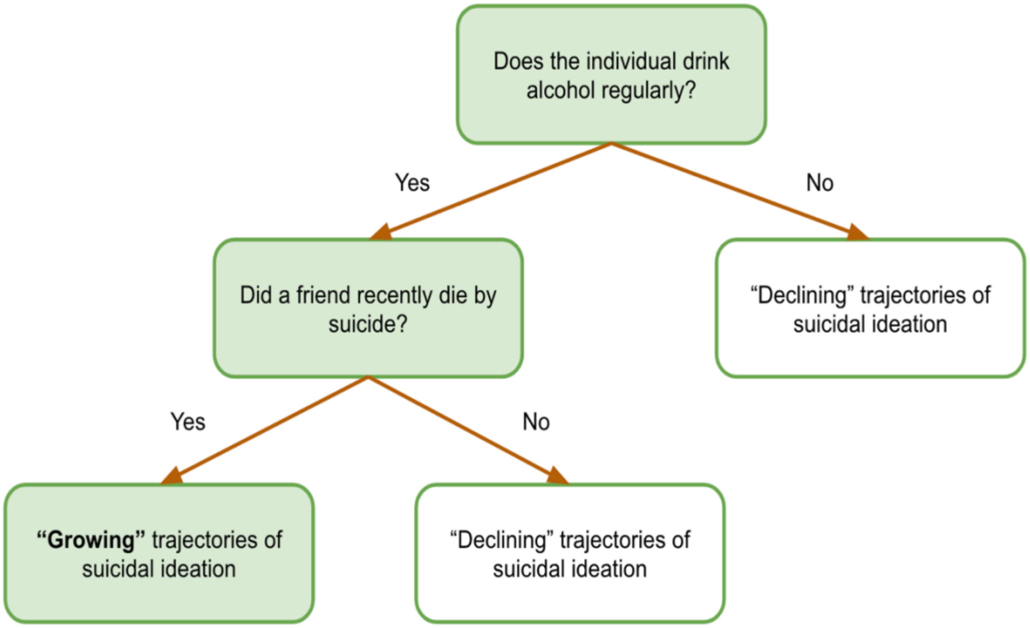
Table 9

The Top 10 Most Important Variables for the Escalating Class (Class 3) according to the Random Forest Model

Variables	Corresponding Survey Question
Frequency of crying	How often did you cry in the past 12 months?
Frequency of physical sickness	How often have you had a headache in the past 12 months?
Prior suicidal behaviors	During the past 12 months, did you every seriously think about committing suicide/how many times did you actually attempt suicide?
Delinquent behaviors	In the past 12 months, how often did you act loud, rowdy, or unruly in a public place?
Measures of sleep quality	How often have you had trouble falling asleep or staying asleep in the past 12 months?
Self-acceptance	You like yourself just the way you are.
Maternal presence at home	How often is mom at home when you return from school?
School belonging	You feel like you are part of your school.
Argumentative personality	You never argue with anyone.
Measures of distress tolerance	Difficult problems make you very upset.

Figure 1

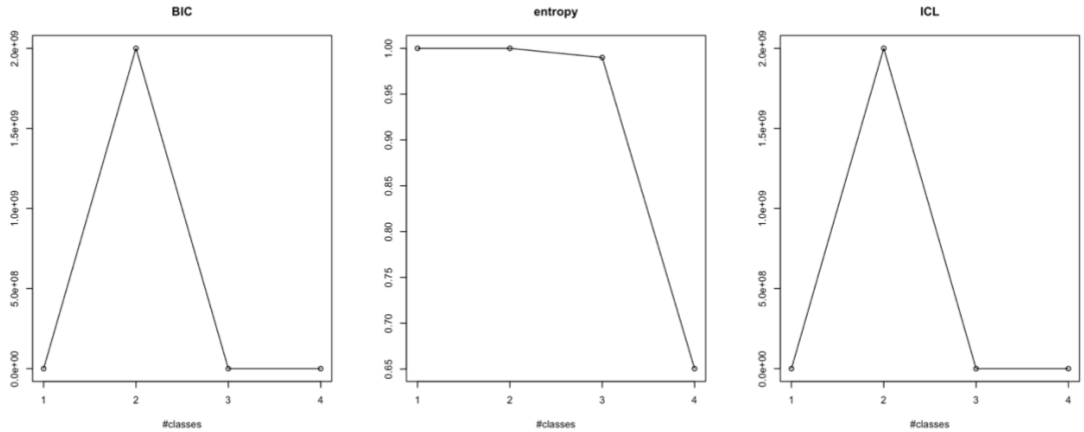
Hypothetical Usage of a Classification Tree



Note. This figure represents the hypothetical usage of a classification tree in which someone who drinks alcohol *and* had a friend who died by suicide are classified into the growing trajectory of suicidal behaviors.

Figure 2

Graph on the Number of Classes and their Corresponding Statistical Fit Indices



Note. This figure displays the BIC, entropy, and ICL values for each of the four models.

Figure 3
Graph of the Predicted Trajectories of the 3 Identified Classes

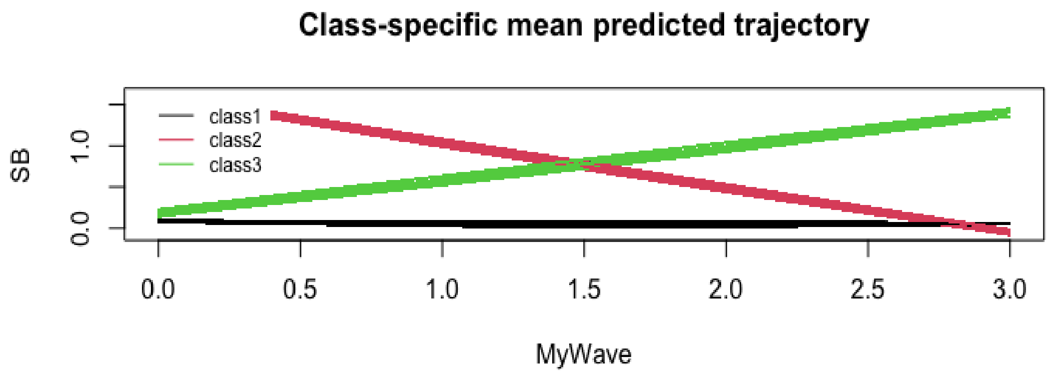
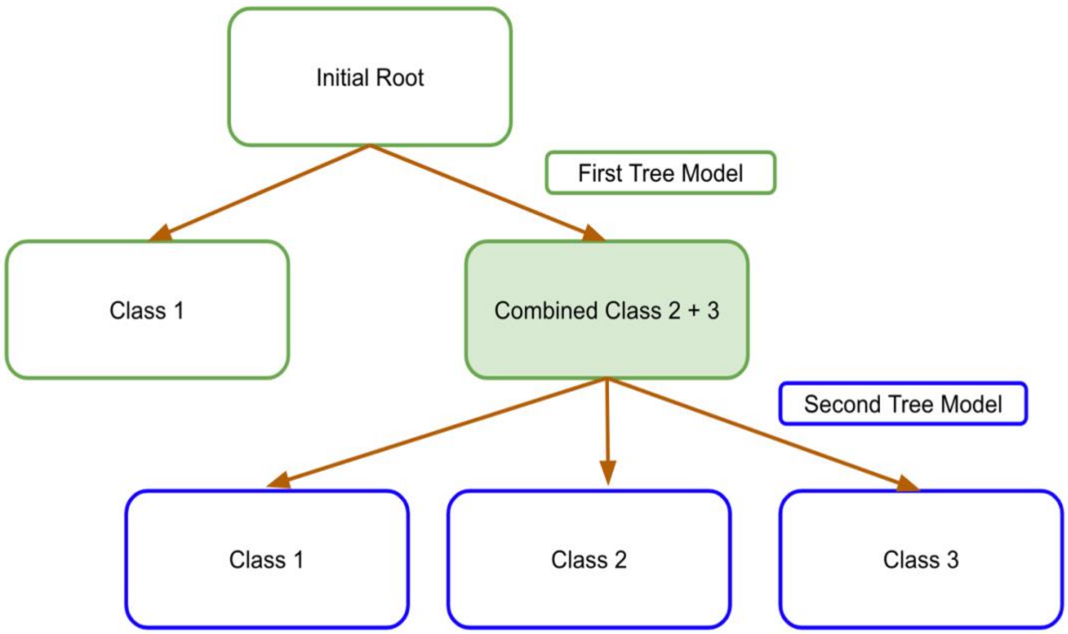


Figure 4

A Graphical Representation of the Stacked Approach to the Classification Tree Models



Note. The green borders represent the first tree model whereas the blue borders represent the second tree model.

Appendix

Variable_Name	**Variable_Description**
AID	RESPONDENT IDENTIFIER
BIO_SEX	BIOLOGICAL SEX-W1
H1GI2	S1Q2 LIVE IN SAME PLACE AS IN 1990-W1
H1GI3	S1Q3 AGE MOVED TO CURRENT RESIDENCE-W1
H1GI10	S1Q10 LANGUAGE SPOKEN AT HOME-W1
H1GI11	S1Q11 BORN IN THE UNITED STATES-W1
H1GI14	S1Q14 BORN A US CITIZEN-W1
H1GH1	S3Q1 GENERAL HEALTH-W1
H1GH2	S3Q2 FREQ-HEADACHES-W1
H1GH3	S3Q3 FREQ-FEELING HOT-W1
H1GH4	S3Q4 FREQ-STOMACHACHE-W1
H1GH5	S3Q5 FREQ-COLD SWEATS-W1
H1GH6	S3Q6 FREQ-FEELING PHYSICALLY WEAK-W1
H1GH7	S3Q7 FREQ-SORE THROAT/COUGH-W1
H1GH8	S3Q8 FREQ-VERY TIRED FOR NO REASON-W1
H1GH9	S3Q9 FREQ-PAINFUL/OFTEN URINATION-W1
H1GH10	S3Q10 FREQ-FEELING VERY SICK-W1
H1GH11	S3Q11 FREQ-WAKE UP FEELING TIRED-W1
H1GH12	S3Q12 FREQ-SKIN PROBLEMS, ACNE-W1
H1GH13	S3Q13 FREQ-DIZZINESS-W1
H1GH15	S3Q15 FREQ-MUSCLE/JOINT ACHES/PAINS-W1
H1GH17	S3Q17 FREQ-POOR APPETITE-W1
H1GH18	S3Q18 FREQ-INSOMNIA-W1
H1GH19	S3Q19 FREQ-TROUBLE RELAXING-W1
H1GH20	S3Q20 FREQ-MOODINESS-W1
H1GH21	S3Q21 FREQ-FREQUENT CRYING-W1
H1GH22	S3Q22 FREQ-FEARFULNESS-W1
H1GH23A	S3Q23A HAVE FOR BREAKFAST-MILK-W1

H1GH23B	S3Q23B HAVE FOR BREAKFAST-COFFEE/TEA-W1
H1GH23C	S3Q23C HAVE FOR BREAKFAST-CEREAL-W1
H1GH23D	S3Q23D HAVE FOR BREAKFAST-FRUIT/JUICE-W1
H1GH23E	S3Q23E HAVE FOR BREAKFAST-EGGS-W1
H1GH23F	S3Q23F HAVE FOR BREAKFAST-MEAT-W1
H1GH23G	S3Q23G HAVE FOR BREAKFAST-SNACK FOODS-W1
H1GH23H	S3Q23H HAVE FOR BREAKFAST-BREAD/TOAST-W1
H1GH23I	S3Q23I HAVE FOR BREAKFAST-OTHER-W1
H1GH23J	S3Q23J HAVE FOR BREAKFAST-NOTHING-W1
H1GH24	S3Q24 LAST PHYSICAL EXAM-W1
H1GH25	S3Q25 LAST DENTAL EXAM-W1
H1GH26	S3Q26 NEEDED BUT NOT GET MEDICAL CARE-W1
H1GH28	S3Q28 WEIGHT IMAGE-W1
H1GH30A	S3Q30A WEIGHT LOSS METHOD-DIET-W1
H1GH30B	S3Q30B WEIGHT LOSS METHOD-EXERCISE-W1
H1GH30G	S3Q30G WEIGHT LOSS METHOD-NONE-W1
H1GH32	S3Q32 ATE YESTERDAY-DAIRY PRODUCTS-W1
H1GH33	S3Q33 ATE YESTERDAY-FRUIT/FRUIT JUICE-W1
H1GH34	S3Q34 ATE YESTERDAY-VEGETABLES-W1
H1GH35	S3Q35 ATE YESTERDAY-BREAD/PASTA/RICE-W1
H1GH36	S3Q36 ATE YESTERDAY-PASTERY PRODUCTS-W1
H1GH39	S3Q39 WEAR HELMET WHILE CYCLING-W1
H1GH40	S3Q40 FREQ-RIDE A MOTORCYCLE-W1
H1GH42	S3Q42 FREQ-WEAR SEAT BELT IN CAR-W1
H1GH44	S3Q44 CHANCES OF GETTING AIDS-W1

H1GH45	S3Q45 NO OF ACQUAINTANCES WITH AIDS-W1
H1GH46	S3Q46 CHANGES OF GETTING OTHER STDS-W1
H1GH47	S3Q47 NO OF ACQUAINTANCES WITH STDS-W1
H1GH48	S3Q48 HEALTH CAUSE SCHOOL ABSENCE-W1
H1GH49	S3Q49 HEALTH CAUSE SOCIAL ABSENCE-W1
H1GH51	S3Q51 TYPICAL HOURS OF SLEEP-W1
H1GH52	S3Q52 DO YOU GET ENOUGH SLEEP-W1
H1GH53	S3Q53 NIGHT FROM HOME W/O PERMISS-W1
H1GH54	S3Q54 EXTENT OF WORST INJURY-W1
H1GH56	S3Q56 DO YOU HAVE PIERCED EAR(S)-W1
H1GH57	S3Q57 BRACES ON YOUR TEETH-W1
H1GH60	WHAT IS YOUR WEIGHT
H1TS1	TAUGHT AT SCHOOL ABOUT FOOD
H1TS2	TAUGHT AT SCHOOL ABOUT EXERCISE
H1TS3	TAUGHT AT SCHOOL ABOUT SMOKING
H1TS4	TAUGHT AT SCHOOL ABOUT BEING OVERWEIGHT
H1TS5	TAUGHT AT SCHOOL ABOUT DRINKING
H1TS7	TAUGHT AT SCHOOL ABOUT PREGNANCY
H1TS8	TAUGHT AT SCHOOL ABOUT AIDS
H1TS9	TAUGHT AT SCHOOL ABOUT STRANGERS
H1TS10	TAUGHT AT SCHOOL ABOUT DENTAL CARE
H1TS11	TAUGHT AT SCHOOL ABOUT CHOKING ON FOOD
H1TS12	TAUGHT AT SCHOOL ABOUT SAFETY AT HOME
H1TS13	TAUGHT AT SCHOOL ABOUT STRESS
H1TS14	TAUGHT AT SCHOOL ABOUT HANDLING CONFLICT
H1TS15	TAUGHT AT SCHOOL ABOUT FIND HELP FOR HEALTH
H1TS16	TAUGHT AT SCHOOL ABOUT UNDERWEIGHT

H1TS17	S4Q17 LEARNED-SUICIDE-W1
H1ED1	S5Q1 FREQ-EXCUSED ABSENCE FROM SCHOOL-W1
H1ED2	S5Q2 FREQ-SKIPPED SCHOOL-W1
H1ED5	S5Q5 HAVE YOU EVER REPEATED A GRADE-W1
H1ED7	S5Q7 RECEIVED OUT-OF-SCHL SUSPENSION-W1
H1ED11	S5Q11 MOST RECENT GRADE-ENGLISH-W1
H1ED12	S5Q12 MOST RECENT GRADE-MATH-W1
H1ED15	S5Q15 TROUBLE-GETTING ALONG TEACHERS-W1
H1ED16	S5Q16 TROUBLE-PAYING ATTENTION-W1
H1ED17	S5Q17 TROUBLE-GETTING HOMEWORK DONE-W1
H1ED18	S5Q18 TROUBLE-WITH OTHER STUDENTS-W1
H1ED19	S5Q19 FEEL CLOSE TO PEOPLE AT SCHOOL-W1
H1ED20	S5Q20 FEEL PART OF YOUR SCHOOL-W1
H1ED21	S5Q21 STUDENTS AT SCHOOL PREJUDICED-W1
H1ED22	S5Q22 HAPPY AT YOUR SCHOOL-W1
H1ED23	S5Q23 TEACHERS TREAT STUDENTS FAIRLY-W1
H1ED24	S5Q24 FEEL SAFE IN YOUR SCHOOL-W1
H1HS1	S7Q1 ROUTINE PHYSICAL EXAM-W1
H1HS2A	S7Q2A LOCATION - PRIVATE DR-W1
H1HS2B	S7Q2B LOCATION - HEALTH CLINIC-W1
H1HS2C	S7Q2C LOCATION - SCHOOL-W1
H1HS2D	S7Q2D LOCATION - HOSPITAL-W1
H1SE4	S9Q4 YOUR INTELLIGENCE-W1
H1FS1	S10Q1 BOTHERED BY THINGS-W1
H1FS2	S10Q2 POOR APPETITE-W1
H1FS3	S10Q3 HAD THE BLUES-W1
H1FS4	S10Q4 JUST AS GOOD AS OTHER PEOPLE-W1
H1FS5	S10Q5 TROUBLE KEEPING MIND FOCUSED-W1

H1FS6	S10Q6 FELT DEPRESSED-W1
H1FS7	S10Q7 TOO TIRED TO DO THINGS-W1
H1FS8	S10Q8 HOPEFUL ABOUT THE FUTURE-W1
H1FS9	S10Q9 LIFE HAD BEEN A FAILURE-W1
H1FS10	S10Q10 FEARFUL-W1
H1FS11	S10Q11 HAPPY-W1
H1FS12	S10Q12 TALKED LESS THAN USUAL-W1
H1FS13	S10Q13 FELT LONELY-W1
H1FS14	S10Q14 PEOPLE UNFRIENDLY TO YOU-W1
H1FS15	S10Q15 ENJOYED LIFE-W1
H1FS16	S10Q16 FELT SAD-W1
H1FS17	S10Q17 FELT PEOPLE DISLIKE YOU-W1
H1FS18	S10Q18 HARD TO START DOING THINGS-W1
H1FS19	S10Q19 LIFE NOT WORTH LIVING-W1
H1HR14	NUMBER OF CHILDREN BIO PARENTS HAVE
H1HR15	WHICH CHILD ARE YOU- FIRST, SECOND, OR WHAT
H1RM1	S14Q1 RES MOM-EDUCATION LEVEL-W1
H1RM2	S14Q2 RES MOM-BORN IN US-W1
H1RM7	S14Q7 RES MOM-WORK HRS/WEEK-W1
H1RM9	S14Q9 RES MOM-RECEIVE PUBLIC ASSIST-W1
H1RM10	S14Q10 RES MOM-DISABLED-W1
H1RM11	S14Q11 RES MOM-AT HOME WHEN LEAVE-W1
H1RM12	S14Q12 RES MOM-AT HOME WHEN RETURN-W1
H1RM13	S14Q13 RES MOM-AT HOME WHEN BED-W1
H1RM14	S14Q14 RES MOM-EVER SMOKE-W1
H1RF7	S15Q7 RES DAD-WORK HRS/WEEK-W1
H1WP1	S16Q1 MAKE OWN DECISION-WKEND CURFEW-W1
H1WP2	S16Q2 MAKE OWN DECISION-FRIEND-W1
H1WP3	S16Q3 MAKE OWN DECISION-CLOTHING-W1
H1WP4	S16Q4 MAKE OWN DECISION-AMOUNT OF TV-W1

H1WP5	S16Q5 MAKE OWN DECISION-TV PROGRAMS-W1
H1WP6	S16Q6 MAKE OWN DECISION-WEEKDAY BED-W1
H1WP7	S16Q7 MAKE OWN DECISION-DIET-W1
H1WP8	S16Q8 FREQ-EAT DINNER W/ PARENT-W1
H1WP9	S16Q9 CLOSE TO MOM-W1
H1WP10	S16Q10 MOM-HOW MUCH DOES SHE CARE-W1
H1WP11	S16Q11 MOM-IF NOT COLLEGE GRADUATE-W1
H1WP12	S16Q12 MOM-IF NOT HS GRADUATE-W1
H1WP17A	S16Q17A RES MOM-WENT SHOPPING-W1
H1WP17B	S16Q17B RES MOM-PLAYED A SPORT-W1
H1WP17C	S16Q17C RES MOM-RELIGIOUS SERVICE-W1
H1WP17D	S16Q17D RES MOM-TALKED ABOUT LIFE-W1
H1WP17E	S16Q17E RES MOM-WENT TO MOVIE/ETC-W1
H1WP17F	S16Q17F RES MOM-DISCUSS PERSONAL PROB-W1
H1WP17G	S16Q17G RES MOM-ARGUED ABOUT BEHAVIOR-W1
H1WP17H	S16Q17H RES MOM-TALKED SCH-GRADES-W1
H1WP17I	S16Q17I RES MOM-WORKED SCH-PROJECT-W1
H1WP17J	S16Q17J RES MOM-TALKED SCH-OTHER-W1
H1PF1	S18Q1 MOM-WARM AND LOVING-W1
H1PF2	S18Q2 MOM-ENCOURAGES INDEPENDENCE-W1
H1PF3	S18Q3 MOM-DISCUSSES ETHICS-W1
H1PF4	S18Q4 MOM-GOOD COMMUNICATION-W1
H1PF5	S18Q5 MOM-GOOD RELATIONSHIP-W1
H1PF7	S18Q7 NEVER ARGUE W/ ANYONE-W1
H1PF8	S18Q8 ACCOMPLISH THROUGH HARD WORK-W1
H1PF10	S18Q10 NEVER GET SAD-W1

H1PF13	S18Q13 NEVER CRITICIZE OTHER PEOPLE-W1
H1PF14	S18Q14 AVOID CONFRONTING PROBLEMS-W1
H1PF15	S18Q15 UPSET BY DIFFICULT PROBLEMS-W1
H1PF16	S18Q16 RELY ON GUT FEELINGS-W1
H1PF18	S18Q18 RESEARCH SOLUTIONS TO PROB-W1
H1PF19	S18Q19 MANY APPROACHES TO PROB-W1
H1PF20	S18Q20 RATIONAL DECISION MAKING APPR-W1
H1PF21	S18Q21 EVALUATE OUTCOME OF DECISION-W1
H1PF26	S18Q26 HAVE LOTS OF ENERGY-W1
H1PF27	S18Q27 SELDOM GET SICK-W1
H1PF28	S18Q28 WHEN SICK, RECOVER QUICKLY-W1
H1PF29	S18Q29 WELL COORDINATED-W1
H1PF30	S18Q30 HAVE LOTS OF GOOD QUALITIES-W1
H1PF31	S18Q31 PHYSICALLY FIT-W1
H1PF32	S18Q32 HAVE A LOT TO BE PROUD OF-W1
H1PF33	S18Q33 LIKE SELF AS ARE-W1
H1PF34	S18Q34 DO EVERYTHING JUST RIGHT-W1
H1PF35	S18Q35 FEEL SOCIALLY ACCEPTED-W1
H1PF36	S18Q36 FEEL LOVED AND WANTED-W1
H1NR1	S26Q1 EVER ATTRACTED TO A FEMALE-W1
H1NR2	S26Q2 EVER ATTRACTED TO A MALE-W1
H1NR5	S26Q5 NON-ROMANCE SEX W/ ANYONE-W1
H1NR7	SINCE 1/94,# OF SEX RELATIONSHIPS-W1
H1NR8	SINCE 1/94,# OF NR SEX RELATIONSHIPS-W1
H1TO1	S28Q1 EVER SMOKED A CIGARETTE-W1
H1TO3	S28Q3 SMOKED CIGARETTES REGULARLY-W1

H1TO5	S28Q5 30 DAYS-DAYS SMOKED-W1
H1TO7	S28Q7 NO. OF CIGARETTES A DAY-W1
H1TO12	S280Q12 DRINK ALCOHOL > 2-3 TIMES-W1
H1TO15	S28Q15 PAST 12 MOS-FREQ DRINK ALCOHOL-W1
H1TO16	S28Q16 NO. OF DRINKS EACH TIME-W1
H1TO18	S28Q18 PAST 12 MOS-GOTTEN DRUNK-W1
H1TO20	S28Q20 PARENT PROB BEC OF ALCOHOL-W1
H1TO24	S28Q24 REGRET ACTION BEC OF ALCOHOL-W1
H1TO25	S28Q25 HUNG OVER-W1
H1TO26	S28Q26 THREW UP AFTER DRINKING-W1
H1TO29	S28Q29 3 FRIENDS-DRINK >1 A MONTH-W1
H1TO50	S28Q50 CIGARETTES IN YOUR HOME-W1
H1TO51	S28Q51 EASY ACCESS TO ALCOHOL IN HOME-W1
H1TO53	S28Q53 EASY ACCESS TO GUN IN HOME-W1
H1DS1	S29Q1 PAST 12 MOS-PAINT GRAFFITI-W1
H1DS2	S29Q2 PAST 12 MOS-DAMAGE PROPERTY-W1
H1DS3	S29Q3 LIE TO PARENTS ABOUT WHEREABOUT-W1
H1DS4	S29Q4 SHOPLIFT-W1
H1DS5	S29Q5 SERIOUS PHYS FIGHT-W1
H1DS6	S29Q6 SERIOUSLY INJURE SOMEONE-W1
H1DS7	S29Q7 RUN AWAY FROM HOME-W1
H1DS8	S29Q8 STEAL A CAR-W1
H1DS13	S29Q13 STEAL WORTH < $50-W1
H1DS14	S29Q14 TAKE PART IN A GROUP FIGHT-W1
H1DS15	S29Q15 LOUD/ROWDY IN A PUBLIC PLACE-W1
H1JO10	S30Q10 DRUNK AT SCHOOL-W1
H1JO11	S30Q11 PAST 12 MOS-PHYSICAL FIGHT-W1

H1JO15	S30Q15 DRINK ALCOHOL WHEN ALONE-W1
H1JO20	S30Q20 HIGH AT SCHOOL-W1
H1JO25	S30Q25 CARRY WEAPON AT SCHOOL-W1
H1FV1	S31Q1 SAW SHOOTING/STABBING OF PERSON-W1
H1FV2	S31Q2 HAD KNIFE/GUN PULLED ON YOU-W1
H1FV5	S31Q5 GOT INTO A PHYSICAL FIGHT-W1
H1FV6	S31Q6 WERE JUMPED-W1
H1FV13	S31Q13 FREQ-SERIOUS INJURY FROM FIGHT-W1
w1_s_Friend	WAVE 1- WHETHER FRIEND HAD DIED BY SUICIDE
H1PA1	S34Q1 MOM-FEEL ABOUT YOUR SEXLIFE-W1
H1PA2	S34Q2 MOM-YOU HAVING SEX WITH STEADY-W1
H1PA3	S34Q3 MOM-USE OF BIRTHCONTROL-W1
H1PA7	S34Q7 CONSIDER HAVING CHILD UNMARRIED-W1
H1PR1	S35Q1 ADULTS CARE ABOUT YOU-W1
H1PR2	S35Q2 TEACHERS CARE ABOUT YOU-W1
H1PR3	S35Q3 PARENTS CARE ABOUT YOU-W1
H1PR4	S35Q4 FRIENDS CARE ABOUT YOU-W1
H1PR5	S35Q5 FAMILY UNDERSTAND YOU-W1
H1PR6	S35Q6 WANT TO LEAVE HOME-W1
H1PR7	S35Q7 FAMIYL HAS FUN TOGETHER-W1
H1PR8	S35Q8 FAMILY PAYS ATTENTION TO YOU-W1
H1NB1	S36Q1 KNOW MOST PEOPLE IN NBORHOOD-W1
H1NB2	S36Q2 PAST MO-STOP & TALK TO NEIGHBOR-W1
H1NB3	S36Q3 NEIGHBORS LOOK OUT FOR EA OTHER-W1
H1NB4	S36Q4 USE REC CTR IN NBORHOOD-W1
H1NB5	S36Q5 FEEL SAFE IN NBORHOOD-W1

H1NB6	S36Q6 HOW HAPPY LIVING IN NBORHOOD-W1
H1NB7	S36Q7 HAPPY/UNHAPPY TO MOVE-W1
H1RE3	HOW OFTEN ATTEND CHURCH SERVICE
H1RE4	HOW IMPORTANT IS RELIGION TO YOU
H1RE6	HOW OFTEN DO YOU PRAY
H1RE7	PAST 12 MONTHS HOW OFTEN ATTEND CHURCH YOUTH SERVICE
H1EE1	S38Q1 WANT TO ATTEND COLLEGE-W1
H1EE2	S38Q2 LIKELY WILL ATTEND COLLEGE-W1
H1EE3	S38Q3 DID YOU WORK FOR PAY-W1
H1EE4	S38Q4 HRS/WEEK WORK-NONSUMMER-W1
H1EE5	S38Q5 MONEY EARNED/WEEK-NONSUMMER-W1
H1EE6	S38Q6 HRS/WEEK WORK-SUMMER-W1
H1EE7	S38Q7 MONEY EARNED/WEEK-SUMMER-W1
H1EE8	S38Q8 WEEKLY ALLOWANCE-W1
H1EE12	S38Q12 CHANCES-LIVE TO AGE 35-W1
H1EE13	S38Q13 CHANCES-MARRIED BY AGE 25-W1
H1EE14	S38Q14 CHANCES-KILLED BY AGE 21-W1
H1EE15	S38Q15 CHANCES-GET HIV/AIDS-W1
COL_groceries	COST OF LIVING GROCERIES
COL_junkfood	COST OF LIVING JUNKFOOD
COL_consumerPriceIndex	COST OF LIVING CONSUMER PRICE INDEX
COL_costLivingXconsumerPrice	COST OF LIVING MULTIPLE CONSUMER PRICE INDEX
Crime_total	TOTAL CRIME IN AREA
Employ_no_1991	EMPLOYMENT YEAR 1991
Employ_no_1994	EMPLOYMENT YEAR 1994
Employ_hightech_1995	EMPLOYMENT IN HIGHTECH YEAR 1995
Employ_publicOrder_1995	EMPLOYMENT IN PUBLIC ORDER YEAR 1995
GSW12345	SAMPLING WEIGHT
race	RACE
age	AGE
s3_generalhealth_heightInches	HEIGHT OF PARTICIPANT

mixed_Race	WHETHER P IS MIXED RACE OR NOT
gay	WHETHER P IS GAY OR NOT
parentStatus	SINGLE PARENT, DUO PARENTS, ORPHAN
w1_suicidalBx	WAVE 1 SUICIDAL BEHAVIORS
Pred_SB_Class	PREDICTED SUICIDAL BEHAVIOR CLASS
Pred_SB_Class2	PREDICTED SUICIDAL BEHAVIOR CLASS2