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Identifying Risk Factors for Youth Hospitalization in Crisis Settings: A Classification and Regression Tree Analysis

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IDENTIFYING RISK FACTORS FOR YOUTH HOSPITALIZATION IN CRISIS SETTINGS: A CLASSIFICATION AND REGRESSION TREE ANALYSIS

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ABSTRACT

Traditionally, treatment option for psychiatric crises was limited to psychiatric hospitalization. However, psychiatric hospitals are expensive and little evidence supports their utility. Youth returning from psychiatric hospitalizations often have difficulties readjusting to everyday life which can increase risk for negative outcomes. Alternative treatment options such as mobile crisis services might be useful for stabilizing youth in the community and garnering better long-term outcomes. For alternative treatment options to work, clinicians must be able to efficiently and accurately distinguish youth in need of psychiatric hospitalization and youth who could be served via an alternative service. Therefore, the purpose of the present study is to examine the predictive utility of risk factors available at the time of the hospitalization decision and develop a decision tree that clinicians could use to aid in the decision-making process. Data consisted of 2,605 youth aged 4.0 – 19.5 years (*M* = 14.07, *SD* = 2.73, 56% female) who utilized the Mobile Crisis Response Team in the State of Nevada between 2014 and 2017. Using Random Forest, the 13 most important risk factors were identified. Classification and Regression Tree provided an interpretable, easy to use decision tree (accuracy = .88, AUC = .82). In summary, the most important risk factors for hospitalization reflected current functioning. Lifetime risk factors (e.g., diagnosis) were not strong predictors of acute decision-making when acute risk factors were available. Clinicians should attend to current symptoms (e.g., suicide behaviors, danger to others, poor judgment, psychotic symptoms) and environmental factors (e.g., poor functioning at home, poor caregiver supervision) that increase a youth's risk for harming oneself or others when deciding whether to hospitalize or stabilize a youth in psychiatric crisis.

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CHAPTER 1

LITERATURE REVIEW

Psychiatric disorders are common in children and adolescents. Approximately 1 in 5 youth live with a mental health condition with impairment or distress (Merikangas, He, Brody, et al., 2010; Merikangas, He, Burstein, et al., 2010). The burden of mental health illness is high with approximately 37% of students with mental illness dropping out of high school (U.S. Department of Education, 2014). At the most severe end, a subset of these youths experiences a psychiatric crisis due to thoughts, behaviors, or attempts to harm oneself or others. Traditionally, the treatment option for youth in crisis has been psychiatric hospitalization. However, hospitalization is meant to be for individuals at risk for harming themselves or another due to a severe mental illness. Many youths in psychiatric crisis are not at risk of harming themselves or others, but require a higher level of care. Psychiatric hospitals are expensive treatment options for these youths. Therefore, appropriate mental health care that can stabilize youth in the community may reduce the rate of inpatient admission and cost of care for our most severely ill youth. The decision to hospitalize or not hospitalize a youth is a high-risk clinical decision. Risk factors for hospitalization range from demographic characteristics to diagnoses to presenting symptoms. Determining who should be hospitalized and who should not be hospitalized is critical to a cost-effective provision of service at scale and to providing appropriate, individualized care to an individual youth.

Psychiatric Hospitalization

Mental health facilities in the United States are classified based on how restrictive the treatment setting is and the specific services provided (Substance Abuse and Mental Health Services Administration, 2017). Psychiatric hospitals represent the most restrictive provision of service at the highest level of intensity. Psychiatric hospitals are locked, inpatient facilities in which youth are supervised 24 hours per day, 365 days per year. Treatment provision typically includes: (a) psychiatry for medication management, (b) psychological assessment, (c) individual therapy, (d) group therapy, (e) family therapy, and (f) structured environment. Many of these services are provided on a daily basis to youth in psychiatric hospitals. In contrast, community-based mental health services are typically the least restrictive services provided at the lowest level of intensity. Outpatient service typically consists of a single treatment modality (e.g., medication or psychotherapy; Olfson & Marcus, 2010). In psychiatric crises, more restrictive and focused services might be provided to an individual via inpatient hospitalization. However, provision of mental health service and treatment of mental illness has changed over time. Since the 1970s, communities have focused on providing individuals service in the least restrictive setting possible. This focus resulted in a drop in psychiatric hospital admissions and censuses (Kiesler et al., 1983; Lamb & Bachrach, 2001). The drop was primarily due to the discovery and use of more effective psychopharmacology and psychotherapy (Manderscheid, Atay, & Crider, 2009). Communities were able to implement services for individuals with less severe psychopathology in less restrictive settings such as community-based and home-based care (Lincoln, 2006). Therefore, hospitalization has been reserved for individuals with severe mental illness with the highest need.

The psychiatric practice of civil commitment and the criteria for hospitalization have changed along with the history of service provision. Prior to the 1970s, the civil commitment was required for treatment purposes based on the assumption that a mentally ill person lacked the capacity to make decisions and required treatment. As part of the broader civil rights movements, mental health professionals, patients, and advocates advanced the idea that psychiatric hospitalization could be extreme and harmful. At the same time, the number of psychiatric hospital admission peaked. However, advocates helped create a system in which deinstitutionalization occurred in the 1970s with the commitment standard changing from a need-for-treatment standard to a dangerousness standard (Testa & West, 2010). The dangerousness standard requires that involuntary hospitalization occur because the person is an imminent threat to the safety of self or others. To protect non-dangerous but mentally ill individuals, the U.S. Supreme Court ruled that for individuals without clear imminent danger, a less restrictive alternative service besides hospitalization should be considered first ("Lake v. Cameron," 1966). The legal requirements aim to minimize inappropriate decision making of who should be hospitalized and who should not. Providing the most appropriate treatment in the least restrictive setting is still a primary goal for mental health systems.

Consistent with the trend of deinstitutionalization in the 1970s and the change in criteria for inpatient admission, state and county hospitals reduced long-term psychiatric inpatient beds steadily. The number of annual psychiatric hospital episodes and the rate of inpatient admission dropped in the U.S. over the prior 6 decades (Hudson, 2016). The rates of inpatient admission declined from .83% in 1990 to .74% in 2002 of the general population. However, in the prior 20 years, the trend has started to reverse with more individuals being hospitalized that this number has increased to .91% in 2004 (National Center for Health Statistics, 2010). Additionally, the length of psychiatric hospitalization increased for children, adolescents and adults over the past two decades (Blader, 2011). The increasing admission rate was primarily due to increases in the provision of acute short-term care in inpatient units and a lack of community support. Therefore, there is a population-level need for community-based services for youth requiring crisis services if the system-level improvements in deinstitutionalization are to be maintained.

The emergency department (ED) in hospitals is an entry point for people in crisis to access to inpatient psychiatric services. EDs primarily focus is on the care of individuals at risk for imminent death. However, individuals in the ED for psychiatric reasons account for up to 4% of ED patients (Barratt et al., 2016). The rate of psychiatric ED visits among adults increased from 1.8% to 2.1% between 1992 and 2000 (Hazlett, McCarthy, Londner, & Onyike, 2004). Similarly, pediatric psychiatric ED visits increased from 1.6% in 1994 – 1996 to 3.3% in 2003 – 2005 and to 4.0% in 2011 – 2015 (Kalb et al., 2019; Mahajan et al., 2009). ED physicians must rapidly decide whether the patients should be hospitalized or could be discharged to the community after a brief evaluation. Youth who visited the ED due to psychiatric symptoms or diagnoses were more likely to be hospitalized than non-psychiatric-related visits (Mahajan et al., 2009). Limited access to mental health resources in the community is one potential cause for increased utilization of ED visits and inpatient hospitalization for psychiatric care (Larkin, Claassen, Emond, Pelletier, & Camargo, 2005). Therefore, to reduce psychiatric-related ED visits and hospitalization and to provide cost-effective utilization of mental health care in youth, well-developed alternative services are needed.

Community-based services were never fully funded or built as part of the move towards deinstitutionalization. In the 1970s, more than 500 community-based mental health centers were in full operation. The intention of deinstitutionalization was to develop a support system for severe mentally ill patients and offer comprehensive treatment and rehabilitation services. However, community-based health centers initially faced the challenge of providing services to a population for which they were not equipped. As a result, many discharged adults with severe mental illnesses were re-hospitalized frequently due to either lack of appropriate care or the lack of care (Bassuk & Gerson, 1978). Additionally, community-based mental health centers faced the challenge of insufficient funding. Community-based services were funded by the federal government with the expectation that costs would transition to a fee for service model in which insurance, state and local governments would reimburse the cost (Bassuk & Gerson, 1978). The transition in funding source did not occur because the majority of people seen in community-based services are from low SES backgrounds and cannot afford the cost of care. Today the investment in appropriate community services is often lacking and this is particularly true in states that are underserved. Clinicians working in crisis settings face the challenge of providing adequate services to individuals who are too severe for traditional outpatient services and may not have access to inpatient services or are not so severe as to require psychiatric hospitalization (Watanabe-Galloway, Watkins, Ryan, Harvey, & Shaffer, 2015). Additionally, psychiatric hospitalization rates and beds are often higher in states that have low rates of outpatient services relative to states with higher rates of outpatient services (Manderscheid et al., 2009). Therefore, the lack of effective community-based services often results in unnecessary, yet more costly use of inpatient services.

Alternative services that increase the frequency and intensity of outpatient services could be a solution to this dilemma. Services such as intensive outpatient or partial hospitalization are one potential solution for some patients. Home-based multi-systemic therapy and intensive home-based crisis intervention services for youth are other options. These services demonstrate significant reductions in symptoms, shorter use of out-of-home placement, and faster returns to school when compared to similar youth who were hospitalized (Shepperd et al., 2009). Alternative services may prevent individuals from developing a dependency on the hospital environment and being stigmatized, facilitate a smoother transfer from treatment to everyday environment, and maximize the sustained effect of treatment outcomes (Katz, Cox, Gunasekara,

& Miller, 2004). Therefore, identifying individuals who would benefit the most from more intensive outpatient services is critical to the efficient allocation of resources.

Mobile Crisis Service as a Solution

Restrictive settings for individuals in crisis such as psychiatric emergency rooms, residential facility, and inpatient hospital do not guarantee optimal outcomes (Heflinger, Simpkins, & Foster, 2002; Hussey & Guo, 2002). The presence of 24-hour monitoring, locked wards, and highly structured milieus prevents youth from engaging in dangerous acts. However, the milieu in psychiatric hospitals is very different from everyday life. Youth are separated from normal life and social supports. After being discharged from the hospital, youths have to adapt to everyday life. Stigma and shame of psychiatric hospitalization increases the difficulty of the adjustment (Loch, 2012). Difficulties experienced while readjusting to everyday life typically result in negative functional setbacks and increased psychological distress that maintain or exacerbate severe mental illness (Loch, 2012). Therefore, alternative services that use intervention teams to provide care in the milieu of the home for psychiatric crisis may provide an option for many severe mentally ill who are at risk for psychiatric hospitalization. These services can be provided to target the environmental and family risk factors that maintain or exacerbate the illness.

The primary goal of mobile crisis services is to reduce unnecessary hospitalization by stabilizing patients with a community-based treatment. The mobile crisis team provides a rapid response at the youth’s location to with an initial clinical assessment and safety planning on a 24 hour, 7 days a week basis. During the crisis response, the mobile crisis team determines whether the youth can be stabilized in the community or requires psychiatric hospitalization. In-home stabilization includes determining treatment options such as short-term, intensive in-home therapy with psychiatry visits as required, while working to rapidly engage longer-term community services such as weekly outpatient psychotherapy. Mobile crisis services decrease the rate of psychiatric hospitalization and mental health spending per youth, while increasing youth's time in the community, and maintaining the youth's safety (Guo, Biegel, Johnsen, & Dyches, 2001). Additionally, mobile crisis services increase the accessibility of mental health care across settings for youth. Mobile crisis services are flexible and able to coordinate services for families, in schools, across providers, and often with police in the process of providing care. As a result, mobile crisis services reduce involvement in juvenile justice (Vanderploeg, Lu, Marshall, & Stevens, 2016). In contrast, psychiatric hospitals often are disconnected from the community they serve and lack the connections with the broader mental health network (Mollenhauer & Kaminsky, 1996). Therefore, the mobile crisis teams are likely more effective for the individual, cost-effective for the system, and when supported by system level funders administratively feasible.

Assessment for Psychiatric Hospitalization

Admission to a psychiatric inpatient unit represents a high risk clinical decision that carries both economic and non-economic costs. Ideally, clinicians who make these decisions would make the ideal decision whether it is to hospitalize someone who needs to be hospitalized (i.e., true positive) or choosing not to hospitalize a person who does not require hospitalization (i.e., true negative). When decision-making is ideal, then the cost-benefit of the decision is optimized. However, decision-making is almost never perfect and errors occur. Admission to a psychiatric inpatient unit has economic costs (i.e., financial costs of service) and non-economic costs such as stigma and increased distress (Katz et al., 2004). Admitting an individual to an inpatient unit when the individual does not need to be admitted (i.e., false positive) has the potential to cause harm. Not providing appropriate services can also result in both economic costs (i.e., opportunity-cost) and non-economic costs (i.e., disillusionment with the mental health system or in the context of risk for suicide – death). Not admitting an individual to a psychiatric inpatient unit when the individual should be admitted (i.e., false negative) also has the potential to cause harm. Therefore, it is important to balance the decision of psychiatric hospitalization to maximize welfare and minimize harm of those who are affected.

Most clinicians assess the dangerousness criterion by using unstructured interviews and relying highly on clinical impression (Stefan, 2006). Unstructured interviewing allows clinicians to tailor the interview and ask follow-up questions as needed. Unstructured interviews are useful for identifying general problems. However, the lack of a standardized assessment process means that the evaluation for inpatient admission is highly variable (Way & Banks, 2001). Across clinical decisions, structuring and standardizing the decision-making process increases the reliability and validity of the decision by reducing inconsistencies in the interpretation of the same clinical information and potential biases in thinking (Rettew, Lynch, Achenbach, Dumenci, & Ivanova, 2009). Therefore, a standardized and structured approach is helpful such that the clinicians would not overlook critical signs related to high risk decisions such as hospitalization due to a psychiatric crisis. Identifying a structured set of risk factors or criteria to examine the needs of psychiatric hospitalization is worthwhile and could help clinicians formulate a better decision-making process.

Risk Factors for Psychiatric Inpatient Services

A risk factor increases the likelihood of a given individual developing or having a specific outcome, such as a psychiatric disorder, compared to others from the general or unexposed population (Kazdin, Kraemer, Kessler, Kupfer, & Offord, 1997). The term "risk factor" is commonly used in the literature. For example, national survey data of French adolescents indicates that adolescents with a history of suicide, school drop-out, smoking, and illicit drug use are at higher risk for hospitalization (du Roscoät, Legleye, Guignard, Husky, & Beck, 2016). However, the commonly used definition and common uses of the term risk factor in the scientific literature is imprecise. A significant association between a history of suicide, school drop-out, smoking and illicit drug use with hospitalization does not carry temporal information that is critical to the decision-making process. Data such as this does not clarify whether a history of smoking increases an adolescent's risk for hospitalization or if a history of hospitalization increases one's risk for smoking. In other words, studies that do not account for the timing of the risk factor are likely to confuse the meaning of the relationship between the identified risk factor and the outcome of interest. Therefore, a more precise definition of risk factor is needed that accounts for the temporal ordering of events.

In medicine, leading biostatisticians defined a risk factor as a characteristic or experience that precedes the outcome and is associated with a change in the probability of the outcome (Kraemer et al., 1997). A risk factor must occur prior to the outcome. In determining whether a youth should be hospitalized, risk factors should be identified prior to the decision to hospitalize and the risk factor must be associated with a change risk for hospitalization. Linking risk factors to clinician decision-making fits within the evidence-based assessment (EBA) framework (Youngstrom, 2008). Risk factors that occur prior to the outcome have the potential to aid in the prediction of a clinically meaningful outcome such as psychiatric hospitalization. However, not all risk factors will be important in the clinical decision-making process. Risk factors are important in EBA if they have a meaningful impact on the decision-making process by changing the odds of an individual being hospitalized. Ideally, a risk factor would have a very strong effect such as reducing the probability of hospitalization by 45%, but most identified assessments tend to change risk by substantially less (e.g., ± 15% change in risk; McGee, 2002). Risk factors that are fixed (e.g., gender, diagnostic history) are important to consider in the decision-making process because they adjust the overall level of risk for psychiatric hospitalization. However, variable risk factors (e.g., suicide ideation) are likely more important in the decision-making process because they represent acute changes that could necessitate hospitalization and are potentially intervention targets (Kraemer, Lowe, & Kupfer, 2005). Therefore, the assessment of risk factors in mobile crisis needs to account for both fixed risk factors and variable risk factors to increase the clinical utility of prediction of hospitalization in crisis settings.

Demographic factors. As an individual increases in age from childhood to adolescence to adulthood, the risk for hospitalization increases (Bryson & Akin, 2015; Huffman et al., 2012; Jendreyschak et al., 2014; Unick et al., 2011). In children and adolescents, the odds of being hospitalized increased 1.2 times for each year older a youth became (Lindsey, Joe, Muroff, & Ford, 2010). However, there are inconsistencies in risk for voluntary hospitalization and future readmission. For example, children are slightly more likely to be hospitalized voluntarily than adolescents (Lindsey et al., 2010). The odds of having future readmission is 1.3 times higher for adolescents compared to children (Fite, Stoppelbein, Greening, & Dhossche, 2008; Stewart, Kam, & Baiden, 2014). In general, as age increases, the risk for being psychiatrically hospitalized also increases.

In adults, women are at higher risk for hospitalization than men (Lincoln, 2006; Unick et al., 2011) and for readmission (Callaly, Hyland, Trauer, Dodd, & Berk, 2010; Mellesdal, Mehlum, Wentzel-Larsen, Kroken, & Jørgensen, 2010). However, in youth, males are more likely to be hospitalized than females (Heflinger et al., 2002). At the high end, males might be six times more likely to be psychiatrically hospitalized than females (Jendreyschak et al., 2014). Therefore, in children and adolescent boys are more likely to be hospitalized than girls while in adults the reverse is true.

Health disparities exist in mental health. In adults, being a member of an ethnic minority group changes one's risk for psychiatric hospitalization. African-Americans are less likely than Whites to be hospitalized, while Hispanic/Latin(o) and Asian-Americans are at a higher risk for inpatient admission compared to Whites (Lincoln, 2006; Unick et al., 2011). However, in youth, the research is more mixed. Some research indicates that all individuals who belong to a minority ethnic/racial group are more likely to be hospitalized than Whites (Huffman et al., 2012; Muroff, Edelsohn, Joe, & Ford, 2008). Other research indicates that White Americans are more likely to be hospitalized (Heflinger et al., 2002; Hunter, Schaefer, Kurz, Prates, & Sinha, 2015). In summary, ethnicity is considered a fixed risk factor with unclear clinical utility in the decision-making process for hospitalization.

The availability of resources affects one's risk for hospitalization. In adults, living alone increases the likelihood of hospitalization (Biancosino et al., 2009) and readmission (Lorine et al., 2015; Yu, Sylvestre, Segal, Looper, & Rej, 2015). Homeless adults are less likely to be hospitalized initially (Unick et al., 2011). For homeless individuals already hospitalized, homelessness increases the risk of readmission (Lorine et al., 2015). Social resources are less well studied in youth. Youth living in rural areas were less likely to be hospitalized than youth in urban areas after ED visits due to a lack of access to available mental health resources (Huffman et al., 2012). Overall, the availability of community resources and social support is likely to protect against risk for hospitalization, while the lack of resources is likely to increase one's risk for psychiatric hospitalization or prevent one from receiving appropriate mental health care.

Having medical insurance is a critical resource to receiving care for many. For example, uninsured adults are discharged more rapidly than insured adults indicating that economic factors could influence the length of stay in hospital (Fisher et al., 2001). However, the role of medical insurance impact on psychiatric hospitalizations in children and adolescents is mixed. According to one study, youth with public health insurance are less likely to be voluntarily hospitalized compared to youth with private health insurance (Lindsey et al., 2010). In other studies, uninsured youth are less likely to be hospitalized after an ER visit (Huffman et al., 2012; Muroff et al., 2008). In summary, the patient's financial resources might be related to psychiatric hospitalization because individuals with fewer resources may have fewer opportunities to negotiate or influence the process of accessing scarce treatment resources (Lincoln, 2006; Malone, 1998). As a result, the lack of health insurance could also be an indicator of a lack of regular or affordable outpatient care that could prevent hospitalization.

Clinical factors. Clinical factors are among the most widely studied risk factors for psychiatric hospitalization. Fixed risk factors under this category is psychiatric diagnoses. Variable risk factors include psychopathology, self-injury and suicidality, and interpersonal relationships. However, diagnoses are consistent predictors of risk of psychiatric hospitalization (e.g., Biancosino et al., 2009; Bryson & Akin, 2015). Most likely, the relationship between diagnosis and psychiatric hospitalization is mediated by current clinical presentation as this variable risk factor should be more readily apparent to the clinician and is mandated to be the decision criteria by law. As a result, both fixed and variable clinical risk factors may be valuable in prediction as they might carry shared information.

Psychiatric diagnoses. Psychiatric diagnoses are significant predictors for both hospitalization and rehospitalization. For adults, mood disorders (Biancosino et al., 2009; Dazzi, Picardi, Orso, & Biondi, 2015; Lin et al., 2010; Lincoln, 2006; Vigod et al., 2015; Yu et al., 2015), schizophrenia or psychotic disorder (Lincoln, 2006), substance use disorder (Mellesdal et al., 2010; Vigod et al., 2015) and personality disorders (Biancosino et al., 2009; Mellesdal et al., 2010; Vigod et al., 2015) are all significant risk factors for hospitalization. Additionally, medical morbidity increases the risk of readmission to psychiatric inpatient setting (Vigod et al., 2015). Similarly, youth with mood disorders (Arnold et al., 2003; Bryson & Akin, 2015; Cheng, Chan, Gula, & Parker, 2017; Hunter et al., 2015; Stewart et al., 2014), schizophrenia or psychotic disorders (Bryson & Akin, 2015; Jendreyschak et al., 2014), substance use disorders (Cheng et al., 2017; Jendreyschak et al., 2014), and medical morbidity (Cheng et al., 2017) are at increased risk for inpatient psychiatric hospitalization.

In contrast to adults, anxiety disorders (Bryson & Akin, 2015; Cheng et al., 2017; Hunter et al., 2015), adjustment disorders (Muroff et al., 2008), and eating disorders (Stewart et al., 2014) are risk factors for youth. Disorders of childhood such as disruptive behavior disorders (Blader, 2004; Bryson & Akin, 2015; Chung, Edgar-Smith, Palmer, Bartholomew, & Delambo, 2008), autism spectrum disorders (Bryson & Akin, 2015; Muroff et al., 2008), and intellectual disability (Fontanella, 2008; Stewart et al., 2014) also increase children and adolescent’s rate of psychiatric hospitalization. Children with trauma history such as sexual abuse, physical abuse, neglect, witness to violence or other trauma are more likely to be readmitted in the future (Stewart et al., 2014; Tossone, Jefferis, Bhatta, Bilge-Johnson, & Seifert, 2014). Finally, comorbidity and severity of psychiatric disorders (Cheng et al., 2017; Heflinger et al., 2002; Huffman et al., 2012; Jendreyschak et al., 2014; Mutlu, Ozdemir, Yorbik, & Kilicoglu, 2015; Yampolskaya, Mowery, & Dollard, 2013) as well as family history of psychiatric disorders (Mutlu et al., 2015) are associated with pediatric hospitalization. In summary, most risk factors for adult hospitalization transport to children and adolescents and youth have additional developmentally specific risk factors.

Psychopathology. A person's psychological and behavioral symptoms are associated with hospitalization. In adults, neurosis/stress-related syndromes, impulsivity, and apathy increases the risk of hospitalization (Biancosino et al., 2009; Dazzi et al., 2015; Lincoln, 2006). Anxiety, cognitive problems, grandiosity, suspiciousness, alcohol or substance abuse, overactive, aggressive, disruptive or agitated behaviors, and threat to others increase the risk of rehospitalization (Hamilton et al., 2015; Lorine et al., 2015; Tulloch, David, & Thornicroft, 2016; Vigod et al., 2015; Zhang, Harvey, & Andrew, 2011). Adult patients with psychotic symptoms such as hallucinations, delusions, and speech irregularities are at higher risk of both hospitalization and future readmission (Beard et al., 2016; Lincoln, 2006; Tulloch et al., 2016; Unick et al., 2011; Vigod et al., 2015). In youth, alcohol or substance abuse and externalizing behaviors are related to higher risk of hospitalization (Fite et al., 2008; Lindsey et al., 2010; Muroff et al., 2008; Mutlu et al., 2015). Severe emotional disturbance, depression, learning difficulties, cognitive problems, conduct problems, and alcohol or substance abuse are predictors for future readmission (Blader, 2004; Fontanella, 2008; Pogge et al., 2008; Tossone et al., 2014; van Alphen et al., 2016). In conclusion, adults received decision of hospitalization due to typical medical or clinical criteria for inpatient admission, while youth are more likely to be hospitalized due to severely disruptive behaviors and developmental-related symptoms.

Self-injury and suicidality. Prior self-injury thoughts and behaviors significantly predict future hospitalization. In adults, suicidal ideation and attempt are both risk factors for inpatient admission (Baca-García et al., 2004; Beard et al., 2016; Lincoln, 2006). Moreover, specific characteristics of the suicide plan and attempt are related to hospitalization decisions in the emergency room. Intent to repeat the suicide attempt, plan to use a lethal method, low psychosocial functioning before the suicide attempt, and patients' belief that nobody would save their life after the suicide attempt increases the likelihood of being hospitalized. On the other hand, a realistic perspective on the future after the suicide attempt, feeling relieved that the suicide attempt was not effective, patients' belief that the suicide attempt would influence others and family support after the suicide attempt increases the likelihood of being discharged home (Baca-García et al., 2004). In youth, suicide behaviors increase the risk of both hospitalization (Hughes, Anderson, Wiblin, & Asarnow, 2016; Mutlu et al., 2015) and rehospitalization (Fontanella, 2008; Tossone et al., 2014). Risk factors associated with hospitalization after adolescent suicide attempts differ between genders. In males, those who attempt suicide with violent behaviors or criminal offenses are more likely to be hospitalized; in females, running away and illicit drug use increases the risk of being hospitalized (Pagès, Arvers, Hassler, & Choquet, 2004). Additionally, youth with non-suicidal self-injury thoughts and behaviors are at higher risk of rehospitalization (van Alphen et al., 2016). In general, adults are more likely to be hospitalized due to suicidal thoughts, while youth are more likely to be hospitalized due to suicidal behavior.

Interpersonal relationships. In adults, poor relationship functioning or interpersonal conflicts increase the risk of both hospitalization and future readmission (Beard et al., 2016; Vigod et al., 2015). In youth, peer problem is related to higher risk of rehospitalization (Tossone et al., 2014). Family plays an important role in predicting psychiatric admission in children and adolescents as well. Permissive parenting style, parental stress, low parental involvement, harsh punishment, dysfunctional family, parental history of mental illness, and family violence increases the risk of rehospitalization (Blader, 2004; Fite, Stoppelbein, & Greening, 2009;

Fontanella, 2008; James et al., 2010; Stewart et al., 2014). In summary, poor interpersonal relationships are related to inpatient admission in all ages. Family problems are specifically related to pediatric hospitalization.

Treatment factors. In adults, history of hospitalization and more prior hospitalizations increase risk for future hospitalization (Callaly et al., 2010; Lorine et al., 2015; Mellesdal et al., 2010; Yu et al., 2015; Zhang et al., 2011). Similarly, prior hospitalization increases risk for readmission in youth (Callaly et al., 2010; Chung et al., 2008). For each additional hospitalization, a youth is nearly two times as likely to have a future readmission (Callaly et al., 2010). Therefore, whether a youth was hospitalized before consistently predicts his or her future readmission and may predict whether a youth is at risk for psychiatric hospitalization.

Length of hospitalization is significantly related to future readmission. In adults, such relationships are U-shaped. Some research suggest that shorter length of previous hospitalization increases the risk of rehospitalization (Bowersox, Saunders, & Berger, 2012; Donisi, Tedeschi, Salazzari, & Amaddeo, 2016; Lorine et al., 2015; Manu et al., 2014; Tulloch et al., 2016), while other research indicates that longer length of stay increases the risk of rehospitalization (Hamilton et al., 2015; Lin et al., 2010; Mellesdal et al., 2010). In contrast, shorter length of hospitalization is a risk factor for youth’s being readmitted (Cheng et al., 2017; James et al., 2010; Yampolskaya et al., 2013). In conclusion, shorter length of stay that indicates inadequate health care could result in readmission to the psychiatric hospital.

Post-discharge services affect the likelihood of rehospitalization in both adults and youths. In adults, patients with no discharge plan are more likely to be readmitted in the future (Callaly, Trauer, Hyland, Coombs, & Berk, 2011); in contrary, patients who have post-discharge individual service plan are at lower risk of readmission (Vigod et al., 2015; Zhang et al., 2011).

Patients who received home-based intervention after discharge have a lower risk of rehospitalization (Chang & Chou, 2015). Post-discharge contact with the emergency room and not attending to consultations after being discharged both increase the risk of rehospitalization (Loch, 2012; Zhang et al., 2011). In youth, receiving post-discharge mental health services decreases the likelihood of readmission (Carlisle, Mamdani, Schachar, & To, 2012; Fontanella, 2008; James et al., 2010). Patients not receiving outpatient psychotherapy within 3 months after discharge are at higher risk of readmission (Blader, 2004; Cheng et al., 2017). No discharge plan and lack of assessment service after discharge increases the risk of readmission, too (Callaly et al., 2011; Yampolskaya et al., 2013). In summary, both adults and youths benefit from planned post-discharge services.

In summary, psychiatric hospitalization is a critical treatment decision. Both demographic and clinical characteristics predict risk for psychiatric hospitalization. Hospitalization is a costly and highly restrictive method for delivering mental health services. While most individuals with mental illness are never hospitalized, clinicians in crisis settings, such as the mobile crisis team, make this decision on a daily basis. Currently, clinical decisions to hospitalize are primarily based on the clinician's clinical judgment of who should be hospitalized and who could be stabilized in the community. However, the evidence regarding high risk decisions overwhelming supports the use of decision aids (Ægisdóttir et al., 2006). Additionally, creating a decision-aid to improve the high-risk decision on whether to hospitalize a youth or not is difficult because most of the evidence for risk factors comes from retrospective billing data. Therefore, there is a need to identify risk factors that prospectively predict youth hospitalization in crisis from data available at the time of decision-making.

CHAPTER 2

AIMS OF THE STUDY

Prior studies have identified a great number of risk factors for psychiatric hospitalization. These risk factors range from demographic characteristics to diagnostic characteristics to presenting symptoms. However, there are substantial limitations to those studies. First, many of the risk factors identified were distal to the decision of inpatient admission (e.g., Tulloch et al., 2016; Yampolskaya et al., 2013). The emphasis was on historical “symptoms” and not acute “signs” critical to determining whether a person was at risk for harming oneself or others. Second, many of prior studies used retrospective billing data with unclear temporal order (e.g., Lindsey et al., 2010; Tossone et al., 2014). The *associations* identified could reflect either reasons for acute hospitalization or how the acute hospital diagnosed patients. Third, prior studies primarily examined main effects of a risk factor (e.g., Unick et al., 2011; Vigod et al., 2015). Risk factors may interact with each to create multiplicative increase in risk not identified in prior studies. Thus, there is a need for our decision-making evidence base for hospitalization to more strongly approximate the clinical decision-making process in acute settings. The purpose of the present study is to examine available risk factors for hospitalization accounting for both previously identified risk factors (e.g., demographics, diagnosis) and potentially novel risk factors (e.g., problem with judgements, risky behavior, caregiver needs or strengths) to predict whether a youth should be hospitalized or not. Using Classification and Regression Tree (CART), we aim to develop an identifiable decision tree model or risk *algorithm* that a clinician could use to aid in the acute psychiatric hospitalization decision-making process.

CHAPTER 3

METHOD

Procedure

In 2014, Nevada's Division of Child and Family Services instituted two mobile crisis response teams (MCRT) to provide immediate and intensive community-based mental health services for children and adolescents in psychiatric crisis. The Southern MCRT began operating in January 2014 throughout the Las Vegas valley, and the Northern MCRT started providing services to the greater Reno/Sparks area in November 2014. Youth, family members, caregivers, or professional providers contact the MCRT via their free hotline. The MCRT typically responds to the youth's home, ED, or school but it may respond to any setting in which the youth is currently present. The goals are to (a) reduce youth's ED visits due to a psychiatric crisis and (b) reduce the rates of psychiatric hospitalizations by providing support and community-based interventions, short-term stabilization and case management services. The MCRT consists of one social worker and one psychiatric case manager. During the initial response, the MCRT completes a standardized, semi-structured assessment with the child and his/her caregiver. The MCRT has bilingual providers and access to certified translators for youth or caregivers who are not fluent in English. At the end of the initial assessment, the MCRT with consultation from a supervisor determines whether the youth should be hospitalized, receive high intensity stabilization, or should be connected to available outpatient treatment resources. For youth referred to high intensity stabilization, hospitalization was recommended for a small subset.

The MCRT database consists of the electronic health record and text entry health record of all youth who completed a routine MCRT service. The standard measures collected in a routine MCRT evaluation and stabilization include intake information, crisis assessment, mental status examination, clinical information, disposition, intervention screening, and stabilization outcomes. The written progress notes by the MCRT clinicians were stored in the text entry health record. All data were de-identified for current research use. Inclusion criteria in this dataset include: (a) MCRT responded to the call, and (b) MCRT collected systematic data. There are no specific exclusion criteria. For the current study, hospitalization was defined as the MCRT recommend psychiatric hospitalization at intake or the youth was hospitalized during crisis stabilization. Hospitalization decisions were informed by our study measures and clinician judgment.

Participants

Data consisted of 2,776 youths who utilized the Mobile Crisis Response Team (MCRT) in the State of Nevada between 2014 and 2017. Youths who had missing values on all predictors to be included in the CART model were excluded. Therefore, the final sample consisted of 2,605 youths. The sample was approximately 44% male and 56% female. Youth's age at assessment ranged from 4.0-19.5 years (*M* = 14.07, *SD* = 2.73). Approximately 63% of the sample were Caucasian (*n* = 1,646), 22% African-American (*n* = 563), 3% Asian-American (*n* = 91), 3% Pacific Islander (*n* = 83), and 9% unknown/did not disclose (*n* = 222). Approximately 40% of youth identified as Hispanic (*n* = 1,032). In the overall sample, 14% youth was hospitalized after the MCRT crisis assessment (*n* = 360).

Measures

Demographics. The MCRT intake screening tool contained demographic information from the youth, including gender, age at first assessment, race and ethnicity.

Clinical variables. The MCRT provides clinical evaluation of a crisis by trained mental health professionals at stage of admission (i.e., at the time clinicians receive phone call). A comprehensive assessment was delivered to evaluate youth's acute "sign" of a crisis in the past 24 hours and history of mental health diagnoses. Table 1 lists the 63 variables assessed including the following general domains: diagnostic classes, risky behaviors, current symptoms, functioning problems, child protective services involvement, and caregiver needs and strengths.

Discharge plan. After the evaluation, the MCRT decides a discharge plan and makes referrals. Referral options include (a) MCRT stabilization services, (b) existing provider, (c) new community provider, (d) Division of Child and Family Services provider, (e) hospitalization, (f) legal involvement (e.g., child arrested, police or 911 involved), (g) insurance resources, (h) psychosocial rehabilitation or basic skills training, (i) day treatment, (j) family declined additional services, (k) no additional services needed, and (l) other. These categories will be collapsed into a single outcome variable of hospitalized yes (i.e., category (e)) or no (all other categories).

CHAPTER 4

ANALYSES

Overview of Machine Learning

Machine learning (ML) is used to produce *algorithms*, a series of systematic steps, derived from large datasets through an interactive, automatic process (King & Resick, 2014; Monuteaux & Stamoulis, 2016). ML's historical roots are in computer science; however, ML is being applied to questions of prediction in medicine (e.g., Leach et al., 2016; Thomssen et al., 1998), social work (e.g., Johnson, Brown, & Wells, 2002), and mental health (e.g., Kessler et al., 2016; Sledjeski, Dierker, Brigham, & Breslin, 2008). There are multiple statistical approaches to classification. Traditional statistical approaches such as regression use simpler algorithms to provide parsimony to what are often complex classification problems. However, there are several limitations to regression-based approaches. Traditional statistical approaches tend to have restrictive assumptions regarding the form of the relationship between predictors and criterion. For example, general linear models (e.g., regression) assumes an underlying linear relationship between predictors and criterion. For more complex relationships (e.g., nonlinear relationships, interactions) traditional approaches require *a priori* specification of the relationships. Whether a relationship is best modeled as an interaction or nonlinear relationship may not be known at the time of modeling. In contrast, ML automatizes the process of identifying how the predictors are related to the outcome (Walsh, Ribeiro, & Franklin, 2017). Therefore, using more complex models from ML may provide more effective methods to answering complex classification problems in mental health.

Analytic Plan

The current study utilized Classification and Regression Tree (CART) with random forests to predict risk for hospitalization from clinical variables. First, data were screened for out of range values and missing data using univariate descriptive statistics (e.g., mean/median/mode and standard deviation for continuous variables; frequency tables for categorical variables). Any values that were "impossible" would be coded as missing. Second, bivariate associations between individual predictors were quantified using Pearson's correlation and its derivatives (e.g., Spearman's rho, point-biserial) because multicollinearity decreases classification accuracy for models based on the general linear model. For sets of variables showing strong associations that are clinically meaningful, summary variables would be created. For example, if diagnostic history of psychosis is strongly related to current presentation of psychotic symptoms, then a single predictor variable carrying this information will be created (e.g., no psychosis history, history of psychosis, current psychotic symptoms). If symptoms of a single disorder (e.g., sadness, anhedonia for depression) are strongly correlated, then a single predictor variable representing the syndrome will be created. Third, the data are from an electronic health record and reflect data collected in clinical interactions and entered by clinicians. Missing data is likely to be a concern. Missing data were handled via multiple imputation using the caret package (Buuren & Groothuis-Oudshoorn, 2010). Fourth, a series of logistic regressions examined whether each predictor was associated with risk for hospitalization. Finally, CART models ensemble via random forests examined the predictive accuracy of the available predictors using the caret package (Kuhn, 2008).

Growing CART Trees

CART models are tree-based models (King & Resick, 2014). First, CART engages in exhaustive evaluation meaning that it evaluates all predictors. It chooses a predictor and a binary split to create nodes, or homogenous subgroups, that are optimal classification of the criterion variable at that point in modelling. CART reduces impurity, or heterogeneity of the larger group, through the partitioning process. The Gini index is a metric of impurity, or heterogeneity, in the classification of the criterion. At each split, CART selects the split that creates nodes with the highest purity possible (i.e., more homogenous subgroups). The Gini index for a given split is defined as:

$$\text{Gini index} = \sum_{j=1}^{K} p_j \left(1\text{-}p_j\right) = 1 - \sum_{j=1}^{K} p_j^2.$$

p_j represents the proportion of individuals in node j who belong to the target class in the criterion variable (Breiman, 1984). If a split results in two pure nodes in which all individuals belong to the same criterion group (i.e., $p_1 = 1.00$ and $p_2 = .00$), then the Gini index is minimized (i.e., Gini index = 0). If the split results in impure nodes that are purely random (i.e., $p_1 = .50$ and $p_2 = .50$), then the Gini index is maximized (i.e., Gini index = .50). CART exhaustively evaluates all cutoff points across all predictors. CART selects the predictor and cutoff that minimize the Gini index so that impurity in the criterion is minimized. Splits will continue as long as the Gini index changes by at least .0005.

CART trees will continue growing almost indefinitely because of how small the Gini coefficient is, so *a priori* stopping criteria are required. There are three common stopping criteria to consider. First, one can pre-determine the minimum sample size in a terminal node. Proponents of this approach argue that setting reasonable minimum sample sizes will prevent the tree from growing too large and having unstable partitions in the model (Hayes, Usami, Jacobucci, & McArdle, 2015). Second, one can specify the maximum tree depth, the number of edges between the root node and the terminal node. The tree stops splitting the data once it reaches the maximum level of tree depth (Lemon, Roy, Clark, Friedmann, & Rakowski, 2003). Third, one can pre-determine the threshold of splitting criterion. If the largest decrease in the impurity function would be less than the threshold, stop the recursive partitioning (Lemon et al., 2003). At this time, there is no clear best approach to setting stopping criteria *a priori*. Current reference texts indicate one should fit at least 20-30 different tree depths to select the most generalizable tree (Cichosz, 2014). Therefore, we will fit trees using a variety of tree depths. Additionally, we will vary the minimum node size to increase stability while software implementations tend to set minimum node size to 1. Both of these tuning parameters will be tuned using random search. Random search is the process of randomly selecting potential tuning parameters from within a range and is considered more efficient and accurate than the more traditional grid search method (Bergstra & Bengio, 2012). For the overall depth of the tree we will use randomly selected values between 2 and k – 10. For the minimum sample size, we will use randomly selected values between 1% and 5% of the sample.

Random Forest

While CART is useful for describing the relationship between predictors and the outcome, a single tree-based algorithm is usually unstable and small changes in the relationship between predictors and criterion could alter the algorithm's preferred tree structure resulting in less than optimal classification solutions (King & Resick, 2014). To overcome the model instability and less-than-optimal predictive performance, different ensembling methods – committees of trees – have been proposed (Breiman, 2001). Ensembling methods consolidate multiple CART trees into a single tree to optimize the accuracy of the prediction (Rosellini, Dussaillant, Zubizarreta, Kessler, & Rose, 2018). *Random forests,* one method of ensembling, uses the CART algorithm but grows many trees by randomly selecting cases and variables for inclusion in a series of models. It aims to prevent missing some predictors and often provides a more diverse and stable tree-based algorithm than a single CART tree (King & Resick, 2014). Random forest employs the bootstrap method to increase the accuracy of the model (Breiman, 2001). A bootstrap sample is a sample generated by re-sampling the overall sample (Efron & Tibshirani, 1994). The bootstrap sample is then used for model training and the rest of the sample is used for testing the new model from the bootstrap procedure (Kohavi, 1995). Each bootstrapped sample consists of 62.3% of the overall sample. We will use at least 100 bootstraps and up to 1,000 bootstraps depending on computational time. In addition to randomly sampling the sample, random forests also randomly sample the predictors so that unique trees can be grown. For classification problems, Breiman (2001) recommends the number of predictors in each bootstrapped sample be tuned. A common default is the square root of the number of predictors in the data. Current recommendations are to conduct a random search to determine the best number of predictors to be randomly sampled for each bootstrap. Therefore, the number of predictors considered for each bootstrap will be randomly selected from between 2 and the square root of k (Bernard, Heutte, & Adam, 2009).

As the random forest grows many trees, the final model only provides a general classification probability. In clinical settings, this is not helpful as data entry typically occurs after the clinical decision is made. Therefore, to identify a human readable, decision tree that could be interpreted in clinical settings, the most important risk factors identified in the random forest model were submitted to CART. This final model was interpreted.

Identifying the Best Fitting Models

The final step of analytic plan is to evaluate the model performance. Several global measures and performance statistic of model evaluation are described as followed.

Confusion matrix. A confusion matrix is a table that provides visualized information about the model performance. Statistics included in a confusion matrix are positive predictive value (PPV), negative predictive value (NPV), sensitivity, and specificity. The PPV is the proportion of individuals who screen positive among those who have the condition. The NPV is the proportion of individuals who screen negative among those who do not have the condition. Sensitivity is the proportion of individuals with the condition who screen positive. Specificity is the proportion of individuals without the condition who screen negative. The overall prediction accuracy, or the hit rate, is the proportion of total number of accurate predictions among all cases. The F_1 score represents the weighted average of the sensitivity and positive predictive value and is considered a better indicator of model performance when there are high costs associated with false positives and false negatives. The PPV, NPV, sensitivity, specificity, and F_1 score ranges between zero and one. On all of these metrics, values closer to 1 are better and values closer to zero are considered poor. There are no standard metrics for interpreting these values. The area under the curve (AUC) measures the ability of the model to correctly classify randomly selected cases with and without the condition. AUC is benchmarked by values ≥.90 indicate "excellent," ≥.80 "good," ≥.70 "fair," and <.70 "poor" (Swets, Dawes, & Monahan, 2000). Depending on the purpose of the screening, different model statistics have more or less value. If the purpose is to maximize the probability that a youth needs hospitalization, one should focus on models with PPV and high specificity. In contrast, if the purpose is to maximize the probability that a youth does not need hospitalization, one should focus on the model with high NPV and high sensitivity. Therefore, the best-fitting models will be evaluated with this in mind.

The kappa statistic. The kappa statistic measures the proportion of accurate predictions after accounting for chance agreement and can be calculated using the following formula:

$$\kappa = \frac{P_o - P_e}{1 - P_e},$$

where P_o is the observed prediction accuracy of the model and P_e is the expected accuracy of the model by chance (Cohen, 1960). The kappa statistic ranges from -1.0 to 1.0, with a kappa of 1.0 indicating perfect performance. Fleiss, Levin, and Paik (1981) suggests that values ≥.75 are "excellent," ≥.40 "fair to good," and <.40 "poor." Kappa is suggested as a good accuracy measure that it is not only well correlated with the AUC but also more robust to the prevalence compared to the PPV and NPV (Freeman & Moisen, 2008; Manel, Williams, & Ormerod, 2001). However, one should be careful when applying the kappa statistic to a new population. If the prevalence is substantially different in the new population, kappa still has limited generalizability from one population to another (Allouche, Tsoar, & Kadmon, 2006).

CHAPTER 5

RESULTS

Individual Risk Factors for Hospitalization

Table 2 presents the demographic characteristics of the sample by hospitalization status. For every one year increase in a youth's age, the youth was 1.10 [1.05, 1.15] times as likely to be hospitalized. For example, a 15-year-old adolescent would be 2.59 times more likely to be hospitalized than a 5-year-old child. A non-Hispanic youth was 1.43 [1.13, 1.81] times as likely to be hospitalized as a Hispanic youth. Gender and race (relative to Whites) were not associated with hospitalization, *p*s > .05.

Table 3 displays the risk associated with individual diagnoses. Youth with psychotic disorders (Odds Ratio = 13.13 [7.20, 24.84]) were substantially more likely to be hospitalized. Youth with bipolar disorders (Odds Ratio = 3.42 [2.05, 5.56]), abuse/neglect (Odds Ratio = 2.12 [1.35, 3.24]), depressive disorders (Odds Ratio = 1.99 [1.59, 2.49]), and substance use disorders (Odds Ratio = 1.93 [1.21, 2.99]) were all more likely to be hospitalized than youth without the respective disorder. In contrast, youth with anxiety disorders (Odds Ratio = .59 [.36, .92]), trauma-related disorders (Odds Ratio = .56 [.42, .74]), and educational/occupational problems (Odds Ratio = .42 [.15, .94]) were less likely to be hospitalized than youth without the respective diagnosis. Youth with neurodevelopmental, disruptive disorders, relationship problems, and attention-deficit hyperactivity disorders were not more or less likely to be hospitalized based on their diagnosis, all *p*s > .05. Some disorders had small cell sizes (n < 5) that make the odds ratios and confidence intervals unreliable; therefore, those disorders were not included in the table. Disorders with small cell sizes were: obsessive-compulsive and related disorders, feeding and eating disorders, sleep-wake disorders, dissociative disorders, somatic symptom and related disorder, elimination disorders, gender dysphoria, neurocognitive disorders, and personality disorders.

Risky and Current Symptoms

Table 4 presents the risk associated with risky behaviors. In general, increases in risky behavior severity, regardless of type of risky behavior, was associated with increased risk for hospitalization. Suicidality (OR = 2.89 [2.53, 3.33]), poor judgment (OR = 2.66 [2.33, 3.04]), danger to others (OR = 2.20 [1.96, 2.48]), risk-taking behavior (OR = 1.95 [1.72, 2.21]), sexual behavior (OR = 1.93 [1.48, 2.52]), non-suicidal self-injury (OR = 1.84 [1.61, 2.09]), runaway (OR = 1.67 [1.50, 1.86]), problematic social behavior (OR = 1.65 [1.47, 1.85]), fire setting (OR = 1.64 [1.36, 1.97]), and bullying (OR = 1.46 [1.23, 1.71]) all increased the risk for hospitalization. Risky behaviors were evaluated on a four-point scale such that the OR of 2.89 for suicide risk translates to a youth with either current ideation and intent or command hallucinations that involve self-harm was 24 times more likely to be hospitalized than a youth with no history of suicide ideation or behavior.

Table 4 also displays the univariate risk associated with ratings of specific psychiatric symptoms. In general, the presence of psychiatric symptoms was associated with increased risk for hospitalization. Youth with psychotic (OR = 2.85 [2.47, 3.30]) or depressive symptoms (OR = 2.53 [2.13, 3.03]) were substantially more likely to be hospitalized than youth without the respective symptoms. Psychiatric symptoms were rated on a four-point scale. For example, youth who were evaluated as having clear evidence of dangerous hallucinations, delusions, or bizarre behavior that places the child or others at risk of physical harm were 23 times as likely to be hospitalized than youth with no evidence of psychosis. Similarly, youth with assessed as having depressed mood that was disabling were 16 times more likely to be hospitalized than youth with no evidence of depression. Youth with impulsive/hyperactive symptoms (OR = 1.87 [1.66, 2.12]), conduct/antisocial behaviors (OR = 1.71 [1.50, 1.95]), anger control problem (OR = 1.61 [1.42, 1.83]), substance use symptoms (OR = 1.59 [1.39, 1.81]), oppositional defiant behaviors (OR = 1.51 [1.35, 1.70]), anxiety (OR = 1.51 [1.31, 1.74]) and PTSD symptoms (OR = 1.39 [1.23, 1.56]) were all more likely to be hospitalized than youth without the respective symptoms.

Functioning Problems, CPS Involvement, and Caregiver Needs and Strengths

Table 5 displays the risk associated with a child's difficulty functioning, child protective services involvement, and caregiver needs and strengths. Difficulties in functioning, having CPS involvement, and caregivers with more needs were all associated with increases in risk hospitalization. Youth with functioning problems at home (OR = 2.16 [1.90, 2.46]) and youth presenting significant risk of danger to the community (OR = 2.14 [1.81, 2.52]) were substantially more likely to be hospitalized. Youth with profound problems at home (i.e., at high risk of removal from home) and youth with profound problems in the community (i.e., at high risk of being removed from the community) were each approximately 10 times as likely to be hospitalized compared to youth with no functioning problems in the respective domain. Problems with peer relationship (OR = 1.82 [1.62, 2.05]), functioning problems in the community (OR = 1.66 [1.44, 1.91]), sleep problems (OR = 1.66 [1.48, 1.86]), medication noncompliance (OR = 1.59 [1.40, 1.80]), developmental delay (OR = 1.54 [1.32, 1.80]), functioning problems in school (OR = 1.45 [1.30, 1.62]), acts of delinquency (OR = 1.37 [1.20, 1.57]) and juvenile justice status (OR = 1.23 [1.04, 1.44]) all increased the risk for hospitalization. In addition, CPS involvements, including youth being at risk of abuse or neglect (OR = 1.61 [1.37, 1.90]) and domestic violence (OR = 1.33 [1.07, 1.64]), both increased the risk. Finally, caregiver's needs and strengths slightly increased the risk for hospitalization, including caregiver's stress management (OR = 1.85 [1.62, 2.11]), caregiver's monitoring and discipline skills (OR = 1.76 [1.56, 1.98]), caregiver's involvement with care (OR = 1.59 [1.38, 1.82]), caregiver's social support (OR = 1.43 [1.27, 1.61]), accessibility to child care services (OR = 1.37 [1.21, 1.54]), caregiver's health condition (OR = 1.36 [1.20, 1.55]), and residential stability/housing problems (OR = 1.18 [1.02, 1.35]). Among the above risk factors, caregiver's stress management has the highest odds ratio that caregiver having significant stress associated with the child's needs increased the risk for hospitalization by six times compared to caregiver having no stress management problems.

Classification and Regression Tree (CART) with Random Forest Analysis

Random Forest models were grown to identify the combination of risk factors most important for predicting psychiatric hospitalization in youth. A limitation of an individual CART model is that the tree will continue grow almost indefinitely and tends to overfit the training data. Random forest models fit a series of CART models that vary randomly selected cases and variables for inclusion in each model to result in a model that is more likely to generalize well. *A priori* stopping criteria and hyperparameters are required. Random search for hyperparameter tuning suggested the minimal sample size in a terminal node should be n = 11 (.4% in the overall sample). Terminal nodes with such a small sample size would risk overfitting the training data and having a model that would not cross validate.

A grid search, which was not included in the original analytic plan, was used to limit the search space to that defined in the analytic plan. The boundaries for the grid search were (a) one to 16 of predictors randomly selected as candidates at each split, and (b) 26 (1%) to 130 (5%) cases as the minimal sample size in a terminal node. Table 6 presents the results of the grid search around the best fitting model. The optimal random forest model consisted of 15 predictors randomly selected at each split and a minimal node size equal to 27 (sensitivity = .48, specificity = .97, AUC = .90, overall accuracy = .91, κ = .53). However, to decrease risk of overfitting, the recommendation of limiting predictors is between two and $\sqrt{\mathrm{k}}$ (in the current study, k = 63, $\sqrt{\mathrm{k}} = 8$; Bernard et al, 2009). Therefore, we interpreted the results in light of this recommendation. As seen in Table 6, changing model parameters resulted in slight differences in model performance. Sensitivity, AUC and overall accuracy appeared relatively stable among models with different parameters. However, the incremental increase in sensitivity leveled off from eight predictors at each split to nine predictors at each split. Additionally, the kappa statistics improves .02 from eight to nine predictors at each split. Therefore, tuning resulted in nine predictors to be randomly selected at each split and a minimum node size of *n* = 26 as hyperparameters for the random forest model.

Model performance was evaluated via the following metrics: overall accuracy, F_1 score, kappa, sensitivity, specificity, the area under the curve (AUC), positive predictive value (PPV), and negative predictor value (NPV). Overall prediction accuracy indicates how accurately the model identifies the correct classification (i.e., true positives, true negatives). The model's overall accuracy was .90, indicating that 90% of cases were classified correctly. The F_1 score represents the weighted average of the sensitivity and the PPV and ranges between zero and one with scores closer to one being better. The F_1 score is a better indicator of model performance when there are high costs associated with false positives and false negatives. The model's F_1 score was .50, indicating poor model performance. The kappa statistic, a measure of accuracy after accounting for chance agreement, was .47, indicating fair to good agreement between predicted and observed classification. Table 7 presents the confusion matrix of the random forest model. Sensitivity is the proportion of true positive cases that are identified as positive. The model's sensitivity was .37. Of youth who should be hospitalized, the model correctly identified only 37% of youth as needing hospitalization. Specificity is the proportion of true negative cases that are identified as negative. The model's specificity was .98. of youth who should not be hospitalized, the model correctly identified 98% as not needing hospitalization. The AUC measures discrimination, the ability of the model correctly classifies cases with and without the condition. The model's AUC was .91. The AUC indicates that a randomly selected hospitalized case would have a higher risk prediction than a randomly selected non-hospitalization case 91% of the time. Among those who were predicted to be hospitalized by the random forest model, 75% received hospitalization as a result of the MCRT assessment, meaning a 536% improvement of the base rate (PPV = .75, base rate = .14). among those who were predicted to not be hospitalized by the random forest model, 91% were not hospitalized as a result of the assessment, meaning a 106% improvement of the base rate (NPV = .91, base rate = .86). In summary, the random forest model improves the hospitalization decision particularly for at-risk cases even though it could be improved for high risk cases.

Variable Importance

The overall goal was to identify an easy to use clinical algorithm. The random forest model consisted of 500 distinct CART trees and no specific algorithm was identified. Therefore, the importance of each predictor was evaluated individually by its Gini index and AUC. The Gini index measures the mean decrease in node impurity, the likelihood of an incorrect classification of a new case of a randomly chosen variable at the split. A receive operating characteristic (ROC) analysis was conducted on each risk factor to predict hospitalization. The AUC from the ROC analysis was used as another measure of variable importance. Table 8 summarizes the results of variable importance. The 15 most important variables indicated by the

Gini index were: suicidal risk, psychotic symptoms, poor judgment and/or decision-making, danger to others, depressive symptoms, functioning at home, age at first assessment, impulsivity/hyperactivity, runaway, non-suicidal self-injury, problems with sleep, problems with peer relationships, other self-harm/risk-taking behaviors, oppositional defiant behaviors, and poor caregiver's supervision. The 15 most important variable identified by the ROC analysis were: suicidal risk, poor judgment and/or decision-making, functioning at home, depressive symptoms, psychotic symptoms, problems with peer relationships, danger to others, impulsivity/hyperactivity, poor caregiver's supervision, caregiver's stress management, non-suicidal self-injury, problems with sleep, other self-harm/risk-taking behaviors, runaway, and problematic or inappropriate social behaviors. The two indicators of variable importance were strongly correlated ($r = .77$ [.64, .85]). In summary, the following 13 variables were most important: suicidal risk, psychotic symptoms, poor judgment and/or decision-making, danger to others, depressive symptoms, functioning at home, impulsivity/hyperactivity, runaway, non-suicidal self-injury, problems with sleep, problems with peer relationship, other self-harm/risk-taking behaviors, and caregiver supervision.

Single Tree Model with Most Important Variables

A single CART model using the 13 most important variables was fit to produce a human interpretable decision-tree. The hyperparameter for maximum tree depth was tuned via random search. Random search indicated that the number of edges between the root node and the terminal node should be no more than 15 (sensitivity = .46, specificity = .95, AUC = .82, overall accuracy = .88, $\kappa = .46$). Table 9 presents the nine best random search result for 25 different tree depths. Sensitivity and overall accuracy appeared relatively stable among models with different tree depths. However, the incremental increases in specificity, AUC and kappa statistic leveled off from a maximum tree depth equal to nine to maximum tree depth equal to 12. Following the principle of parsimony, we selected a less complex model that has maximum tree depth equal to nine.

Model performance was evaluated via the following metrics: overall accuracy, F_1 score, kappa, sensitivity, specificity, the AUC, PPV and NPV. Table 10 presents the confusion matrix of the single tree model. The model's overall accuracy was .89, indicating that 89% of cases were classified correctly. The model's F_1 score was .53, indicating poor performance. The kappa statistic was .61, indicating fair to good performance. The model's sensitivity was .46, meaning the model correctly identified 46% of youth who needed hospitalization among those who were indeed hospitalized. The model's specificity was .95, meaning the model correctly identified 95% of youth who did not need hospitalization among those who were not hospitalized. The model's AUC is .82, indicating that if a hospitalization case was randomly selected and compared to a randomly selected non-hospitalization case, the model indicated the hospitalization case as having more risk 82% of the time. Among those who were predicted to be hospitalized by the single tree model, 61% received hospitalization as a result of the assessment, meaning a 436% improvement of the base rate (PPV = .61, base rate = .14). among those who were not hospitalized, the model correctly predicted 92% of cases, a 107% improvement over the base rate (NPV = .92, base rate = .86). In summary, the single tree model with most important variables improves the predictive utility of data for the hospitalization decision.

Figure 1 presents an illustration of the CART model using the 13 most important variables identified in random forest analysis. One reads the decision tree based on the response to the variable. For example, the root node addresses a youth's suicide risk. If a youth has acute suicide risk (e.g., suicide plan with means), then the next point of evaluation is whether the youth has poor judgment/decision-making. If the youth did not present with acute suicide risk, then the next point of assessment should consider whether the youth is dangerous to others.

As seen in Figure 1, several pathways led to higher likelihood of not being hospitalized. Of the overall sample, the most prevalent pathway (74% of overall referrals) was a “do not hospitalize” pathway. This pathway consisted of youth who presented without current suicidal ideation and intent, without acute homicidal ideation with a plan or physical aggression that caused harm, and had no evidence/history of psychotic symptoms. Youths in this pathway were rarely hospitalized (NPV = .97). There were other “do not hospitalize” pathways that accounted for another 13% of all assessed youth. Youths who presented without current suicide ideation and intent, without acute homicidal ideation with a plan or physical aggression that caused harm, with acute psychotic symptoms (e.g., dangerous or bizarre hallucinations/delusions), had no evidence/history of running away, but presented with current psychotic symptoms (e.g., hallucinations/delusions present) were at low risk of hospitalization (NPV = .86) and were 2% of overall referrals. Some pathways were less clinically obvious. For example, 5% of youth were assessed as being at acute risk for current suicidal ideation and intent; those youths who did not evidence poor decision-making (e.g., decisions that placed them at risk of harm), had moderate or less depression, and had moderate or less problems functioning at home were also at low risk for hospitalization (NPV = .89). Similarly, another 5% of youth presented with acute risk for current suicide ideation and intent; those youths who did not evidence poor decision-making that placed them at harm, did not present with acute depressive symptoms, presented problems with functioning at home, did not run away, and whose caregiver provided adequate to good supervision were less likely to be hospitalized (NPV = .73). In summary, youth who were not at acute risk of harming themselves or others and had higher functioning family systems were less likely to be hospitalized.

In contrast to the “do not hospitalize” pathways, the “do hospitalize” pathways accounted for fewer youths overall. There was not a dominant “do hospitalize” pathway as each individual pathway accounted for a small percentage of assessed youth. The strongest of the “do hospitalize” pathways accounted for 3% of overall referrals. Among the “do hospitalize” pathways, youth who presented with acute risk for current suicidal ideation and intent and who also had acute concerns regarding their judgment/decision-making were most likely to be hospitalized (PPV = .79). The “do hospitalize” pathways tended to fit with clinical sense. For example, youths with acute risk for current suicidal ideation and intent, but not acutely poor judgment, and were severely depressed were likely to be hospitalized (PPV = .71). Youth who presented acute risk for current suicidal ideation and intent, but not acutely poor judgment and severe depressive symptoms, who had moderate to severe problems with functioning at home, had a history of running away or presented current/acute risk of running away, and did not present current psychotic symptoms had high risk for hospitalization (PPV = .70). Finally, youths who did not present acute suicidal risk, but presented with acute homicidal ideation with a plan or physical aggression that caused harm and had moderate to severe problems with functioning at home were more likely to be hospitalized (PPV = .63). In summary, the “do hospitalize” pathways focused on youth who were at risk of imminent harm to themselves or others and youth who may not have been able to be kept safe in the community for family systems reasons.

CHAPTER 6

DISCUSSION

The purpose of the study was to develop a clinically meaningful decision tree for psychiatric hospitalization. Psychiatric hospitalization is a high-risk decision that bares both economic and non-economic benefits and costs. This is the first study to develop an optimized algorithm for psychiatric hospitalization using machine learning. Risk factors were screened individually using logistic regression, submitted as indicators in a random forest model to identify the most important risk factors, which were then used to build a clinically relevant decision tree.

Logistic regression examined whether individual risk factors were associated with psychiatric hospitalization. Consistent with previous findings, risk factors across demographics (Bryson & Akin, 2015), diagnoses (Lincoln, 2006), clinical symptoms (Fontanella, 2008), and functioning (Tossone et al., 2014) were associated with increased risk for hospitalization. Among the demographic risk factors, age was the strongest predictor. Adolescents were significantly more likely to be hospitalized than children. Among diagnoses, youth with a history of psychotic disorders had the highest risk of hospitalization followed by youth with a history of bipolar disorders, neglect/abuse, unipolar depressive disorders, and substance use disorders. History of trauma-related disorders and anxiety disorders reduced risk. Current symptoms and functioning were also strongly related to risk for hospitalization. Like diagnoses, the presence of psychotic symptoms and depressive symptoms were the strongest predictors of hospitalization. In terms of the youth's current risk presentation, severity of suicide-related thoughts/behaviors, poor judgment, and severity of danger to others were the strongest predictors of hospitalization. In terms of functioning, youth with more impairment in their home life and who were more of a risk to community safety were at highest risk for hospitalization. However, almost all risk factors across domains were associated with psychiatric hospitalization. Bivariate analyses are unable to determine which combination of risk is most important for deciding whether a youth should be hospitalized.

Risk factors were submitted to a random forest model that grew many CART models to identify the most important risk factors for psychiatric hospitalization. The random forest model correctly classified 90% of all cases, had an excellent AUC of .91, and had very high specificity (.98). However, the random forest model only demonstrated fair to good agreement in decisions due to low sensitivity. The sensitivity of the random forest model was .37 indicating that of youth who were hospitalized it only predicted 37% of those youth as needing hospitalization. Despite this low sensitivity, the model’s high specificity helps a clinician rule-in risk for hospitalization. As the model accurately identifies 98% of youth who were not hospitalized as not needing hospitalization, youth who were not identified are more likely to require hospitalization. Therefore, the random forest model resulted in substantial improvements in predicting risk for hospitalization over the base rate.

From the random forest model, the most important predictors were evaluated. Thirteen risk factors were identified as the most important risk factors across two indicators of variable importance. In order of importance, the risk factors were: suicidal risk, psychotic symptoms, poor judgment and/or decision-making, danger to others, depressive symptoms, functioning at home, impulsivity/hyperactivity, runaway, non-suicidal self-injury, problems with sleep, problems with peer relationship, other self-harm/risk-taking behaviors, and caregiver supervision. Suicidal behaviors and dangerous to others were expected to be among the most important risk factors for hospitalization because these two variables are the primary legal requirements for hospitalization ("Lake v. Cameron," 1966). Psychosis, mood symptoms, impulsivity, and non-suicidal self-injury are high risk presentations for harm to self and others (Auerbach, Stewart, & Johnson, 2017; Lindgren et al., 2017; Sarkisian, Van Hulle, Lemery-Chalfant, & Goldsmith, 2017; Taylor, Hutton, & Wood, 2015). However, other risk factors identified have not been considered risk factors for psychiatric hospitalization. Running away, poor peer functioning, and poor caregiver supervision likely represent indirect environmental factors that increase risk for harm to self or others. Therefore, the most important predictors were risk factors that either directly or indirectly increased a youth's potential for the primary legal requirements for hospitalization – harming oneself or others.

The 13 most important risk factors were used as indicators in a single CART model to provide a human interpretable decision tree. The CART model yielded similar, but slightly worse performance as the random forest model. The CART model correctly classified 88% of youth and had high specificity. However, like the random forest model, the CART model's sensitivity was low (.46) and agreement between predictions and observed outcomes was only fair to moderate. The model's extremely high specificity lends utility for ruling in psychiatric hospitalization as the decision algorithm is best at identifying youth who should not be hospitalized. If a youth is not identified as not needing hospitalization, then the youth is likely to require hospitalization. Therefore, the decision tree has substantial clinical utility.

A decision tree based on the results of the CART model provides a roadmap for clinicians to consider in determining whether a youth requires psychiatric hospitalization or community stabilization. Several pathways led to higher likelihood of not being hospitalized. For example, youths who presented without current suicidal ideation and intent, without acute homicidal ideation with a plan or physical aggression that caused harm, and had no evidence/history of psychotic symptoms were rarely hospitalized. Youths who presented without current suicidal ideation and intent, without acute homicidal ideation with a plan or physical aggression that caused harm, without acute psychotic symptoms, had no evidence/history of running away, but presented with current psychotic symptoms were at low risk of hospitalization. In contrast, the “do hospitalize” pathways accounted for fewer youths overall as youth who were hospitalized represented the minority of youths evaluated. Among the “do hospitalize” pathways, youth who presented with acute risk for current suicidal ideation and intent and who also had acute concerns regarding their judgment/decision-making were most likely to be hospitalized. Youths with acute risk for current suicidal ideation and intent, but not acutely poor judgment, who were severely depressed were also more likely to be hospitalized. Therefore, clinicians could use the decision paths identified by the CART model to aid in the determination of which youth should or should not be psychiatrically hospitalized.

Limitations

The current study has limitations. First, the sample included youths who utilized the MCRT service between 2014 to 2017 and all youth were included in the training of the models. Prediction algorithms are always at risk of overfitting the training sample and not generalizing to new samples as a result (Lever, Krzywinski, & Altman, 2016). In the current study, this risk was reduced via k-folds cross validation in which training and test samples were artificially created during the random forest models. Future directions should include cross-validating the current model in a new sample. Second, the current model represents youth seeking MCRT services and not all youth in psychiatric crisis (e.g., youth presenting to emergency departments who do not call MCRT). Systematic differences between these two populations might represent a meaningful limitation on the current model’s applicability to a new population. Prior to applying the current decision-tree to all settings, thoughtful consideration should be given as to whether the model matches the clinical setting. A future direction includes testing the current model in these different populations to determine what might vary as a result of systematic differences in presentations across settings. Third, there is class imbalance in the current sample. Class imbalance occurs when the proportions of one or more classes are substantially lower than others in the training data (Kuhn & Johnson, 2013). In the current sample, the majority of youths were not hospitalized (86%) while only a small proportion of youths were hospitalized (14%). Class imbalance usually results in skewed predicted probability distribution which often causes good specificity but poor sensitivity (Kuhn & Johnson, 2013) as seen in the current model. Future directions include modifying the models to account for class imbalances in an effort to improve the sensitivity of the model. Fourth, the quality of a predictive model is dependent on the quality of the training data. The criterion variable – hospitalization – was based on clinical judgement. In the context of psychopathology, clinical diagnosis tends to have lower reliability than structured approaches (Regier et al., 2013; Rettew et al., 2009). As a result, the criterion variable is imperfect and could result in a poorer decision-making model. However, the primary pathways of the fitted model are consistent with current laws regarding involuntary psychiatric hospitalization ("NRS 433A-115," 2017) and with guidelines regarding who should and should not be hospitalized. The model allows for some high risk youth to remain in the community that might otherwise be hospitalized. Future directions include obtaining inter-rater reliability on clinical hospitalization decision and moving towards a stronger study design in which the criterion and the predictors are masked.

Clinical Implications

The current study helps improve the efficiency and accuracy of risk assessment among youths who were assessed by MCRT. Psychiatric hospitalization represents a high-risk clinical decision that carries both economic (e.g., financial costs of service, opportunity-cost) and non-economic (e.g., stigma and increased distress, disillusionment with mental health system) for involved youth. Ideally, clinicians who make these decisions would make decisions without errors whether the decision is to hospitalize someone who needs to be hospitalized (i.e., true positive) or choose not to hospitalize a person who does not require hospitalization (i.e., true negative). However, decades of research indicate that clinical decisions tend to have substantial error and perform poorer than actuarial decisions (Ægisdóttir et al., 2006; Grove, Zald, Lebow, Snitz, & Nelson, 2000). The current study represents one method for structuring the high-risk decision for psychiatric hospitalization. Structured clinical decisions improve on unstructured clinical decisions, are more clinician-friendly, and result in similar outcomes to purely actuarial approaches (Ægisdóttir et al., 2006; Falzer, 2013; Grove et al., 2000). Results from the current study provide an empirically-derived decision-making rubric for clinicians.

In determining psychiatric hospitalization, clinicians should continue to identify many potential risk factors as many risk factors are associated with the decision to hospitalize. However, prior to finalizing the decision, clinicians or their supervisors should consider applying the decision tree identified in the current study. For example, if the clinician and rubric agree (e.g., clinician decides to hospitalize a youth & the decision tree indicates high risk for hospitalization), then the clinician could feel more confident and comfortable with his/her decision. In contrast, when the clinician and rubric disagree (e.g., clinician decides not to hospitalize a youth & the decision tree indicates high risk for hospitalization), then this should cue thoughtful questions about the accuracy of the clinical decision. The rubric should not "override" the clinical decision as it is imperfect. The thoughtful questions to ask might be: "explain why this youth cannot be stabilized in the community" or "explain why it is necessary to hospitalize this youth." Asking a question that causes more clinical thought is among the strongest methods for overcoming common clinical heuristics and improving clinical decision-making (Croskerry, 2003). Therefore, the decision tree should be used as an aid in the clinical decision-making process that helps clinicians thoughtfully consider hospitalization risk for any individual youth.

APPENDIX: TABLES AND FIGURE

Table 1.

Clinical Variables Included in the Current Study

Clinical Variable	Description
DSM Diagnostic Classes	
Neurodevelopmental disorders	Intellectual disability, global developmental delay, unspecified intellectual disability, language disorder, speech sound disorder childhood-onset fluency disorder (stuttering), social (pragmatic) communication disorder, unspecified communication disorder, autism spectrum disorder, specific learning disorder, developmental coordination disorder, Tourette's disorder, provisional tic disorder, persistent chronic motor or vocal tic disorder, provisional tic disorder, other specified neurodevelopmental disorders, unspecified neurodevelopmental disorder
Attention-deficit/ hyperactivity disorders	Attention-deficit/hyperactivity disorder, other specified attention-deficit/hyperactivity disorder, unspecified attention-deficit/hyperactivity disorder
Schizophrenia spectrum and other psychotic disorders	Delusional disorder, brief psychotic disorder, schizophreniform disorder, schizophrenia, schizoaffective disorder, catatonia, other specified schizophrenia spectrum and other psychotic disorder, unspecified schizophrenia spectrum and other psychotic disorder
Bipolar and related disorders	Bipolar I disorder, bipolar II disorder, cyclothymic disorder, other specified bipolar and related disorder, unspecified bipolar and related disorder
Depressive disorders	Disruptive mood dysregulation disorder, major depressive disorder, persistent depressive disorder, premenstrual dysphoric disorder, depressive disorder due to another medical condition, other specified depressive disorder, unspecified depressive disorder
Anxiety disorders	Separation anxiety disorder, selective mutism, specific phobia, social anxiety disorder, panic disorder, agoraphobia, generalized anxiety disorder, substance/medication-induced anxiety disorder, anxiety disorder due to another medical condition, other specified anxiety disorder, unspecified anxiety disorder

Clinical Variable	Description
Obsessive-compulsive and related disorders	Obsessive-compulsive disorder, body dysmorphic disorder, hoarding disorder, trichotillomania, excoriation disorder, substance/medication-induced obsessive-compulsive and related disorder, obsessive-compulsive and related disorder due to another medical condition, other specified obsessive-compulsive and related disorder, unspecified obsessive-compulsive and related disorder
Trauma- and stressor-related disorders	Reactive attachment disorder, disinhibited social engagement disorder, posttraumatic stress disorder, acute stress disorder, adjustment disorders, other specified trauma- and stressor-related disorder, unspecified trauma- and stressor-related disorder
Dissociative disorders	Dissociative identity disorder, dissociative amnesia, depersonalization/derealization disorder, other specified dissociative disorder, unspecified dissociative disorder
Somatic symptom and related disorders	Somatic symptom disorder, illness anxiety disorder, conversion disorder, psychological factors affecting other medical conditions, factitious disorder, other specified somatic symptom and related disorder, unspecified somatic symptom and related disorder
Feeding and Eating disorders	Pica, rumination disorder, avoidant/restrictive food intake disorder, anorexia nervosa, bulimia nervosa, binge-eating disorder, other specified feeding or eating disorder, unspecified feeding or eating disorder
Elimination disorders	Enuresis, encopresis, other specified elimination disorder, unspecified elimination disorder
Sleep-wake disorders	Insomnia disorder, hypersomnolence disorder, narcolepsy, obstructive sleep apnea hypopnea, central sleep apnea, sleep-related hypoventilation, circadian rhythm sleep-wake disorders, non-rapid eye movement sleep arousal disorders, nightmare disorder, rapid eye movement sleep behavior disorder, restless legs syndrome, other specified insomnia disorder, unspecified insomnia disorder, other specified hypersomnolence disorder, unspecified hypersomnolence disorder, other specified sleep-wake disorder, unspecified sleep-wake disorder
Gender dysphoria	Gender dysphoria in children, gender dysphoria in adolescents and adults, other specified gender dysphoria, unspecified gender dysphoria

Clinical Variable	Description
Disruptive, impulse-control, and conduct disorders	Oppositional defiant disorder, intermittent explosive disorder, conduct disorder, pyromania, kleptomania, other specified disruptive, impulse-control, and conduct disorder, unspecified disruptive, impulse-control, and conduct disorder
Substance-related and addictive disorders	Alcohol-related disorders, caffeine-related disorders, cannabis-related disorders, hallucinogen-related disorders, inhalant-related disorders, opioid-related disorders, sedative-, hypnotic-, or anxiolytic-related disorders, stimulant-related disorders, tobacco-related disorders, other (or unknown) substance-related disorders, gambling disorder
Neurocognitive disorders	Delirium, other specified delirium, unspecified delirium, major or mild neurocognitive disorder due to Alzheimer's disease, major or mild frontotemporal neurocognitive disorder, major or mild neurocognitive disorder with lewy bodies, major or mild vascular neurocognitive disorder, major or mild neurocognitive disorder due to traumatic brain injury, substance/medication-induced major or mild neurocognitive disorder, major or mild neurocognitive disorder due to HIV infection, major or mild neurocognitive disorder due to prion disease, major or mild neurocognitive disorder due to Parkinson's disease, major or mild neurocognitive disorder due to Huntington's disease, major or mild neurocognitive disorder due to another medical condition, major or mild neurocognitive disorder due to multiple etiologies, unspecified neurocognitive disorder
Personality disorders	Paranoid personality disorder, schizoid personality disorder, schizotypal personality disorder, antisocial personality disorder, borderline personality disorder, histrionic personality disorder, narcissistic personality disorder, avoidant personality disorder, dependent personality disorder, obsessive-compulsive personality disorder, personality change due to another medication condition, other specified personality disorder, unspecified personality disorder
Other conditions – Relational problems	Parent-child relational problem, sibling relational problem, upbringing away from parents, child affected by parental relationship distress, relationship distress with spouse or intimate partner, disruption of family by separation or divorce, high expressed emotion level within family, uncomplicated bereavement

Clinical Variable	Description
Other conditions – Abuse and neglect	Child physical abuse confirmed, child physical abuse suspected, other circumstances related to child physical abuse, child sexual abuse confirmed, child sexual abuse suspected, other circumstances related to child sexual abuse, child neglect confirmed, child neglect suspected, other circumstances related to child neglect, child psychological abuse confirmed, child psychological abuse suspected, other circumstances related to child psychological abuse
Other conditions – Educational and occupational problems	Academic or educational problem, problem related to current military deployment status, other problem related to employment
Risky Behaviors	
Suicidal risk	Suicidal ideation, intent or behavior or command hallucinations that involve self-harm
Non-suicidal self-injury	Engaged in non-suicidal self-injury
Other self-harm/risk-taking behaviors	Engaged in behavior other than suicide or self-injury that places youth in danger, including reckless behavior or intentional risk-taking behavior
Danger to others	Homicidal ideation or plan, physically harmful aggression, dangerous fire setting, or command hallucinations that involve the harm to others
Sexual behaviors	Engaged in sexually aggressive behavior or sexually inappropriate behavior that troubles others
Runaway	Runaway behavior, attempt or ideation
Judgment or poor decision	Problems with judgment in which youth makes decisions that are harmful to his/her development and/or well-being
Fire setting	Fire setting behavior that may or may not endangered the lives of others
Social behavior	Problematic or inappropriate social behavior
Engaged in bullying/bully other youth	Engaged in bullying at school or in the community
Current Symptoms	
Psychosis	Evidence of hallucinations, delusions, or bizarre behavior that might be associated with some form of psychotic disorder
Impulse/hyperactivity	Evidence with impulsive, distractible or hyperactive behavior that places the child at risk of functioning difficulties
Depression	Evidence of depression associated with depressed mood or significant irritability
Anxiety	Evidence of anxiety associated with anxious mood or significant fearfulness
Oppositional defiant behavior	Evidence of oppositional and/or defiant behaviors that interferes with the youth's functioning or involves harm or threat of physical harm to others

Clinical Variable	Description
Conduct problem/antisocial behavior	Evidence of antisocial behavior or conduct problems that places the youth or community at risk of physical harm
Adjustment to trauma/PTSD symptoms	Evidence of adjustment problems associated with traumatic life event(s) that interferes with youth's functioning
Anger control	Anger control problems that peers and family are likely fearing him/her due to problems with controlling anger
Substance use	Evidence of substance abuse that interferes with functioning in any life domain
Functioning Problems	
Living situation	Problems with functioning at home
Community	Problems with functioning in the community
School	Problems with school attendance, behavior, and/or achievement
Peer functioning	Problems with peers or experiences with severe disruptions in his/her peers
Developmental	Developmental delays or intellectual disability
Sleep	Problems with sleep, including wakening, bed wetting, nightmares, sleep disruption or sleep deprivation
Medication compliance	Non-compliance with prescribed medications or abuses prescription medication
Juvenile Justice	
Juvenile justice status	Juvenile delinquency or offenses against persons or property
Community safety	Behavior representing a risk of physical danger to community members or a significant risk of other negative outcomes
Delinquency	Acts of delinquency that may place other at risk
Child Protective Services Involvement	
Risk of abuse or neglect	Risk of abuse or neglect with the current caregivers
Domestic violence	Exposure to domestic violence in family or household
Caregiver Needs and Strengths	
Health	Caregiver's medical, physical, mental health and/or substance use problems that interfere with their parenting role
Supervision	Difficulties monitoring and/or disciplining the youth
Involvement with care	Participation in services and/or interventions intended to assist their child
Social resources	Family, friend, or social networks that may be to help the family and child
Residential stability	Housing is relatively unstable
Accessibility to child care services	Access to child care services or current services do not meet the caregiver's needs
Caregiver's stress management	Managing stress of child/children's need that interferes with caregiver's capacity to give care

Table 2.

Demographic Characteristics

	Hospitalization		
	Yes (*n* = 360)	No (*n* = 2,245)	OR [95% CI]
Age* – Mean (*SD*)	14.63 (*2.42*)	13.98 (*2.76*)	1.10 [1.05, 1.15]
Gender			
Male	150 (42%)	984 (44%)	
Female	210 (58%)	1,261 (56%)	1.09 [.87, 1.37]
Race			
White	228 (64%)	1,418 (63%)	
African American	91 (25%)	472 (21%)	1.20 [.92, 1.56]
Pacific Islander	14 (4%)	69 (3%)	1.26 [.67, 2.21]
Asian American	8 (2%)	83 (4%)	.60 [.26, 1.18]
Unknown	19 (5%)	203 (9%)	.58 [.35, .93]
Ethnicity*			
Hispanic	117 (32%)	915 (41%)	
Non-Hispanic	243 (68%)	1,330 (59%)	1.43 [1.13, 1.81]

Note. OR = odds ratio. For the comparisons, male, White, and Hispanic were the reference categories for the respective comparisons. CI = confidence interval.

* OR *p*-value < .05

Table 3.

Univariate Odds Ratios for DSM Diagnoses

	Hospitalization Yes (*n* = 360)	No (*n* = 2,245)	OR [95% CI]
Schizophrenia Spectrum and Other Psychotic Disorders*	31 (8%)	16 (1%)	13.13 [7.20, 24.84]
Bipolar and Related Disorders*	25 (6%)	48 (2%)	3.42 [2.05, 5.56]
Other Conditions – Abuse and Neglect*	29 (7%)	89 (4%)	2.12 [1.35, 3.24]
Depressive Disorders*	200 (49%)	867 (37%)	1.99 [1.59, 2.49]
Substance-Related and Addictive Disorders*	26 (6%)	87 (4%)	1.93 [1.21, 2.99]
Anxiety Disorders*	21 (5%)	212 (9%)	.59 [.36, .92]
Trauma- and Stressor-Related Disorders*	70 (17%)	673 (28%)	.56 [.42, .74]
Other Conditions – Educational and Occupational Problems*	5 (1%)	73 (3%)	.42 [.15, .94]
Neurodevelopmental Disorders	19 (5%)	74 (3%)	1.63 [.95, 2.68]
Disruptive, Impulse-Control, and Conduct Disorders	58 (14%)	319 (13%)	1.16 [.85, 1.56]
Other Conditions – Relational Problems	44 (11%)	337 (14%)	.79 [.56, 1.09]
Attention-Deficit/Hyperactivity Disorder	15 (4%)	132 (6%)	.70 [.39, 1.16]

Note. OR = odds ratio; CI = confidence interval.

* OR *p*-value < .05

Table 4.

Univariate Odds Ratios for Risky Behaviors and Symptoms

	Hospitalization		
	Yes (*n* = 360)	No (*n* = 2,245)	OR [95% CI]
Risky Behaviors			
Suicidal Risk*	2.33 (*1.04*)	1.30 (*1.01*)	2.89 [2.53, 3.33]
Judgment or Poor Decision Making*	1.78 (*.99*)	.96 (*.86*)	2.66 [2.33, 3.04]
Danger to Others*	.99 (*1.14*)	.36 (*.67*)	2.20 [1.96, 2.48]
Other Self-Harm/Risk-Taking Behavior*	.89 (*.98*)	.43 (*.70*)	1.95 [1.72, 2.21]
Sexuality/Sexual Behavior*	.14 (*.51*)	.05 (*.27*)	1.93 [1.48, 2.52]
Non-Suicidal Self-Injury*	1.15 (*.92*)	.71 (*.79*)	1.84 [1.61, 2.09]
Runaway*	.86 (*1.11*)	.38 (*.79*)	1.67 [1.50, 1.86]
Problematic Social Behavior*	1.06 (*1.03*)	.61 (*.84*)	1.65 [1.47, 1.85]
Fire Setting*	.30 (*.64*)	.15 (*.45*)	1.64 [1.36, 1.97]
Engaged in Bullying/Bully Other Youth*	.36 (*.74*)	.21 (*.54*)	1.46 [1.23, 1.71]
Symptoms			
Psychotic*	.80 (*1.01*)	.21 (*.50*)	2.85 [2.47, 3.30]
Depressive*	1.89 (*.76*)	1.42 (*.76*)	2.53 [2.13, 3.03]
Impulsive/Hyperactive*	1.44 (*1.01*)	.92 (*.85*)	1.87 [1.66, 2.12]
Conduct/Antisocial*	.76 (*.93*)	.41 (*.69*)	1.71 [1.50, 1.95]
Anger Control*	1.48 (*.98*)	1.09 (*.87*)	1.61 [1.42, 1.83]
Substance Use*	.75 (*.92*)	.44 (*.72*)	1.59 [1.39, 1.81]
Oppositional Defiant*	1.15 (*1.09*)	.78 (*.88*)	1.51 [1.35, 1.70]
Anxiety*	1.34 (*.88*)	1.08 (*.78*)	1.51 [1.31, 1.74]
Adjustment to Trauma/PTSD*	1.29 (*.99*)	1.00 (*.90*)	1.39 [1.23, 1.56]

Note. OR = odds ratio; CI = confidence interval.

* OR *p*-value < .05

Table 5.

Univariate Odds Ratios for Functioning Problems, CPS Involvement, and Caregiver Needs and Strengths

	Hospitalization		
	Yes (*n* = 360)	No (*n* = 2,245)	OR [95% CI]
Functioning Problems			
Functioning at Home*	1.61 (*.92*)	.99 (*.87*)	2.16 [1.90, 2.46]
Risk to the Community*	.44 (*.82*)	.15 (*.45*)	2.14 [1.81, 2.52]
Problems with Peer Relationships*	1.64 (*.97*)	1.08 (*.95*)	1.82 [1.62, 2.05]
Functioning in the Community*	.56 (*.86*)	.29 (*.61*)	1.66 [1.44, 1.91]
Problems with Sleep*	1.52 (*1.06*)	1.04 (*.95*)	1.66 [1.48, 1.86]
Medication Compliance*	.49 (*.98*)	.20 (*.62*)	1.59 [1.40, 1.80]
Developmental Delay*	.45 (*.75*)	.26 (*.57*)	1.54 [1.32, 1.80]
Problems in School*	1.76 (*1.02*)	1.37 (*1.04*)	1.45 [1.30, 1.62]
Acts of Delinquency*	.53 (*.83*)	.34 (*.70*)	1.37 [1.20, 1.57]
Juvenile Justice Status*	.31 (*.72*)	.22 (*.59*)	1.23 [1.04, 1.44]
Child Protective Services Involvement			
Risk of Abuse or Neglect*	.46 (*.75*)	.27 (*.54*)	1.61 [1.37, 1.90]
Domestic Violence*	.34 (*.53*)	.27 (*.48*)	1.33 [1.07, 1.64]
Caregiver Needs and Strengths			
Caregiver's Stress Management*	1.54 (*.88*)	1.10 (*.82*)	1.85 [1.62, 2.11]
Caregiver's Monitoring and Discipline Skills*	1.25 (*.97*)	.76 (*.86*)	1.76 [1.56, 1.98]
Caregiver's Involvement with Care*	.86 (*.81*)	.59 (*.70*)	1.59 [1.38, 1.82]
Caregiver's Social Support*	1.23 (*.93*)	.92 (*.89*)	1.43 [1.27, 1.61]
Accessibility to Child Care Services*	.65 (*.91*)	.42 (*.77*)	1.37 [1.21, 1.54]
Caregiver's Health Condition*	.69 (*.91*)	.47 (*.77*)	1.36 [1.20, 1.55]
Residential Stability/Housing Problems*	.44 (*.83*)	.35 (*.72*)	1.18 [1.02, 1.35]

Note. OR = odds ratio; CI = confidence interval.

* OR *p*-value < .05

Table 6.

Parameter Tuning in the Random Forest Model

# of predictors selected at each node	Minimal node size	Sensitivity	Specificity	AUC	Accuracy	Kappa
6	26	.27	.99	.91	.89	.38
6	27	.27	.99	.91	.89	.38
6	28	.26	.99	.91	.89	.37
7	26	.31	.98	.91	.89	.42
7	27	.31	.98	.91	.89	.41
7	28	.31	.99	.91	.89	.41
8	26	.35	.98	.91	.90	.45
8	27	.35	.98	.91	.90	.44
8	28	.34	.98	.91	.90	.45
9	**26**	**.37**	**.98**	**.91**	**.90**	**.47**
9	27	.37	.98	.91	.90	.47
9	28	.37	.98	.91	.90	.47
10	26	.40	.98	.91	.90	.48
10	27	.39	.98	.91	.90	.48
10	28	.39	.98	.91	.90	.48
11	26	.43	.98	.91	.90	.50
11	27	.41	.98	.91	.90	.50
11	28	.42	.98	.91	.90	.50
12	26	.44	.97	.91	.90	.51
12	27	.43	.97	.91	.90	.50
12	28	.43	.97	.91	.90	.51
13	26	.46	.97	.91	.90	.52
13	27	.46	.97	.91	.90	.52
13	28	.45	.97	.91	.90	.51
14	26	.47	.97	.91	.90	.53
14	27	.47	.97	.91	.90	.53
14	28	.47	.97	.91	.90	.53
15	26	.48	.97	.91	.90	.53
15	27	.48	.97	.91	.90	.53
15	28	.48	.97	.91	.90	.53

Table 7.

Confusion Matrix for the Random Forest Model

		True condition (Reference)		
		Hospitalization	No hospitalization	
Prediction	Hospitalization	1,343 (TP)	453 (FP)	PPV = .75
	No hospitalization	2,257 (FN)	21,997 (TN)	NPV = .91
		Sensitivity = .37	Specificity = .98	Accuracy = .90 F_1 score = .50

Table 8.

Summary of Variable Importance

Variable	Gini index	Variable	AUC
Suicidal risk*	100.00	Suicidal risk*	100.00
Psychotic symptoms*	35.30	Poor judgement/decision-making*	84.78
Poor judgement/decision-making*	34.05	Functioning at home*	69.48
Danger to others*	29.87	Depressive symptoms*	62.00
Depressive symptoms*	22.72	Psychotic symptoms*	60.48
Functioning at home*	16.43	Problems with peer relationships*	58.23
Age at first assessment	14.25	Danger to others*	57.08
Impulsivity/hyperactivity*	12.38	Impulsivity/hyperactivity*	54.72
Runaway*	12.12	Caregiver's supervision*	53.13
Non-suicidal self injury*	11.49	Caregiver's stress management	52.90
Problems with peer relationships*	10.51	Non-suicidal self injury*	50.38
Problems with sleep*	10.14	Problems with sleep*	49.42
Oppositional defiant symptoms	9.24	Other risky behaviors*	48.83
Other risky behaviors*	9.18	Runaway*	46.81
Caregiver's supervision*	8.83	Problems with social interaction	46.54

* Risk factor that appears important indicated by both indicators.

Table 9.

Parameter Tuning in the Single Tree Model

Maximum tree depth	Sensitivity	Specificity	AUC	Accuracy	Kappa
3	.32	.97	.78	.88	.36
5	.37	.96	.79	.88	.39
9	**.45**	**.95**	**.81**	**.88**	**.45**
12	.46	.95	.82	.88	.46
15	.46	.95	.82	.88	.46
16	.46	.95	.82	.88	.46
18	.46	.95	.82	.88	.46
22	.46	.95	.82	.88	.46
24	.46	.95	.82	.88	.46
27	.46	.95	.82	.88	.46

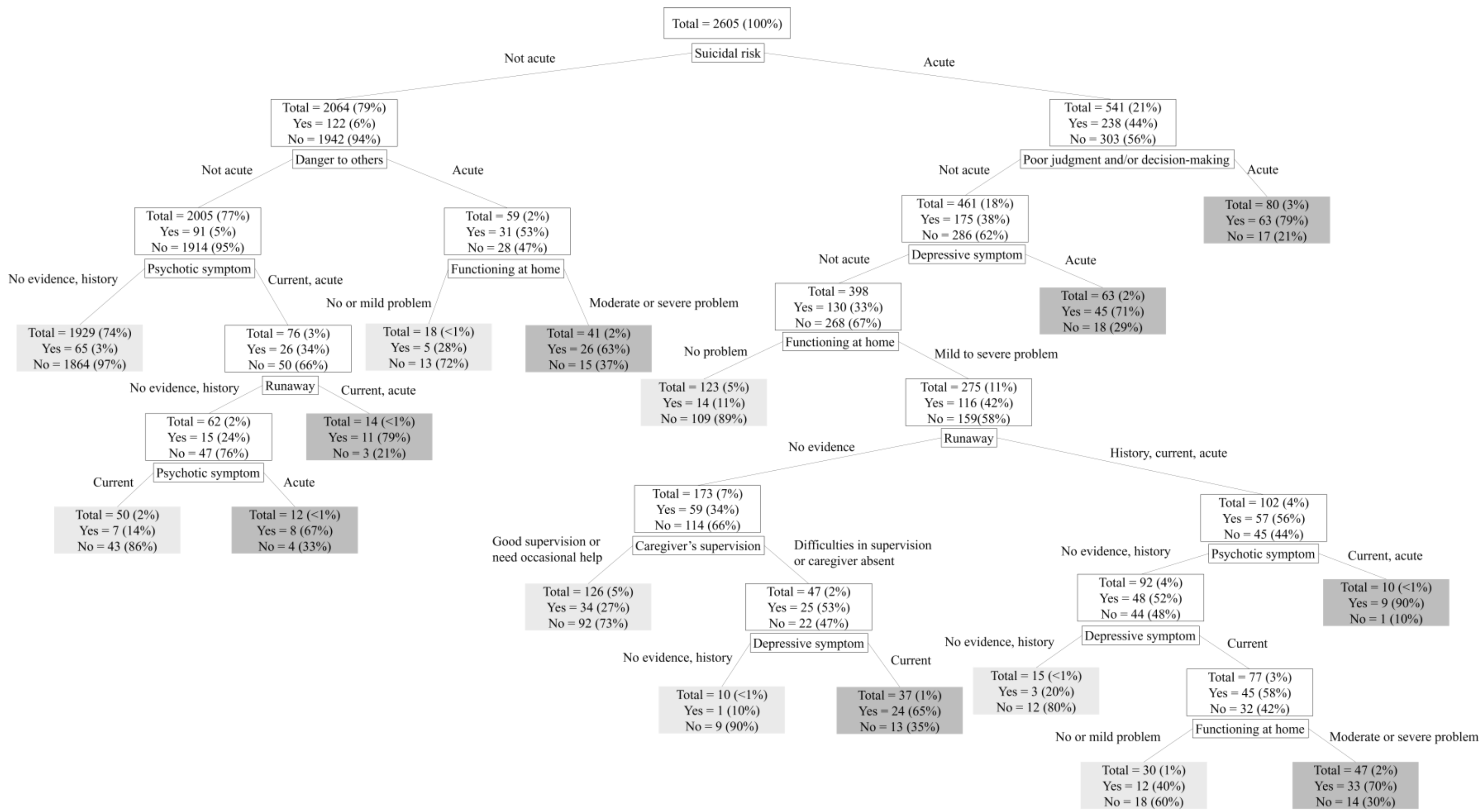
Table 10.

Confusion Matrix for the Single Tree Model

		True condition (Reference)		
		Hospitalization	No hospitalization	
Prediction	Hospitalization	1,660 (TP)	1,053 (FP)	PPV = .61
	No hospitalization	1,940 (FN)	21,397 (TN)	NPV = .92
		Sensitivity = .46	Specificity = .95	Accuracy = .89 F_1 score = .53

Figure 1.

Illustrative Single Classification Tree for Psychiatric Hospitalization in Youth



Note. The first row in grey boxes presents the sample size in each node. The second row presents the sample size of being hospitalized and the positive predictive values. The third row presents the sample size of not being hospitalized and the negative predictive values.

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Vanderploeg, J. J., Lu, J. J., Marshall, T. M., & Stevens, K. (2016). Mobile crisis services for children and families: Advancing a community-based model in Connecticut. *Children and Youth Services Review, 71*, 103-109.

Vigod, S. N., Kurdyak, P. A., Seitz, D., Herrmann, N., Fung, K., Lin, E., . . . Gruneir, A. (2015). READMIT: A clinical risk index to predict 30-day readmission after discharge from acute psychiatric units. *Journal of Psychiatric Research, 61*, 205-213. doi:10.1016/j.jpsychires.2014.12.003

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Zhang, J., Harvey, C., & Andrew, C. (2011). Factors associated with length of stay and the risk of readmission in an acute psychiatric inpatient facility: a retrospective study. *Australian and New Zealand Journal of Psychiatry, 45*(7), 578-585.

CURRICULUM VITAE

CHEN, YEN-LING

PERSONAL

Address: Department of Psychology
4505 S. Maryland Parkway, Mail Stop 5030, Las Vegas, NV 89154-5030
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EDUCATION

University of Nevada, Las Vegas — Las Vegas, NV
Department of Psychology, Clinical Ph.D. Program — *Fall 2016 – present*
University of North Carolina at Chapel Hill — Chapel Hill, NC
Full-time Exchange Student — *Fall 2014 – Spring 2015*
National Taiwan University — Taipei, Taiwan
Department of Psychology, Bachelor of Science — *Fall 2012 – June 2016*

GRANTS, HONORS, AND AWARDS

The Delaware Project Student Award – Honorable Mention
Awarded by University of Delaware — *March 2019*
Graduate and Professional Student Association Conference Travel Funding (Fall)
$600 awarded by the University of Nevada, Las Vegas — *November 2018*
The Society of Clinical Child and Adolescent Psychology Travel Award
$500 awarded by the American Psychological Association, Division 53 — *June 2018*
Government Scholarship to Study Abroad
$32,000 awarded by the Ministry of Education, Taiwan — *June 2018*
Graduate and Professional Student Association Conference Travel Funding (Summer)
$650 awarded by the University of Nevada, Las Vegas — *June 2018*
College of Liberal Arts Ph.D. Student Summer Research Stipends
$3,000 awarded by the University of Nevada, Las Vegas — *May 2018*
Graduate College Summer Session Scholarship
$2,000 awarded by the University of Nevada, Las Vegas — *April 2018*
Graduate and Professional Student Association Conference Travel Funding (Fall)
$440 awarded by the University of Nevada, Las Vegas — *November 2017*

GRANTS, HONORS, AND SCHOLARSHIPS (Continued)

Graduate and Professional Student Association Conference Travel Funding (Summer)
$800 awarded by the University of Nevada, Las Vegas *August 2017*

Graduate and Professional Student Association Conference Travel Funding (Summer)
$800 awarded by the University of Nevada, Las Vegas *August 2017*

The 2017 APA Student Travel Award
$300 awarded by the American Psychological Association *May 2017*

Graduate and Professional Student Association Conference Travel Funding (Fall)
$270 awarded by the University of Nevada, Las Vegas *October 2016*

The Neuroscience of Youth Depression Conference Travel Funding
Registration fee waiver awarded by the UNC-Chapel Hill *November 2016*

College of Science International Conference Travel Award
$150 awarded by National Taiwan University *July 2016*

Dean's Award of College of Science
Students with excellent academic and/or research achievement
Awarded by National Taiwan University *May 2016*

Excellent Exchange Student Scholarship
$5,000 awarded by National Taiwan University *August 2014 – June 2015*

Presidential Award
GPA ranking with the top 5% of class
Awarded by National Taiwan University *March 2014, November 2013, March 2013*

PEER REVIEWED PUBLICATIONS

Freeman, A. J. & **Chen, Y.-L.** (in press). Assessment of child intelligence. In G. Goldstein, J. DeLuca & D. N. Allen (Eds.), *Handbook of psychological assessment*. Oxford, UK: Elsevier Science.

Salcedo, S., **Chen, Y.-L.,** Youngstrom, E. A., Fristad, M. A., Gadow, K. D., Horwitz, S. M., ... & Kowatch, R. A. (2018). Diagnostic efficiency of the Child and Adolescent Symptom Inventory (CASI-4R) Depression Subscale for identifying youth mood disorders. *Journal of Clinical Child and Adolescent Psychology, 47* (5), 832-846. doi: 10.1080/15374416.2017.1280807

CONFERENCE PRESENTATIONS

Symposium Co-Chair

De Los Reyes, A., & **Chen, Y.-L.** (2019 Januray). Becoming part of the family: Selecting mentors when applying to doctoral programs in psychology. Symposium accepted to the 2019 Annual Convention of American Psychological Association, Chicago, IL.

CONFERENCE PRESENTATIONS (Continued)

Symposium talk

<u>Chen, Y.-L.</u>, & Youngstrom, E. A. (2018 August). Dissemination of psychological science in college: An international collaborative tele-education project. Symposium presented at the 2018 Annual Convention of American Psychological Association, San Francisco, CA.

Posters (indicates undergraduate or post-baccalaureate mentees)*

<u>Chen, Y.-L.</u>, Freeman, M. J., & Freeman, A. J. (2019 March). Identifying risk factors for youth hospitalization in crisis settings: A classification and regression tree (CART) analysis. Poster submitted to the 53rd Annual Convention of the Association of Behavioral and Cognitive Therapy, Atlanta, GA.

<u>Chen, Y.-L.</u>, Freeman, M. J., & Freeman, A. J. (2019 January). Identify risk factors for youth hospitalization in crisis settings. Poster accepted to the 2019 Annual Convention of American Psychological Association, Chicago, IL.

*Tsai, Y.-H., **<u>Chen, Y.-L.</u>**, & Youngstrom, E. A. (2019 January). The relationship between sleep quality, chronotype, and emotion: A cross-cultural sample. Poster accepted to the 2019 Annual Convention of American Psychological Association, Chicago, IL.

*Cherng, Y.-T. M., **<u>Chen, Y.-L.</u>**, & Youngstrom, E. A. (2019 January). Personality as potential moderator of the relationship between sleep quality and affect. Poster accepted to the 2019 Annual Convention of American Psychological Association, Chicago, IL.

*Guo, Z., **<u>Chen, Y.-L.</u>**, & Youngstrom, E. A. (2019 January). Intergenerational transmission of parenting style in a cross-cultural college student sample. Poster accepted to the 2019 Annual Convention of American Psychological Association, Chicago, IL.

*Baro, L., **<u>Chen, Y.-L.</u>**, & Youngstrom, E. A. (2018 December). Associations between mood symptoms, sleep quality, and creativity in young adults. Poster accepted to the 2019 Annual Convention of American Psychological Association, Chicago, IL.

*Yeh, S.-Y., **<u>Chen, Y.-L.</u>**, & Youngstrom, E. A. (2018 December). Does adherence to Asian values result in lower creative achievement? Poster accepted to the 2019 Annual Convention of American Psychological Association, Chicago, IL.

*Kang, H., **<u>Chen, Y.-L.</u>**, & Youngstrom, E. A. (2018 December). The relationship between parenting style, creativity, and mood symptoms in young adults. Poster accepted to the 2019 Annual Convention of American Psychological Association, Chicago, IL.

*Aygün, E. E., **<u>Chen, Y.-L.</u>**, & Youngstrom, E. A. (2018 December). The relationship between chronotype, depressive symptoms, and sleep quality. Poster accepted to the 2019 Annual Convention of American Psychological Association, Chicago, IL.

*Dang, T., **<u>Chen, Y.-L.</u>**, Garcia, B., & Freeman, A. J. (2018 December). The relationship between BIS/BAS, alcohol use, and mood symptoms among college students. Poster submitted to the 2019 Annual Convention of American Psychological Association, Chicago, IL.

Chen, Y.-L., Freeman, M. J., & Freeman, A. J. (2018 June). Identifying risk factors for youth hospitalization in crisis settings. Poster presented at the 52nd Annual Convention of the Association of Behavioral and Cognitive Therapy, Washington, D.C.

*Tsai, J.-M., **Chen, Y.-L.**, & Youngstrom, E. A. (2018 August). The relationship between body dysmorphic disorder, hypomania, depression and cultural differences. Poster presented at the 2018 Annual Convention of American Psychological Association, San Francisco, CA.

*Ho, H.-R., **Chen, Y.-L.**, & Youngstrom, E. A. (2018 January). Do people with different personalities show different emotion patterns? Poster presented at the 2018 Annual Convention of American Psychological Association, San Francisco, CA.

Shih, H.-W., **Chen, Y.-L.**, Youngstrom, E. A., & Freeman, A. J. (2018 August). Do the behavioral inhibition and activation systems affect individuals' sleep quality? Poster presented at the 2018 Annual Convention of American Psychological Association, San Francisco, CA.

*Sun, J.-T., **Chen, Y.-L.**, & Youngstrom, E. A. (2018 August). Cross-cultural to single cultural experience and difference in mental illness stigma. Poster accepted to the 2018 Annual Convention of American Psychological Association, San Francisco, CA.

*Diaz, V., **Chen, Y.-L.**, *Cohen, M., & Freeman, A. J. (2018 June). The relationship between mood, risky behaviors, and emotion regulation. Poster accepted to the 52nd Annual Convention of the Association of Behavioral and Cognitive Therapy, Washington, D.C.

Chen, Y.-L., Freeman, M. J., & Freeman, A. J. (2018 June). Identifying risk factors for youth hospitalization in crisis settings. Poster presented at the Journal of Clinical Child and Adolescent Psychology Future Direction Forum, Washington, D.C.

Chen, Y.-L., Youngstrom, E. A., Findling, R. L., & Freeman, A. J. (2017, November). What makes a screening false positive for youth mood disorders? Poster presented at the 51st Annual Convention of the Association of Behavioral and Cognitive Therapy, San Diego, CA.

Chen, Y. -L., Sherwood, S. N., & Freeman, A. J. (2017, August). Cultural differences in mania: Gender but not ethnicity matters. Poster presented at the 2017 Annual Convention of American Psychological Association, Washington, D.C.

Sherwood, S. N., **Chen, Y. -L.**, & Freeman, A. J. (2017, January). Chronotype does not predict non-suicidal self-injury. Poster presented at the 2017 Annual Convention of American Psychological Association, Washington, D.C.

*Diaz, V., **Chen, Y. -L.**, *Saucedo, M., Sherwood, S. N., & Freeman, A. J. (2017, January). The relationship between irritability, mood and anxiety in college students. Poster presented at the 2017 Annual Convention of American Psychological Association, Washington D.C.

*Ibarra, M., Rogers, E., *Santarsieri, B., Sherwood, S. N., **Chen, Y.-L.**, & Freeman, A. J. (2017, May). Gender, Chronotype, and Affective Symptoms. Poster accepted to the 51st Annual Convention of the Association of Behavioral and Cognitive Therapy, San Diego, CA

CONFERENCE PRESENTATIONS (Continued)

Chen, Y. -L., Youngstrom, E. A., Youngstrom, J. K., & Findling, R. L. (2016, October). Diagnostic efficiency of the Child Behavior Checklist (CBCL) Internalizing score for identifying mood disorders. Poster presented at the 50th Annual Convention of the Association for Behavioral and Cognitive Therapy, New York, NY.

Freeman, L., Youngstrom, E. A., Ruiz, M. C., **Chen, Y. -L.**, Egerton, G., Genzlinger, J., & Van Meter, A. (2016, October). Meta-analysis of the discriminative validity of the Altman Self-Rating Mania Scale in adults. Poster accepted to the 50th Annual Convention of the Association for Behavioral and Cognitive Therapy, New York, NY.

Salcedo, S., **Chen, Y. -L.**, Youngstrom, E. A., Fristad, M. A., Gadow, K. D., Horwitz, S. M., Frazier, T. W., Arnold, L. E., Phillips, M. L., Birmaher, B., Kowatch, R. A., & Findling, R. L. (2016, October). Diagnostic efficiency of the Child and Adolescent Symptom Inventory (CASI-4R) Depression subscale for identifying youth mood disorders. Poster accepted to the 50th Annual Convention of the Association for Behavioral and Cognitive Therapy, New York NY.

Chen, Y. -L. & Youngstrom, E. A. (2016, July). Diagnostic efficiency of the Child Behavior Checklist (CBCL) Internalizing score for identifying mood disorders. Poster presented at the 31st International Congress of Psychology, Yokohama, Japan.

Chen, Y. -L., Chiu, W., & Kuo, P. (2016, March). Evaluating effect of sleep problems on suicidality in youth: Is emotion regulation a moderator? Poster presented at the 4th International Pediatric Sleep Association Congress, Taipei, Taiwan.

Chen, Y. -L., Halverson, T. F., Ong, M., Youngstrom, J. K., Findling, R. L., & Youngstrom, E. A. (2015, November). The relationship between sleep disturbance and diagnosis of bipolar disorder: Testing incremental effect after controlling for age and gender. Poster presented at the 49th Annual Convention of Association for Behavioral and Cognitive Therapy, Chicago, IL.

Chen, Y. -L., Halverson, T. F., Ong, M., Youngstrom, J. K., Findling, R. L., & Youngstrom, E. A. (2015, April). The relationship between sleep disturbance and diagnosis of bipolar disorder: Testing incremental effect after controlling for age and gender. Poster presented at the 2015 North Carolina Psychological Association Spring Conference, Chapel Hill, NC.

PROFESSIONAL AFFILIATIONS

Society for Clinical Child and Adolescent Psychology (APA Division 53)

Student representative (term 2019 – 2020) *January 2019 – present*

Student member *February 2015 – present*

International Psychology (APA Division 52)

Student member *November 2018 – present*

Taiwan Psychology Network

Student member *August 2017 – present*

PROFESSIONAL AFFILIATIONS (Continued)

American Psychological Association of Graduate Students
Student member *April 2017 – present*
Association of Behavioral and Cognitive Therapy
Student member *November 2015 – present*

RESEARCH EXPERIENCES

Development of Irritability, Mood and Emotions Lab
University of Nevada, Las Vegas Las Vegas, NV
Research assistant *August 2016 – present*
Mentor: Andrew Freeman, Ph.D.
Developmental and Forensic Psychology Lab
National Taiwan University Taipei, Taiwan
Research study interviewer *April 2016 – June 2016*
Mentor: Yee-San Teoh, Ph.D. & Kathy Zhang, M.A.
Institute of Ethnology
Academia Sinica Taipei, Taiwan
Research assistant *September 2015 – June 2016*
Mentor: Kuang-Hui Yeh, Ph.D.

Psychiatric Epidemiology Lab
National Taiwan University Taipei, Taiwan
Research assistant *September 2015 – March 2016*
Mentor: Po-Hsiu Kuo, Ph.D.
Mood, Emotions, and Clinical Child Assessment Lab
University of North Carolina at Chapel Hill Chapel Hill, NC
Research assistant *August 2014 – January 2016*
Mentor: Eric Youngstrom, Ph.D.
Culture and Emotion Lab
National Taiwan University Taipei, Taiwan
Research assistant *September 2013 – June 2014*
Mentor: Jenny Su, Ph.D.

CLINICAL EXPERIENCE

Dessert Willow Treatment Center (Residential and Day Treatment Service)

State of Nevada, Division of Child and Family Services — Las Vegas, NV
Psychology practicum student — *August 2018 – present*
Supervisor: Caron Evans, Ph.D. & Robert Kutner, Psy.D.

- Conduct psychological evaluations and assessments, including the WISC-V, WRAT-5, MMPI-A-RF, Vineland-3, and the Children's Uniform Mental Health Assessment (CUMHA)
- Conduct risk assessment and develop safety plan with adolescents with severe mental illness
- Provide individual psychotherapy services using traditional cognitive behavioral therapy and dialectical behavioral therapy for adolescents and their families
- Participate in weekly treatment team and coordinate care with other health care providers, including psychiatrists, nurses, clinical social workers, recreational therapists, mental health technicians

The PRACTICE – UNLV Community Mental Health Training Clinic

University of Nevada, Las Vegas — Las Vegas, NV
Graduate student clinician — *August 2017 – July 2018*
Supervisor: Rachele Diliberto, Ph.D. & Michelle Paul, Ph.D.

- Conduct psychological evaluations and assessments, including the WJ-IV, WISC-V, WAIS-IV, WRAML-2, WRAVMA, D-KEFS, NEPSY-II, CTOPP-2, K-SADS, SCID, ASEBA, and other self-report measures
- Provide individual psychotherapy services using a cognitive behavioral approach for children and adolescents
- Provide tele-health counseling services for schools in rural Nevada
- Provide translation services in Mandarin

MENTORSHIP AND TEACHING EXPERIENCES

General Psychology (PSY 101)

University of Nevada, Las Vegas — Las Vegas, NV
Graduate student instructor — *August 2018 – present*

Statistics for Psychologists II (PSY 709)

University of Nevada, Las Vegas — Las Vegas, NV
Teaching assistant — *January 2018 – May 2018*

Senior Capstone in Psychology (PSY 490)

University of Nevada, Las Vegas — Las Vegas, NV
Teaching assistant — *January 2018 – May 2018*

Mood, Emotions, and Clinical Child Assessment Lab

University of North Carolina at Chapel Hill — Chapel Hill, NC
Senior research seminar teaching mentor — *August 2017 – January 2018*

MENTORSHIP AND TEACHING EXPERIENCES (Continued)

Abnormal Psychology (PSY 341)

University of Nevada, Las Vegas — Las Vegas, NV
Teaching assistant — *August 2017 – December 2017*

Outreach Undergraduate Mentorship Program

University of Nevada, Las Vegas — Las Vegas, NV
Graduate student mentor — *October 2016 – May 2017*

Adolescent Psychiatry Daycare Center

Taipei Veteran General Hospital — Taipei, Taiwan
Academic tutor — *September 2015 – January 2016*

TRAINING CERTIFICATES

2019 Inter-professional Education Training

A full-day workshop held by the University of Nevada, Las Vegas
Table discussion facilitator — *March 2019*

2018 Inter-professional Education Training

A full-day workshop held by the University of Nevada, Las Vegas — *March 2018*

HIPPA Awareness of Mental Health Training

Entered in the UNLV Community Mental Health Clinic database — *February 2017*

Collaborative Institutional Training Initiative (CITI) Research Ethics Training

Entered in national certification database — *August 2016*

COMMUNITY AND CAMPUS SERVICES

Taiwanese Student Association

University of Nevada, Las Vegas — Las Vegas, NV
President — *August 2017 – present*

ABILITIES AND SKILLS

Languages

Taiwanese Mandarin Chinese (native), English (fluent)

Statistical Software

R, SPSS (including syntax)