DISSERTATION

DEEP TRANSFER LEARNING FOR PREDICTION OF HEALTH RISK BEHAVIORS IN ADOLESCENT PSYCHIATRIC PATIENTS

Submitted by

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ABSTRACT

DEEP TRANSFER LEARNING FOR PREDICTION OF HEALTH RISK BEHAVIORS IN ADOLESCENT PSYCHIATRIC PATIENTS

Binge drinking and non-suicidal self-injury are significant health-risk behaviors that are often initiated during adolescence and contribute to a host of negative outcomes later in life. Selective prevention strategies are targeted toward individuals most at-risk for developing these behaviors. Traditionally, selective interventions are tailored based on risk factors identified by human experts. Machine learning algorithms, such as deep neural networks, may improve the effectiveness of selective interventions by accounting for complex interactions between large numbers of predictor variables. However, their use in psychological research is limited due to the tendency to overfit and the need for large volumes of training data. Deep transfer learning can overcome this limitation by leveraging samples of convenience to facilitate training deep neural networks in small, clinically relevant samples. The author trained deep neural networks on data from a sample of adolescent psychiatric inpatients to retrospectively classify individuals according to their history of alcohol misuse and nonsuicidal self-injury. Next, the performance of these models was compared to deep neural networks that were pretrained in a convenience sample of college undergraduates and fine-tuned in the sample of psychiatric patients. Deep transfer learning did not improve classification accuracy but buffered against overfitting. The deep neural networks that were not pretrained maintained maximum classification accuracy for a very small number of training epochs before performance deteriorated due to overfitting the training data. Conversely, the pretrained networks maintained their maximum classification accuracy across many training epochs and performance was not hindered by overfitting. This suggests that convenience samples can be utilized to reduce the risk of overfitting when training complex deep neural networks on small clinical samples. In the future, this process may be employed to facilitate powerful predictive models that inform selective prevention programs and contribute to the reduction of health risk behavior prevalence amongst vulnerable adolescent populations.

Keywords: self-injury, binge drinking, deep learning, deep neural networks, transfer learning

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DEDICATION

This dissertation is dedicated to my wife Stacy, who continuously inspires me to do my best. She has provided a steadfast belay during this long and difficult climb. It is also dedicated to my children, Sophia and James, who keep me young and remind me what's important.

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CHAPTER 1

INTRODUCTION

Health risk behaviors, such as alcohol misuse and nonsuicidal self-injury (NSSI) are significant public health concerns that disproportionately impact adolescents and young adults (Eaton et al., 2012). Binge drinking, consuming enough alcohol in a single occasion to raise one's blood alcohol concentration (BAC) above 0.08%, is especially risky when begun during adolescence (S. A. Jones et al., 2018). Initiation of binge drinking during this critical period impacts neurodevelopmental processes (Squeglia et al., 2009) and is associated with a host of negative psychosocial outcomes in adulthood (Viner & Taylor, 2007). NSSI, causing deliberate self-harm without the intent to die, similarly confers risk for morbidity and mortality (L. K. Brown et al., 2008; Buser et al., 2017), is linked to multiple internalizing and externalizing disorders (Nock et al., 2006), and is a cardinal risk-factor for death by suicide (Joiner et al., 2012). Selective prevention approaches are effective for reducing binge drinking rates among adolescents (Conrod et al., 2008) and are promising for reducing rates of NSSI, as well (Heath et al., 2014). However, current practice for developing selective interventions is based on identification of risk factors by subject matter experts and is limited by the ability of human experts to consider low-order combinations of a few variables simultaneously. Deep learning (DL) is a powerful predictive algorithm that can improve targeting of prevention efforts to at-risk individuals by accounting for complex nonlinear interactions between large numbers of predictors (Skansi, 2018). However, DL is rarely used in psychological research due to the paucity of available training data and the tendency to overfit that data (Dwyer et al., 2018). Deep transfer learning is a technique that may be able to leverage the convenience samples often studied by psychologists to overcome this problem. This will allow for the implementation of DL in selective prevention programs.

CHAPTER 2

REVIEW OF THE LITERATURE

Prevention, Prediction, and Deep Transfer Learning

Nonsuicidal Self-Injury

NSSI refers to the deliberate self-directed act of bodily harm without the intent of taking one's own life (Nock, 2009). Rates of NSSI typically peak during adolescence (Plener et al., 2015), but data suggest the presence of a secondary peak in prevalence of NSSI among young adults (Kiekens et al., 2019). Thus, NSSI is a phenomenon that is uniquely relevant to both adolescents and young adults. Although scientists and philosophers have deliberated about the nature of self-harm throughout history (Nock et al., 2009), current theories on NSSI point to a decisional balance between the perceived benefits of NSSI and the barriers to engaging in such behaviors (Hooley & Franklin, 2018). Individuals who endorse NSSI report various positive consequences associated with the behavior. NSSI is a powerful regulator of negative affect, fulfills an individual's need to punish themself, signals group affiliation (a particularly salient benefit during adolescence), and communicates messages of distress or strength. Despite these perceived benefits, most people do not partake in NSSI because of several instinctive barriers, including avoidance of pain, social norms, and avoidance of NSSI stimuli (blood, etc.).

NSSI represents a significant public health burden (Glenn et al., 2017; Muehlenkamp et al., 2012). Prevalence of NSSI amongst adolescents and young adults had increased steadily year after year until the onset of the COVID-19 pandemic and resulting public health restrictions (Hasking et al., 2021; Plener, 2021; Tang et al., 2021). During the pandemic, rates of NSSI increased exponentially. For instance, one sample of Taiwanese adolescents reported a prevalence of 41% (Tang et al., 2021). These trends are concerning because NSSI is associated with elevated risk for internalizing, externalizing, substance use, and personality disorders (Nock et al., 2006). NSSI is a common deleterious outcome that cuts across several vulnerable subpopulations. Individuals with developmental disabilities and autism (Davies & Oliver, 2013; Maddox et al., 2017; Moseley et al., 2019) are more likely to engage in NSSI, as are individuals with schizophrenia (Mork et al., 2012), anxiety and depression (Klonsky & Moyer, 2008; Koposov et al., 2021), personality disorders (Patel et al., 2021), eating disorders (Claes & Muehlenkamp, 2016), and obsessive-compulsive disorder (Patel et al., 2021). NSSI is common among individuals exposed to all types of trauma, including violence, sexual abuse, and incarceration (Koposov et al., 2021. Transgender and LGBTQ youth are also at increased risk for NSSI (Jackman et al., 2016; Liu et al., 2019). Additionally, NSSI is a risk factor in and of itself for subsequent negative outcomes (Brown et al., 2008; Buser et al., 2017; Nock et al., 2006). Engagement in NSSI can result in injuries that are more severe than intended, including unintentional death (Buser et al., 2017). A history of NSSI places individuals at greater risk for contracting human immune deficiency virus (HIV; Brown et al., 2008). Critically, NSSI is a major risk factor for future suicide attempts and death by suicide (Joiner et al., 2012; Nock et al., 2006; Ribeiro et al., 2016a), a leading cause of death amongst adolescents (Centers for Disease Control [CDC], 2021). In fact, the risk conferred by a history of NSSI is as great as an individual's history of previous suicide attempts, a variable that was long upheld as the most important predictor of suicide risk (Hooley & Franklin, 2018). Due to its relevance to the current study's adolescent population and robust associations with a vast range of comorbidities and negative outcomes, this research examined NSSI as one of the primary study outcomes.

The simplest way to operationalize NSSI is to assess for the lifetime presence of the behavior (the “ever/never” question), but there are other important factors to consider as well, including frequency, severity, age at onset, function, and method. Naturally, individuals who engage in more frequent (Anestis et al., 2015) and severe (Jenkins et al., 2011) NSSI experience worse outcomes in both the short and long term. Similarly, individuals with a longer history of NSSI who initiate the behavior at a young age are more likely to face negative consequences, including death by suicide (Ammerman et al., 2018; Nock et al., 2006). Thorough assessment of NSSI should include an understanding of the role the behavior serves for the individual, or its functional aspect (Nock & Printstein, 2004). There is a rich history of scientific inquiry into the functions of self-injurious behavior (M. Z. Brown et al., 2002; Favazza, 1998; Nock & Prinstein, 2004) and this work has informed current conceptualizations of NSSI, such as the benefits and barriers model (Hooley & Franklin, 2018). An assessment of the different methods of NSSI (e.g., cutting, burning, hair pulling, etc.) is also important because the number of different NSSI methods is one of the strongest predictors of future suicide attempts (Anestis et al., 2015; Jenkins et al., 2011; Nock et al., 2006).

Given the many salient facets of NSSI, and the complicated interactions between them (Anestis et al., 2015), a multidimensional approach to assessing NSSI is ideal. For example, the Self-Injurious Thoughts and Behaviors Interview (SITBI; Nock et al., 2007) queries the presence, frequency, age at onset, and function of NSSI behaviors in a structured interview format. The Form and Function of Self-Injury Scale (FAFSI; Jenkins et al., 2011) assess those same factors, as well as methods of NSSI in a self-report format. Because the current study comprised secondary data analyses, the selection of an operational definition of NSSI was limited by the data available. Furthermore, the nature of the analyses required two samples with matching variables. This means that only the intersection of two sets of variables could be analyzed, further limiting the options for measuring NSSI. As a matter of fact, some items from the FAFSI were given to many individuals in the two samples (e.g., age at onset), but there were also many participants who were not administered any FAFSI items except for lifetime presence (the "ever/never" question). Due to the nature of the analyses performed, it was possible to include these FAFSI items as predictors by imputing missing values. However, it was not possible to include them as outcome variables. Therefore, a single item measuring lifetime presence was selected as the operational definition of NSSI.

Binge Drinking

Alcohol is the most prevalent substance used by adolescents (Johnston, 2021). Problematic drinking is the third most common preventable cause of death in the United States (National Institute on Alcohol Abuse and Alcoholism [NIAAA], 2021) and leads to impairments in psychological (Shivani et al., 2002), and physical (World Health Organization [WHO], 2019) health. Alcohol use is frequently involved in emergency department visits and plays a role in one out of five opioid overdoses (Jones et al., 2014). Binge drinking is an especially risky form of drinking (Viner & Taylor, 2007) that commonly refers to a pattern of intermittent heavy alcohol consumption (DeJong, 2003). However, the National Institute of Alcohol Abuse and Alcoholism define binge drinking as drinking enough alcohol in a single occasion to raise one's blood alcohol concentration (BAC) above 0.08%. Binge drinking is particularly harmful when initiated in adolescence (Jones et al., 2018). Longitudinal data show that binge drinking during adolescence prospectively predicts substance use disorders, other mental health disorders, legal involvement, probability of homelessness, and poor occupational achievement in adulthood (Viner & Taylor, 2007). Given the profound public health impacts of binge drinking and the intensification of those effects by adolescent initiation, this research examined binge drinking as one of the primary outcomes in this study.

There is some dispute about how to best measure binge drinking. The definition used most often in the literature is consuming more than four drinks for females or five drinks for males (Read et al., 2008). Some researchers argue that this definition neglects many important variables, including duration of the drinking episode and body mass of the individual drinker (DeJong, 2003). As a result, previous studies have demonstrated that many individuals who meet this criterion do not have blood alcohol content high enough to cause significant impairment (e.g., Lange & Voas, 2001). It has also been shown that many individuals, especially among college students, drink quantities far greater than the traditional five drink cut-off (Read et al., 2008). Consequently, the phenomenon of high intensity drinking (drinking two or more times the traditional cutoff for binge drinking) has been highlighted as a potentially more relevant construct (Patrick & Azar, 2018).

It is worth noting that this debate has largely played out in the literature on drinking in adults, and the majority of previous studies have utilized adult samples (e.g., White et al., 2006). Creswell et al. (2020) found that high intensity drinking is associated with more negative outcomes in adolescents than it is in adults. But, there is comparatively little extant research to inform the conceptual definition of binge drinking in adolescence, and caution is warranted when generalizing to this unique population. For instance, despite indications that high intensity drinking is a useful construct for study in adults, it is rare amongst teenagers (Patrick & Terry-McElrath, 2019). In fact, only 3% of 10th graders endorse high intensity drinking (Mehus & Patrick, 2020). However, binge drinking (as defined by the traditional four/five drink cut-off) still confers significant risk (Viner & Taylor, 2007) and occurs at rates high enough to be feasibly studied (Patrick & Terry-McElrath, 2019). Furthermore, there are important physiological difference between adults and adolescents that inform the debate about binge drinking definitions. Donovan (2009) provides calculations for the number of drinks required for boys and girls of various ages to meet the 0.08 BAC level established for binge drinking by the NIAAA. In general, BAC increases more rapidly for children and adolescents than for adults, and fewer drinks are required to reach 0.08% BAC for the younger group.

There is yet another faction of alcohol researchers who argue that it is more clinically relevant to define problematic drinking by alcohol-related consequences rather than by an arbitrary number of drinks (DeJong, 2003). Alcohol related consequences are typically assessed across eight dimensions: social consequences, impaired control, self-perception, self-care, risky behavior, occupational consequences, physical dependence, and blackout drinking (Read et al., 2006). These consequences are predictive of future alcohol use disorder diagnoses (Read et al., 2008). This is reflected in the diagnostic criteria for alcohol use disorder, which do not refer at all to quantity of drinks, but rather the disruptions caused by an individual's drinking (American Psychiatric Association [APA], 2013). Similarly, validated diagnostic tests, such as the Michigan Alcohol Screening Test (MAST; Selzer, 1971) and the Alcohol Use Disorders Identification Test (AUDIT; Bohn et al., 19995), emphasize the importance of alcohol-related consequences rather than focusing exclusively on quantity.

Given the ongoing debate, the best way to define binge drinking remains an open question. However, there are some central ideas that are widely accepted. Firstly, the construct is based on BAC and criteria based on quantities of drinks are proxies for this (NIAAA, 2021). Nevertheless, the NIAAA guidance specifically states that for most adults this is equivalent to four/five drinks within 2 hours. Several studies support the notion that drinking beyond this level, so called "high intensity drinking," is associated with more extreme negative outcomes in both adults (White et al., 2006) and adolescents (Mehus & Patrick, 2020). But the low base rate of high intensity drinking in adolescents makes it difficult to study (Patrick & Terry-McElrath, 2019). When considering adolescent binge drinking, it is important to remember that fewer drinks lead to higher BAC, and to use age-appropriate cut-offs (Donovan, 2009). Finally, consequences of alcohol use, rather than simply quantity, should be considered as well (Read et al., 2006; Read et al., 2008).

An ideal operationalization of binge drinking should incorporate all these elements. However, the current study was a secondary data analysis and faced several constraints (see Chapter 3 for further details). Within the available data, binge drinking was assessed using the common four/five cutoff for adults. Consequences of alcohol use were not assessed in this data set and could not be incorporated into the operational definition of binge drinking. High intensity drinking was not assessed either. However, because the typical adult cutoffs were applied to an adolescent population, it is safe to assume that the level of drinking measured was somewhat higher than the traditional notion of binge drinking. Ultimately, binge drinking was operationalized as lifetime presence of consuming four drinks for females or five drinks for males.

Prevention and Machine Learning

Efforts to prevent NSSI and binge drinking can be broadly classified into universal and selective approaches (Kuntsche et al., 2017). Universal prevention strategies are not concerned with identifying at-risk individuals, but rather apply the same intervention to an entire population. For example, a program to teach psychosocial coping skills with the intention to prevent alcohol use might be applied to every middle school student in a given region (Mewton et al., 2018). In contrast, selective prevention strategies are targeted at individuals believed to be at-risk for a given behavior (Kuntsche et al., 2017). The PreVenture program using personality traits to target interventions to specific groups has been moderately successful in preventing binge drinking among adolescents (Conrod et al., 2008). However, compared to binge drinking, very little research has been done on prevention of NSSI, selective or otherwise (Heath et al., 2014).

Targeted prevention requires understanding of risk factors for a given behavior (Heath et al., 2014), and there are several risk factors that are common to both binge drinking and NSSI. Several personality traits have been linked to NSSI and binge drinking, including sensation seeking, a personality trait that involves a desire for novel and intense experiences (Doumas et al., 2017; Kentopp et al, 2021). Impulsivity is another such trait (Glenn & Klonsky, 2010; Shin et al., 2012). Impulsivity is a multidimensional construct that encompasses negative urgency, lack of premeditation, lack of perseverance, sensation seeking, and positive urgency (Whiteside & Lynam, 2001). Various combinations of these facets of impulsivity are related to NSSI (Glenn & Klonsky, 2010) and binge drinking (Shin et al., 2012). Emotion dysregulation, or difficulty managing the content or experience of one's emotions in order to achieve long-term goals (Gross 1999), is another trait with well-known relations to NSSI and binge drinking (Lannoy et al., 2021; McKenzie & Gross, 2014). In addition to personality variables, past health-risk behavior is highly predictive of current binge drinking (Norman & Conner, 2006) and NSSI (Glenn & Klonsky, 2010).

Prevention science research shows that selective approaches tend to be more effective than universal approaches (Gottfredson & Wilson, 2003). But selective prevention is limited by current understanding of risk factors for the target behavior (Conrod et al., 2008). Typically, developing a secondary prevention program involves lengthy review of the scientific literature on a target behavior by subject matter experts and the identification of important risk factors (see Akyea et al. (2020) for an example of this process for preventing adverse cardiovascular events). However, mere knowledge of risk factors is of limited utility. An illustrative example is the prediction of suicide, an outcome closely related to NSSI. There is a robust literature on risk factors for suicide and it is straightforward to identify individuals who are "at risk," but only a fraction of those individuals will actually attempt suicide (Pokorny, 1983; Van Orden et al., 2010). One reason for this phenomenon is that current theories of engagement in health-risk behaviors such as NSSI and binge drinking are limited by the emphasis in psychological research on explanation rather than prediction (Yarkoni & Westfall, 2017). Explanatory models are limited by the ability of human experts to consider relatively few variables simultaneously. Machine learning (ML), an automated predictive modelling technique, searches high-dimensional data for complex interactions between large numbers of explanatory variables and is only limited by the data that is available (Kuhn & Johnson, 2013). Applying this technique to prevention can improve the efficacy of selective interventions by moving beyond the limitations of our current knowledge of risk factors. ML has recently been incorporated into selective prevention of medical conditions such as Alzheimer's disease (Angehrn et al., 2018; Langford et al., 2020) and lung cancer (Rizzo et al., 2020), but has not yet been adopted for prevention of health-risk behaviors such as NSSI and binge drinking.

Deep Learning

ML is defined as the process of a computer program becoming better at a given task with experience (Mitchell, 1997). ML algorithms improve the accuracy of predicting an outcome from a set of explanatory variables over the course of observing several training examples (James et al., 2013; Kuhn & Johnson, 2013). ML algorithms consume training data and generate predictive models. New data are then supplied as inputs to the model and predictions of the outcome are generated as output. The performance of an ML model is judged on the accuracy of its predictions in new unseen test data. For example, media streaming services use ML to predict what kind of content users will enjoy (Melville & Sindhwani, 2010). An ML model is trained on a user's preferences and ratings of previous content and the model predicts the user's ratings of new content. The model is considered successful if its predictions match the user's actual ratings of new content that was not included in the set of examples on which the model was trained.

DL is a powerful form of ML that has advanced the state of the art in many domains. For a thorough and accessible review of DL, we refer the reader to LeCun et al. (2015). DL refers to a specific type of ML: artificial neural networks with multiple hidden layers (Skansi, 2018). A neural network is a nonlinear ML algorithm that is made up of interconnected layers of units or nodes (Kuhn & Johnson, 2013; LeCun et al., 2015; Skansi, 2018). See Figure 1 for an example of a "shallow" neural network (i.e., a network that contains a single hidden layer).

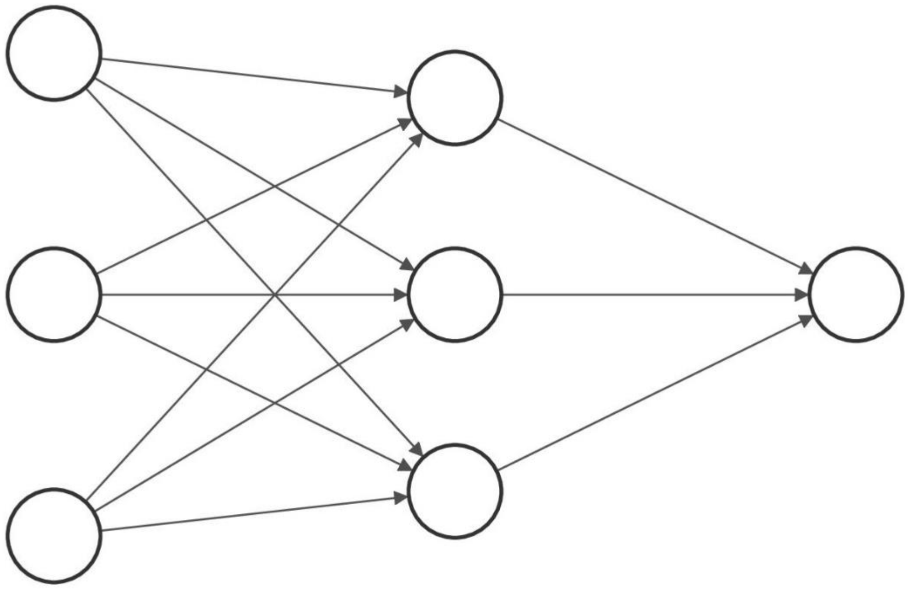


Figure 1. “Shallow” fully connected feedforward neural network with one hidden layer.

The first layer in a shallow neural network is referred to as the input layer and represents all the explanatory variables in a data set (Kuhn & Johnson, 2013; LeCun et al., 2015; Skansi, 2018). No operations are performed in this layer; each unit simply takes on the value of the variable to which it corresponds. The next layer is referred to as the hidden layer. Each individual unit of the hidden layer receives the values contained in the first layer as input. The output, or activation, of each unit in the hidden layer is calculated in two steps. The first step in the activation of a single unit is equivalent to linear regression. The inputs are multiplied by their respective weights and added together, then a bias is added to the weighted sum. Weights and biases are analogous to betas and intercepts in a linear regression framework. In the second step, the sum of the bias and weighted inputs is passed through a nonlinear activation function, producing the unit’s final output. The use of a nonlinear activation function, such as the hyperbolic tangent function, gives neural networks the capability to model complex nonlinear relationships between variables. The final layer is referred to as the output layer and generates the model's predictions. For example, consider a neural network constructed to predict a binary categorical outcome. This is referred to as a "classification" problem in ML. The objective is to correctly predict the class, or level of the categorical outcome, to which an individual case belongs. In the case of a dichotomous outcome, the output layer consists of a single unit that represents the probability of membership in one of the two classes. This unit uses a sigmoid activation function to perform a logistic regression on the activations of the units in the hidden layer.

Training a neural network enables it to learn a mapping between a set of inputs and desired outputs through exposure to training data (Kuhn & Johnson, 2013; LeCun et al., 2015; Skansi, 2018). This is accomplished by finding the optimal combination of the model's parameters (i.e., weights and biases) through a procedure known as backpropagation. Backpropagation, short for "backward propagation of errors," consists of a forward pass and a backward pass. When the network is first constructed, all parameters are randomly initialized. Training data is fed into the network and an output is obtained; this is the "forward pass." The data used during training are already labeled with the correct value. This allows the prediction produced by the model to be compared to the actual value and the error of the prediction to be calculated. The average error over multiple training examples is summarized by an expression called a "loss function." Simple examples of loss functions that will be familiar to most readers are the sum of squared errors and mean squared error. The loss function provides a differentiable equation that represents the network's inaccuracy and can be minimized through gradient descent optimization. Gradient descent refers to the process of finding the partial derivatives that describe the change in the loss function with respect to changes in each of the model's parameters. The changes that yield the largest reduction in the loss function are identified and the model's parameters are updated accordingly until the loss function reaches a minimum. This is called the "backward pass." A training "epoch" is complete when the network has been exposed to all training examples one time. Typically, neural networks are trained for multiple epochs (Chollet & Allaire, 2018).

DL models, also known as deep neural networks (DNNs), extend the shallow neural network by adding multiple hidden layers between the input and output layers (Kuhn & Johnson, 2013; LeCun et al., 2015; Skansi, 2018; see Figure 2). The outputs of each successive hidden layer in the network represent increasingly abstract representations of the input variables. For example, a DNN can be constructed to perform facial recognition on images (e.g., Schroff et al., 2015). Early hidden layers in the network, closer to the input layer, will represent very basic visual information such as lines, edges, and regions of lightness and darkness. Subsequent layers will combine these basic visual features into simple patterns. Layers deep in the network will combine the patterns into abstract representations that begin to resemble features that are germane to the goal of facial recognition, such as prototypical noses, eyes, etc. The simple extension of a shallow neural network through the addition of hidden layers is called a fully connected feedforward network, or multilayer perceptron. More complex DNN architectures, such as convolutional and recurrent neural networks, confer even greater predictive power and flexibility.

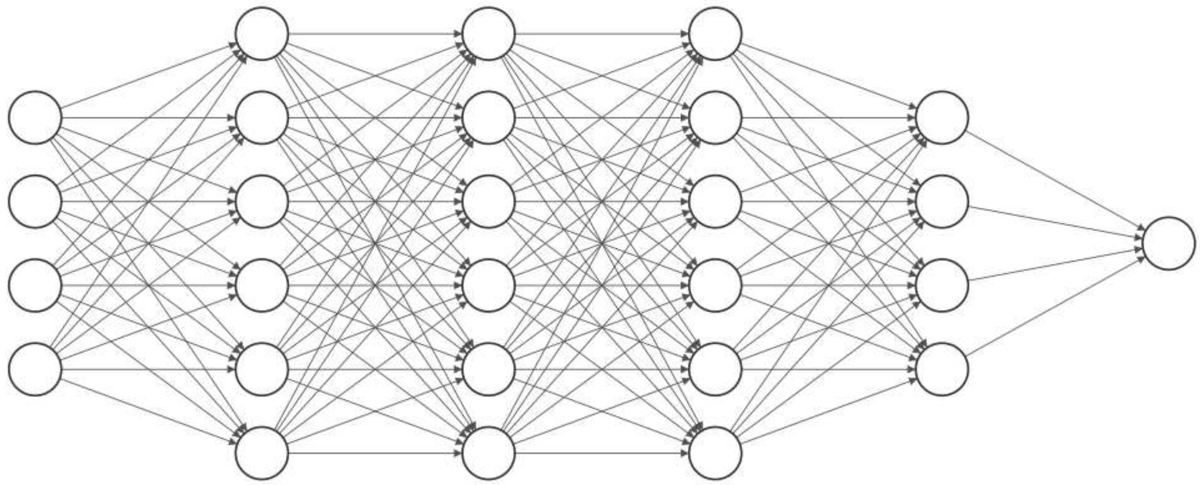


Figure 2. "Deep" fully connected feedforward neural network with many hidden layers.

Transfer Learning

Despite their impressive performance, DL models are rarely applied to the fields of clinical psychology and psychiatry (Dwyer et al., 2018; Yarkoni & Westfall, 2017). All ML requires training data, and larger amounts of training data generally lead to more accurate models (Yarkoni & Westfall, 2017). Due to their complexity, DNNs are particularly data intensive (Dwyer et al., 2018). DNNs are highly parameterized, often requiring the optimization of thousands of parameters (Dwyer et al., 2018; LeCun et al., 2015). Because of their flexibility, DNNs tend to learn not just relations between variables, but also statistical "noise" that is present in the training data. This process, known as overfitting, hinders the generalization of the DNN to new data and is the biggest barrier to training complex models on small samples. Overcoming these problems requires ever larger amounts of training data. This requirement is problematic when training data are expensive or difficult to obtain, as is often the case in clinical psychology and psychiatry. Collecting training data from specialized clinical populations, for instance, often involves lengthy navigation of institutional review boards and other organizational processes. It can also be expensive, as participants are typically compensated for their time. Furthermore, one assumption of ML and DL is that training data and unseen test data are independent and identically distributed (Pan & Yang, 2010; Tan et al., 2018). This effectively restricts learning to the domain from which the training data originated.

A technique known as transfer learning is one possible solution to the problem of expensive and inaccessible training data (Pan & Yang, 2010; Tan et al., 2018). Transfer learning is the process of translating the learning achieved in a source domain where data are plentiful to a related target domain where data are scarce and difficult to obtain. For example, compared to clinical samples, convenience samples of college undergraduates are easy and inexpensive to access, as college students typically participate in research as part of course requirements. Through transfer learning, an easily obtained convenience sample (a source domain) can partially satisfy the requirement of training data for implementing ML and DL in a clinical sample (a target domain).

The logic of transfer learning states that the early layers of a neural network form basic generalizable representations of the input data during pretraining. Layers deeper in the network, on the other hand, represent highly abstract representations of the input data that are specific to the source domain. Transfer learning is widely used in object recognition research where massively deep networks are trained on large data sets of ordinary images (e.g., house, cat, car, etc.), then applied to specialized image recognition tasks such as identifying a plant's species from images of its leaves and classifying images of skin lesions as cancerous or benign (Esteva et al., 2017; Kaya et al., 2019). As discussed previously, in neural networks that perform object recognition on images, early layers represent basic visual information such as lines and edges.

Layers deeper in the network form more specific and abstract features such as shapes, patterns, and components of larger objects. Transfer learning capitalizes on this hierarchy of feature representation (Kaya et al., 2019; Tan et al., 2018). When the source domain and target domain are related, it is likely that the low-level features learned in a neural network's early layers will be applicable to both. For example, although images of cats (a source domain) are very different from images of skin cells (a target domain), many basic visual features are universal (e.g., lines, patterns, etc.). Rather than training a new neural network in the target domain, the applicable components of a neural network trained in the source domain can be repurposed.

Deep transfer learning is achieved through pretraining a DNN in the source domain (Kaya et al., 2019; Tan et al., 2018). A DNN is constructed, and its parameters updated according to the process described previously until the loss function is minimized. After pretraining, the learning that has taken place in the source domain is encoded in the values of the network's parameters. Following pretraining, the old output layer of the network is replaced with a new untrained output layer and the network is exposed to training data from the target domain. At this point, the initial layers of the network can either be frozen or fine-tuned. If the initial layers are frozen, only the parameters within the new output layer are updated during training in the target domain. If the initial layers are fine-tuned, then their parameters are further updated along with the parameters of the new output layer during training in the target domain. Fine-tuning in the target domain is possible even with small samples because the optimal values of the parameters have been approximated through pretraining in the source domain rather than randomly initialized. This serves to truncate the parameter space the optimization algorithm must search to minimize the loss function. In other words, the learning that was performed in the source domain is transferred to the target domain via the information that is gained about the new starting values of the model's parameters.

Present Study

Health risk behaviors, including substance misuse and NSSI, are a significant public health problem (Miech et al., 2018; Muehlenkamp et al., 2012). Selective prevention programs for these behaviors are promising but are limited by current knowledge of risk factors. ML is an atheoretical approach that can handle complex interrelations between large numbers of explanatory variables, transcending the traditional approach of targeting prevention based on a handful of risk factors. DL is a particularly powerful form of ML, but it is seldom deployed in psychological research because large amounts of data are required to prevent overfitting (Dwyer et al., 2018; Yarkoni & Westfall, 2017). However, researchers commonly have access to large samples of college undergraduates, and deep transfer learning may facilitate training DNNs in a small clinical sample by leveraging information learned in a large convenience sample.

This study sought to demonstrate proof of these concepts. I recruited a sample of adolescent psychiatric inpatients and trained fully connected feedforward DNNs on cross sectional self-report demographic, personality, and behavioral assessments to model the likelihood that an individual had engaged in risky substance use or NSSI. It was hypothesized that DNNs configured to classify psychiatric inpatients by the status of those outcomes would exhibit improved performance when they were first pre-trained in a sample of college undergraduates. To evaluate model performance, classification accuracy was examined by constructing bootstrapped confidence intervals for baseline models trained exclusively in the clinical sample, transfer models pretrained in the college sample then transferred to the clinical sample, and a null model based on the most prevalent class represented in the clinical sample.

The biggest barrier to training complex ML models in small data sets is overfitting. Therefore, performance was also evaluated by examining the extent to which the baseline and transfer models overfit their training data throughout the course of their training history.

CHAPTER 3
METHODOLOGY

Participants

College Sample

The college sample consisted of 10,251 undergraduate students recruited from a large state university in the western United States. Participants earned credit in psychology courses for their participation. Participants responded to electronic surveys in a computer lab on campus, or on their own computers online. This protocol received IRB approval. Descriptive statistics for the demographics of the college sample are presented in Table 1.

Table 1

Descriptive Statistics

	College Sample		Clinical Sample	
	N	%	N	%
N=	10,251		200	
Sex				
Male	5508	53.7	65	32.5
Female	2957	28.8	133	66.5
DNR	1786	17.4	2	1.0
Race				
American Indian	72	0.7	4	2.0
Asian	355	3.5	3	1.5
African American	247	2.4	6	3.0
Hawaiian/ Pacific Islander	25	0.2	3	1.5
White	7001	68.3	152	76.0
Multiracial	448	4.4	16	8.0
DNR	2103	20.5	16	8.0
Ethnicity				
Hispanic or Latino	1288	12.6	41	20.5
Not Hispanic or Latino	6859	66.9	142	71.0
DNR	2104	20.5	17	8.5
Age				
Mean	19.7		16.12	
SD	2.3		1.11	
Behavioral Outcomes				
Alcohol Misuse	5130	50.0	62	31.0
DNR	2350	22.9	74	37.0
Ever engaged in self-injury	1377	13.4	164	82.0
DNR	6287	61.3	9	4.5

Clinical Sample

The clinical sample consisted of 200 adolescent inpatients recruited from a secured psychiatric hospital unit. Participants in the clinical sample were hospitalized at the time of data collection due to posing a danger to themselves, posing a danger to others, and/or exhibiting grave disability. The most common reasons for hospitalization were NSSI, suicidal ideation, and attempted suicide. Participants responded to electronic surveys on the unit where they were hospitalized. This protocol received IRB approval. Descriptive statistics for the demographics of the clinical sample are presented in Table 1.

Measures

Participants from both samples completed similar survey batteries containing measures of demographics, personality, and health risk behavior. All available variables were used to predict the outcomes of interest. A full listing of variables is provided in Appendix A.

Personality

Survey batteries contained measures of sensation seeking, impulsivity, meaning, and emotion dysregulation.

Sensation Seeking. Sensation seeking, as conceptualized by Conner (2021), is a personality construct comprised of two facets: experience seeking and risk seeking. Experience seeking describes an individual's desire for novel or intense experiences, whereas risk seeking refers to an individual's willingness to take risks to attain novel and exciting experiences. Sensation seeking was operationalized via the Sensation Seeking Personality Type Questionnaire (SSPT; Conner, 2021). The SSPT contains an experience seeking subscale (e.g., "I think variety is what makes life interesting") and a risk seeking subscale (e.g., "I enjoy participating in unsafe activities"). Responses were given on a five-point Likert-type response scale. Because DL models are designed to maximize the information provided by all variables, subscale scores were not created. Instead, all items were entered individually.

Impulsivity. Impulsivity is described by Whiteside and Lynam (2001) as a multidimensional personality construct that contains five facets: negative urgency, lack of premeditation, lack of perseverance, sensation seeking, and positive urgency. These facets were operationalized by the short version of the UPPS-P Impulsive Behavior Scale (SUPPS-P; Cyders et al., 2014). The negative urgency subscale of the SUPPS-P assesses an individual's tendency to engage in rash behavior in the presence of negative emotions. The lack of premeditation subscale contains items that assess an individual's tendency to act before reflecting upon the consequences of their actions. The lack of perseverance subscale captures an individual's tendency to easily give up a task after starting it. The positive urgency subscale contains items that measure an individual's tendency to act rashly in the presence of positive emotions. Because sensation seeking was measured by the SSPT, the sensation seeing subscale of the SUPPS-P was omitted. All responses were given on a four-point Likert-type response scale. Subscale scores were not created and all items were entered individually.

Emotion Dysregulation. Emotion dysregulation refers to an individual's inability to modulate the content or experience of their emotions in service of long-term goals (Gross, 1999). Emotion dysregulation was operationalized via the Difficulties with Emotion Regulation Scale (DERS), which contains five subscales (Gratz & Roemer, 2004). The nonacceptance subscale assesses an individual's nonacceptance of emotional responses. The goals subscale assesses an individual's difficulty engaging in goal-directed behavior in the presence of emotions. The impulse subscale assesses an individual's impulse control difficulties in the presence of strong emotions. The awareness subscale assesses an individual's lack of emotional awareness. The strategies subscale assesses the extent to which an individual's access to emotion regulation strategies is limited. All responses were given on a five-point Likert-type response scale. Subscale scores were not created and all items were entered individually.

Meaning. Meaning in life reflects individuals' perceptions that their life is significant and has a clear purpose (Steger, 2016). The present study utilized the Meaning in Life Questionnaire (MLQ; Steger et al. 2006), which formulates meaning in life as presence of meaning and search for meaning. The presence subscale contains items that measure the extent to which participants perceive purpose and significance in their lives. The search subscale captures the extent to which participants are engaged in seeking out greater purpose and significance. All responses were given on a seven-point Likert-type response scale. Subscale scores were not created and all items were entered individually.

Health Risk Behavior

Survey batteries contained measures of nonsuicidal self-injury and a large inventory of other risk-taking behaviors. In psychological research, these measures are typically treated as dependent variables or outcomes. In an ML framework, however, these can be viewed as additional features of the dataspace that may contribute to a model's predictions. For instance, an individual's health risk sexual behavior may provide some information that improves a model's ability to predict the individual's alcohol misuse.

Nonsuicidal Self-Injury. Nonsuicidal self-injury (NSSI) is defined as intentionally harming oneself through actions such as cutting, scratching, and burning (Klonsky, 2007). NSSI was operationalized by items that assess the frequency and age at onset of NSSI.

Risk-Taking Behavior. A broad assessment was conducted via the Risky Behavior Inventory (RBI; Conner & Henson, 2011). The RBI is a large behavioral inventory that asks detailed questions about participants' alcohol use, other substance use, sexual behavior, and criminal behavior. The outcomes of interest in the present study were assessed by single RBI items. Alcohol misuse was operationalized as binge drinking: consuming four or more drinks in a single episode for females and five or more drinks in a single episode for males. Alcohol misuse was assessed by the item, *In the past 30 days, how many times have you consumed five or more drinks (if you are male) or four or more drinks (if you are female) on one drinking occasion?*. Responses of zero were coded as negative endorsement and responses greater than zero were coded as positive endorsement. An individual's status regarding ever engaging in self-injurious behavior was assessed by the item, *Have you ever hurt yourself on purpose?*. Descriptive statistics for these outcomes are presented in Table 1.

Analysis Plan

Sample Size

There are no published guidelines of sample size requirements for DL, and it is not possible to conduct a power analysis, as in inferential statistics. The amount of data required to train DNNs must be determined empirically and is a function of the number of parameters to be estimated and the complexity of the relations between model inputs and outputs. To keep the number of parameters low, parsimony was prioritized during the model selection process. Models with fewer hidden layers and fewer units per hidden layer were considered first, then complexity was added incrementally.

Data Visualization

A series of data visualizations were created to explore the multivariate distributions and linear relations with the two outcomes within each sample.

Preprocessing. To prepare data for preprocessing, variables that did not appear in both data sets were dropped, as were character ("string") variables. Furthermore, some variables were only assessed in one wave of data collection for the clinical sample; these were also omitted. The lower limit of possible values for all variables was zero. Therefore, any negative values were deleted. Categorical variables that were not already binary were encoded as dummy variables. Some items in the survey battery asked about the frequency of a given behavior (e.g., *How many times in the past 6 months have you used marijuana?*). These open-ended frequency questions were vulnerable to extreme responses (e.g., 1×10^{47}), resulting in outliers in the data set. Therefore, all such variables were winsorized at their 95th percentile. A list of all variables with potential outliers, along with their 95th percentiles, is provided in Appendix B.

Many items in the survey batteries were members of question series, consisting of a "parent" item (e.g., *Have you ever used marijuana?*) and several "children" items (e.g., *How many times in the past 6 months have you used marijuana?*). If participants responded "No" to the parent question, they could skip the children questions, resulting in missing data. These “structural zeros” were assigned a value of zero. However, some children questions assessed age at onset of a particular behavior (e.g., *How old were you the first time you used marijuana?*). In these special cases, a value of 87 was assigned (1.5 times the age of the oldest participant across both samples). If a participant reported an age at onset that was greater than their chronological age, the response was deleted. All remaining missing data were singly imputed by random forests with predictive mean matching using the missRanger package (Mayer, 2019).

t-SNE. t-Distributed Stochastic Neighbor Embedding (t-SNE) is an ML data visualization technique that projects data from a multivariate hyperspace into two or three dimensions for viewing (van der Maaten & Hinton, 2008). t-SNE produces visualizations that preserve spatial relations between data points in the high-dimensional space. If the high-dimensional Euclidean distance between two data points is large, then the resulting pairwise distance between the points in the low-dimensional space will also be large (van der Maaten & Hinton, 2008). If the high-dimensional Euclidean distance between two data points is small, then the resulting pairwise distance between the points in the low-dimensional space will also be small. t-SNE plots illustrate potential clusters within the data, and the distance between clusters (both within and across samples) convey their relative similarity to each other. Individuals within the college and clinical samples should cluster together and, within those clusters, individuals should be grouped together by the status of their behavioral outcomes. Divergence from this expected pattern may suggest the presence of unique subpopulations within the respective samples.

Five combined data sets were created for t-SNE plots. To accommodate the large discrepancy in sample sizes, five random subsamples of 200 cases from the college data were joined with the clinical data to form five unique data sets. Within each of these, variables with zero variance were identified and removed. Next, all variables within the combined data sets were converted to Z-scores. Because standardization puts variables on the same scale, this was done after combining the data, rather than before. As a result, the rescaled variables still reflected the relative similarity/dissimilarity between the two populations. Each combined data set was then used to produce a series of tSNE plots with 10,000 maximum iterations and perplexity value equal to 50 using the Rtsne package (Krijthe, 2015). tSNE plots, color coded by sample and outcome are presented in Figures 3 and 4.

Regression Coefficient Weights. Line plots of the bivariate logistic regression weights between individual predictors and the outcomes of interest within both samples were created for binge drinking (see Figure 5) and NSSI (see Figure 6). Variables with variance equal to zero were identified for each sample. The union of these two sets of variables was dropped from both data sets. Prior to analysis, all predictor variables were standardized (converted to Z scores). Predictors that were inappropriate or too powerful for a given outcome were dropped from the data set. For the binge drinking outcome, all predictors that referred to alcohol were removed. For the NSSI outcome, all predictors that referred to self-harm were removed. The similarity of the bivariate regression weights across the two samples is an indicator of how well learned patterns will transfer across samples. Furthermore, the magnitude of the largest weights may be diagnostic of potential problems in the data (e.g., large outlier values).

Deep Learning Models

To test the study hypothesis, two competing DNNs for each outcome of interest were developed. One was trained exclusively in the clinical sample, while the other was pretrained in the college sample and transferred to the clinical sample. To determine if the hypothesis was supported, I examined the classification accuracy of each model compared to a null model using a 50% decision threshold, as well as the extent to which each model overfit its training data throughout the course of its training history.

All DNNs were implemented as fully connected feedforward networks using the Keras package in R (Allaire & Chollet, 2020) with the “Adam” stochastic optimization algorithm (Kingma & Ba, 2014) and the hyperbolic tangent activation function in the hidden layers. The output layer consisted of a single unit with sigmoid (logistic) activation. Because the outcomes to be predicted were categorical, binary cross-entropy was used for the loss function (Kuhn & Johnson, 2013). The model development and selection process is described in detail below. Briefly, the best network architecture and hyperparameter values were found for each outcome in the college data. The weights were transferred to networks which were then fine-tuned in the clinical data. The performance of the fine-tuned networks was then compared to the performance of networks trained from scratch in the clinical data, as detailed below.

Preprocessing. First, the outcome variables were encoded as described in the Measures subsection, above. All predictor variables that referred to alcohol use or self-injury, respectively, were dropped from the data set. It was determined *a priori* that these predictors were too powerful and that their relations to the outcomes were too facile for the purposes of this study. Next, cases with missing values on the outcome variables were deleted listwise. It should be noted that the binge drinking outcome is conditional on the parent question, *Have you ever drank alcohol?*. The data were structured such that participants who responded negatively to the parent question had missing data for the child question, *In the past 30 days, how many times have you consumed five or more drinks (if you are male) or four or more drinks (if you are female) on one drinking occasion?*. As a result, the analyses involving binge drinking were only conducted on participants who had consumed alcohol at least once before.

Predictor variables were preprocessed in a separate pipeline. First, variables that represented potential outliers were winsorized at their 95th percentile (see Appendix B). Structural zeros were imputed to zero, as with the data visualization preprocessing. Then, predictor values were "standardized." However, due to the presence of extreme outliers, the typical approach of centering at the mean and scaling by standard deviation was not uniformly appropriate. Instead, robust statistics (median and inter-quartile range) were used to standardize any predictor variables that had the potential to contain outliers. This approach is modeled on a utility available in the popular Python ML module Scikit-learn (Pedregosa et al., 2011). Predictor variables with zero or near-zero variance were identified using the Caret package (Kuhn, 2008) and were imputed to their median value. This assignment of a constant value was preferred over deletion to preserve the number of predictor variables across various training iterations. Finally, missing values were imputed using single classification and regression tress with the mlr package for R (Bischl et al., 2016). The preprocessing pipeline for the predictor variables frequently occurred within a cross-validation training loop where data were split into training and validation sets. Care was taken to prevent data leakage in this situation. The parameters for each preprocessing step were estimated from the training sets, then applied to the validation sets.

College Sample. Given its plentiful nature, the bulk of model tuning and selection was performed using the college data. All models were evaluated using five-fold cross-validation, with folds stratified by prevalence of the outcome variable. Regularization of these neural networks was performed using dropout on every hidden layer. Dropout is a regularization technique that randomly removes nodes from a network during training according to a predefined probability, the dropout rate (Srivastava et al., 2014). In effect, this simulates an ensemble of many different networks and helps mitigate overfitting. The hyperparameters and architectural specifications that were tuned were the dropout rate [0, 0.2, 0.5, 0.7]; number of hidden layers [1, 5, 10], number of units per hidden layer [1 – 32], and number of training epochs [1 – 100]. A 4 x 3 x 32 grid search was performed and the average binary cross-entropy and classification accuracy were plotted by epoch for each network configuration (see Figure 7 for example). The network with the highest classification accuracy for each outcome was selected and retrained on the full college data for the number of epochs that produced the maximum average classification accuracy during cross-validation. The weight matrices were saved for transfer to the clinical domain.

Clinical Sample. A baseline model for each outcome was trained from scratch for 200 epochs on the clinical data within a five-fold cross-validation loop using the best hyperparameters and network architecture from the college data. Average binary cross-entropy and classification accuracy were plotted by epoch for each network configuration (see Figure 11 for example).

A transfer model was initialized using the weights saved during training on the full college data. The weight matrix of the output layer of this network was replaced with zeros and the remaining hidden layers were frozen. The new output layer was then trained for 100 epochs. Retraining the output layer first in this manner facilitates fine-tuning by preventing very large errors from being propagated backwards through the neural network (Chollet & Allaire, 2018). Next, five-fold cross-validation was used to evaluate the optimal number of hidden layers to fine-tune. Within each iteration of the cross-validation loop, I transferred the pretrained weights, replaced and trained the output layer, then systematically varied the number of hidden layers in the network that were fine-tuned. I examined the maximum classification accuracy and minimum binary cross-entropy for each iteration to select the appropriate number of hidden layers to fine-tune (see Table 2 for example). Finally, average binary cross-entropy and classification accuracy were plotted by epoch for the best transfer model (see Figure 13 for example).

To compare the performance of the baseline and transfer models against each other, and against a null model, 95% confidence intervals were constructed from 850 bootstrap samples of the clinical data. Within each bootstrap sample, the data were split into training and test sets and preprocessed. A null model was implemented that uniformly predicted cases in the test set to be members of the majority class in the training set. The baseline model was trained using the number of epochs that produced the best results during cross validation. The transfer model was trained using the optimal number of epochs and number of fine-tuned hidden layers. Classification accuracy on the test set of the bootstrap samples was calculated for all three models and used to construct sampling distributions, from which the 95% confidence intervals were derived. Additionally, the training history of each model was examined for indications of overfitting. Overfitting is evident when continual improvement in accuracy or loss on the training data coincides with deterioration in the accuracy or loss on the validation data.

Finally, the information learned by the neural networks was explored using variable importance plots, individual conditional expectation (ICE) plots, and partial dependence plots. These are model-agnostic methods for interpreting ML models, including nonlinear algorithms such as neural networks (Greenwell et al., 2018). The rank order and relative magnitude of variable importance was calculated with the permutation method averaged across 10 Monte Carlo simulations using the vip package in R (Greenwell & Boehmke, 2020). Interpretation of the resulting bar plot is intuitive: larger bars represent more influential predictors. Partial dependence and ICE plots were then constructed to explore the top four predictors for each model. Individual conditional expectation plots (grayscale lines) show the conditional effect of a single variable on the predicted probability of positive class membership for all individuals in the data set. Partial dependence plots (red lines) show the average effect of a single variable across all individuals.

CHAPTER 4

RESULTS

Data Visualization

t-SNE

t-SNE plots for 5 combined data sets, color coded by sample and binge drinking status, are presented in Figure 3 (maximum iterations = 10,000, perplexity = 50).

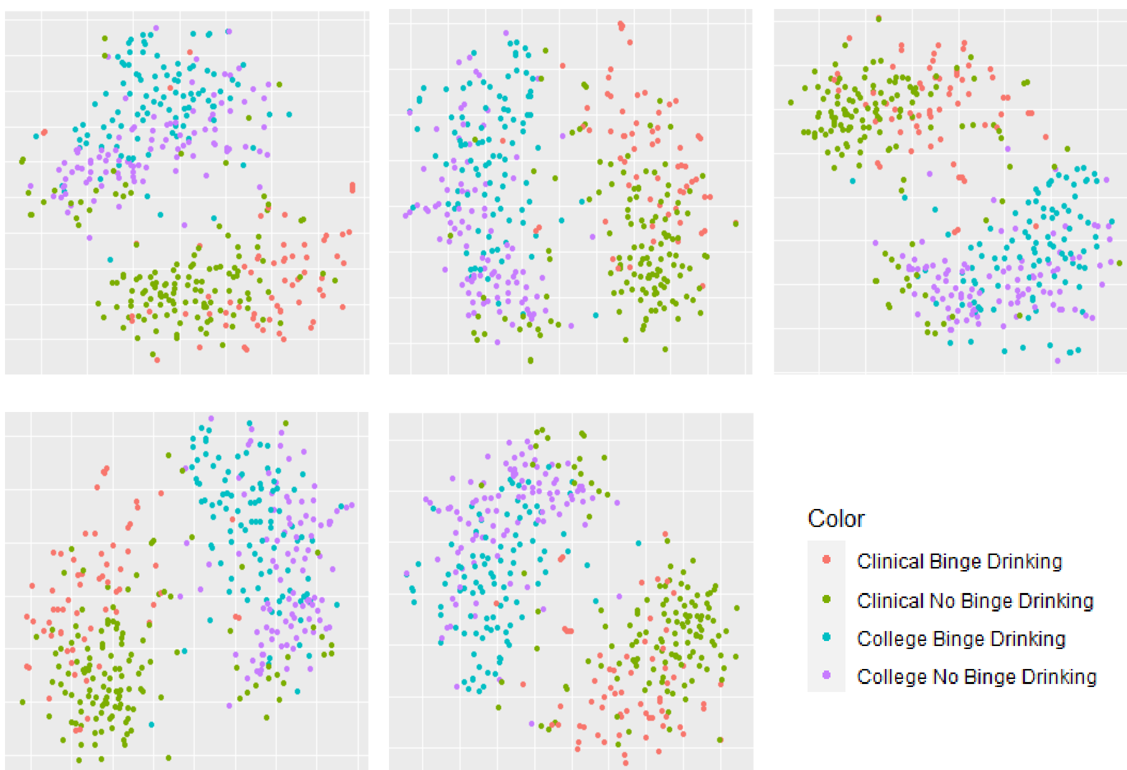


Figure 3. t-SNE Plots (Binge Drinking).

t-SNE plots for 5 combined data subsets, color coded by sample and NSSI status, are presented in Figure 4 (maximum iterations = 10,000, perplexity = 50).

Figure 4. t-SNE plots (NSSI).

Regression Weights

Line plots of standardized bivariate logistic regression weights between all predictors and binge drinking are presented in Figure 5.

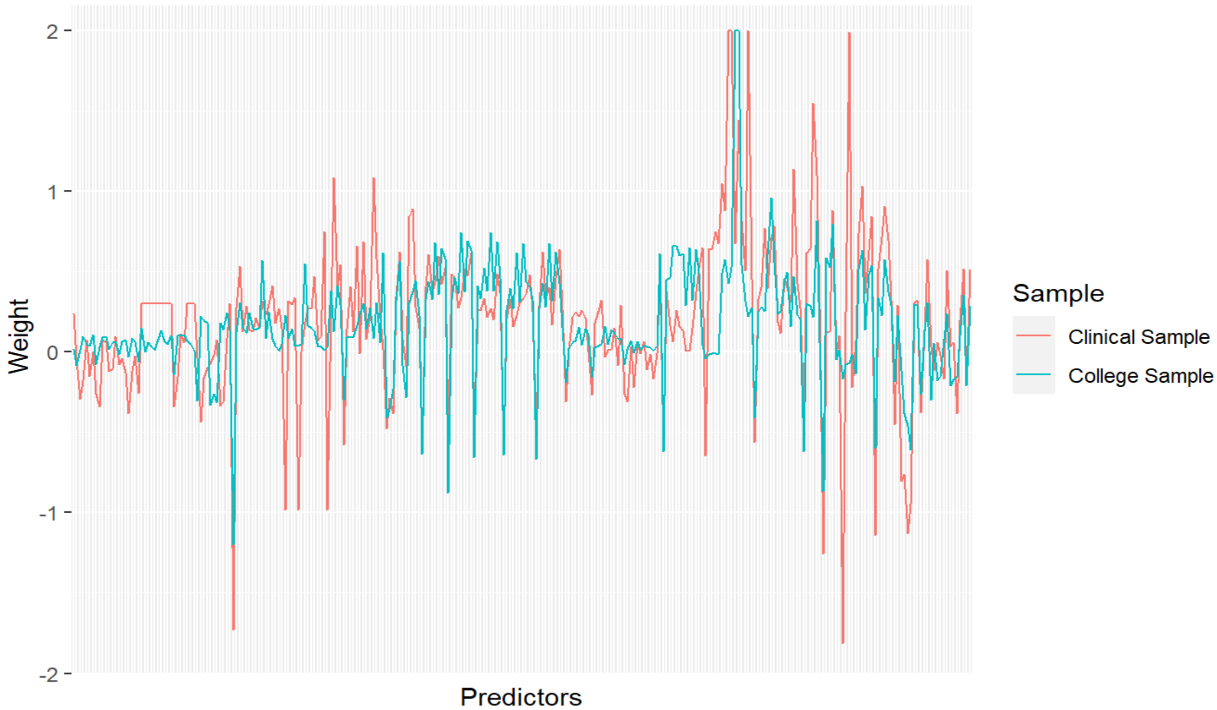


Figure 5. Standardized regression weights by sample (Binge Drinking).

Line plots of standardized bivariate logistic regression weights between all predictors and NSSI are presented in Figure 6.

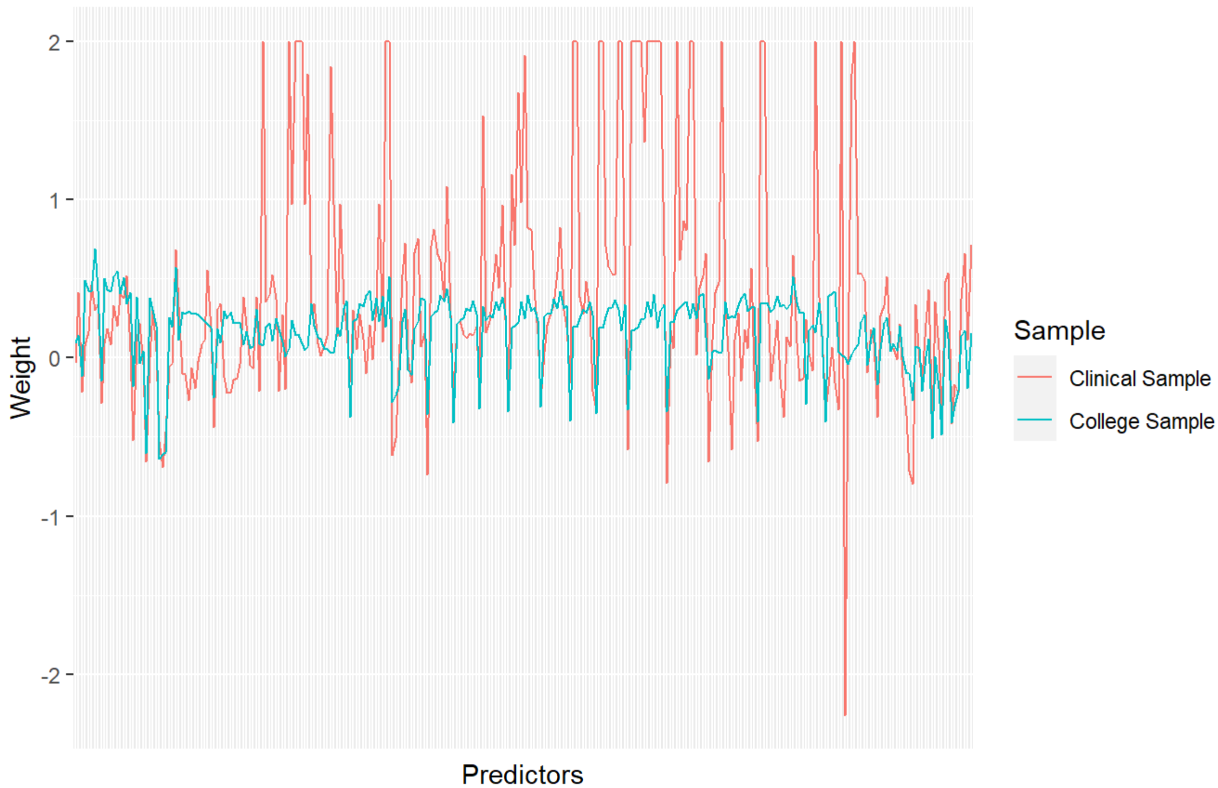


Figure 6. Standardized regression weights by sample (NSSI).

Deep Neural Networks

College Sample

For binge drinking, cross-validation revealed that, on average, a DNN with five hidden layers, 26 units per hidden layer, and a dropout rate of 0.7 classified participants in the college sample most accurately. Figure 7 depicts the best cross-validated classification accuracy for five-layer neural networks with dropout rate of 0.7 and units per hidden layer ranging from 1 to 32.

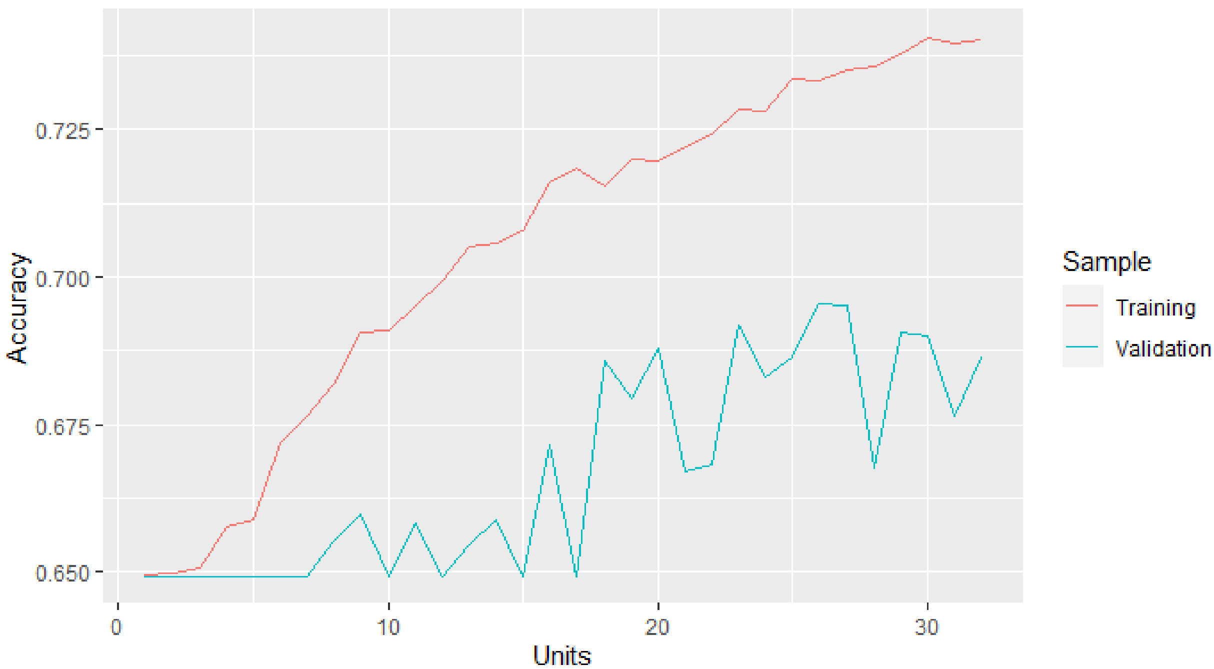


Figure 7. Cross-validated classification accuracy (Binge Drinking - College Sample).

Note. 5 hidden layers, 0.7 dropout rate, 1-32 units per hidden layer.

Figure 8 illustrates the training history of the best network. The maximum cross-validated classification accuracy (69.5%) was achieved at Epoch 92. After the network was selected, it was trained on the full college data for 92 epochs and the weight matrices were saved for transfer to the clinical domain.

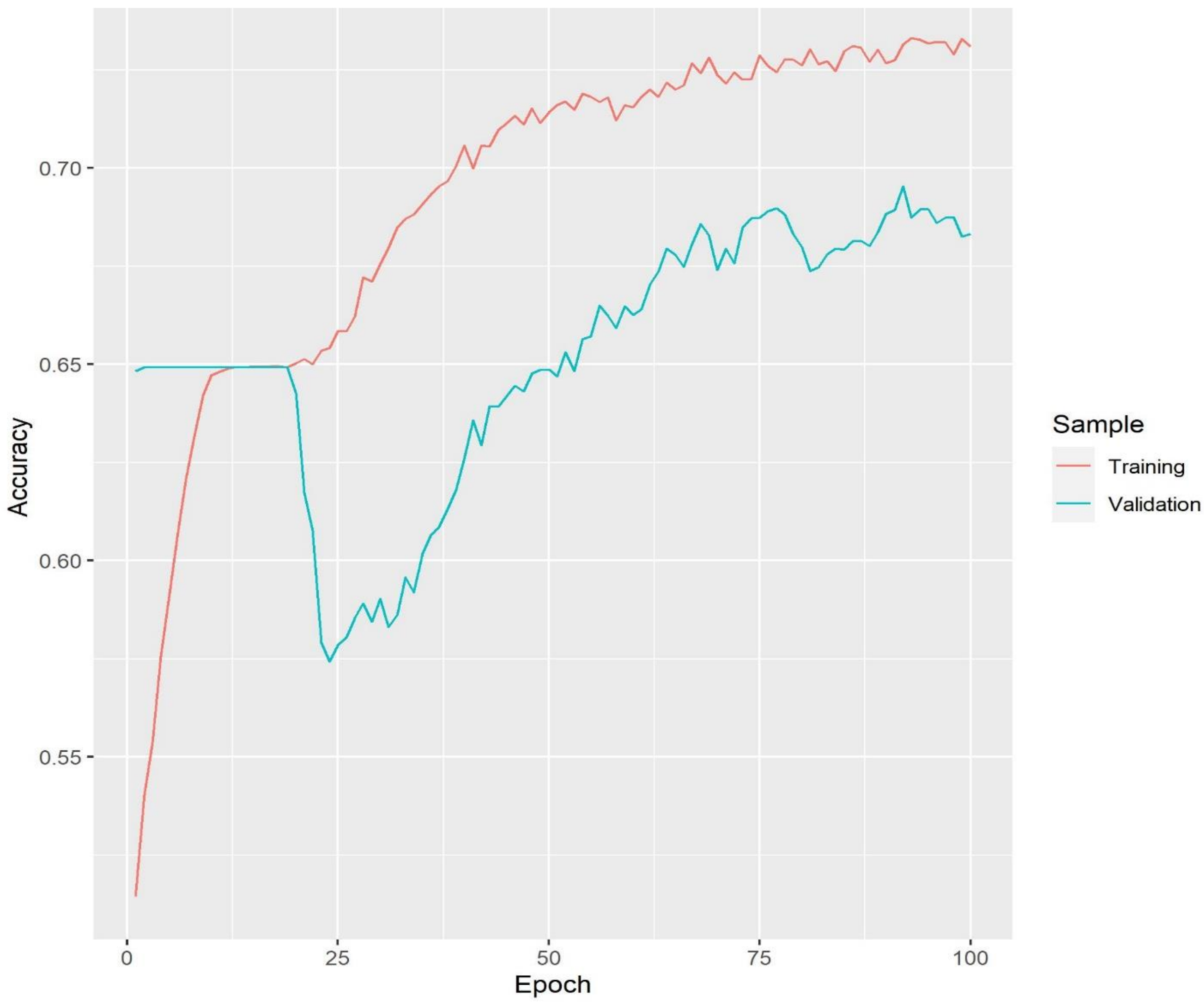


Figure 8. Training history by epoch (Binge Drinking – College Sample).

Note. 5 hidden layers, 0.7 dropout rate, 26 units per hidden layer.

For NSSI, cross-validation revealed that, on average, a DNN with 10 hidden layers, five units per hidden layer, and a dropout rate of 0.2, classified participants in the college sample most accurately. Figure 9 illustrates the best cross-validated classification accuracy for 10-layer neural networks with dropout rate of 0.2 and units per hidden layer ranging from 1 to 32.

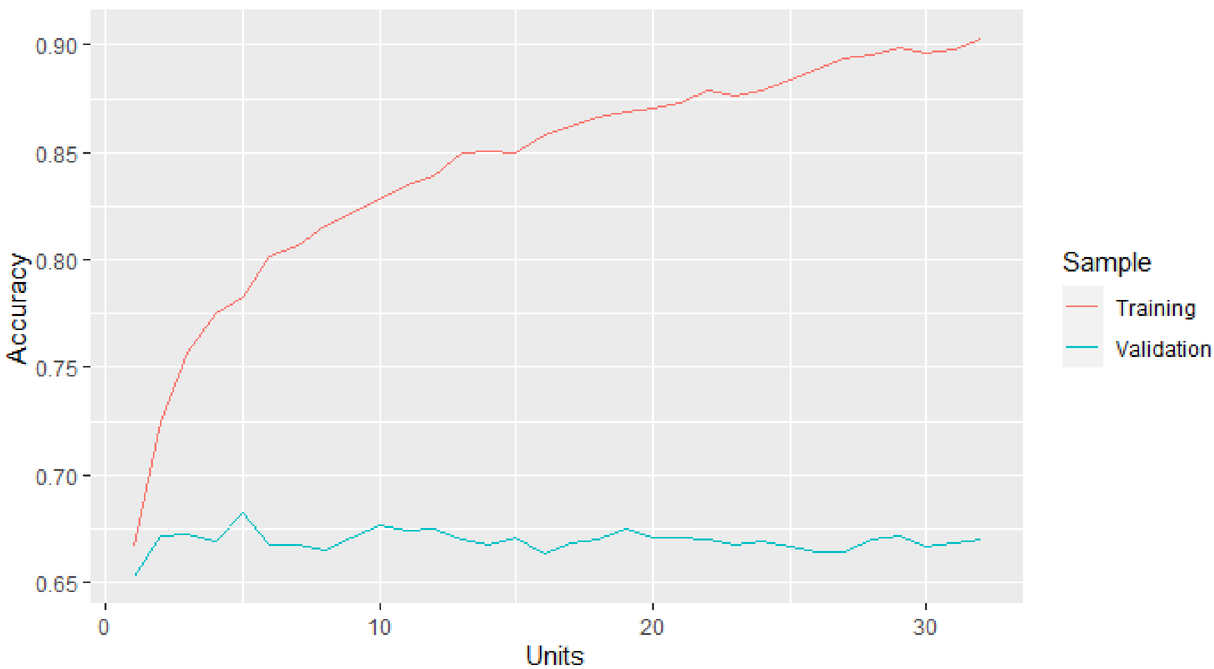


Figure 9. Cross-validated classification accuracy (NSSI – College Sample).

Note. 10 hidden layers, 0.2 dropout rate, 1-32 units per hidden layer.

Figure 10 shows the training history of the best network. The maximum cross-validated classification accuracy (68.2%) was achieved at Epoch 18. After the network was selected, it was trained on the full college data for 18 epochs and the weight matrices were saved for transfer to the clinical domain.

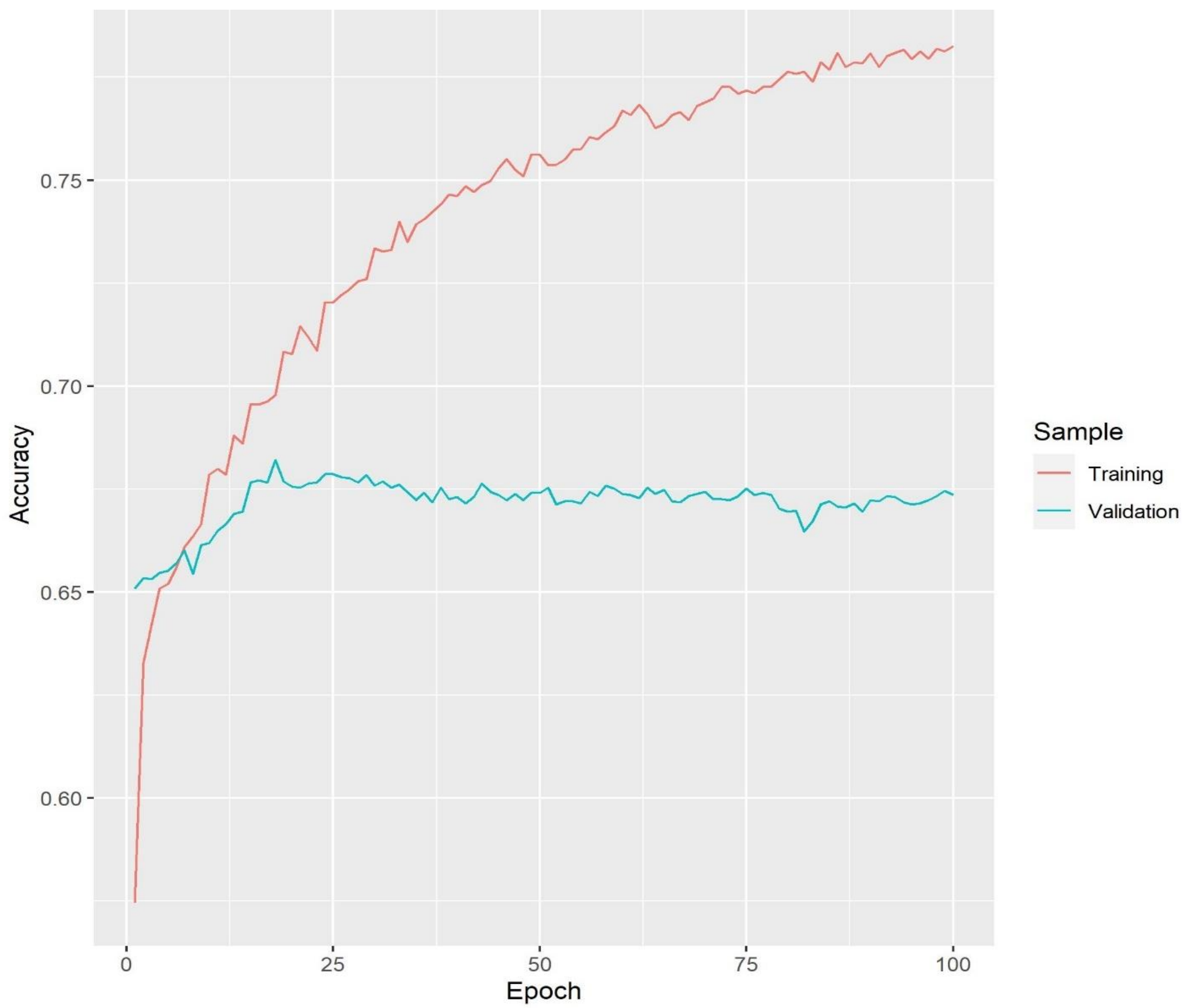


Figure 10. Training history by epoch (NSSI – College Sample).

Note. 10 hidden layers, 0.2 dropout rate, 5 units per hidden layer

Clinical Sample

Binge Drinking.

Baseline Model. A neural network with five hidden layers, 26 units per hidden layer, and dropout rate of 0.7, was trained for 200 epochs on the clinical data resulting in a maximum cross-validated classification accuracy of 53.1% and a minimum binary cross-entropy of 0.705. The accuracy and loss training history are presented in Figure 11.

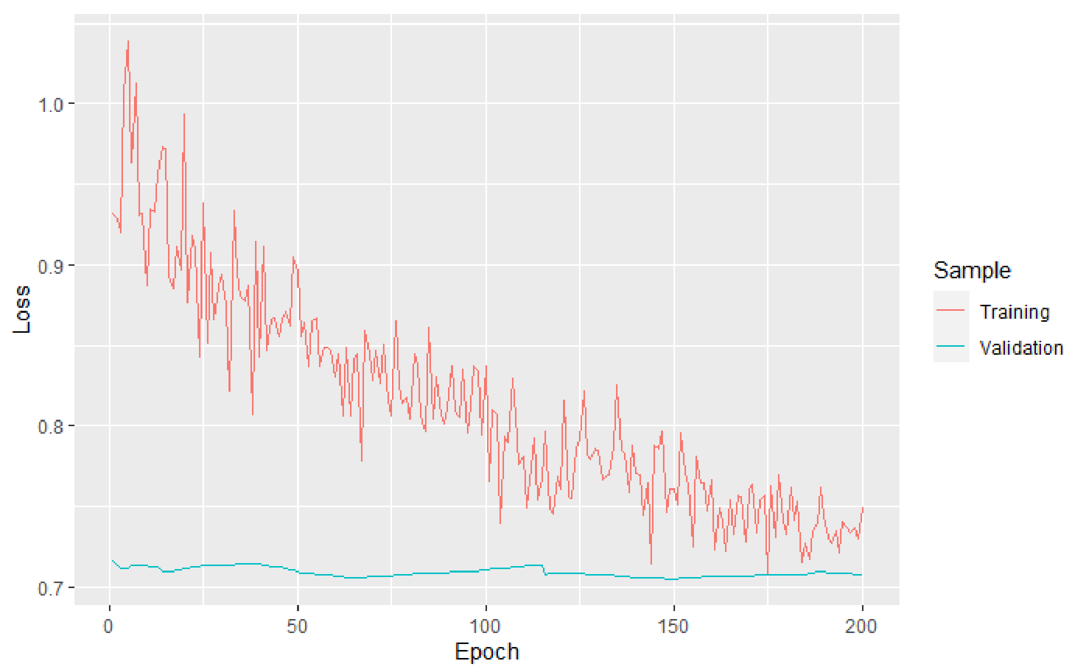


Figure 11. Cross-validated classification accuracy and binary cross-entropy (Binge Drinking – Baseline Model).

Note. 5 hidden layers, 0.7 dropout rate, 26 units per hidden layer.

The 95% bootstrapped confidence interval for classification accuracy was [.375, 0.667]. This was not a significant improvement over the null model 95% CI [.500, .583]. A histogram of bootstrapped classification accuracy for the baseline model is shown in Figure 12.

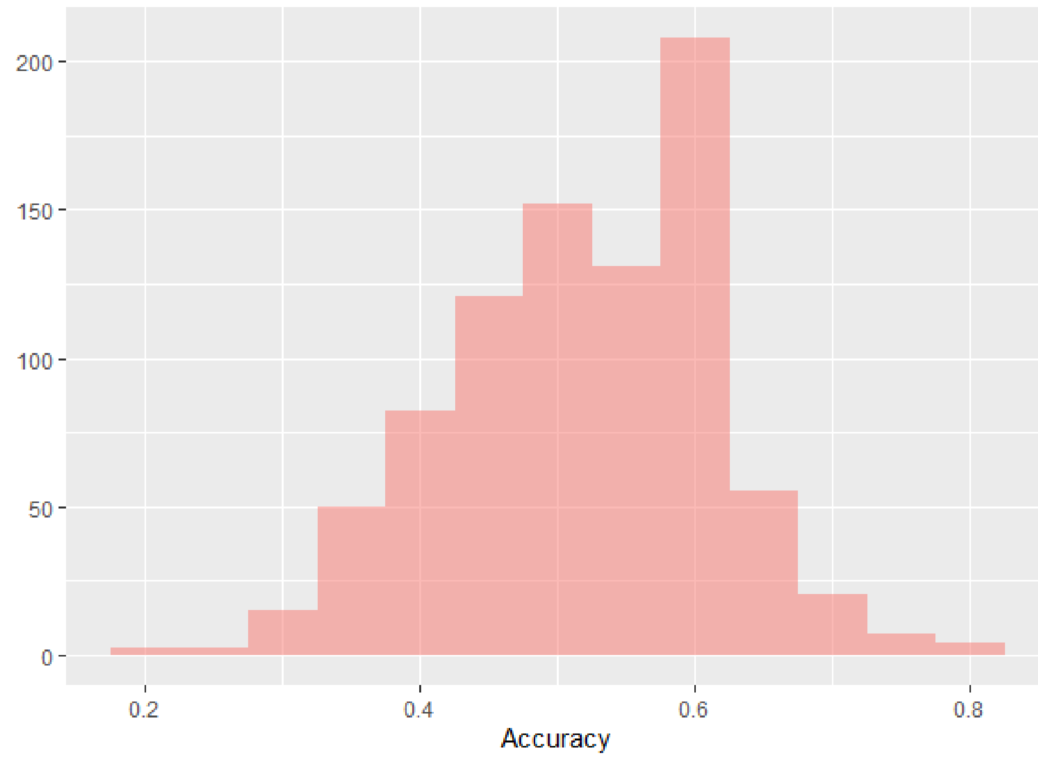


Figure 12. Histogram of bootstrapped classification accuracy (Binge Drinking – Baseline Model).

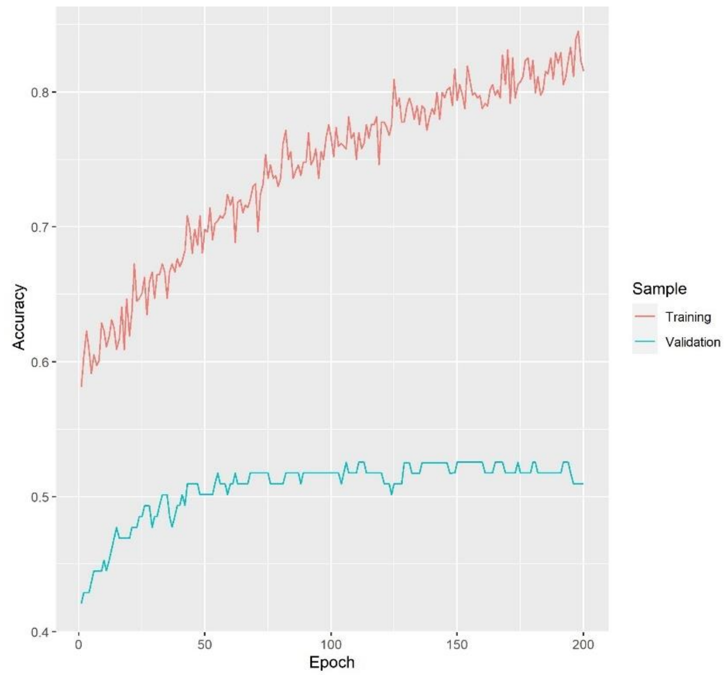
Note. 5 hidden layers, 0.7 dropout rate, 26 units per hidden layer.

Transfer model. A neural network with five hidden layers, 26 units per hidden layer, and dropout rate of 0.7, was initialized using the saved weight matrices from the college sample then fine-tuned on the clinical data. Table 2 displays the maximum classification accuracy and minimum binary cross-entropy obtained by fine-tuning the network from progressively shallower layers. The best result was obtained by fine-tuning the network from the first hidden layer, yielding a maximum cross-validated classification accuracy of 52.6% and a minimum binary cross-entropy of 0.752. The accuracy and loss training history for the best model are presented in Figure 13.

Table 2

Fine-Tuning Cross-Validation Results (Binge Drinking)

Network Fine-Tuned From	Accuracy	Loss
Hidden Layer 1	0.526	0.752
Hidden Layer 2	0.453	0.751
Hidden Layer 3	0.437	0.755
Hidden Layer 4	0.429	0.757
Hidden Layer 5	0.429	0.758



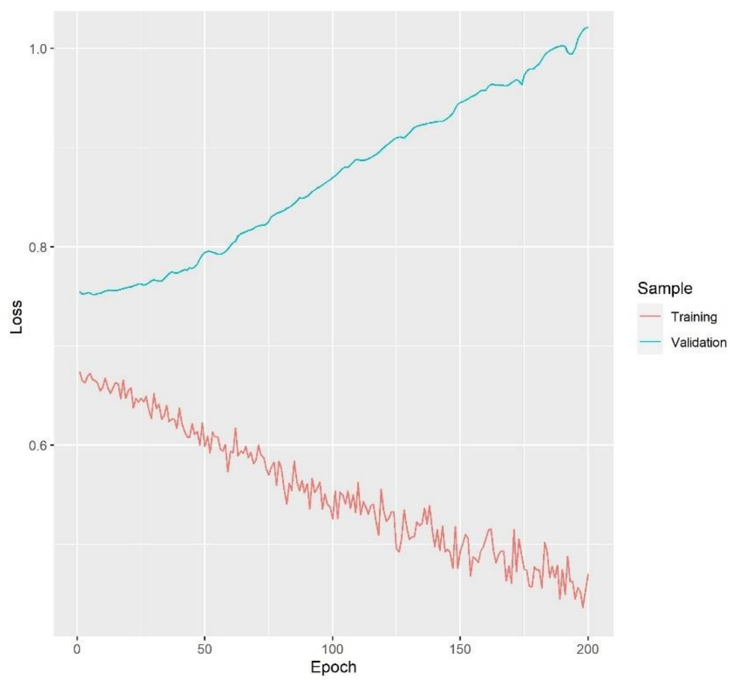


Figure 13. Cross-validated classification accuracy and binary cross-entropy (Binge Drinking – Transfer Model).

Note. 5 hidden layers, 0.7 dropout rate, 26 units per hidden layer.

The 95% bootstrapped confidence interval for classification accuracy was [0.375, 0.708]. This was not a significant improvement over the null model (95% CI [0.500, 0.583]). A histogram of bootstrapped classification accuracy for the transfer model is shown in Figure 14.

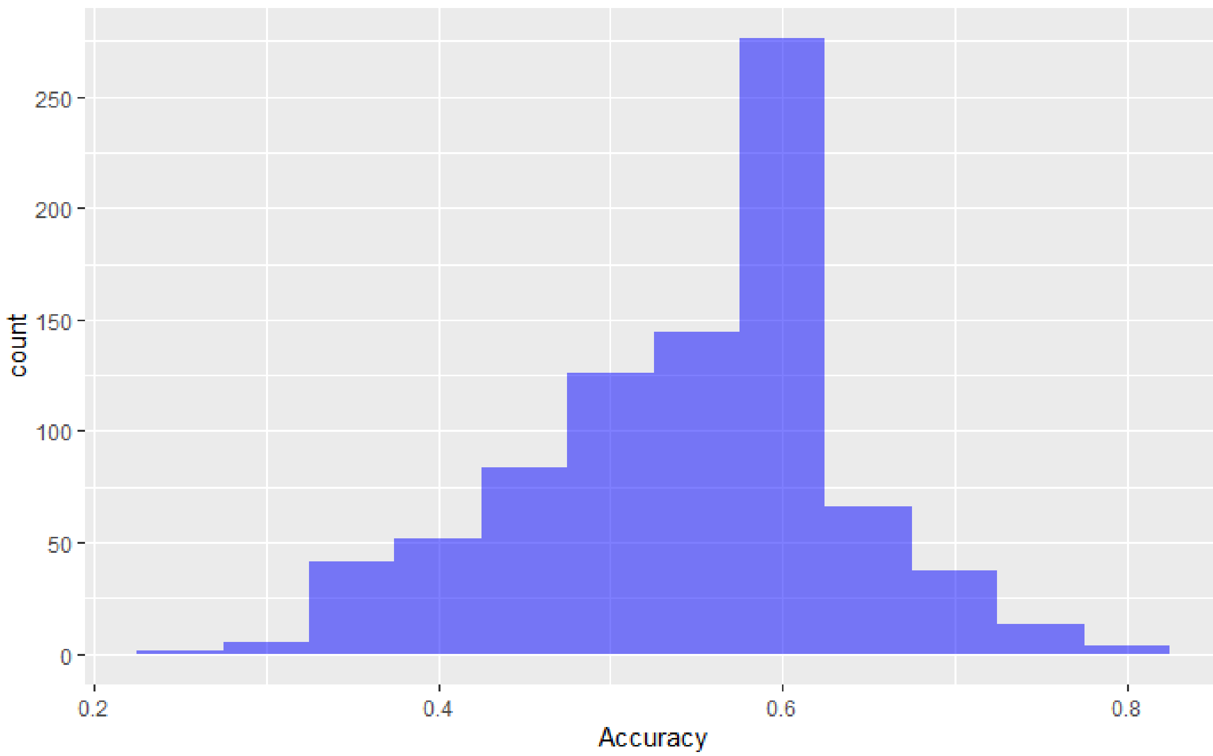


Figure 14. Histogram of bootstrapped classification accuracy (Binge Drinking – Transfer Model).

Note. 5 hidden layers, 0.7 dropout rate, 26 units per hidden layer.

A bar plot of variable importance for the transfer model, alongside partial dependence and individual contribution expectation plots for the four most influential predictors, is presented in Figure 15. The most influential predictors were: *How many times did you go to school while you were drunk or high in the last 30 days?* (R.Sub21a); *How many times in your life have you [used a combination of substances to get a better high]?* (R.Sub16c); *How many times in the last*

12 months have you had UNPROTECTED vaginal intercourse? (R.Sex4l); *How many times in the last 30 days have you had vaginal intercourse?* (R.Sex4b).

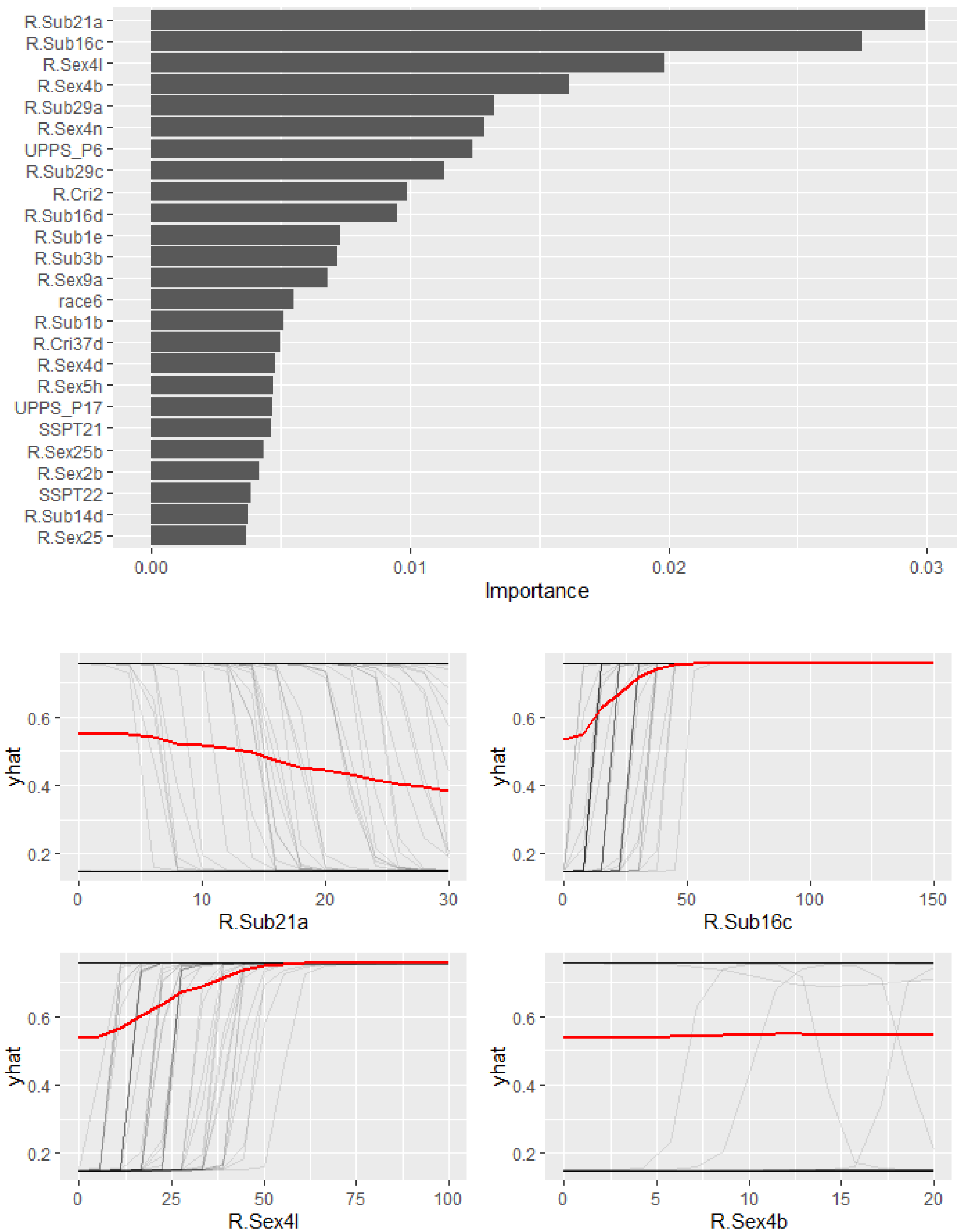


Figure 15. Variable importance, partial dependence, and ICE plots (Binge Drinking – Transfer Model).

Note. 5 hidden layers, 0.7 dropout rate, 26 units per hidden layer.

NSSI.

Baseline Model. A neural network with 10 hidden layers, 5 units per hidden layer, and dropout rate of 0.2, was trained for 200 epochs on the clinical data, resulting in a maximum cross-validated classification accuracy of 86.4% and a minimum binary cross-entropy of 0.471. The accuracy and loss training history are presented in Figure 16.

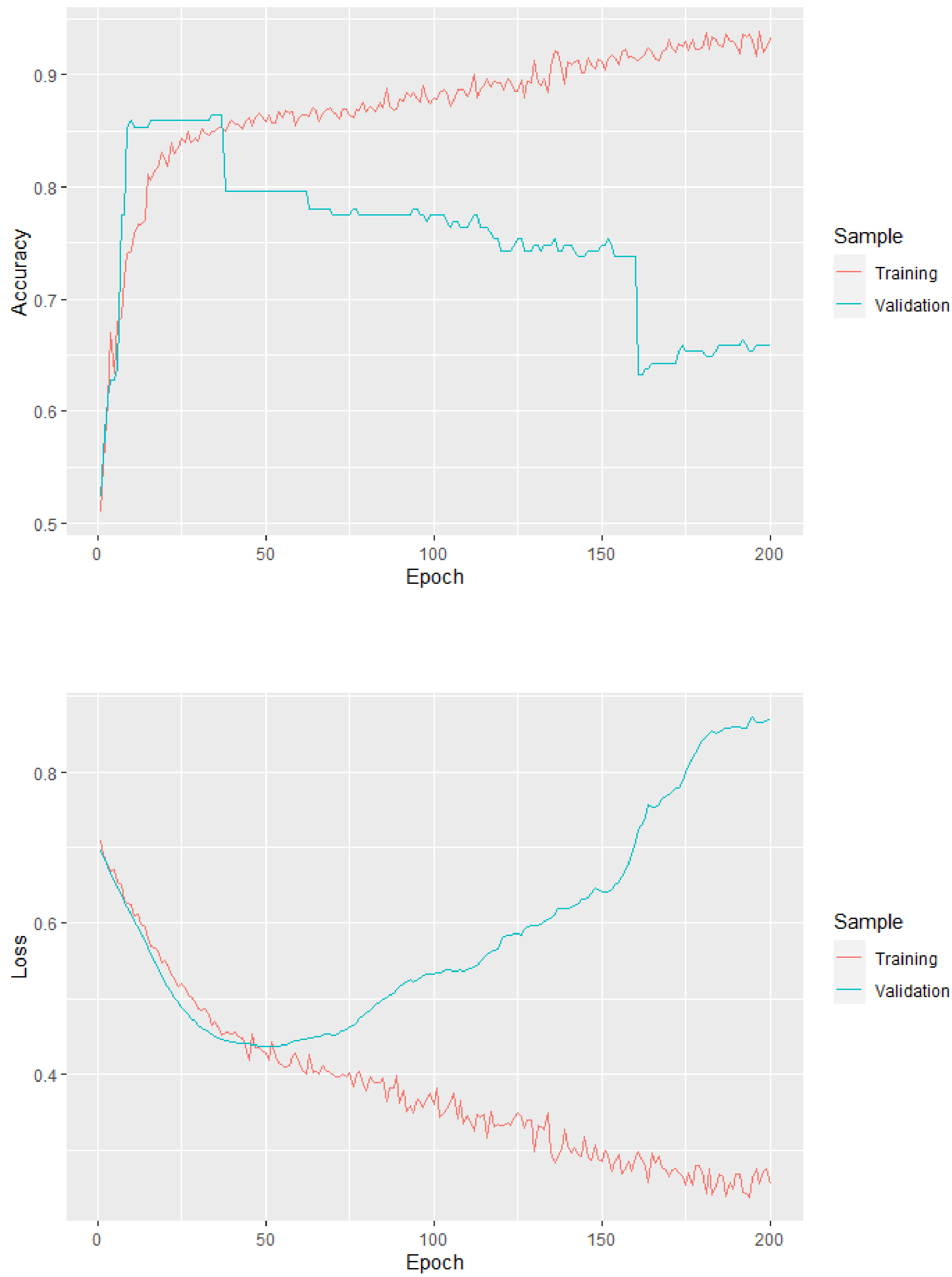


Figure 16. Cross-validated classification accuracy and binary cross-entropy (NSSI – Baseline Model).

Note. 10 hidden layers, 0.2 dropout rate, 5 units per hidden layer.

The 95% bootstrapped confidence interval for classification accuracy was [0.243, 0.892]. This was not a significant improvement over the null model (95% CI [0.812, 0.914]). A histogram of bootstrapped classification accuracy for the baseline model is shown in Figure 17.

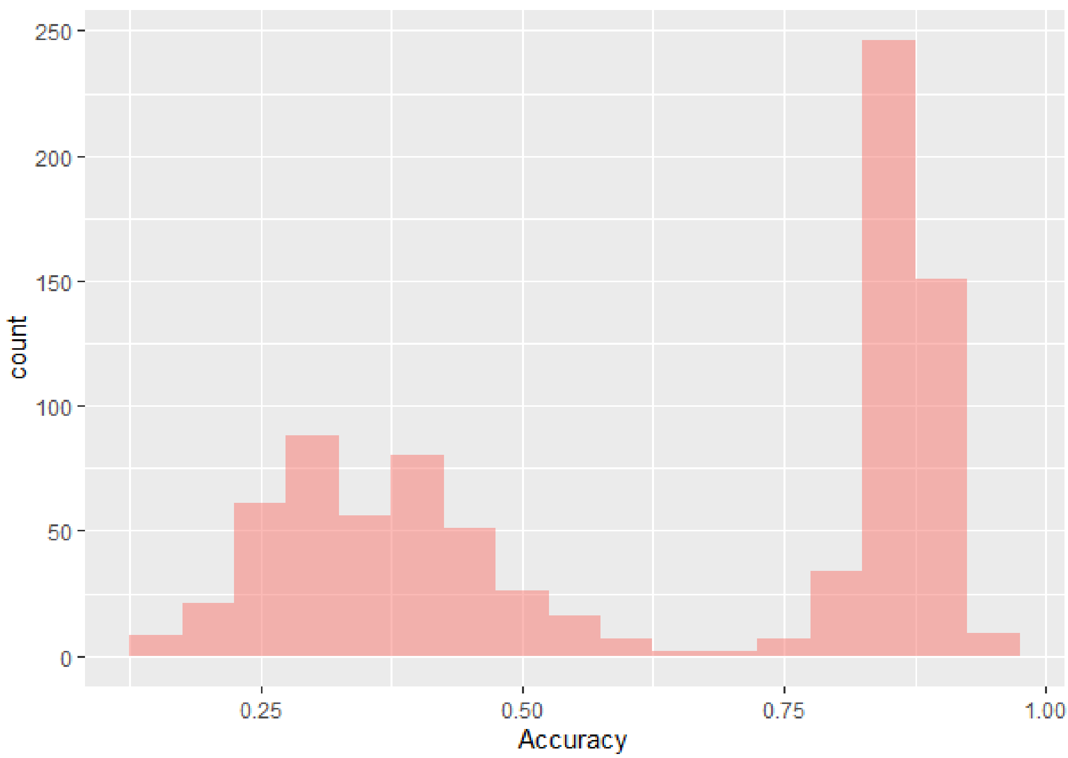


Figure 17. Histogram of bootstrapped classification accuracy (NSSI – Baseline Model).

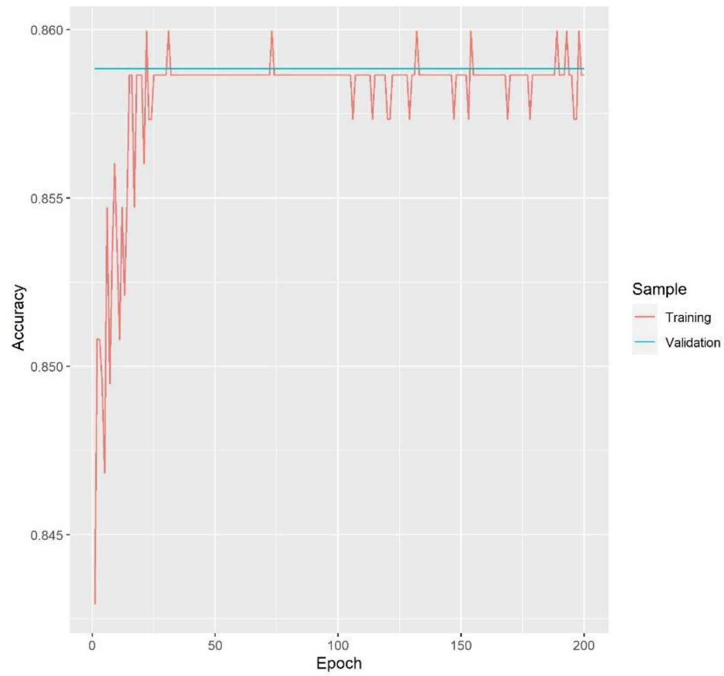
Note. 10 hidden layers, 0.2 dropout rate, 5 units per hidden layer.

Transfer model. A neural network with 10 hidden layers, 5 units per hidden layer, and dropout rate of 0.2 was initialized using the saved weight matrices from the college data, then fine-tuned on the clinical data. Table 3 displays the maximum classification accuracy and minimum binary cross-entropy obtained by fine-tuning the network from progressively shallower layers. The best result was obtained by fine-tuning the network from the third hidden layer, yielding a maximum cross-validated classification accuracy of 85.9% and a minimum binary cross-entropy of 0.413. The accuracy and loss training history for the best model are presented in Figure 18.

Table 3

Fine-Tuning Cross-Validation Results (NSSI)

Network Fine-Tuned From	Accuracy	Loss
Hidden Layer 1	0.859	0.507
Hidden Layer 2	0.859	0.413
Hidden Layer 3	0.859	0.413
Hidden Layer 4	0.859	0.413
Hidden Layer 5	0.859	0.414
Hidden Layer 6	0.859	0.414
Hidden Layer 7	0.859	0.414
Hidden Layer 8	0.859	0.415
Hidden Layer 9	0.859	0.417
Hidden Layer 10	0.859	0.416



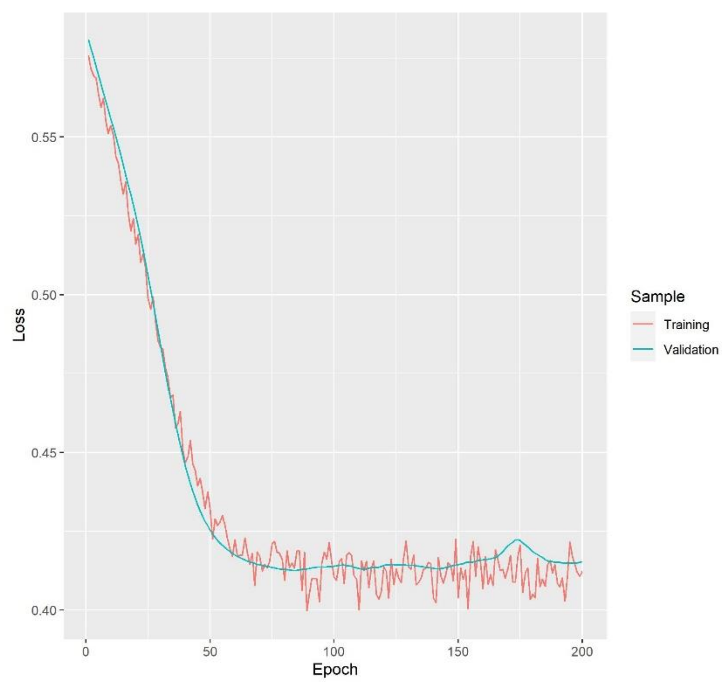


Figure 18. Cross-validated classification accuracy and binary cross-entropy (NSSI – Transfer Model).

Note. 10 hidden layers, 0.2 dropout rate, 5 units per hidden layer.

The 95% bootstrapped confidence interval for classification accuracy was [0.375, 0.708]. This was not a significant improvement over the null model (95% CI [0.812, 0.914]). A histogram of bootstrapped classification accuracy for the transfer model is shown in Figure 19.

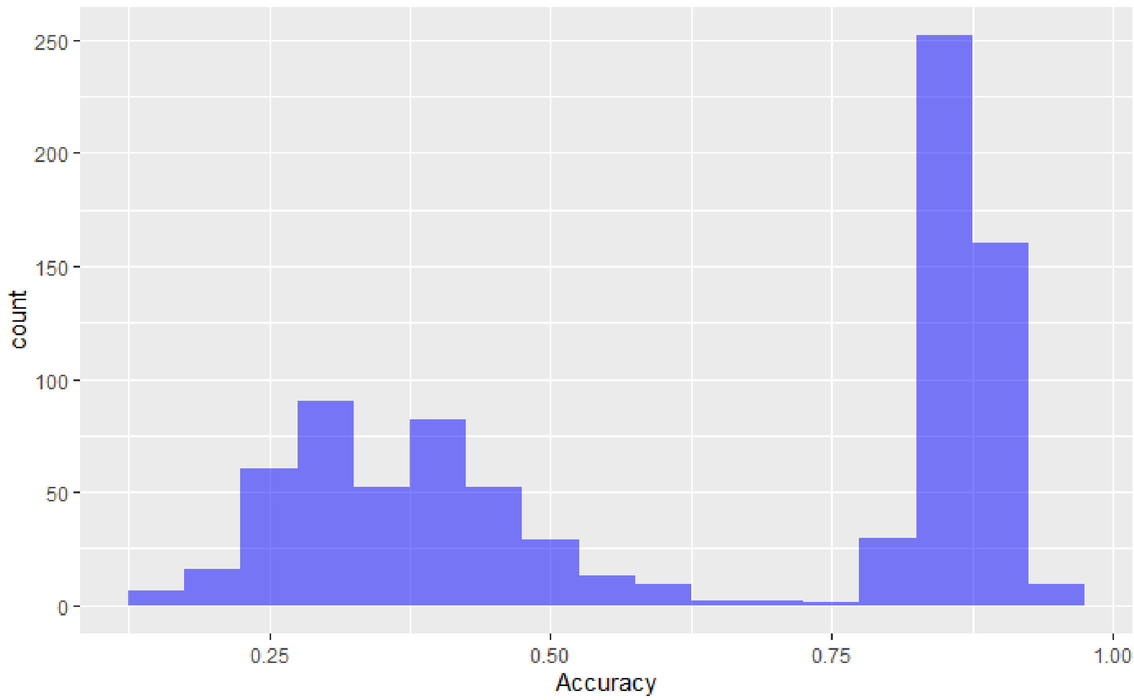


Figure 19. Histogram of bootstrapped classification accuracy (NSSI – Transfer Model).
Note. 10 hidden layers, 0.2 dropout rate, 5 units per hidden layer.

A bar plot of variable importance for the transfer model, alongside partial dependence and individual contribution expectation plots for the four most influential predictors, is presented in Figure 20. The most influential predictors were: *How many times in your life have you used alcohol or drugs in the morning/when you first wake up?* (R.Sub29c); *How many times in your life did you go to school while you were drunk or high?* (R.Sub21c); *How many times in the last 12 months have you had vaginal intercourse?* (R.Sex4d); *How many times have you smoked cigarettes in the last 6 months?* (R.Sub1e).

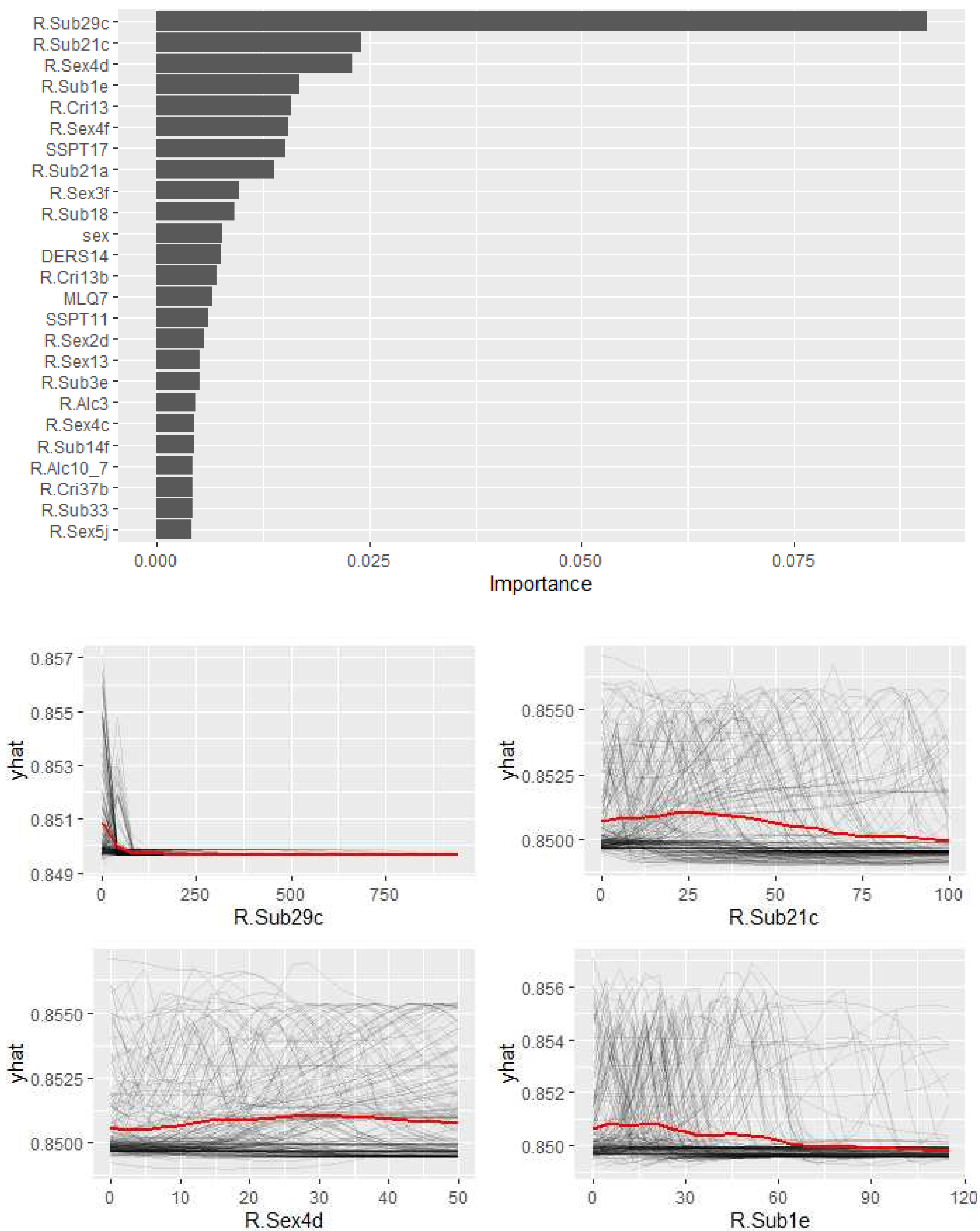


Figure 20. Variable importance, partial dependence, and ICE plots (NSSI – Transfer Model).

Note. 10 hidden layers, 0.2 dropout rate, 5 units per hidden layer.

CHAPTER 5

DISCUSSION

The goal of this study was to demonstrate proof of concept that large convenience samples of college undergraduates could be leveraged to facilitate training DNNs in small clinical samples using deep transfer learning. I hypothesized that DNNs pretrained in a college sample (the “transfer” models) would outperform DNNs trained exclusively in a clinical sample (the “baseline” models) in classifying adolescent psychiatric inpatients according to their binge drinking and NSSI status. The results reported herein support this prediction. Classification accuracy achieved by the baseline and transfer models for both alcohol misuse and NSSI were essentially equivalent and neither of these were significantly better than a null model that classified individuals according to the base rate of the outcome in the training data. However, the transfer models outperformed the baseline models with respect to overfitting.

This advantage is best illustrated by comparing the training history shown in Figure 11 to the history shown in Figure 13 (for alcohol misuse) and in Figure 16 to that shown in Figure 18 (for NSSI). In both cases, it is evident that the baseline models maintain maximum classification accuracy for a small number of training epochs. Then, classification accuracy decreases sharply as the model begins to overfit the training data. If one were to use these models in production, it would be necessary to first train them for a specified number of epochs before applying them to unseen data. In this sense, number of training epochs is a hyperparameter that needs to be tuned. With the baseline models there is a very narrow range of values that will produce optimal results. Additionally, the optimal value tends to vary with each training iteration due to random initialization of the model weights. On the other hand, once the transfer models reach maximum classification accuracy, they maintain that performance indefinitely. It is very difficult to overtrain these models and it would be simple to select any number of training epochs that yield optimal results. The trajectory of the loss function for the NSSI transfer model (Figure 14) provides further support for an improvement in performance over the baseline model. The validation loss tracks closely to the training loss throughout the training history. In contrast, the baseline model's loss function (Figure 16) reaches a minimum, then increases as overfitting occurs. Overall, these results indicate that pretraining DNNs in the college sample acted as a buffer against overfitting. This is not a trivial quality. The mandate to avoid overfitting is a cardinal rule of ML, and proneness to overfitting is the primary barrier to using such models in psychological research (Dwyer et al., 2018; Yarkoni & Westfall, 2017).

To my knowledge, this is the first study that has attempted to use deep transfer learning to commute information garnered from a convenience sample of college undergraduates to a clinical psychiatric sample in order to predict health risk outcomes. Previous studies have implemented ML models to predict related outcomes, such as suicide risk, with relative success (e.g., Desjardins et al., 2016; Walsh et al., 2017). However, these studies were concerned with maximizing predictive utility. Consequently, they chose to include variables known to be highly predictive of the outcome (e.g., suicidal ideation, psychiatric diagnoses, history of suicide attempts, etc.). In contrast, the present study was intended as proof of concept that data from college undergraduates can be used to augment the training of DNNs in small clinical samples. This was a secondary data analysis performed on data that were collected as part of a study investigating personality and health risk behavior. These data were not originally intended for predictive modelling and did not include the kinds of variables mentioned above. In fact, the models were intentionally constrained by excluding overpowered predictors. Thus, the relatively poor classification accuracy of the DNNs reported herein is not surprising, and the buffer against overfitting provided by pretraining these networks in the college data remains promising.

One unexpected finding is the apparent heterogeneity in the clinical sample with respect to NSSI. The t-SNE plot for alcohol misuse (see Figure 3) shows two distinct populations (college and clinical) with two classes represented within each cluster (binge drinking and no binge drinking). On the other hand, the t-SNE plot for NSSI (see Figure 4) suggests that the two populations are not as distinct. Individuals in the clinical sample with a history of NSSI may belong to their own unique population, whereas individuals in the clinical sample with no history of NSSI appear to be members of the same population as individuals in the college sample. Within this cluster, they appear to be more closely related to individuals in the college sample with no NSSI history. The bimodal distributions of bootstrapped classification accuracy in Figures 17 and 19 also convey significant heterogeneity within the clinical sample. It is possible that the models are performing poorly in bootstrap samples where the minority class is overrepresented because those individuals belong to a distinct population. It may be germane for future research to investigate these clusters further, by performing latent profile analysis, for instance.

The current study possesses many noteworthy strengths. One of these strengths is the size and provenance of the data sets that were collected. Psychological research often relies on samples of convenience, typically undergraduate students who participate in research for course credit. Samples from clinical populations are comparatively rare, and samples from pediatric clinical populations even more so. Additionally, the number of participants in the college sample is relatively large in the context of psychological research. The primary strength of the current study is the use of methods that bridge these two samples. It is critically important for psychologists to study members of the populations they intend to benefit (in this case, adolescent psychiatric inpatients), but such data are difficult to access. The techniques employed in this study expand the repertoire of analyses that can be performed on these scarce, but impactful, data sets. The execution of deep transfer learning using the Keras package in R (Allaire & Chollet, 2020) is also notable. Before the recent release of the Keras package, feed forward neural networks were available in R, or even SPSS. But advanced operations, such as transfer learning and complex network architectures, required the use of the Python programming language. This approach allows R users to execute DL studies in a programming language they are already familiar with.

Findings of the current study should be interpreted with certain limitations in mind. Although a diverse range of psychopathology was included, both the college and clinical samples were majority White and did not necessarily represent diverse racial and ethnic populations. The ability to predict the outcomes of interest was limited by cross-sectional self-report data. This kind of tabular data is not particularly well-suited for DL, which excels at learning from unstructured data such as images or text. However, optimizing DL for tabular data is an active area of research (Arik & Pfister, 2019).

Another limitation is the preponderance of missing values in these data sets. Data were collected over the course of several years, and the survey battery that was administered changed over time. This, in addition to the fact that participants could skip any questions they wished, resulted in high rates of missingness. For example, in the college sample, 61.3% of participants did not respond to the question about NSSI. How to best handle missing data is an open question in the ML field. The approach used here, single imputation with simple ML models predicting missing values, is typical but not ideal. Khan and colleagues (2018) proposed an ensemble method that uses multiple imputation, the gold standard for handling missing data in inferential statistics. Although this technique was beyond the scope of the current study, it represents a potentially more robust way to deal with missing data.

These data sets were also characterized by frequent outlier values. Many of the variables were self-reported counts of behaviors and contained extremely high values. Neural networks are most efficient when all inputs have an average that is close to zero and have similar variance (LeCun et al., 2012). Therefore, I made the conservative decision to winsorize potential outliers at their 95th percentile and to scale them using robust statistics (median and inter-quartile range). However, it is clear from the partial dependence and individual conditional expectation plots in Figures 15 and 20 that these preprocessing steps did not produce inputs with the desired distributions. For both outcomes, multiple input variables with extreme values are among the most influential predictors. The models learned to over-rely on these noisy variables, likely at the expense of classification accuracy. Further evidence of the effect of outliers can be seen in the regression weights plots in Figure 6. This plot depicts several “spikes,” which represent highly inflated regression weights in the clinical sample caused by extreme values. Additional research is needed to determine how to best handle this kind of self-reported behavioral data in ML models.

A post hoc exploration of predictions made by the DNNs further highlights the impact of these limitations. I retrained the final models on a new randomly selected subset of the clinical data and explored the predictions that they generated on new validation data by examining the five cases for each outcome with the largest prediction errors. For both alcohol misuse and NSSI, these five cases predominantly belonged to the negative class (i.e., no history of binge drinking/NSSI). On average, they had a greater proportion of missing data and the magnitude of responses to potential outlier questions was smaller.

Nevertheless, the findings reported herein encourage a broad range of future research directions inasmuch as they demonstrate the feasibility of using deep transfer learning on small clinical data sets. In the near term, is will be necessary to demonstrate that deep transfer learning improves not only the stability, but also the accuracy, of predictions. This may be possible by including more relevant training data (both structured and unstructured), effectively imputing missing values, and minimizing the noise caused by outliers. Additionally, further consideration should be given to the performance metric in future studies. I used classification accuracy in this study. However, the utility of classification accuracy is limited because it requires the selection of a decision threshold. The decision threshold can be optimized through cross-validation to produce the greatest proportion of correctly classified cases, but in this instance, I simply used the default threshold of 50%. Other metrics, such as area under the receiver operating characteristic curve, take into account classification accuracy across a range of all possible decision thresholds. Ultimately, if this research is translated to clinical applications, clinical scientists should consider sensitivity and specificity, rather than simple accuracy. This involves an ethical decision based on the invasiveness of a potential intervention. When dealing with selective prevention, there is fairly low risk associated with the intervention and a model with high sensitivity may be preferred. However, given that NSSI can result in involuntary hospitalization in some cases, specificity should be prioritized as well.

One area of potential future research is the application of deep transfer learning to Just-in-Time Adaptive Interventions (JITAIs). JITAIs monitor data in real time and are designed to provide intervention at the optimal moment to prevent harmful behavior (Wang & Miller, 2020).

Meta-analyses show that JITAIs that are tailored to individuals by automated algorithms are more efficacious than those driven by human agents, and many leading researchers have called for increased use of ML in the prediction of phenomena such as suicidal thoughts and behaviors (e.g., Ribeiro et al., 2016b, Torous et al., 2018). A particularly ambitious JITAI might involve tailoring based on ecological momentary assessments (EMAs) of relevant psychological constructs (e.g., Czyz et al., 2018), biometric sensor measurements (e.g., Kleiman et al., 2019), and analyzing speech patterns (e.g., Belouali, 2021). Biomedical data and clinical assessments from an individual's electronic health records could be included to inform the decision rule (e.g., Rajkomar et al., 2018), as could community-level data about social determinants of health (e.g., National Research Council, 2007). But such a complex model would require vast amounts of training data and would be prone to overfitting. However, by building on the design of the current study, researchers could run parallel experiments with college undergraduates concurrently with clinically relevant populations. DNNs could be pretrained on the college data and a public repository of electronic health records, then transferred to a small clinical sample. In addition to protecting against overfitting the clinical data, the parallel nature of this design would drastically reduce the time and cost of data collection.

The findings of this study are relevant to clinicians and prevention scientists working on reducing the public health burden of NSSI and binge drinking. Some European biomedical researchers have adopted ML to bolster their selective prevention program for Alzheimer's disease (Langford et al., 2020). Rather than screening individuals based on the traditional risk factors in their area of study, these scientists established a large pool of potential participants in selective prevention trials. By using ML algorithms on this pool, they can efficiently identify individuals who would most benefit from the prevention program. A similar process can be developed for NSSI or binge drinking. Multimodal data from electronic health records, social media, and large epidemiological studies can be processed by DL models and identify adolescents for whom selective interventions will be most beneficial.

In sum, current findings support the study hypotheses that pretraining DNNs in a college sample will improve their performance in a clinical sample. Although predictions were not significantly more accurate than the null model, they were more stable for the pretrained networks compared to the baseline networks. It appears that pretraining DNNs in the college sample achieved the desired effect of buffering against overfitting when fine-tuning in a small clinical sample. This opens up the possibility for ambitious DL projects to be completed on small, but meaningful, clinical samples. Such models can potentially improve the effectiveness of selective prevention programs by moving beyond reliance on a handful of risk factors and incorporating complex interactions between a large and diverse set of explanatory variables.

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APPENDICES

APPENDIX A

VARIABLES INCLUDED IN ANALYSES

Table 1-A

Variables Included in Analyses

Variable Name	Description
Demographics	
Dem1	What is your date of birth? (mm/dd/yyyy)
Dem2	What is your sex?
Dem3_1	What is your race? {Choose all that apply} American Indian or Alaska Native
Dem3_2	What is your race? {Choose all that apply} Asian
Dem3_3	What is your race? {Choose all that apply} Black or African American
Dem3_4	What is your race? {Choose all that apply} Native Hawaiian or Other Pacific Islander
Dem3_5	What is your race? {Choose all that apply} White
Dem3_6	What is your race? {Choose all that apply} Do not wish to respond
Ethnicity1	What is your ethnicity? {Choose all that apply} Hispanic or Latino
Ethnicity2	What is your ethnicity? {Choose all that apply} Not Hispanic or Latino
Ethnicity3	What is your ethnicity? {Choose all that apply} Do not wish to respond
Sensation Seeking Personality Type Questionnaire	
SSPT1	I like to do things that other people think are dangerous.
SSPT2	I enjoy participating in unsafe activities.
SSPT3	I don't enjoy trying new things.
SSPT4	I avoid activities if there is a chance that I could get hurt.
SSPT5	I would describe myself as careful and cautious.
SSPT7	I do not do things if I know that doing them would be bad for me.
SSPT8	I think variety is what makes life interesting.
SSPT9	I think it is important to try as many new things as I can.
SSPT10	I do things even if I know that doing them will get me in trouble.
SSPT11	I love challenging myself with new and interesting tasks.
SSPT14	I think that excitement is more important than safety.
SSPT15	I have the most fun when I am doing risky or dangerous things.
SSPT16	I rarely do things that seem risky.
SSPT17	I like to experience anything and everything I can.
SSPT18	I don't often act in a way that people approve of.
SSPT21	I enjoy the unfamiliar.
SSPT22	I like to explore new areas.
SSPT23	I do not like surprises.
SSPT24	I am curious.
UPPS-P Impulsive Behavior Scale	
UPPS_P4	I generally like to see things through to the end.

Variable Name	Description
UPPS_P6	My thinking is usually careful and purposeful.
UPPS_P10	When I am in great mood, I tend to get into situations that could cause me problems.
UPPS_P14	Unfinished tasks really bother me.
UPPS_P16	I like to stop and think things over before I do them.
UPPS_P17	When I feel bad, I will often do things I later regret in order to make myself feel better now.
UPPS_P19	Once I get going on something I hate to stop.
UPPS_P20	I tend to lose control when I am in a great mood.
UPPS_P22	Sometimes when I feel bad, I can't seem to stop what I am doing even though it is making me feel worse.
UPPS_P27	I finish what I start.
UPPS_P28	I tend to value and follow a rational, "sensible" approach to things.
UPPS_P29	When I am upset I often act without thinking.
UPPS_P34	When I feel rejected, I will often say things that I later regret.
UPPS_P35	Others are shocked or worried about the things I do when I am feeling very excited.
UPPS_P48	I usually think carefully before doing anything.
UPPS_P52	I tend to act without thinking when I am really excited.
Difficulties with Emotion Regulation Scale	
DERS2	I pay attention to how I feel.
DERS4	I have no idea how I am feeling.
DERS5	I have difficulty making sense out of my feelings.
DERS8	I care about what I am feeling.
DERS9	I am confused about how I feel.
DERS10	When I'm upset, I acknowledge my emotions.
DERS12	When I'm upset, I become embarrassed for feeling that way.
DERS13	When I'm upset, I have difficulty getting work done.
DERS14	When I'm upset, I become out of control.
DERS16	When I'm upset, I believe that I'll end up feeling very depressed.
DERS18	When I'm upset, I have difficulty focusing on other things.
DERS25	When I'm upset, I feel guilty for feeling that way.
DERS26	When I'm upset, I have difficulty concentrating.
DERS27	When I'm upset, I have difficulty controlling my behaviors.
DERS28	When I'm upset, I believe that there is nothing I can do to make myself feel better.
DERS29	When I'm upset, I become irritated with myself for feeling that way.
DERS32	When I'm upset, I lose control over my behaviors.
DERS35	When I'm upset, it takes me a long time to feel better.
Form and Function of Self-injury Scale	
FAFSI62	How old were you the first time you hurt yourself on purpose?
FAFSI63	How many times in your life have you hurt yourself on purpose?
FAFSI64	How many times in the last 12 months have you hurt yourself on purpose?
FAFSI65	How many times in the last 30 days have you hurt yourself on purpose?
Meaning in Life	
MLQ1	I understand my life's meaning.
MLQ2	I am looking for something that makes my life feel meaningful.
MLQ3	I am always looking to find my life's purpose.

Variable Name	Description
MLQ4	My life has a clear sense of purpose.
MLQ5	I have a good sense of what makes my life meaningful.
MLQ6	I have discovered a satisfying life purpose.
MLQ7	I am always searching for something that makes my life feel significant.
MLQ8	I am seeking a purpose or mission for my life.
MLQ9	My life has no clear purpose.
MLQ10	I am searching for meaning in my life.
Risky Behavior Inventory- Alcohol	
R.Alc1	Have you ever consumed alcohol?
R.Alc2	On how many days during the past 30 days did you consume alcohol?
R.Alc3	On how many days during the past 30 days did you drink to the point of being drunk?
R.Alc4	On how many days during the past 30 days did you pass out or get sick from drinking alcohol?
R.Alc5	How old were you the first time you drank alcohol?
R.Alc6	In the past 30 days, how many times have you consumed five or more drinks (if you are male) or four or more drinks (if you are female) on one drinking occasion?
R.Alc7	Think of the day you consumed the most alcohol in the last month: How many standard drinks did you consume on that day?
R.Alc8	On this heaviest drinking day, approximately how many hours passed from the beginning of the first drink to the finishing of the last?
R.Alc9_1	How many standard drinks did you consume each day during a TYPICAL week during the past month? – Sunday
R.Alc9_2	How many standard drinks did you consume each day during a TYPICAL week during the past month? – Monday
R.Alc9_3	How many standard drinks did you consume each day during a TYPICAL week during the past month? – Tuesday
R.Alc9_4	How many standard drinks did you consume each day during a TYPICAL week during the past month? – Wednesday
R.Alc9_5	How many standard drinks did you consume each day during a TYPICAL week during the past month? – Thursday
R.Alc9_6	How many standard drinks did you consume each day during a TYPICAL week during the past month? – Friday
R.Alc9_7	How many standard drinks did you consume each day during a TYPICAL week during the past month? – Saturday
R.Alc10_1	How many standard drinks did you consume each day during the week of HEAVIEST consumption last month? – Sunday
R.Alc10_2	How many standard drinks did you consume each day during the week of HEAVIEST consumption last month? – Monday
R.Alc10_3	How many standard drinks did you consume each day during the week of HEAVIEST consumption last month? – Tuesday
R.Alc10_4	How many standard drinks did you consume each day during the week of HEAVIEST consumption last month? – Wednesday
R.Alc10_5	How many standard drinks did you consume each day during the week of HEAVIEST consumption last month? – Thursday
R.Alc10_6	How many standard drinks did you consume each day during the week of HEAVIEST consumption last month? – Friday
R.Alc10_7	How many standard drinks did you consume each day during the week of HEAVIEST consumption last month? – Saturday
Risky Behavior Inventory- Substance use	
R.Sub1	Have you ever smoked a cigarette?
R.Sub1a	How old were you the first time you smoked a cigarette?

Variable Name	Description
R.Sub1b	How many times have you smoked cigarettes in the last 30 days?
R.Sub1e	How many times have you smoked cigarettes in the last 6 months?
R.Sub1g	For an average week, how many times do you smoke cigarettes?
R.Sub2	Have you ever used tobacco not in cigarette form (i.e., chewing tobacco)?
R.Sub2a	How old were you the first time you used tobacco not in cigarette form (i.e., chewing tobacco)?
R.Sub2b	How many times have you used tobacco not in cigarette form in the last 30 days?
R.Sub2e	How many times have used tobacco not in cigarette form in the last 6 months?
R.Sub2g	For an average week, how many times do you use tobacco not in cigarette form?
R.Sub3	Have you ever used marijuana (smoked or other method)?
R.Sub3a	How old were you the first time you used marijuana?
R.Sub3b	How many times have you used marijuana in the last 30 days?
R.Sub3e	How many times have used marijuana 6 months?
R.Sub3g	For an average week, how many times do you use marijuana?
R.Sub14	Have you ever used a substance not yet mentioned to get high?
R.Sub14b	How old were you the first time you used this substance?
R.Sub14c	How many times have you used this substance in the last 30 days?
R.Sub14f	How many times have you used this substance in the last 6 months
R.Sub14d	How many times in your life have you used this substance?
R.Sub14h	For an average week, how many times do you use this substance?
R.Sub16	Have you ever used a combination of substances to get a better high?
R.Sub16b	How many times have you combined these drugs in the last 30 days?
R.Sub16d	How many times have you combined these drugs in the last 6 months?
R.Sub16c	How many times in your life have you combined these drugs?
R.Sub18	On how many of the last 30 days did you hang out with more than 3 people in a social situation (including parties) where drugs or alcohol were present?[If you wish to not respond, please enter -99 to continue]
R.Sub18a	In how many of these situations did you use alcohol or drugs to the point of being drunk or high?
R.Sub19	Have you ever used alcohol or drugs to the point of being drunk or high when you were alone?
R.Sub19a	In the last 30 days, how many days were you alone when you used drugs or alcohol?
R.Sub19c	In the last 6 months, how many days were you alone when you used drugs or alcohol?
R.Sub19b	On how many days in your lifetime were you alone when you used drugs or alcohol?
R.Sub20	On how many of the last 30 days did you use any alcohol or drugs to the point of being drunk or high regardless of where you were or who you were with?
R.Sub21	Have you ever gone to school or work while drunk or high?
R.Sub21a	How many times did you go to school while you were drunk or high in the last 30 days?
R.Sub21c	How many times in your life did you go to school while you were drunk or high?
R.Sub22	Have you ever missed school, work, or social engagements because you were drunk or high?
R.Sub23	Have you ever used alcohol or drugs while driving? (do not count medication taken for medical reasons)
R.Sub26	Have you ever self-harmed (cut yourself, burned yourself, bit yourself, etc.) while drunk or high?
R.Sub29	Have you ever used alcohol or drugs in the morning/when you first wake up (not including caffeine or tobacco) to get drunk or high?
R.Sub29a	How many times have you used alcohol or drugs in the morning/when you first wake up during the last 30 days?
R.Sub29c	How many times in your life have you used alcohol or drugs in the morning/when you first wake up?

Variable Name	Description
R.Sub33	Have you ever been in treatment for alcohol or drug abuse or dependence/addiction?
Risky Behavior Inventory- Sex	
R.Sex2	Have you ever performed oral sex on anyone?
R.Sex2a	How old were you the first time you performed oral sex on someone?
R.Sex2b	How many times in the last 30 days have you performed oral sex on someone?
R.Sex2c	How many different people have you performed oral sex on in the last 30 days?
R.Sex2d	How many times in the last 12 months have you performed oral sex on someone?
R.Sex2e	How many different people have you performed oral sex on in the last 12months?
R.Sex2f	How many times in your life have you performed oral sex on someone?
R.Sex2g	How many different people have you performed oral sex on in your life?
R.Sex3	Have you ever had oral sex performed on you?
R.Sex3a	How old were you the first time oral sex was performed on you?
R.Sex3b	How many times in the last 30 days was oral sex performed on you?
R.Sex3c	How many different people have performed oral sex on you in the last 30days?
R.Sex3d	How many times in the last 12 months was oral sex performed on you?
R.Sex3e	How many different people have performed oral sex on you in the last 12months?
R.Sex3f	How many times in your life has oral sex been performed on you?
R.Sex3g	How many different people have performed oral sex on you in your life?
R.Sex4	Have you ever had vaginal intercourse?
R.Sex4a	How old were you the first time you had vaginal intercourse?
R.Sex4b	How many times in the last 30 days have you had vaginal intercourse?
R.Sex4c	How many different people have you had vaginal intercourse with in the last 30 days?
R.Sex4d	How many times in the last 12 months have you had vaginal intercourse?
R.Sex4e	How many different people have you had vaginal intercourse with in the last 12 months?
R.Sex4f	How many times in your life have you had vaginal intercourse?
R.Sex4g	How many different people have you had vaginal intercourse with in your life?
R.Sex4h	Have you ever had UNPROTECTED vaginal intercourse?
R.Sex4i	How old were you the first time you had UNPROTECTED vaginal intercourse?
R.Sex4j	How many times in the last 30 days have you had UNPROTECTED vaginal intercourse?
R.Sex4k	How many different people have you had UNPROTECTED vaginal intercourse with in the last 30 days?
R.Sex4l	How many times in the last 12 months have you had UNPROTECTED vaginal intercourse?
R.Sex4m	How many different people have you had UNPROTECTED vaginal intercourse with in the last 12 months?
R.Sex4n	How many times in your life have you had UNPROTECTED vaginal intercourse?
R.Sex4o	How many different people have you had UNPROTECTED vaginal intercourse with in your life?
R.Sex4p	How many of these people were you in a serious, committed, monogamous relationship with at the time you were having UNPROTECTED vaginal intercourse with them?
R.Sex4q	Of these, how many did you have UNPROTECTED vaginal intercourse with when you first met, before you were in a relationship with them?
R.Sex4r	Have you ever had UNDER PROTECTED vaginal intercourse?
R.Sex4s	How old were you the first time you had UNDER PROTECTED vaginal intercourse?
R.Sex4t	How many times in the last 30 days have you had UNDER PROTECTED vaginal intercourse?
R.Sex4u	How many different people have you had UNDER PROTECTED vaginal intercourse with in the last 30 days?

Variable Name	Description
R.Sex4v	How many times in the last 12 months have you had UNDER PROTECTED vaginal intercourse?
R.Sex4w	How many different people have you had UNDER PROTECTED vaginal intercourse with in the last 12 months?
R.Sex4x	How many times in your life have you had UNDER PROTECTED vaginal intercourse?
R.Sex4y	How many different people have you had UNDER PROTECTED vaginal intercourse with in your life?
R.Sex4z	How many of these people were you in a serious, committed, monogamous relationship with at the time you were having UNDER PROTECTED vaginal intercourse with them?
R.Sex4aa	Of these, how many did you have UNDER PROTECTED vaginal intercourse with when you first met, before you were in a relationship with them?
R.Sex5	Have you ever had anal intercourse?
R.Sex5a	How old were you the first time you had anal intercourse?
R.Sex5b	How many times in the last 30 days have you had anal intercourse?
R.Sex5c	How many different people have you had anal intercourse with in the last 30 days?
R.Sex5d	How many times in the last 12 months have you had anal intercourse?
R.Sex5e	How many different people have you had anal intercourse with in the last 12 months?
R.Sex5f	How many times in your life have you had anal intercourse?
R.Sex5g	How many different people have you had anal intercourse with in your life?
R.Sex5h	Have you ever had UNPROTECTED anal intercourse?
R.Sex5i	How old were you the first time you had UNPROTECTED anal intercourse?
R.Sex5j	How many times in the last 30 days have you had UNPROTECTED anal intercourse?
R.Sex5k	How many different people have you had UNPROTECTED anal intercourse with in the last 30 days?
R.Sex5l	How many times in the last 12 months have you had UNPROTECTED anal intercourse?
R.Sex5m	How many different people have you had UNPROTECTED anal intercourse with in the last 12 months?
R.Sex5n	How many times in your life have you had UNPROTECTED anal intercourse?
R.Sex5o	How many different people have you had UNPROTECTED anal intercourse with in your life?
R.Sex5p	How many of these people were you in a serious, committed, monogamous relationship with at the time you were having UNPROTECTED anal intercourse with them?
R.Sex5q	Of these, how many did you have UNPROTECTED anal intercourse with when you first met, before you were in a relationship with them?
R.Sex7	Have you ever had a sexual encounter (oral, vaginal and/or anal sex) with a member of the same sex as you?
R.Sex7a	How old were you the first time you had a sexual encounter with someone of the same sex as you?
R.Sex7b	How many times in the last 30 days have you had a sexual encounter with someone of the same sex as you?
R.Sex7c	How many different people of the same sex have you had a sexual encounter with in the last 30 days?
R.Sex7d	How many times in the last 12 months have you had a sexual encounter with someone of the same sex as you?
R.Sex7e	How many different people of the same sex have you had a sexual encounter with in the last 12 months?
R.Sex7f	How many times in your life have you had a sexual encounter with someone of the same sex as you?
R.Sex7g	How many different same sex partners have you had sexual intercourse with in your life?
R.Sex7h	Have you ever had UNPROTECTED vaginal or anal intercourse with a member of the same sex has you?
R.Sex7i	How many different same sex partners have you had UNPROTECTED vaginal or anal intercourse with in your life?

Variable Name	Description
R.Sex7j	How many of these same sex partners were you in a serious, committed, monogamous relationship with at the time you were having UNPROTECTED vaginal or anal intercourse with them?
R.Sex7k	Of these, how many did you have UNPROTECTED vaginal or anal intercourse with when you first met, before you were in a relationship with them?
R.Sex9	Have you ever had a one-night stand--a single sexual encounter (oral, vaginal, and/or anal sex) without an immediate plan for forming a long-term sexual or romantic relationship with the other individual?
R.Sex9a	How old were you the first time you had a one-night stand?
R.Sex9b	How many times in the last 30 days have you had a one-night stand?
R.Sex9c	How many different people have you had a one-night stand with in the last 30 days?
R.Sex9d	How many times in the last 12 months have you had a one-night stand?
R.Sex9e	How many different people have you had a one-night stand with in the last 12 months?
R.Sex9f	How many times in your life have you had a one-night stand?
R.Sex9g	How many different people have you had a one-night stand with?
R.Sex9h	Have you ever had UNPROTECTED vaginal or anal intercourse during a one-night stand?
R.Sex9i	How many different people have you had UNPROTECTED vaginal or anal intercourse as part of a one-night stand with in your life?
R.Sex9j	Have you ever had UNDER PROTECTED vaginal intercourse during a one-night stand?
R.Sex9k	How many different people have you had UNDER PROTECTED vaginal intercourse as part of a one-night stand with in your life?
R.Sex11	Have you ever cheated on a partner in any way?
R.Sex11a	How old were you the first time you cheated on a partner?
R.Sex11b	How many times in the last 30 days have you cheated on a partner?
R.Sex11c	How many different people have you cheated on a partner with in the last 30 days?
R.Sex11d	How many times in the last 12 months have you cheated on a partner?
R.Sex11e	How many different people have you cheated on a partner with in the last 12 months?
R.Sex11f	How many times in your life have you cheated on a partner?
R.Sex11g	How many different people have you cheated on a partner with in your life?
R.Sex11i	Have you ever had UNPROTECTED vaginal or anal intercourse while cheating on a partner?
R.Sex11j	How many different people did you have UNPROTECTED vaginal or anal intercourse with while cheating on a partner in your life?
R.Sex11k	Have you ever had UNDER PROTECTED vaginal intercourse while cheating on a partner?
R.Sex11m	Did you cheat on a partner for the excitement/rush/dangerousness of the experience?
R.Sex12	Have you ever had a sexual encounter (oral, vaginal, and/or anal sex) in exchange for alcohol, drugs, money, or other goods or services?
R.Sex13	In your entire life how many DIFFERENT people have you had a sexual encounter with?
R.Sex15	How often do you use condoms when having vaginal or anal intercourse with a serious partner?
R.Sex16	How often do you use condoms when having vaginal or anal intercourse with casual partners?
R.Sex17	How often do you use other forms of contraception besides condoms (i.e., birth control pills/patch/shot/ring, IUDs, spermicidal foam, etc.) when having vaginal intercourse?
R.Sex18	Have you ever gotten tested for sexually transmitted diseases or infections?
R.Sex25	Do you ask your partners if they have been recently tested for sexual transmitted diseases or infections before having sex?
R.Sex25a	What reason have you had for not asking your partner(s) if they have been recently tested for sexual transmitted diseases or infections? (Please check one response that is the most appropriate).
R.Sex25b	How many of these people were you in a serious, committed, monogamous relationship with at the time you were having sexual intercourse?

Variable Name	Description
R.Sex25c	How many did you have sexual intercourse with, using withdrawal, when you first met, before you were in a relationship with them?
R.Sex27	Have you have ever relied on withdrawal (i.e. "pull-out") as your method of contraception?
R.Sex27a	How many times have you relied on withdrawal (i.e. "pull-out") as your method of contraception?
Risky Behavior Inventory- Crime	
R.Cri1	Have you ever driven an automobile while underage?
R.Cri1b	Have you ever been arrested for or charged with driving while underage?
R.Cri1c	How many times have you been convicted for underage driving?
R.Cri2	Have you ever driven without a valid driver's license (count expired, suspended, or revoked licenses or not having gotten a license, do not count simply driving without your driver's license with you)?
R.Cri2b	Have you ever been arrested for or charged with driving without a valid driver's license?
R.Cri2c	How many times have you been convicted for driving without a valid driver's license?
R.Cri3	Have you ever operated a motorized vehicle under the influence of drugs or alcohol?
R.Cri3b	Have you ever been arrested for or charged with driving without operated a motorized vehicle under the influence of drugs or alcohol?
R.Cri3c	How many times have you been convicted for operating a motorized vehicle under the influence of drugs or alcohol?
R.Cri7	Have you ever ridden in a car with someone who was driving while drunk or high?
R.Cri7b	Have you ever been arrested for or charged with riding in a car with someone who was driving while drunk or high?
R.Cri7c	How many times have you been convicted for riding in a car with someone who was driving while drunk or high?
R.Cri11	When underage, did you ever violate the curfew laws of your area?
R.Cri11b	Have you ever been arrested for or charged with violating curfew laws?
R.Cri11c	How many times have you been convicted for violating curfew?
R.Cri13	Have you ever shoplifted items?
R.Cri13b	Have you ever been arrested for or charged with shoplifting?
R.Cri13c	How many times have you been convicted for shoplifting?
R.Cri17	Have you ever vandalized (damage, defacement, graffiti, tagging, etc.) public or private property?
R.Cri17c	How many times have you been convicted for vandalizing public or private property?
R.Cri18	Have you ever purchased alcohol or tobacco while under the legal age?
R.Cri18c	How many times have you been convicted with purchasing alcohol or tobacco while under the legal age?
R.Cri20	Have you ever sold illegal drugs?
R.Cri20a	Would/did you consider yourself a drug dealer?
R.Cri21	Have you ever carried a concealed weapon (include guns, knives, etc.)?
R.Cri21c	Have you ever been arrested for or charged with carrying a concealed weapon?
R.Cri21d	How many times have you been convicted carrying a concealed weapon?
R.Cri24	Have you ever purposely harmed an animal?
R.Cri24c	How many times have you been convicted for harming an animal?
R.Cri25	Have you ever purposely set a fire to structures or wilderness area?
R.Cri25c	Have you ever been arrested for or charged with purposely setting a fire to a structure or wilderness area?
R.Cri25d	How many times have you been convicted for purposely setting a fire to a structure or wilderness area?

Variable Name	Description
R.Cri28	Have you ever taken a vehicle (car, motorcycle, boat, etc.) owned by someone you know (include family members) without their permission or against their wishes? Only include times when you planned on returning the vehicle.
R.Cri28a	Was this for joyriding?
R.Cri28b	Did you have a valid driver's license when you did this?
R.Cri28d	Have you ever been arrested for or charged with taking a vehicle without permission?
R.Cri29	Have you ever stolen a vehicle (car, motorcycle, boat, etc.)? Only include times when you did not plan on returning the vehicle.
R.Cri30	Have you ever gone into a structure (home, business, abandoned building) that you did not have permission to go in?
R.Cri30a	Was this with the intent to commit any crime inside (include to use drugs as a crime)?
R.Cri30d	Have you ever been arrested for or charged with going into a structure that you did not have permission to go in?
R.Cri30e	How many times have you been convicted for going into a structure that you did not have permission to go in?
R.Cri32	Have you ever assaulted another person (include physical fights)?
R.Cri32b	Have you ever been arrested for or charged with assaulting another person?
R.Cri32c	How many times have you been convicted for assaulting another person?
R.Cri37	Have you engaged in any other illegal activities that you have not already reported?
R.Cri37b	How many times have you done this illegal activity?
R.Cri37d	How many times have you been convicted for doing this illegal activity?
R.Cri38	Have you ever run from the police?

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APPENDIX B

POTENTIAL OUTLIERS AND THEIR 95TH PERCENTILES

Table 2-A

Potential Outliers and Their 95th Percentiles

Variable	College Sample 95th Percentile	Clinical Sample 95th Percentile
FAFSI63	190	495
FAFSI64	22	100
FAFSI65	2	32
R.Alc2	15	15
R.Alc3	10	10
R.Alc4	2	5
R.Alc6	10	10
R.Alc7	15	15
R.Alc8	8	10
R.Alc9_1	1	4
R.Alc9_2	0	2
R.Alc9_3	1	3
R.Alc9_4	1	3
R.Alc9_5	5	2
R.Alc9_6	10	9
R.Alc9_7	10	10
R.Alc10_1	3	7
R.Alc10_2	2	6
R.Alc10_3	2	6
R.Alc10_4	4	7
R.Alc10_5	7	6
R.Alc10_6	12	12
R.Alc10_7	12	12
R.Sub1b	53	183
R.Sub1e	215	345
R.Sub1g	8	8
R.Sub2b	30	7
R.Sub2e	100	51
R.Sub2g	8	1
R.Sub3b	50	78
R.Sub3e	300	860
R.Sub3g	9	9
R.Sub14c	30	9

Variable	College Sample 95th Percentile	Clinical Sample 95th Percentile
R.Sub14f	100	19
R.Sub14d	397	69
R.Sub14h	7	3
R.Sub16b	10	10
R.Sub16d	50	30
R.Sub16c	262	300
R.Sub19a	20	27
R.Sub19c	100	96
R.Sub19b	365	195
R.Sub21a	20	30
R.Sub21c	268	200
R.Sub29a	30	20
R.Sub29c	500	470
R.Sex2b	10	11
R.Sex2c	2	2
R.Sex2d	80	50
R.Sex2e	5	6
R.Sex2f	200	100
R.Sex2g	13	12
R.Sex3b	15	10
R.Sex3c	2	2
R.Sex3d	90	43
R.Sex3e	6	5
R.Sex3f	200	89
R.Sex3g	14	10
R.Sex4b	20	19
R.Sex4c	2	2
R.Sex4d	200	100
R.Sex4e	6	9
R.Sex4f	600	109
R.Sex4g	16	12
R.Sex4h	1	1
R.Sex4j	20	20
R.Sex4k	2	3
R.Sex4l	150	100
R.Sex4m	4	7
R.Sex4n	361	157
R.Sex4o	9	9
R.Sex4p	4	4
R.Sex4q	5	5
R.Sex4r	1	1
R.Sex4t	20	15
R.Sex4u	2	1

Variable	College Sample 95th Percentile	Clinical Sample 95th Percentile
R.Sex4v	200	100
R.Sex4w	5	6
R.Sex4x	400	110
R.Sex4y	10	9
R.Sex4z	4	2
R.Sex4aa	5	5
R.Sex5b	3	3
R.Sex5c	1	1
R.Sex5d	15	6
R.Sex5e	3	3
R.Sex5f	30	8
R.Sex5g	4	3
R.Sex5h	1	1
R.Sex5j	3	3
R.Sex5k	1	1
R.Sex5l	19	6
R.Sex5m	3	4
R.Sex5n	30	6
R.Sex5o	4	4
R.Sex5p	2	1
R.Sex5q	2	3
R.Sex7b	14	3
R.Sex7c	2	2
R.Sex7d	60	30
R.Sex7e	7	3
R.Sex7f	150	18
R.Sex7g	16	5
R.Sex7h	1	1
R.Sex7i	10	5
R.Sex7j	4	2
R.Sex7k	6	3
R.Sex9b	2	2
R.Sex9c	2	2
R.Sex9d	8	7
R.Sex9e	7	6
R.Sex9f	17	11
R.Sex9g	12	8
R.Sex9h	1	1
R.Sex9i	10	12
R.Sex9j	1	1
R.Sex9k	10	2
R.Sex11b	1	4
R.Sex11c	1	3

Variable	College Sample 95th Percentile	Clinical Sample 95th Percentile
R.Sex11d	4	8
R.Sex11e	2	4
R.Sex11f	10	18
R.Sex11g	4	6
R.Sex11i	1	1
R.Sex11j	8	3
R.Sex11k	1	0
R.Sex11l	3	1
R.Sex11m	3	4
R.Sex13	40	12
R.Sex25a	9	9
R.Sex25b	4	2
R.Sex25c	4	4
R.Sex27a	200	59
R.Cri1b	0	0
R.Cri1c	0	1
R.Cri2b	1	1
R.Cri2c	0	1
R.Cri3b	1	0
R.Cri3c	0	26
R.Cri7b	0	0
R.Cri7c	0	8
R.Cri11b	1	1
R.Cri11c	1	10
R.Cri13b	1	1
R.Cri13c	1	2
R.Cri17b	1	0
R.Cri17c	0	2
R.Cri18b	0	0
R.Cri18c	0	1
R.Cri20a	1	1
R.Cri20c	0	0
R.Cri20d	0	0
R.Cri21c	0	1
R.Cri21d	0	1
R.Cri24b	0	0
R.Cri24c	0	2
R.Cri25a	0	0
R.Cri25c	1	1
R.Cri25d	0	1
R.Cri28a	1	1
R.Cri28b	1	1
R.Cri28d	0	1

Variable	College Sample 95th Percentile	Clinical Sample 95th Percentile
R.Cri28e	0	1
R.Cri29a	0	1
R.Cri29b	1	0
R.Cri29d	0	0
R.Cri29e	0	0
R.Cri30a	1	1
R.Cri30d	0	1
R.Cri30e	0	1
R.Cri32b	1	1
R.Cri32c	0	3
R.Cri37b	100	137
R.Cri37c	1	0
R.Cri37d	2	1