A Longitudinal Study of Speculative Trading Activities and Health Correlates in Young Adults

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Abstract

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Problem gambling is a significant public health concern linked to profound behavioral health consequences, particularly for young adults who are affected by higher vulnerability to risky behaviors. In the backdrop of online gambling's growing popularity, speculative short-term trading of stocks and cryptocurrencies (e.g., Bitcoin) have seen major gains in popularity among young adults. Emerging evidence suggests speculative trading entails many of the same risks and harms as traditional gambling, warranting efforts to explore and minimize trading-related health harms. The present study investigated behavioral health and substance use correlates of young adult speculative trading through a longitudinal study design utilizing generalized linear mixed models (GLMMs). The study aimed to 1) evaluate between-person associations between trading and health indices, 2) assess within-person associations between trading and health indices, and 3) explore moderators of the relationship between trading and health indices based on

theoretically supported links. We hypothesized that greater speculative trading activity would predict greater depression, anxiety, and substance use behaviors at both between-person and within-person levels. The results demonstrated a positive between-person association between trading frequency and nicotine use intensity. They also highlighted the roles of financial stress, sensation seeking, perceived norms and attitudes towards trading in moderating trading's connections to behavioral health and substance use. Descriptive statistics from the study yielded additional key insights into trading behaviors and related harms in our cohort of young adults. Theoretically and empirically supported explanations and potential implications are discussed. The current study serves as the first of its kind known to assess the longitudinal associations between speculative trading activities and health correlates among young adults.

Introduction

Gambling and Problem Gambling: Definition and Prevalence

Gambling behaviors are defined as activities in which items of value (e.g., money) are wagered upon outcomes largely influenced by chance (King & Delfabbro, 2020). Gambling is a widespread activity, with 85% of adults in the United States estimated to have participated in gambling over their lifetime (National Council on Problem Gambling, 2024). In 2021, US legal gambling revenue was estimated to be $215 billion dollars, encompassing activities such as land-based casino games, slot machines, lottery ticket sales, offline and online sports betting activities, and representing a more than threefold increase over the past two decades on an inflation adjusted basis (Friess, 2022).

Alongside increasing availability of gambling in the past two decades, prevalence and scope of gambling have also grown in part due to the increased diversity of those who partake, increased social acceptability of gambling, and myriad novel gambling options that cater to a wider range of people and interests (Abbott, 2020; Wardle, 2019). Notably, many of the novel gambling options increasing in popularity (e.g., online sports betting and sophisticated card games) focus on the user believing they possess a skill or knowledge as opposed to activities purely determined by chance (e.g., lottery, slot machines). While risks and harms associated with traditional gambling are relatively well-documented, far less is known about the risks and harms of novel forms of gambling that are rapidly increasing in popularity (Kolandai-Matchett & Wenden, 2021).

While most people who participate in gambling experience few negative consequences, some of them have difficulty controlling their gambling behaviors and experience disproportionately large gambling-related harms (Potenza et al., 2002). Problem gambling refers to such persistent gambling behaviors despite negative consequences (Livazović et al., 2019; Raylu et al., 2002). Problem gambling has clear adverse associations with various mental health concerns (Johnstone & Regan, 2020), and there are negative interpersonal impacts of gambling behaviors that impact those around people with problem gambling, including criminal activities and abuse/neglect of partners and children (Wardle et al., 2019). These issues are concerning given the prevalence of problem gambling which is estimated at around 1 to 3% worldwide (Tran et al., 2024).

Problem Gambling: Wide-ranging Consequences and Comorbidities

Problem gambling is a significant public health concern associated with risk of profound harm to individuals, their social networks, and the society as a whole (Wardle et al., 2019). At the individual level, problem gambling is a salient risk factor for a wide range of negative mental and physical health consequences (Cowlishaw et al., 2017; Livazović et al., 2019). Problem gambling is linked to increased suicide attempts and completions (Lee et al., 2021; Nower et al., 2007), and estimates from data collected across Sweden show a 15 times higher suicide mortality risk among adults aged 20-74 with gambling disorder compared to the age-matched overall population (Karlsson et al., 2018). Problem gamblers are also more likely to struggle from debt-related stress (Swanton et al, 2020) and suffer physical ailments such as cardiovascular and gastrointestinal problems (Shaffer et al., 2002).

Problem gambling has also been linked to disruptions in relationships and families (Arthur et al., 2014; Bland, et al., 1993; Thompson et al., 1997), abuse or neglect of partners and children (Suomi et al., 2018; Wardle et al., 2019) and negative societal outcomes such as higher rates of homelessness (Holdsworth & Tiyce, 2013) and criminal activities. Despite these detrimental health and social consequences linked to problem gambling, it has rarely received attention as a significant public health concern (Cunningham-Williams et al., 1998; Shaffer & Korn, 2002; Johnstone & Regan, 2020), and thus advances in gambling research and treatment have been largely neglected and underfunded.

Various studies have assessed links between problem gambling and comorbid conditions including substance use disorders, mood disorders, personality disorders, attention deficit hyperactivity disorder (ADHD) (Grall-Bronnec et al., 2011; Karlsson et al., 2018; Lee et al., 2021; Romo et al., 2018). In particular, problem gambling and substance use disorders comorbidity is particularly commonplace, with lifetime substance use disorders in people with problem gambling estimated to be as high as 57% (Lorains et al., 2011). Among all substances, alcohol and tobacco/nicotine use problems have been most frequently reported among problem gamblers, with alcohol use disorder found in up to 75% and nicotine dependence found in 60% of problem gamblers (Grant et al., 2020; McGrath et al., 2009). Rates of drug problems are estimated to be 4 to 7 times higher among problem gambling compared to non-gamblers or recreational gamblers (Kessler et al., 2008; Potenza, 2017).

Young Adult Problem Gambling

Young adulthood is a developmental period characterized by high vulnerability to problem gambling (Calado et al., 2017; Shaffer et al., 1999). Younger age is in fact one of the most salient risk factors for both gambling activity participation and problem gambling consequences, consistent with past findings that young adults are in a vulnerable developmental period for risk-taking behaviors in general, exhibiting more behaviors such as violence, drug use, sexual and financial risk-taking compared to older adults (Romer, 2010; Steinberg, 2008).

Among all age groups, young adults have been documented to have the highest prevalence of problem gambling (Derevensky, 2019; Hodgins et al., 2011; Volberg et al., 2010).

Gambling is an increasingly popular activity among young adults (Hollén et al., 2020). In 2011-2013, past year prevalence of gambling among young adults aged 18-29 in the US was 78.1% (Welte et al., 2015). In 2020, lifetime prevalence of gambling among young adults aged 18-29 in Maryland was 85.2% (Tracy et al., 2020). While there are few identified longitudinal datasets on gambling participation rates among young adults in the US, survey data point to increasing rates of gambling participation in recent years along with the wider availability of gambling activities (The Annenberg Public Policy Center of the University of Pennsylvania, 2008; 2010; Lehman, 2024; Rainone et al., 2007; U.S. Department of Justice Office of Justice Programs, 2009).

Problem gambling in young adults carries public health significance because of their high – and rising – prevalence of gambling activity participation (Allami et al., 2021; Barrera-Algarín & Vázquez-Fernández, 2021; Welte et al., 2015). Furthermore, early onset of gambling behaviors is related to greater gambling involvement and problem gambling throughout later adulthood (Burge et al., 2004). As such, early prevention would be a prudent investment into the larger issue of problem gambling at the population level. Early prevention efforts are also pertinent as young adulthood is a critical period for the onset of other addictive disorders and mental disorders, with which gambling disorder is known to be highly comorbid (Floros, 2018; Grant & Chamberlain, 2020; Sussman & Arnett, 2014), suggesting that the prevention and treatment of gambling problems in young adults could reduce the risk of other comorbid disorders (Grant & Chamberlain, 2020; Szerman et al., 2020).

Concerningly, between 4 and 8 percent of young adults report serious gambling problems, with another 10 to 15 percent at risk for the development of serious gambling problems in the future (Delfabbro et al., 2016; Gupta & Derevensky, 2000). In comparison, overall adult problem gambling rates are estimated at between 1 and 3 percent (Calado & Griffiths, 2016; Welte et al., 2015).

Among young adults, several features have been identified as key risk factors of problem gambling. Males (based on sex assigned at birth) reported both greater participation in gambling and gambling problems than females (Kang et al., 2019; Sanscartier et al., 2019), specifically socioemotional harms from problem gambling (Melendez-Torres et al., 2019). Another key factor is the attitude of family members and friends toward gambling; young adults were more likely to view gambling positively, engage in gambling, and have gambling problems if their family members or friends had positive attitudes toward gambling (Canale et al., 2016). A related risk factor is the perceived social norm of gambling, such that perceiving greater gambling activity and endorsement as the norm predicted increased risk of problem gambling (Marchica & Derevensky, 2016; Moore & Ohtsuka, 1999). Excitement or sensation seeking tendencies was also a strong predictor of young adult problem gambling (Donati et al., 2020; Pisarska et al., 2020), consistent with known associations between sensation seeking and other high risk behaviors, notably substance use (Farhat et al., 2021) which is itself commonly cited as a risk factor of young adult problem gambling – especially alcohol (Buja et al., 2019; Jaisoorya et al., 2017) and tobacco use (Jaisoorya et al., 2017; Weinberger et al., 2015). Lacking social connectedness, including being the only child (Sharman et al., 2019), poor parental attachment (Gori et al., 2015; Jauregui & Estévez, 2020) – which has been shown to be mediated by alexithymia (condition that makes identifying, understanding, and expressing emotions difficult;

Estévez et al., 2021) – and poor social connectedness at school (Melendez-Torres et al., 2020) were also linked to gambling problems in young adults. Lastly, participation in skill-based online gambling activities such as online poker games was associated with higher risk of problem gambling in young adults (Oksanen et al., 2018).

Common Theories of Young Adult Problem Gambling

Several theories of young adult problem gambling behaviors have received empirical support to date. First among them is the theory of reasoned action (TRA)/theory of planned behavior (TPB) (Ajzen, 1991; Ajzen & Fishbein, 1980). TRA proposes that the immediate cause of any volitional behavior is an individual's intention to engage in that behavior, which represents motivation expressed as a conscious plan to exert effort in performing the behavior. Intentions to perform the behavior are determined by the individual's attitudes and subjective norms (Ajzen & Fishbein, 1980). Later, to address TRA's lack of consideration for environmental constraints, the theory of planned behavior (TPB) was proposed, incorporating perception of control over performance of the behavior as an additional predictor of behavior (Ajzen, 1991). In the TPB, perceived behavioral control moderates the relationship between intentions and future behaviors.

The TPB model has received empirical support for young adult problem gambling behaviors. In a cohort of young adults, the key components of TPB (attitudes, subjective norms, intentions, and perceived behavioral control) have been shown to predict increased likelihood of and greater frequency of gambling behaviors, and intention to gamble mediated the link between gambling frequency and the other TPB determinants (Martin et al., 2010). In the same sample, for problem gamblers gambling-related attitudes independently predicted gambling frequency as opposed to being mediated by intention to gamble (Martin et al., 2011). In another study with young adults, positive gambling attitudes, positive subjective norms regarding gambling, and poor perceived control over gambling accounted for as much as 56% of explained variance in intention to gamble (Wu & Tang, 2012). The TPB model provides a salient explanation for the roles of attitudes toward gambling, perceived social norms of gambling, and impulsivity (difficulty with behavioral self control; Kalenscher et al., 2006) as risk factors of future problem gambling behaviors.

The TPB has also drawn comparisons to the Problem Behavior Theory (Jessor & Jessor, 1977; Schlegel et al., 2008), a theoretical framework seeking to explain the development and nature of behaviors that deviate from social and legal norms (e.g., substance use). The model comprises three systems of psychosocial influences, namely personality system (social cognitions, personal values, beliefs, and expectations), perceived environmental system (family and peer expectations), and the behavior system (problem and conventional behavioral structures that work in opposition to each other; Mckellar & Sillence, 2020). The theory (Jessor, 2016; Jessor & Jessor, 1977) posits an underlying link between dysfunctional behaviors through shared function (e.g., coping with stress, relieving boredom, achieving a sense of excitement) such that involvement in one problem behavior contributes to the likelihood and level of engagement in another and thus implicates substance use and other problem behaviors as risk factors of problem gambling in young adults. While the Problem Behavior Theory has been conceptually applied in understanding problem gambling behaviors (Wickwire et al., 2008; Zangeneh et al., 2010), it has not yet received empirical support in this domain.

The theoretical framework that has gained the most significant empirical support in young adult problem gambling to date is the Pathways Model, developed specifically for subtyping the development of problem gambling (Blaszczynski & Nower, 2002). The Pathways

Model proposes three clinically relevant distinct subgroups of problem gambling: behaviorally conditioned subgroup with a lack of premorbid social and psychological pathology, emotionally vulnerable subgroup with psychological deficits in self-efficacy and self-esteem, and antisocial impulsivist subgroup characterized by excessive pleasure-seeking (Blaszczynski & Nower, 2002). It has been empirically tested and supported in a wide range of clinical populations using relevant validated measures of subgroupings (Black & Allen, 2022; Bonnaire et al., 2022; Excell et al., 2022). Notably, the three subgroups have been validated in groups of young adults meeting the criteria for or at risk of problem gambling using the latent class analysis technique (Allami et al., 2017; Gupta et al., 2013), providing support for impulsivity, sensation seeking, and poor social connectedness as risk factors of problem gambling in young adults.

Online Gambling and Problem Gambling

One of the top factors contributing to the increasing prevalence of gambling in young adults in recent years is the development and proliferation of online gambling, given how closely intertwined young adults' lives are with technology (Kolandai-Matchett & Wenden, 2022). As internet and smartphone technologies have advanced, the past decade has seen rapid growth in novel forms of gambling that are understudied to date (Wardle et al., 2021). Online gambling possesses unique features that make participants more vulnerable to negative consequences than traditional (offline) gambling, including increased availability (i.e., available anywhere and anytime internet access is present), lower barrier to entry, greater access to money through online withdrawals, and ease of making frequent bets (McCormack & Griffiths, 2013; Wood et al., 2007). These online gambling-specific factors translate to higher likelihood of developing or exacerbating problem gambling symptoms, as demonstrated through data from countries with legalized online gambling (Hing et al., 2014; Hing et al., 2015; McBride & Derevensky, 2009).

For instance, in a 2007 British prevalence survey, fewer than 60% of online gamblers were classified as non-problem gamblers, compared with more than 80% of non-online (offline) gamblers (Griffiths et al., 2011). Longitudinal studies have yet to meaningfully establish the causation of online gambling-related problems, however (Gainsbury, 2015).

In the United States, online sports betting and online casino gaming have become legalized in an increasing number of states in recent years, notably since the Professional and Amateur Sports Protection Act of 1992 was overturned in 2018 effectively allowing all states to legalize and regulate sports betting including online sports betting (Purdum, 2018). As of January 2023, online sports betting was legal in 26 states, online casinos in six states, and online poker games in six states (PlayUSA, 2023). At least six other states are projected to legalize some form of online gambling in the near future, at which time 33 of 50 states and the District of Columbia will offer some form of legal online gambling (American Gaming Association, 2023; World Population Review, 2023). Through aggressive marketing efforts, social acceptability of online gambling has since grown substantially, especially online sports betting which is commonly advertised as a skill-based social activity rather than luck-based gambling (FinancialBuzz.com, 2021; Houghton et al., 2019; Lopez-Gonzalez & Griffiths, 2018; Lopez-Gonzalez et al., 2021).

The Rise of Speculative Trading among Young Adults

In the backdrop of the expanding popularity of online gambling, online trading of stocks and cryptocurrencies (e.g., Bitcoin) have also seen major gains in popularity, especially among young adults (Perrin, 2021; Steinmetz et al., 2021). Online trading is increasingly facilitated through smartphone applications which provide access to financial trading anywhere and anytime internet access is available, in a similar way that gambling and sports betting applications have enabled nearly ubiquitous and instant access to gambling.

Speculative trading is the act of conducting financial transactions that have a substantial risk of losing money but also hold the expectation of a significant gain for short term profits (Nguyen, 2022). Speculative trading is more volatile than traditional investing which is focused on long term profits, and speculative traders believe they can offset the risk of loss through substantial gains from profitable trades over a repeated process. Speculative traders typically seek to close their positions (e.g., sell the stocks they bought) within short time windows, ranging from several seconds to several days, with a goal of consistently making profitable predictions.

Speculative trading activities are appealing to young adults as they often underestimate their risks and overestimate the likelihood of realizing substantial profits, viewing the activity as a low-risk form of investment (Arthur et al., 2016) when in fact, without proper discipline and knowledge, they are more akin to casino gambling than investing (Delfabbro et al., 2021b). Unlike legal gambling activities, speculative trading is regulated as a form of investment by agencies such as the Securities and Exchange Commission and Financial Industry Regulatory Authority and is accessible to all adults in every jurisdiction in the United States.

For minors (those who are under 18 years of age), trading stocks and derivatives generally requires parental consent and using a custodial account; however, anecdotal evidence from crowdsourced web forums indicates that, like with legal forms of gambling, minors can and do gain access trading platforms through available means without parental consent (Quora, 2019; 2021). Since there is no legal age requirement for cryptocurrency ownership, even though U.S.-based cryptocurrency trading platforms impose age limits, minors can easily access means to buy and trade them using alternative methods (Peters, 2022). Thus, concerns of speculative trading-related harms among minors are also warranted.

Speculative Trading as Gambling: Similarities

While the scope of harms associated with speculative trading have yet to be fully evaluated, there is early indication that speculative trading behaviors entail many of the same risks and harms as traditional gambling, and perhaps to an even greater extent given their great accessibility and common misperception that these are low-risk forms of investing (Delfabbro et al., 2021a; Newall et al., 2022). Recent studies have highlighted similarities between speculative trading and gambling across several key dimensions. Key behavioral features of problem gambling have been identified among speculative traders (Delfabbro et al., 2021a; Mills et al., 2019), including losing control over their money, chasing losses, developing tolerance, and experiencing withdrawal symptoms (Arthur et al., 2016; Grall-Bronnec et al., 2017; Holtgraves, 2008; Williams et al., 2022). Shared personality traits, such as sensation-seeking and impulsiveness (Jadlow & Mowen, 2010; Markiewicz & Weber, 2013), and shared motivation for profit and entertainment (Newall et al., 2022; Tabri et al., 2022) between gamblers and speculative traders have also been noted. Gamblers and speculative traders were also found to share cognitive biases in their respective activities, including overconfidence bias, confirmation bias, and illusion of control (Arthur et al., 2016; Barber & Odean, 2001; Woolley et al., 2013).

Moreover, engagement in rapid online trading platforms has been found to be a predictor of problem gambling symptoms in a longitudinal study of adults who hold stock trading accounts (Oksanen et al., 2022). Several studies have also identified behavioral patterns among retail traders in Germany, Taiwan, and the United States indicating that stock and derivative trading and lottery gambling activities are negatively correlated with one another, acting as effective substitutes (Barber et al., 2009; Dorn et al., 2015; Gao & Lin, 2015).

Design and business practices of popular mobile trading platforms have also shown close resemblance to those of online gambling platforms. Mobile trading forms facilitate repeated trading activities within a short window of time which in turn increases the frequency with which individuals can trade, analogous to a common feature among gambling products used by individuals who experience gambling harms (Livingstone & Woolley, 2008; Newall and Cohen, 2022). First time users and existing users who refer first time users are rewarded with sign up bonuses similar to online gambling and sports betting platforms, often in the form of a randomly selected stock within a predefined value range which in itself introduces an element of randomness and is comparable to entering a raffle, a form of gambling (Robinhood Markets, 2023b; Webull, 2023). The trading platforms' visual design principles have also been cited to be similar to those employed in gambling platforms or casinos rather than investment platforms, exemplified by features such as full-screen visual reinforcements upon placing a trade, bold and bright color schemes, and constant notifications and nudges (Newall et al., 2022; Pasztor, 2021).

Harms of Speculative Trading

Importantly, emerging evidence suggests that speculative trading shares negative health harms with problem gambling. Recent media reports have identified instances of severe depression, sleep problems, and even suicide caused by speculative trading, all of them from young adult populations (Chang, 2022; Khorram et al., 2020; Verma, 2022). In a case study of adult speculative traders seeking help to curb their trading behaviors, behavioral dependence on trading, major depression, generalized anxiety disorder, and substance use disorder were identified; it is worth noting that half of the subjects demonstrated a causal relationship between their speculative trading and depression such that speculative trading caused depression based on analyses of temporal links (Grall-Bronnec et al., 2017). In the same study, negative functional outcomes, including detrimental financial consequences such as exorbitant debt problems, relationship difficulties, and job losses were reported in addition to adverse mental health consequences (Grall-Bronnec et al., 2017).

While these limited findings on the harms of speculative trading thus far mirror the known harms of gambling on mental health, empirical evidence on the subject is scarce (Delfabbro et al., 2021; Oksanen et al., 2022). A primary concern among researchers who are monitoring the rapid growth of speculative trading is the potential for mental health concerns, especially for young adults (Newall et al., 2022). Alongside the mental health comorbidities of speculative trading, substance use behaviors are an area of concern given emerging evidence of concurrent use in help-seeking populations including instances in which speculative trading was conceptualized as a substitute to substance use behavior (Grall-Bronnec et al., 2017; Sonkurt, 2023), in addition to robust evidence of gambling disorder-substance use disorder comorbidity (Black & Shaw, 2019). Given the known similarities between gambling and speculative trading across a range of domains suggesting speculative trading can act as a form of problem gambling – a dysfunctional behavior – for some individuals (Newall et al., 2022), a link between substance use and speculative trading can be explained by the Problem Behavior Theory (Jessor, 2016; Jessor & Jessor, 1977) which posits an underlying link between dysfunctional behaviors through shared function (e.g., coping with stress) such that involvement in one problem behavior contributes to the likelihood and level of engagement in another.

Need for Further Research on Young Adult Speculative Trading

In sum, given increasing prevalence of speculative trading in young adults (Perrin, 2021; Steinmetz et al., 2021), known similarities between speculative trading and gambling (Newall and Cohen, 2022), and burgeoning evidence of speculative trading's behavioral health harms in young adults (Delfabbro et al., 2021), efforts to minimize speculative trading-related negative consequences to health outcomes in this population should be prioritized as a public health concern. Although some prevention programming is available for traditional gambling behaviors, few have focused on young adults and none currently focus on speculative trading behaviors, which may require unique efforts given young adults typically do not view these behaviors within the same framework as traditional gambling (Hing et al., 2015).

In order to inform and guide speculative trading-focused prevention and intervention efforts in young adults, a deep and comprehensive understanding of the harms and risks of speculative trading in this population is needed, including the mechanism by which speculative trading may cause harm. Reviewing the empirically supported theoretical underpinnings of problem gambling (i.e., TPB and the pathways model; Ajzen, 1991; Blaszczynski & Nower, 2002), it is plausible that speculative trading shares with problem gambling key risk factors associated with the models, namely attitudes toward gambling, perceived social norms of gambling, impulsivity, sensation seeking, and poor social connectedness (high loneliness). In terms of consequences, thus far, several studies have identified cross sectional associations between speculative trading and harms to mental health and functional outcomes analogous to problem gambling symptoms among broader adult populations, including severe anxiety and depression, disturbances to professional lives, and negative impacts on personal relationships (Bin Abdulrahman et al., 2022; Grall-Bronnec et al., 2017; Mills & Nower, 2019). While these findings are useful indicators of the correlates of speculative trading that occur simultaneously, in order to be able to discern temporal associations and potential causality (e.g., between impulsivity and speculative trading, or between speculative trading and depressive symptoms), analyses of longitudinal data are necessary, as has been done with problem gambling behaviors that have shown causal links to risk factors and consequences (Allami et al., 2017; Dussault et al., 2011; Hartmann & Blaszczynski, 2018). However, to date, no published study has assessed the link between speculative trading activities and mental health and functional outcomes on a longitudinal basis in any population group.

With the goal of expanding our knowledge of the association between speculative trading and behavioral health correlates in young adults, there is a need to examine person-level correlates of speculative trading that have been evinced with regards to traditional gambling but not yet studied for speculative trading. A more translational analytic approach would entail estimating associations both at the stable between-person (e.g., those who engage in speculative trading more heavily also exhibit more stress and anxiety) and at the within-person level (e.g., when people engage in more speculative trading they exhibit more stress and anxiety). Therefore, time-varying correlates of speculative trading are yet unexplored but important in enabling the identification of higher-risk periods that can be targeted in prevention and intervention. It naturally follows that speculative trading activity and its health correlates must be together examined across time points to determine whether they co-vary over time.

The Present Study

Building on the supported theoretical frameworks for young adult problem gambling (TPB, Problem Behavior Theory, and the pathways model; Ajzen, 1991; Blaszczynski & Nower, 2002; Jessor & Jessor, 1977) and the known similarities between speculative trading and gambling, the present study sought to address the gap in the literature of health correlates of young adult speculative trading through a generalized linear mixed model (GLMM) (Moscatelli et al., 2012). The model utilized data from young adults who engage in speculative trading at least three times and three hours a week, who completed weekly assessments of their trading behaviors and health indices over nine weeks. The present study has three primary aims:

Aim 1: Between-Person Associations between Speculative Trading and Health Indices. These between-person associations reflect longer-term links across the entire survey period. **Hypothesis 1a**: between-person estimates would reveal positive associations between speculative trading and measures of anxiety, depression, and substance use behaviors. This hypothesis is consistent with preliminary evidence on speculative trading's harms (Bin Abdulrahman et al., 2022; Grall-Bronnec et al., 2017; Mills & Nower, 2019) and known associations between gambling activities and these health indices (Cowlishaw et al., 2017; Johnston & Regan, 2020). These associations theoretically fit into the Problem Behavior Theory (Jessor & Jessor, 1977) conceptualization of speculative trading in that the problem behavior, speculative trading, would be associated with internalizing (anxiety and depression) and externalizing (substance use) problems through a shared function (e.g., coping with stress, achieving a sense of excitement).

Aim 2: Within-Person Associations between Speculative Trading and Health Indices. These parameters enable assessment of the association between speculative trading and health indices at the intra-individual level over the nine-week study period. For instance, they could indicate that when an individual reports an increase in speculative trading activity, they are likely to also report an increase in depression. Such associations could be particularly important to detect as they could highlight a harmful cycle. **Hypothesis 2a**: within-person estimates would reveal positive associations between speculative trading and measures of anxiety, depression, and substance use behaviors.

Evidence from problem gambling research has demonstrated bidirectional links of young adult problem gambling with both mood and anxiety disorders and substance use disorders (Afifi et al., 2016; Buchanan et al., 2020), consistent with the Problem Behavior Theory (Jessor & Jessor, 1977) which identifies the problem behaviors as sharing the same function, and also fitting the pathways model (Blaszczynski & Nower, 2002) in which mood dysfunctions predict problem gambling behaviors. Meanwhile, anecdotal evidence of young adult speculative trading from media reports suggests severe anxiety, stress, depression, and behavioral dependence result from excessive speculative trading activities in some individuals (Chang, 2022; Verma, 2022). Given the novelty of these longitudinal associations, this aim was somewhat exploratory in nature; nevertheless, clarifying these temporal links was expected to be a critical task for informing effective development of prevention and intervention strategies for speculative trading harms.

Aim 3: Explore the Interaction Effects of Speculative Trading and Covariates on Health Indices. The goal of exploring interaction effects was to determine whether the associations assessed in aims 1 and 2 were particularly stronger or weaker for certain people (i.e., for whom was this association more salient?). Moderators tested included age, attitudes toward speculative trading, perceived social norms of speculative trading, sensation seeking personality trait, impulsivity, loneliness, financial stress, and speculative trading contexts (i.e., socially versus alone).

While this moderation aim was also somewhat exploratory in nature given the scarcity of supporting literature in the young adult speculative trading domain, we tested several hypotheses, reflecting the theoretical conceptualizations and empirical evidence of young adult problem gambling behaviors.

Hypothesis 3a: attitudes toward speculative trading, perceived social norms of speculative trading, and impulsivity moderate the speculative trading-health indices connection. This hypothesis is in line with the risk factors of problem gambling conceptualized by the TPB (Ajzen, 1991). In addition, considering the underlying psychosocial links between problem behaviors (in this case, speculative trading and substance use) posited by the Problem Behavior Theory (Jessor & Jessor, 1977), **Hypothesis 3b:** sensation seeking personality trait and loneliness were hypothesized to be moderators of the speculative trading-substance use relationship.

Mirroring the findings from young adult problem gambling research, we also anticipated that **Hypothesis 3c:** the positive associations between speculative trading and behavioral health would be stronger for younger relative to older subjects (Calado et al., 2017; Marchica et al., 2019), for those with greater sensation seeking traits (Donati et al., 2020; Pisarska et al., 2020), and for those experiencing greater loneliness (Estévez et al., 2020; Gori et al., 2015).

Lastly, based on preliminary evidence of the harms of young adult speculative trading reported in the press (Chang, 2022; Verma, 2022), **Hypothesis 3d:** we hypothesized that greater financial stress and more isolated speculative trading context (i.e., trading alone) would moderate the relationship between speculative trading and health indices.

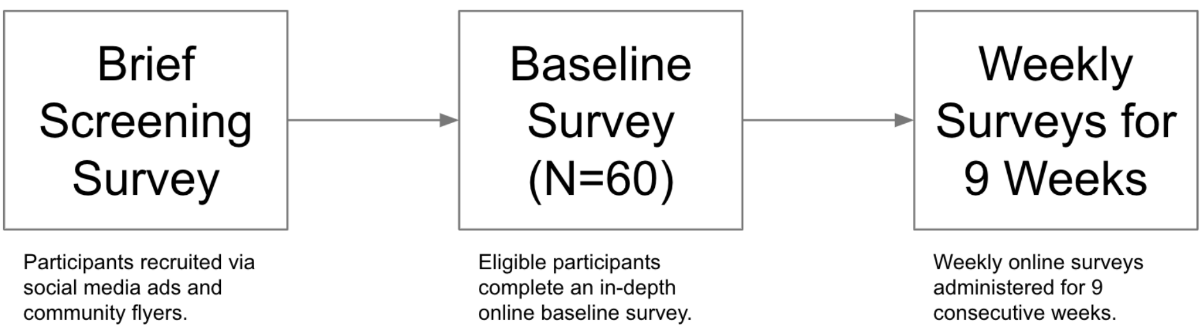
Method

Design Overview

The study used a longitudinal design approach to assess the association between speculative trading and health indices among young adults. The purposes of the study were to test both between-person and within-person links between young adults' speculative trading and health indices and to better understand the role of proposed moderating variables, with known health harms linked to problem gambling as guiding posts. Figure 1 shows the study design.

Figure 1

Overview of study design and participant flow



Participants and Recruitment

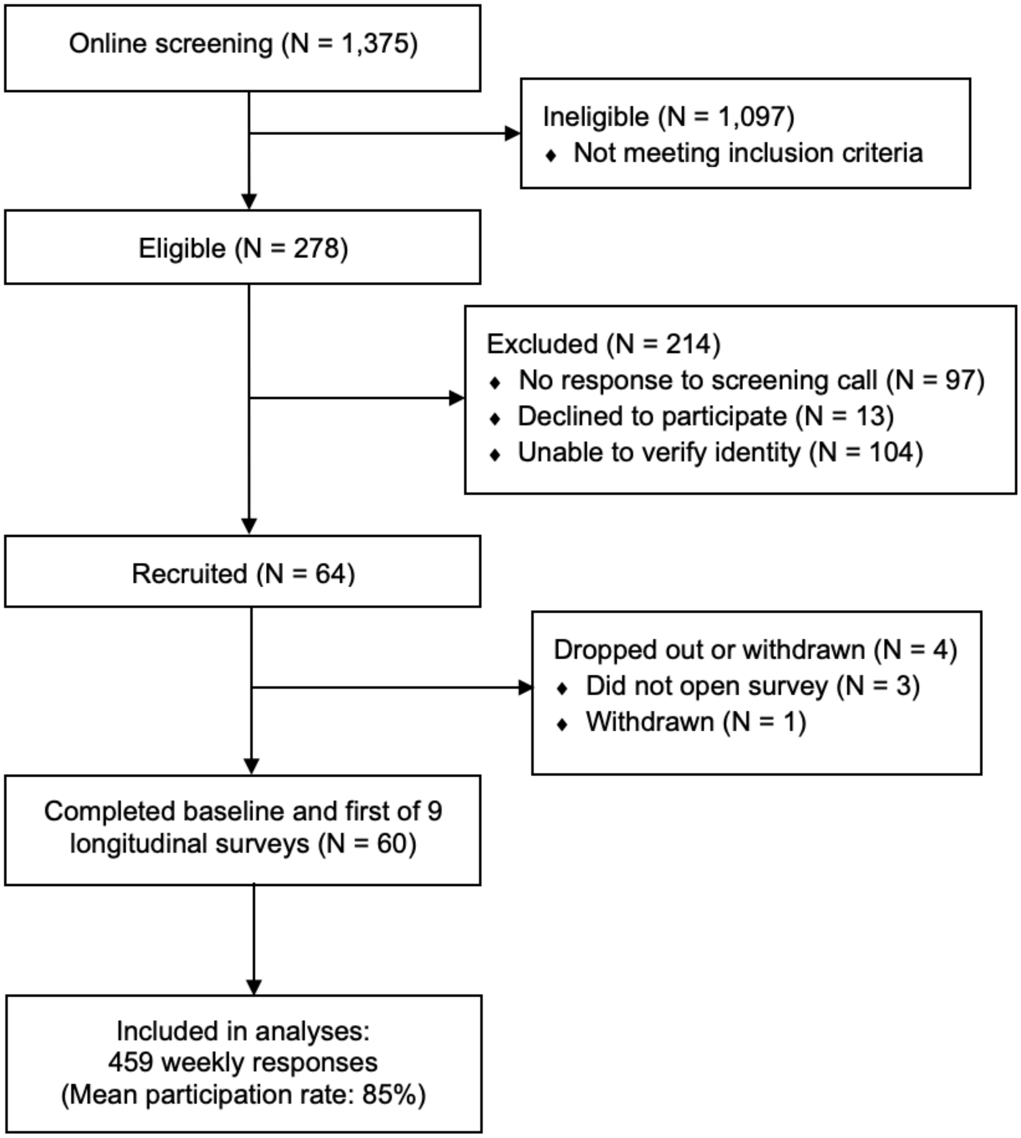
Participants were a national sample of 60 young adult volunteers between the ages of 18-29 recruited via advertising. Young adults were invited to participate in a brief screening survey using a hybrid recruitment strategy, consisting of community advertisements through flyers and online advertisements across social media sites and discussion platforms. Flyers advertising the screening survey were posted across the University of Washington (Seattle) campus. Online paid advertisements for the screening survey were posted on social media platforms Instagram and Facebook and discussion platform Reddit. These online recruitment methods are shown to attract a diverse sample of young adults for health-related surveys including those on behaviors considered to be sensitive subjects (Ford et al., 2019; Zapcic et al., 2023). Social media use is ubiquitous among young adults, and prior research has demonstrated that a significant number of stock and cryptocurrency speculative traders use social media and discussion websites to obtain and share trading related information (Duz Tan & Tas, 2021; Maule et al., 2021). Past longitudinal studies of health indices and behaviors in young adults have successfully recruited and retained large cohorts using social media platforms (e.g., Cadigan et al., 2019; Lee et al., 2020).

Administration of surveys and informed consent processes were performed using the REDCap platform and all measures and procedures were reviewed and approved by the University of Washington Human Subjects Division (Institutional Review Board). The screening survey was used to determine whether potential participants met the eligibility criteria, which included being willing to participate in surveys related to trading, living in the United States, being between 18 and 29 years of age, spending 3 or more hours per week on trading and related activities, placing at least 3 trades per week, having no history of seeking or receiving problem gambling treatment, and having no experience or training as an institutional trader (i.e., trading professionally as an employee of a financial institution or company). Trading was defined as making a trade (e.g., buying or short selling a security) with real money with the intent of realizing profit (e.g., selling or buying to cover) within 30 days. The age range of 18 to 29 was determined based on the generally accepted upper limit for young adult age range of 29 (Lynch et al., 2004; Slutske et al., 2003) and the minimum age for informed consent for a nationwide study of 18, which is also the minimum age requirement for using most trading platforms. Speculative trading-specific eligibility criteria (spending 3 or more hours per week engaged in trading and related activities, placing at least 3 trades per week, no history of seeking or receiving problem gambling treatment) were selected to recruit a sample of non-treatment-seeking young adults who regularly engaged in speculative trading.

The study was advertised across all states given the nationwide availability of speculative trading activities (i.e., no state-specific restrictions) and in an effort to recruit a representative sample. In total, 278 individuals who completed the online screening survey were initially deemed eligible for further participation. These prospective eligible participants were required to speak with a member of the research team (i.e., principal investigator or research assistant) over the phone to verify their eligibility. A total of 60 eligible participants were ultimately recruited for the study from the pool of 278 who initially met the eligibility criteria based on the screening survey. Reasons for exclusion among the initial participant pool included failure to verify identity and lack of follow-up response. Figure 2 shows participant flow.

Figure 2

Participant flow



The 60 participants who met eligibility criteria and enrolled in the longitudinal study had a mean age of 23.7 years with a standard deviation of 3.4, and 83% of participants were assigned male at birth. Household income above the area median (calculated by zip code) was reported by 37% of the sample. In terms of race, 43% identified as Asian, 40% White, 12% mixed race, and 5% Black; 12% identified their ethnicity as Hispanic. About half (49%) of participants were students, and in terms of employment 53% were full time employed, 23% part time employed, and 24% were not working. In total, 16 U.S. states were represented in the survey. Descriptive statistics for the study participants are shown in Table 1.

Table 1

Descriptive statistics for participant demographics (N=60)

Assigned Sex	
Male	83%
Female	17%
Race	
Asian	43%
White	40%
Mixed	12%
Black	5%
American Indian/Native American	0%
Native Hawaiian/Other Pacific Islander	0%
Ethnicity	
Non-Hispanic	88%
Hispanic	12%
Household Income	
Above Area Median (Zip Code)	37%
Mean	$97,416
Median	$87,500
Standard Deviation	$72,286
Student status	
Not a student	51%
Full time student	42%
Part time student	7%
Employment	
Full time employed	53%
Part time employed	23%

Not working	24%
Locations	
Number of US states represented	16

Baseline Survey

Eligible participants were screened over the phone to verify identification, location, and basic knowledge of trading, and to confirm their understanding of and commitment to participating in the longitudinal survey. Once they agreed to participate in the longitudinal survey, they received via email a link to a confidential online baseline survey, which included a comprehensive demographic questionnaire and key measures related to the study aims (e.g., sensation seeking trait, financial stress, perceived social norms of trading; see Table 2 for the list of study measures). From the time of invitation, potential participants were given one week to access the baseline survey. A series of email reminders were used to encourage completion.

Weekly Survey

After the baseline survey was completed, participants received via email unique links for each weekly survey for nine consecutive weeks. Weekly surveys were sent Monday mornings and made available for two full days for participants to complete, after which time the weekly survey was counted as missed. As with the baseline survey, email reminders were sent to encourage completion.

During the survey period, participants were able to contact the research team by email. At any point during the study, participants could withdraw their participation by contacting the research team.

The full battery of items used in the baseline and weekly surveys and their functions are listed in the Measures section below.

Participant Incentives

Participants received compensation in the form of electronic gift cards upon completing baseline and weekly surveys. The brief screening survey did not include participant incentives, to allay concerns of fraudulent or repeated completion. Remuneration for the initial baseline survey was a $20 gift card for online shopping, sufficient incentive given the in-depth baseline survey was expected to take up to 30 minutes. Weekly surveys were relatively brief at approximately 20 minutes but high response rates were critical for the study's success; thus remuneration for weekly surveys was a $15 gift card per completion, with an additional $25 bonus upon completing all 9 weekly surveys. In total, participants could earn up to $135 from completing all surveys.

Measures

Table 2 lists the variables, functions, and measures assessed in the baseline (BL) and weekly (W) surveys. These measures were selected to assess key elements of relevant theories of problem gambling and related health and risk behaviors – the TPB (Azjen, 1991), Problem Behavior Theory (Jessor et al., 1997; Schlegel et al. 2008), and Pathways Model (Blaszczynski et al., 2002) – as well as potential risk factors, correlates, and outcomes previously identified in the gambling and speculative trading literature. Several measures, marked as "secondary" in function, were collected for descriptive statistics rather than being included in the primary analyses. Further details are described in the following paragraphs. Tables 17 and 18 in the

Appendix section list the reliability statistics for the main baseline and weekly measures in our sample.

Table 2

List of study measures

VARIABLE	FUNCTION	MEASURE(S)	TIME
Demographics	Screener /Covariate	Key person-level descriptors including age, sex assigned at birth, race/ethnicity, employment, student status, income, asset	BL
Sensation seeking measure	Covariate	Brief Sensation Seeking Scale (Hoyle et al., 2002)	BL
Impulsivity	Covariate	Abbreviated Impulsiveness Scale (Coutlee et al., 2014)	BL
Financial stress	Covariate	Affective section of APR Financial Stress Scale (Heo et al., 2020)	BL
Attitudes towards gambling and speculative trading	Covariate	Attitudes Towards Gambling Scale (Orford et al., 2009) and an adapted scale for speculative trading activity	BL
Perceived descriptive and injunctive social norms for speculative trading	Covariate	Items asking participants to estimate and to endorse speculative trading attitudes and behaviors for peers (i.e., typical adolescents in the U.S.)	BL
Problem gambling history	Covariate	Problem Gambling Severity Index (Holtgraves, 2009)	BL
Speculative trading motives	Secondary	Speculative trading-specific items adapted from Reasons for Gambling Questionnaire (Wardle et al., 2011)	BL
Problem gambling-like trading history	Secondary	Speculative trading-specific behavioral dependence and functional consequences adapted from Problem Gambling Severity Index (Holtgraves, 2009)	BL
Mood and anxiety symptoms	Primary	PHQ-2, GAD-2 (Kroenke et al., 2009a)	W
Social isolation and loneliness	Covariate	Three-Item Loneliness Scale (Hughes et al., 2004)	W

Sleep quality	Covariate	Abbreviated version of Brief Version of the Pittsburgh Sleep Quality Index (B-PSQI) (Sancho-Domingo et al., 2021)	W
Substance use behaviors (weekly)	Primary	Modified ASSIST-Lite (Ali et al., 2013)	W
Speculative trading activity	Primary	Frequency, time spent, participation in trading related activities, expenditures, profit/loss, security type (stocks, cryptocurrency, derivatives, etc.), margin use, holding period, etc.	W
Speculative trading at work/school	Secondary	Items about trading activity participation in workplace/school settings	W
Contexts of speculative trading	Covariate/ Secondary	Checklist for in-person contexts of speculative trading (e.g., alone, with friends)	W
Gambling activity	Secondary	Time spent, expenditures, profit/loss, gambling type, etc.	W

Demographics. Participants reported on several demographic items in the baseline survey. These items were age, gender, sex assigned at birth, racial and ethnic identities, state of residence, relationship status, student status, employment, income, asset/debt levels, and education level.

Sensation seeking measure. Brief Sensation Seeking Scale (BSSS; Hoyle et al., 2002) is a validated 8-item brief measure of sensation seeking that assesses four primary dimensions of sensation seeking (experience seeking, boredom susceptibility, thrill and adventure seeking, and disinhibition) using a five-point scale. The measure includes items such as "I like to do frightening things" and "I like wild parties." Cronbach's alpha for the scale is 0.74 (Hoyle et al., 2002). The measure has been shown to strongly predict a range of risky behaviors including substance use and gambling behaviors (Hoyle et al., 2002; Primi et al., 2011), and it was included in the baseline survey.

Impulsivity. Impulsivity, a commonly cited risk factor for gambling problems (Blaszczynski & Nowers, 2002; Chambers et al., 2003; Ioannidis et al., 2019), was assessed using the 13-item, 4-point-scale Abbreviated Impulsiveness Scale (ABIS) which assesses impulsivity in the areas of attention, motor, and non-planning (Coutlee et al., 2014). The measure includes items such as "I am self-controlled" (attention) and "I say things without thinking" (motor). The internal consistency of the abbreviated scales, indexed by Cronbach's alpha, is 0.71 for attention, 0.64 for motor, and 0.69 for nonplanning (Coutlee et al., 2014). It was included in the baseline survey.

Financial stress. The affective section of the APR Financial Stress Scale (Heo et al., 2020) was included in the baseline survey. The 8-item measure includes items such as "I feel depressed because of my financial situation." and "I worry a lot because of my financial situation." and is assessed on a 5-point scale. Cronbach's alpha for the affective section of the scale is 0.95.

Attitudes towards gambling and speculative trading. Participants' attitudes towards gambling and speculative trading were assessed using the validated 8-item, 4-point-scale Attitudes Towards Gambling Scale (ATGS-8; Orford et al., 2009) and a measure adapted from it specific to speculative trading in the baseline survey. The adapted scale includes items such as "Trading livens up life" and "On balance trading is good for society." Cronbach's alpha for the ATGS-8 is 0.88 (Orford et al., 2009).

Perceived descriptive and injunctive social norms for speculative trading. A set of questions asking participants to estimate peers' speculative trading attitudes ("How much do you agree with the statement: My friends think it would be a good idea to make a new trade in the next week.") and participation ("What percentage of your friends do you think will make a new trade in the next week?") was included in the baseline survey for analyses as covariates, analogous to measures from studies that have found that perceived social norms of gambling are risk factors of problem gambling (Marchica & Derevensky, 2016; Moore & Ohtsuka, 1999).

Problem gambling history. Problem Gambling Severity Index (PGSI; Holtgraves, 2009), a widely used and validated 9-item, 4-point-scale measure of problem gambling symptom severity over the past 12 months, was used to measure participants' problem gambling severity in the baseline survey. Cronbach's alpha for the PGSI is 0.84 (Holtgraves, 2009). The measure included items such as "Has your gambling caused any financial problems for you or your household?" and "When you gambled, did you go back another day to try to win back the money you lost?" Additionally, the baseline survey assessed family history of gambling problems among participants.

Perceived risks and benefits of speculative trading. Items from the Perceived Availability, Risks, and Benefits of Gambling scale (Wickwire et al., 2007), which consists of a range of 4-point-scale measures, were adapted to fit the speculative trading context and included in the baseline survey. The measure includes items such as "I could win a lot of money trading" (perceived benefit) and "Trading can lead to problems just like alcohol or other drugs can." (perceived risk).

Speculative trading motives. The Reasons for Gambling Questionnaire (Wardle et al., 2011), which contains a series of 4-point-scale items, was adapted for speculative trading and asked in the baseline survey. The adapted measure includes items such as [How often do you trade] "because it's exciting?" (enhancement) and "to make money?" (financial).

Mood and anxiety symptoms. An abbreviated 2-item version of the PHQ-8, a validated measure of depression (Kroenke et al., 2009b), known as the PHQ-2 as well as an abbreviated 2-item version of the GAD-7, a validated measure of anxiety (Spitzer et al., 2006), known as the

GAD-2 were used to survey participants' past-week mood and anxiety symptoms on a weekly basis. PHQ-2 consists of items "Little interest or pleasure in doing things" and "Feeling down, depressed or hopeless" and GAD-2 includes items "Feeling nervous, anxious or on edge" and "Not being able to stop or control worrying," and both measures are 4-point scale measures. Cronbach's alpha for the PHQ-2 and GAD-2 are 0.81 and 0.82, respectively (Kroenke et al., 2009a).

Social isolation and loneliness. Using the Three-Item Loneliness Scale (Hughes et al., 2004), self-rated social isolation and loneliness were measured in the weekly survey for potential secondary analyses. The three-item scale includes items such as "How often do you feel left out: Hardly ever, some of the time, or often?" Cronbach's alpha is 0.72 for the Three-Item Loneliness Scale (Hughes et al., 2004).

Problem gambling-like trading history. Problem Gambling Severity Index (Holtgraves, 2009) was adapted to measure speculative trading-specific behavioral dependence and negative functional consequences analogous to those of problem gambling in the baseline survey. The adapted measure was labeled Problem Gambling Severity Index - Speculative Trading (PGSI-ST).

Sleep quality. A brief version of the Pittsburgh Sleep Quality Index (B-PSQI), a 6-item version with demonstrated reliability and validity (Sancho-Domingo et al., 2021), was abbreviated to measure sleep duration, sleep latency, night-time awakenings, and subjective sleep quality at each weekly survey for potential secondary analyses. The question about sleep and wake times was omitted for brevity. Cronbach's alpha for the B-PSQI is 0.79. The scale includes items such as "How long has it usually taken you to fall asleep each night?" and "How many hours of actual sleep did you get at night?"

Substance use behaviors. The ASSIST-Lite (Ali et al., 2013), a shortened version of the Alcohol, Smoking, and Substance Involvement Screening Test (ASSIST) (Humeniuk et al., 2010), was included in the weekly survey for participants to report their substance use over the past week. ASSIST-Lite consists of twenty questions, with three or four yes/no questions for each of six common psychoactive substances regarding participation, frequency and intensity (e.g., alcohol-related questions in the measure are "Did you have a drink containing alcohol?", "On any occasion, did you drink more than 4 standard drinks of alcohol?", "Have you tried and failed to control, cut down or stop drinking?", and "Has anyone expressed concern about your drinking?"). A minor modification was made to the measure, adding scored questions about the use of any other unlisted substances. The resulting subscore for each substance corresponds to the level of risk of harm from the substance.

Speculative trading activity. Trading-related items such as trading frequency, total time spent on trading and related activities, expenditure (earned/lost), percentage of personal income spent (wagered), types of financial instrument(s) traded (e.g., stocks, cryptocurrencies, derivatives), use of margin (borrowed money) for trading, and holding period were assessed in the weekly survey.

Speculative trading functional consequences. Questions such as "While at your job or in class, have you placed a trade?" and "While at your job or in class, have you been distracted or lost focus due to trading and related activities?" were included in the weekly survey to assess how trading has impacted participants' educational and/or occupational experiences and functioning.

Contexts of speculative trading. Context of speculative trading (e.g., alone, with in-person friends, with online friends) were assessed in the weekly survey for potential covariate or secondary analysis.

Gambling activity. Time spent on gambling, expenditure (earned/lost), and types of gambling the participants engaged in were assessed (e.g., slots, lottery tickets, sports betting) in the weekly survey.

Data Analysis

Preliminary Analyses

Prior to inferential statistics for the study's aims, descriptive statistics for the collected data were calculated and used to assess simple relations between study variables and distributions. These statistics are summarized by mean, standard deviations, range, intraclass correlation coefficient (ICC), and key percentage values in Tables 4, 5, 6, and 7. Evidence of associations and distributional abnormalities such as overdispersion and zero-inflation were also assessed during this stage, in order to determine appropriate modeling assumptions and specifications.

In addition, given the broader aim of better understanding speculative trading activities in the young adult population, inferential analyses on trading-related variables were performed using Student's t-tests and Pearson's correlation analyses where appropriate in order to generate additional relevant insights and contextualize the main findings of study aims.

Statistical Power Analysis

A statistical power analysis was performed to determine the appropriateness of using GLMM. A sample size of 60 participants with up to 7 time points per participant were used, accounting for a conservative retention rate prediction of 75 to 80%. We set alpha = .05 and a correlation of $r = 0.3$ for within-person residuals. We assumed an intraclass correlation (ICC) of 0.5, meaning that 50% of the total variance is attributable to differences between participants. In addition, anticipating the need to account for overdispersion, we used a negative binomial distribution assumption with an overdispersion parameter (theta, or θ) of 0.5. The theta (θ) parameter controls overdispersion, with lower values indicating greater variability in the outcome distribution. A statistical power analysis for the GLMM was conducted using a Monte Carlo simulation of 1000 repetitions with the 'glmmTMB' package to determine if there was sufficient power for the proposed aims of the study. Given these conservative constraints, a sample of 60 was powered at 0.89 to detect the main associations of $\beta = 0.1$ or greater.

Primary Analyses

All analyses were conducted in R (R Core Team, 2024), an open-source statistical software with a robust library of packages for testing many types of models. Between-person and within-person associations between trading activity and health indices were estimated using generalized linear mixed models (GLMMs). GLMM accounts for the nested data structure, where repeated assessments were nested within individuals, allowing us to estimate both within-person (intra-individual) associations and between-person (inter-individual) differences while accounting for non-independence of observations. Between-person predictors were grand-mean centered, and time-varying predictors were person-mean centered to isolate within-person effects (Hamaker & Muthén, 2020; Wang & Maxwell, 2015). This decomposition disentangles within-person fluctuations from stable between-person differences. Effect estimates were derived using maximum likelihood estimation with the Laplace approximation, which provides computationally efficient estimation for mixed-effects models and handles missingness appropriately under the assumption of missing at random. The glmmTMB package in R enables fine-tuning specifications of the model including zero-inflation modeling, model distribution settings and numerical optimization of complex models to improve convergence. Negative binomial distribution was used across models, given the outcome variables for the models essentially behaved like count data, exhibited overdispersion and were right-skewed (Green et al., 2021).

Speculative trading activity was measured and quantified in terms of the amount of time spent (in minutes) and the frequency of trading (in days per week). Time and frequency were chosen as measures of trading, instead of a measure based on trading expenditure or number of trades, for three reasons. First, the wide heterogeneity of possible trading styles and risk profiles across individuals could make using between-person comparisons of trading expenditures or number of trades as a measure of the intensity of trading activity inappropriate. While standardizing trading expenditure as a percentage of personal income or asset was considered, this method does not address potential between-person variations stemming from trading strategies with different risk profiles (e.g., a strategy with a larger expenditure but lower overall financial risk, versus another with a lower expenditure but higher overall financial risk). Second, potential variability in the dispersion of week-to-week trading dollar figures across individuals poses a challenge in using the measure to account for the within-person effect of trading participation. Third, past trading gains and losses can influence week-to-week trading expenditures, controlling for which may not be feasible. Duration and frequency of trading behavior speaks to the allocation of a uniformly finite resource, time, between and within individuals.

Depression and anxiety, measured weekly using the PHQ-2 and GAD-2 scales (Kroenke et al., 2009a), were fit as dependent variables for behavioral health given the wide support for the two measures as key indicators of behavioral health (Kilbourne et al., 2018) as well as robust past literature supporting their links to problem gambling (Karlsson et al., 2018; Welte et al., 2017) and emerging connections to speculative trading (Bin Abdulrahman et al., 2022; Grall-Bronnec et al., 2017). Alcohol and nicotine use were chosen as dependent variables for substance use given that the two substances account for the highest rates of comorbidity with problem gambling among documented substance use connections in past literature (Grant et al., 2020; McGrath et al., 2009) and assessed using the ASSIST-Lite (Ali et al., 2013), a brief, validated measure of substance use involvement.

In constructing the model, several covariates were considered and incrementally added to the model using established measures of model fit. First, time trend (sequence within nine weekly time points) was added as a fixed effect to control for temporal changes in each dependent variable. Using a random linear slope of time was also considered, however it was not implemented due to inferior model fit. Table 19 in the Appendix section illustrates a comparison between the random intercept model and the random linear slope model with PHQ-2 as the dependent variable and trading frequency as the weekly trading variable, showing a negligible variance of random effect for time as a linear slope and no meaningful difference in residual error. This finding was consistent across dependent variables and trading variables.

Potential for a quadratic effect of time was also evaluated, however it was not included due to a lack of meaningful change in explanatory power or model outcomes. A random intercept was added, allowing each individual to have their own baseline level of chosen health correlate, capturing individual differences that are not explained by the other variables in the model. Other covariates were incrementally added to the model, with consideration of each covariate's effects on the model's AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), log-likelihood and deviance values as measures of model fit (Roback et al., 2021).

Following this process, age (mean-centered), sex, racial/ethnic identity (dummy coded separate variables), student status, employment status, and being above median household income were added as demographic covariates. Estimates for racial/ethnic identity were not reported based on an a priori decision not to interpret these effects, to avoid conflating these identities with lived experiences of racism and discrimination.

In addition, several covariates with theoretically supported links to health indices were considered. Among them, attitudes toward speculative trading (Azjen, 1991), financial stress (Viseu et al., 2018), sleep quality (Alvaro et al., 2013), sensation seeking personality trait (Ortin et al., 2012), and trade loss (i.e., whether or not the individual suffered a financial loss from trading on a weekly basis; Chang, 2022) were added as given each of their contribution to improving model fit. Injunctive and descriptive norms of speculative trading and impulsivity were considered but removed, as sensitivity analyses demonstrated these covariates did not contribute to model fit.

As a representative example of the covariate selection process, Table 3 demonstrates the corresponding improvements in model fit statistics (lower values indicate better fit) with the addition of demographic covariates and theoretically supported covariates for one of the tested models. AIC, log-likelihood, and deviance value consistently decreased, while BIC, which places a heavier penalty on model complexity than the AIC, saw a modest increase upon the addition of demographic covariates.

Table 3

Model fit statistics for trading frequency model predicting PHQ-2

Included Covariates	AIC	BIC	Log-Likelihood	Deviance	Residual df
Time Variable	1141.9	1166.6	-564.9	1129.9	448
+ Demographic Covariates	1141.6	1207.5	-554.8	1109.6	438
+ Theoretically Supported Covariates	1119.6	1206.0	-538.8	1077.6	432

The chosen covariates' links to health indices were covered alongside trading activity's association with health indices in the Results and Discussion sections, given the covariates' potential role in contextualizing the main findings and providing novel insights into young adults who engage in speculative trading.

Model fit statistics for the final models used in primary analyses are reported in Table 12 of the Results section where the statistics are further discussed. A correlation matrix for the key variables of the study is shown in Table 20 of the Appendix section.

Aim 1 estimated the between-person effects of trading on health indices (behavioral health and substance use) by aggregating the data collected in weekly surveys. Between-person associations are crucial for examining broad indicators of person-level relationships between two given behaviors. Analyses focused on testing Hypothesis 1a, that greater speculative trading activity is associated with more negative health indices and more substance use at the trait level. Weekly speculative trading data was separated into between-person and within-person effects through grand-mean centering and person-mean centering processes (Curran et al., 2011). For the between-person effects, only one value exists for each participant.

Aim 2 expanded the knowledge of these relationships between speculative trading and health indices by estimating within-person level associations that identify the extent to which speculative trading and other health indices co-vary over time, compared to an individual's usual level – that is, aggregated into person means and person-mean-centered parameters (Enders & Tofighi, 2007). We sought to test Hypothesis 2a, or positive within-person associations between speculative trading and measures of anxiety, depression, and substance use behaviors. Aim 2 was explored using the same model as Aim 1, as a GLMM enables the assessment of both between-person and within-person associations at the same time. The model structure used for Aim 1 and Aim 2 is demonstrated below:

Health Variable (e.g., Weekly PHQ-2 Score) ~

$\beta_0 + \beta_1 \cdot \text{Time Trend}_{it} + \beta_2 \cdot \text{Age}_i + \beta_3 \cdot \text{Sex Assigned At Birth}_i + \beta_4 \cdot \text{Racial/Ethnic Identity}_i +$

$\beta_5 \cdot \text{Student}_i + \beta_6 \cdot \text{Employment}_i + \beta_6 \cdot \text{Household Income Above Median}_i +$

$\beta_7 \cdot \text{Attitudes Toward Trading}_i + \beta_8 \cdot \text{Financial Stress}_i + \beta_9 \cdot \text{Sensation Seeking}_i +$

$\beta_{10} \cdot \text{Weekly Trade Loss}_{it} + \beta_{11} \cdot \text{Weekly Sleep Quality}_{it} +$

$\beta_{12} \cdot \textbf{Between-Person Effects of Weekly Trading (Aim 1)}_{it} +$

$\beta_{13} \cdot \textbf{Within-Person Effects of Weekly Trading (Aim 2)}_{it} +$

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Lastly, Aim 3 examined the potential moderators of associations between speculative trading and health indices, thus identifying for whom given associations are relatively stronger and laying the groundwork for further research and developing targeted intervention strategies. We assessed these effects by adding interaction effects to the model constructed for Aim 1 and Aim 2. Interaction with both between-person and within-person effects of trading were assessed to better understand the nature of each moderator. In line with our hypotheses 3a, 3b, 3c, and 3d, we assessed age, attitudes toward speculative trading, perceived social norms of speculative trading, sensation seeking personality trait, impulsivity, loneliness, financial stress, and speculative trading contexts (i.e., alone vs. with others) as interaction variables. The model structure used for Aim 3 is shown below:

Health Variable (e.g., Weekly PHQ-2 Score) ~

$\beta_0 + \beta_1 \cdot$ Time Trend$_{it}$ + $\beta_2 \cdot$ Age$_i$ + $\beta_3 \cdot$ Sex Assigned At Birth$_i$ + $\beta_4 \cdot$ Racial/Ethnic Identity$_i$ +

$\beta_5 \cdot$ Student$_i$ + $\beta_6 \cdot$ Employment$_i$ + $\beta_6 \cdot$ Household Income Above Median$_i$ +

$\beta_7 \cdot$ Attitudes Toward Trading$_i$ + $\beta_8 \cdot$ Financial Stress$_i$ + $\beta_9 \cdot$ Sensation Seeking$_i$ +

$\beta_{10} \cdot$ Weekly Trade Loss$_{it}$ + $\beta_{11} \cdot$ Weekly Sleep Quality$_{it}$ +

$\beta_{12} \cdot$ **Moderator Variable (e.g., Impulsivity)** +

$\beta_{12} \cdot$ Between-Person Effects of Weekly Trading (Aim 1)$_{it}$ *** Moderator Variable**$_i$ +

$\beta_{13} \cdot$ Within-Person Effects of Weekly Trading (Aim 2)$_{it}$ *** Moderator Variable**$_i$ +

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Results

Descriptive Statistics and Preliminary Analyses

Study Participation

Participants (N=60) completed 85% of weekly assessments (459 of 540). Participation rate ranged from 11% (1 of 9) to 100% (9 of 9), with 83% of participants reporting a participation rate of 67% (6 of 9) or higher.

Speculative Trading (Baseline Measures)

Descriptive statistics for trading-related baseline measures are reported in Table 4. In measuring problem gambling-like symptoms from trading activities, an adaptation of the validated Problem Gambling Severity Index (PGSI) measure specific to trading called the Problem Gambling Severity Index - Speculative Trading (PGSI-ST) was used. The mean score for PGSI-ST was 4.1, significantly higher than the mean PGSI score of 2.5 ($p = 0.002$). To contextualize these results, the moderate problem gambling range for the PGSI is 3-7. While PGSI-ST is not a validated measure, the score suggests that problem-gambling like symptoms do occur from speculative trading and are more severe than those from traditional gambling in this cohort.

Participants' attitudes toward trading were considerably more favorable than their attitudes toward gambling. Using the Attitudes Towards Gambling Scale, participants reported a mean score of 12.4 out of 32 (SD = 3.9), while using the analogous scale modified for trading, participants reported a mean score of 17.7 out of 32 (SD = 3.8), yielding a statistically significant difference using the paired Student's t-test ($p < 0.0001$). Among the individual items, all scores were higher (more favorable) for trading items compared to their gambling counterparts and the difference was statistically significant at alpha = 0.05 for all items except "Gambling/Trading livens up life" ($p = 0.06$).

In response to a descriptive norms question ("What percent of your friends do you think will make a new trade in the next week?"), participants reported a mean of 27.6%, with standard deviation of 24.7%. In response to an injunctive norms question ("How much do you agree with this statement: My friends think it would be a good idea to make a new trade in the next week.") the mean score was 3.2 on a scale from 1 to 5, with a standard deviation of 1.1. Participants' top three motives for engaging in speculative trading in response to an adaptation of the Reasons for Gambling Questionnaire measure were “to make money” (mean score of 3.5/5), “because of the sense of achievement when you profit” (2.8/5), and “for the mental challenge or to learn about trading.” (2.6/5).

Table 4

Descriptive statistics for trading and gambling-related baseline measures

Person level (N=60)	**M**	**SD**	**Possible Range**	**Observed Range**	**Scoring Guidelines**
Problem Gambling Severity Index - Speculative Trading	4.1	4.4	0-27	0-20	N/A
Positive Attitudes Toward Trading	17.7	3.8	0-32	8-25	N/A
Trading descriptive norms	27.6%	24.7%	0-100%	0-76%	N/A
Trading injunctive norms	3.2	1.1	1-5	1-5	N/A
Problem Gambling Severity Index	2.5	4.6	0-27	0-24	3-7: moderate, 8+: severe
Positive attitudes toward gambling (ATGS-8)	12.4	3.9	0-32	5-25	N/A

Behavioral Health and Substance Use (Weekly Measures)

Descriptive statistics for weekly behavioral health and substance use measures are reported in Table 5. Mean values were obtained by first calculating the person-level mean for each participant and then taking the mean of the person-level mean values across all participants. Between-person and within-person standard deviation values were calculated separately. Intraclass correlation coefficient (ICC) refers to the proportion of variability explained by between-person fluctuations, as opposed to within-person fluctuations. For PHQ-2, as an example, ICC value was 0.52, meaning 52% of its variability was explained by between-person fluctuations, while the remaining 48% was explained by within-person fluctuations.

ICC values for the behavioral health-related weekly measures (PHQ-2, GAD-2, abbreviated B-PSQI, and Three-Item Loneliness Scale) ranged between 0.45 and 0.57, suggesting close to an even split among between-person and within-person variability, whereas ICC for substance use measures (ASSIST-Lite and its subscores) ranged between 0.8 and >0.99, demonstrating small to negligible within-person differences in substance use intensity relative to between-person variability.

For the ASSIST-Lite items, 60% of participants reported substance use (scored greater than 0) at least once during the 9-week survey period. For PHQ-2 and GAD-2, 78% and 88% of participants reported a score greater than 0 at least once, respectively.

Table 5

Descriptive statistics for behavioral health and substance use-related weekly measures

Survey level (N=459 weekly responses)	Mean	Between Person SD	Within Person SD	Range	ICC
PHQ-2 (Depression)	1.25	1.32	0.79	0-6	0.52
GAD-2 (Anxiety)	1.38	1.33	0.89	0-6	0.45
Abbreviated B-PSQI (Sleep Problems)	2.9	1.6	1.3	0-12	0.56
Loneliness (Three-Item Loneliness Scale)	4.5	1.3	1.0	3-9	0.57
ASSIST Lite	0.78	1.35	0.87	0-20	0.85
ASSIST Lite - Tobacco/Nicotine	0.12	0.35	0.21	0-3	>0.99
ASSIST Lite - Alcohol	0.38	0.55	0.44	0-4	0.8
ASSIST Lite - Cannabis	0.16	0.53	0.18	0-3	>0.99
ASSIST Lite - Stimulant	0.05	0.17	0.23	0-3	>0.99

ASSIST Lite - Sedative	0.03	0.14	0.17	0-3	>0.99
ASSIST Lite - Opioid	0.02	0.11	0.15	0-2	>0.99
ASSIST Lite - Other (modified)*	0.05	0.17	0.2	0-2	>0.99

***Modification added analogous, scored questions about unlisted substances**

Trading (Weekly Measures)

Descriptive statistics for weekly trading-related measures are reported in Tables 6 and 7. In Table 6, mean values were obtained by first calculating the person-level mean for each participant and then taking the mean of the person-level mean values across all participants. Percentage values in Table 7 were calculated in a similar manner. Each week, participants reported on a range of trading-related experiences (e.g., placing a trade for a stock, trading alone, placing a trade at work/school). Person-level mean endorsement rate across all nine weeks in each category was calculated, followed by between-person mean rates across all participants.

In terms of weekly trading frequency, on average participants placed a trade 73% of the time. A distinction must be noted between placing a trade, which involves risking money, and trading-related activities, such as checking market data (e.g., prices) and trading-related news. Breaking down by security type, they traded stocks 44% of the time, exchange-traded funds (ETFs) 23% of the time, and stock derivatives 32% of the time, using the mean-of-mean method described in the previous paragraph. Cryptocurrencies were traded 13% of the time, followed by cryptocurrency derivatives at 3%. ETFs are investment funds that are traded on a stock exchange, and they are made up of a collection of stocks or other securities. While they are generally less volatile than stocks, some ETFs are leveraged (meaning they achieve amplified returns by using debt), making them risky investments. Derivatives are financial contracts based on the values of underlying assets that enable a highly risky form of trading more akin to gambling, and examples include options and futures.

Average holding period for a trade was 9.7 days, signaling a short-term trading bias, with a standard deviation of 24.9 days. Participants placed trades 1.9 days per week on average, and they spent 154 minutes (2 hours and 34 minutes) per week on average on all trading-related activities. Among them, they spent the most time monitoring market prices (52 minutes), followed by reading or listening to trading related information. Breaking down time spent on trading and related activities by security type, on average participants spent 75 minutes per week on stock trading-related activities, 24 minutes per week on cryptocurrency trading-related activities, and 41 minutes per week on other (e.g., derivatives, currencies, etc.) trading-related activities. Since participants were asked to estimate time spent on trading by activity type and by security type separately, total time spent on trading differs slightly between the two constructs.

Participants' margin trading (using borrowed money to trade) was assessed as a gauge of their appetite for high-risk financial trading. On average, participants reported using 1.5x margin when trading stocks and 2.5x margin when trading cryptocurrencies. Using 1.5x margin is the equivalent of a trader using $100 of own money to buy $150 worth of stocks, with the remaining $50 borrowed from the brokerage. Thus it assumes a 50% larger risk than if the trader made a non-margin trade. Similarly, a 2.5x margin trade allows the trader to take on 150% larger risk than making a non-margin trade. Cryptocurrency traders also made margin trades more frequently than stock traders; they made margin trades 48% of all weeks on average, compared to 37% on average for stock traders.

In terms of social context of trading, on average participants reported trading while alone 78% of the time, trading with someone they know who is aware of their trading 14% of the time, trading with people they know unaware of their trading 5% of the time, and trading while with strangers 3% of the time. On average, 44% of participants reported placing a trade while at work or school on a weekly basis, 68% reported monitoring market data while at work or school, and 60% reported reading or exchanging trade related information at work or school; 32% reported being distracted from work or school due to trading.

Table 6

Descriptive statistics for trading-related weekly measures (1)

Survey level (N=459 weekly responses)	**Mean**	**Between Person SD**	**Within Person SD**	**Range**	**ICC**
Stock trading time (minutes)	75	71	75	0-720	0.46
Crypto trading time (minutes)	24	42	42	0-600	0.88
Other securities trading time (incl. derivatives) (minutes)	41	60	63	0-720	0.61
Trading frequency (days/week)	1.9	1.1	1.2	0-7	0.45
Total time spent on trading and related activities (min/week)	154	155	132	0-1,920	0.46
Structuring and placing trades (min/week)	30	31	39	0-600	0.43
Monitoring market data (min/week)	52	53	57	0-600	0.48
Reading or listening to trading related information (min/week)	46	61	46	0-721	0.6
Talking with others about trading related information (min/week)	22	24	35	0-360	0.71
Other trading related activities (min/week)	4	10	15	0-180	0.97
Stock margin (leverage)	1.5x	0.86	0.8	1-15x	0.23

Crypto margin (leverage)	2.5x	3.1	1.8	1-15x	0.68
Holding period (days)	9.7	24.9	34.2	0-400	0.79

Table 7

Descriptive statistics for trading-related weekly measures (2)

Security Traded	
Any security	73%
Stocks	44%
ETFs (exchange-traded funds)	23%
Stock derivatives	32%
Cryptocurrencies	13%
Cryptocurrency derivatives	3%
Social Context	
Trade alone (vs. trading in the presence of others)	78%
Trade with people I know who don't know I'm trading	5%
Trade with people I know who know I'm trading	7%
Trade with people I know who know I'm trading and they trade	7%
Trade with strangers	3%
Functional Consequences	
Placed a trade at work/school	44%
Monitored market data at work/school	68%
Read or exchanged trade related information at work/school	60%
Distracted from work or school due to trading	32%
Margin Use	
% of stock trading weeks where margin was used (person mean)	37%
% of crypto trading weeks where margin was used (person mean)	48%

Note: Person-level mean endorsement rates were calculated across all weekly timepoints, which were then mean-averaged to obtain between-person mean values across all participants.

Primary Analyses

To estimate the between-person and within-person effects of trading on behavioral health and substance use (Aim 1 and Aim 2), a generalized linear mixed model (GLMM) was fit for each selected weekly measure of trading intensity: 1) trading frequency in days per week, and 2) time spent on trading measured in minutes. The dependent variables for each of the models were: 1) weekly PHQ-2 (depression) score, 2) weekly GAD-2 (anxiety) score, 3) weekly ASSIST-Lite scores for alcohol use, and 4) weekly ASSIST-Lite scores for tobacco use (including nicotine products).

Associations between Trading Frequency and Behavioral Health (Aims 1 and 2)

In our analysis of the link between the frequency of placing a trade (measured in number of days per week) and weekly measures of depression (PHQ-2) and anxiety (GAD-2) shown in Table 8, there was no statistically significant association at alpha = 0.05 at between-person or within-person level. In terms of the effect of covariates, weekly sleep problems were significantly associated with both depression and anxiety scores ($p<0.001$), such that each additional point in the abbreviated B-PSQI score, ranging from 0 to 12, corresponded to a 9.8% increase in the depression score and 10.9% increase in the anxiety score.

Among the baseline measures, both financial stress ($p<0.05$ for depression, $p<0.01$ for anxiety) and sensation seeking ($p<0.05$) were associated with depression and anxiety. Each point on the APR Financial Stress Scale (Affective portion) corresponded to a 4.0% and 4.1% increase in depression and anxiety, while each point on the Brief Sensation Seeking Scale indicated a 5.1% increase in depression and 3.8% increase in anxiety. Both baseline measures range from 8 to 40.

Table 8

Generalized linear mixed models estimating associations between trading frequency and behavioral health indices

	Depression (PHQ-2)	Anxiety (GAD-2)
	Count Ratio [95% CI]	Count Ratio [95% CI]
(Intercept)	0.583 [0.064, 5.262]	0.930 [0.139, 6.188]
Time	1.000 [0.966, 1.036]	0.971 [0.939, 1.003]
Age	0.929 [0.845, 1.021]	1.013 [0.931, 1.101]
Male Birth Sex (Yes/No)	1.358 [0.671, 2.749]	0.784 [0.421, 1.459]
Student (Yes/No)	0.581 [0.305, 1.106]	0.797 [0.447, 1.420]
Employed (Yes/No)	0.879 [0.468, 1.652]	0.956 [0.539, 1.694]
Household Income Above Area Median (Yes/No)	0.707 [0.402, 1.246]	0.962 [0.578, 1.600]
Sleep Problems	1.098 [1.041, 1.159]***	1.109 [1.054, 1.168]***
Positive Attitudes Toward Trading	0.988 [0.921, 1.060]	0.958 [0.901, 1.018]
Financial Stress	1.040 [1.007, 1.075]*	1.041 [1.011, 1.072]**
Sensation Seeking	1.051 [1.010, 1.094]*	1.038 [1.002, 1.074]*
Lost Money From Trading (Yes/No)	1.137 [0.864, 1.496]	1.151 [0.886, 1.495]
Trading Frequency (Between-Person, GMC)	0.820 [0.655, 1.028]	0.844 [0.688, 1.034]
Trading Frequency (Within-Person, PMC)	1.028 [0.950, 1.112]	1.003 [0.930, 1.081]

Note: GMC = grand-mean centered. PMC = person-mean centered. Models also adjusted for racial and ethnic identities, but estimates are not shown due to a priori decision not to interpret these effects. *p<.05, **p<.01, ***p<.001.

Associations between Trading Frequency and Substance Use (Aims 1 and 2)

The association between trading frequency and substance use was assessed next as shown in Table 9, using the alcohol use and nicotine use portions of the weekly ASSIST-Lite measure. In our analysis, the between-person effect of trading frequency was positively associated with higher nicotine use involvement (p<0.001) such that each additional day of trading in a week corresponded to a 146% increase in nicotine use involvement, but no within-person effect was found.

Among the covariates, higher age was negatively associated with nicotine use (-27.4%, p<0.01), being a student was negatively associated with both alcohol (-83.3%, p<0.05) and nicotine use (-88.1%, p<0.05), and sensation seeking was positively associated with nicotine use (11.7%, p<0.05).

Table 9

Generalized linear mixed models estimating associations between trading frequency and substance use indices

	Alcohol Use	**Nicotine Use**
	Count Ratio [95% CI]	Count Ratio [95% CI]
(Intercept)	1.049 [0.009, 113.5]	0.000 [0.000, 0.020]***
Time	0.977 [0.921, 1.036]	0.903 [0.809, 1.009]
Age	1.080 [0.883, 1.321]	0.726 [0.574, 0.919]**
Male Birth Sex (Yes/No)	0.682 [0.147, 3.144]	3.116 [0.443, 21.90]
Student (Yes/No)	0.167 [0.038, 0.726]*	0.119 [0.022, 0.641]*
Employed (Yes/No)	0.549 [0.121, 2.485]	1.252 [0.147, 10.64]
Household Income Above Area Median (Yes/No)	0.457 [0.127, 1.635]	0.823 [0.248, 2.727]
Sleep Problems	0.990 [0.887, 1.104]	1.035 [0.817, 1.311]
Positive Attitudes Toward Trading	0.941 [0.802, 1.103]	1.065 [0.915, 1.238]
Financial Stress	0.975 [0.905, 1.050]	1.002 [0.932, 1.077]
Sensation Seeking	1.044 [0.954, 1.143]	1.117 [1.014, 1.231]*
Lost Money From Trading (Yes/No)	0.778 [0.460, 1.316]	0.325 [0.041, 2.556]
Trading Frequency (Between-Person, GMC)	0.889 [0.536, 1.473]	2.462 [1.449, 4.183]***
Trading Frequency (Within-Person, PMC)	1.123 [0.996, 1.266]	1.067 [0.886, 1.284]

Note: GMC = grand-mean centered. PMC = person-mean centered. Models also adjusted for racial and ethnic identities, but estimates are not shown due to a priori decision not to interpret these effects. *p<.05, **p<.01, ***p<.001.

Associations between Time Spent on Trading and Behavioral Health (Aims 1 and 2)

In our analysis of the connection between the weekly amount of time spent on trading activities (trading time) and weekly measures of depression (PHQ-2) and anxiety (GAD-2) as shown in Table 10, there was no statistically significant association at alpha = 0.05 at between-person or within-person level.

In terms of the effect of covariates, weekly sleep problems corresponded to 10.0% higher depression ($p<0.001$) and 11.0% higher anxiety scores ($p<0.001$) per each point in the abbreviated B-PSQI score, ranging from 0 to 12. APR Financial Stress Scale (Affective portion) corresponded to a 4.9% ($p<0.01$) and 5.5% ($p<0.001$) increase in depression and anxiety, respectively, per point on the scale ranging from 8 to 40. Each point on the Brief Sensation Seeking Scale, which also ranges from 8 to 40, corresponded to a 4.8% ($p<0.05$) increase in depression. Higher scores on the Attitudes Toward Trading Scale were negatively correlated with anxiety (i.e., more positive attitudes toward trading was linked to being less anxious) such that each 1-point increase on the scale (ranging from 8 to 40) corresponded to a 9.4% ($p<0.05$) decrease in anxiety.

Table 10

Generalized linear mixed models estimating associations between trading time and behavioral health indices

	Depression (PHQ-2)	**Anxiety (GAD-2)**
	Count Ratio [95% CI]	Count Ratio [95% CI]
(Intercept)	0.817 [0.069, 9.620]	2.042 [0.262, 15.90]
Time	0.999 [0.966, 1.034]	0.971 [0.940, 1.002]
Age	0.921 [0.833, 1.018]	1.001 [0.912, 1.098]
Male Birth Sex (Yes/No)	1.269 [0.606, 2.656]	0.708 [0.375, 1.336]

Student (Yes/No)	0.631 [0.323, 1.235]	0.848 [0.469, 1.535]
Employed (Yes/No)	1.030 [0.535, 1.984]	1.169 [0.657, 2.080]
Household Income Above Area Median (Yes/No)	0.725 [0.400, 1.314]	1.004 [0.585, 1.722]
Sleep Problems	1.099 [1.041, 1.159]***	1.110 [1.054, 1.169]***
Positive Attitudes Toward Trading	0.975 [0.906, 1.050]	0.937 [0.880, 0.998]*
Financial Stress	1.049 [1.013, 1.087]**	1.055 [1.022, 1.088]***
Sensation Seeking	1.048 [1.005, 1.092]*	1.034 [0.999, 1.071]
Lost Money From Trading (Yes/No)	1.137 [0.863, 1.498]	1.154 [0.888, 1.500]
Trading Time (Between-Person, GMC)	1.026 [0.901, 1.168]	1.092 [0.980, 1.218]
Trading Time (Within-Person, PMC)	1.018 [0.972, 1.067]	1.000 [0.963, 1.039]

Note: GMC = grand-mean centered. PMC = person-mean centered. Models also adjusted for racial and ethnic identities, but estimates are not shown due to a priori decision not to interpret these effects. *p<.05, **p<.01, ***p<.001.

Associations between Time Spent on Trading and Substance Use (Aims 1 and 2)

The assessment of the relationship between weekly time spent on trading and substance use (alcohol and nicotine) yielded no significant association at alpha = 0.05 at between-person or within-person level. Student status was negatively associated with alcohol use (-82.9%, p<0.05).

Table 11

Generalized linear mixed models estimating associations between trading time and substance use indices

	Alcohol Use	**Nicotine Use**
	Count Ratio [95% CI]	Count Ratio [95% CI]
(Intercept)	0.916 [0.007, 106.5]	0.001 [0.000, 0.572]*
Time	0.973 [0.917, 1.032]	0.895 [0.797, 1.004]
Age	1.082 [0.884, 1.324]	0.862 [0.627, 1.184]
Male Birth Sex (Yes/No)	0.674 [0.145, 3.113]	1.472 [0.130, 16.62]
Student (Yes/No)	0.171 [0.039, 0.741]*	0.255 [0.029, 2.185]
Employed (Yes/No)	0.535 [0.117, 2.449]	0.387 [0.042, 3.516]
Household Income Above Area Median (Yes/No)	0.440 [0.121, 1.592]	1.664 [0.250, 11.05]

Sleep Problems	0.991 [0.890, 1.105]	1.008 [0.774, 1.313]
Positive Attitudes Toward Trading	0.945 [0.805, 1.110]	1.015 [0.816, 1.264]
Financial Stress	0.969 [0.897, 1.048]	1.001 [0.898, 1.116]
Sensation Seeking	1.039 [0.950, 1.136]	1.139 [0.998, 1.299]
Lost Money From Trading (Yes/No)	0.811 [0.480, 1.370]	0.582 [0.063, 5.331]
Trading Time (Between-Person, GMC)	0.910 [0.670, 1.235]	1.137 [0.811, 1.595]
Trading Time (Within-Person, PMC)	1.031 [0.953, 1.115]	0.989 [0.869, 1.125]

Note: GMC = grand-mean centered. PMC = person-mean centered. Models also adjusted for racial and ethnic identities, but estimates are not shown due to a priori decision not to interpret these effects. *p<.05, **p<.01, ***p<.001.

Model Fit Across Individual Models

Table 12 lists model fit statistics for the eight models used to estimate the between-person and within-person effects of trading and effects of covariates on selected outcome variables. Between the trading frequency models and trading time models, the trading frequency models demonstrated marginally better model fit based on AIC, BIC, log-likelihood and deviance values. This improvement was most noticeable among the models predicting nicotine use.

Table 12

Model fit statistics for generalized linear mixed models (GLMMs) across outcome and trading variables

Outcome Variable	**Trading Variable**	**AIC**	**BIC**	**Log-Likelihood**	**Deviance**
PHQ2 (Depression)	Trading Frequency	1129.3	1211.6	-544.7	1089.3
PHQ2 (Depression)	Trading Time	1132.2	1218.7	-545.1	1090.2
GAD2 (Anxiety)	Trading Frequency	1224.2	1306.5	-592.1	1184.2
GAD2 (Anxiety)	Trading Time	1225.1	1311.5	-591.6	1183.1
Alcohol Use	Trading Frequency	594.8	681.2	-276.4	552.8
Alcohol Use	Trading Time	597.6	684.1	-277.8	555.6
Nicotine Use	Trading Frequency	229.3	315.7	-93.6	187.3
Nicotine Use	Trading Time	239.8	326.2	-98.9	197.8

Interaction Effects between Selected Covariates and Trading on Health Indices (Aim 3)

Interaction effects between moderators and trading activity were explored through a series of separate generalized linear mixed models (GLMMs) as described in the Data Analysis section. For each moderator, a GLMM was fitted twice, once with between-person and within-person trading time (time spent on trading) variables and once for between-person and within-person trading frequency variables. This process was repeated for each dependent variable: PHQ-2 (depression), GAD-2 (anxiety), alcohol use, and nicotine use, as shown in Tables 13, 14, 15, and 16.

Interaction between Moderators and Between-Person Effects of Trading on Health Indices

Several moderators exhibited significant interactions with the between-person effects of trading at alpha = 0.05 across health indices. Higher age moderated the relationship between trading frequency and nicotine use. Injunctive norms of trading demonstrated a positive interaction effect with trading frequency in predicting depression and nicotine use. Both sensation seeking and financial stress measures had positive interactions with trading frequency in predicting nicotine use.

Interaction between Moderators and Within-Person Effects of Trading on Health Indices

Positive attitudes toward trading moderated the link between time spent on trading and anxiety. Injunctive norms of trading had a negative moderating effect on trading frequency's link to depression as well as anxiety, for which the interaction effect was significant at alpha = 0.001. That is, if a participant more strongly believed their friends approved of trading, they were less susceptible to being more depressed or anxious when they traded more often. Lastly, loneliness positively interacted with trading frequency in predicting alcohol use.

Generalized Estimating Equations Sensitivity Analyses

Sensitivity analyses were performed using generalized estimating equations (GEEs) to help determine the validity of main results obtained through GLMMs. In GEEs, estimated effects are averaged over the entire sample, instead of allowing subject-specific random effects. GEEs are also able to integrate autoregressive modeling, enabling the assessment of whether autoregressive modeling would be beneficial for model fit.

GEEs with autoregressive modeling were performed using the same parameters as those used for GLMMs, and the findings (patterns of significance) closely matched those obtained using GLMMs as demonstrated in Table 21 of the Appendix section. Main findings of the study remained unchanged. Given these results of the GEE sensitivity analysis, the decision to use GLMMs was retained as they can account for inter- and intra-individual variability in ways that GEE is designed to ignore or average over.

Table 13

Interaction Effect Estimates (Trading Time Predictor Variable - Behavioral Health Dependent Variables)

	Depression (PHQ-2) (Between-Person)	**Depression (PHQ-2) (Within-Person)**	**Anxiety (GAD-2) (Between-Person)**	**Anxiety (GAD-2) (Within-Person)**
	Count Ratio [95% CI]	Count Ratio [95% CI]	Count Ratio [95% CI]	Count Ratio [95% CI]
Age	0.99962 [0.99904, 1.00019]	1.00006 [0.99983, 1.00028]	0.99963 [0.99915, 1.00012]	1.00005 [0.99982, 1.00028]
Attitudes Toward Trading	0.99971 [0.99906, 1.00035]	1.00024 [0.99997, 1.00051]	0.99948 [0.99887, 1.00008]	1.00028 [1.00005, 1.00052]*
Injunctive Norms of Trading	1.00237 [1.0007, 1.00404]	0.99964 [0.99904, 1.00025]	1.00102 [0.99949, 1.00255]	0.9997 [0.99919, 1.0002]
Descriptive Norms of Trading	0.99998 [0.99995, 1.00002]	1.00002 [0.99998, 1.00005]	1.00144 [0.99965, 1.00322]	0.99916 [0.99857, 0.99976]**
Sensation Seeking	1.00000 [0.9996, 1.00039]	0.99999 [0.99988, 1.0001]	1.00001 [0.99965, 1.00037]	0.99996 [0.99987, 1.00005]
Impulsivity	1.00032 [0.99922, 1.00142]	0.99987 [0.99963, 1.00011]	1.00078 [0.9999, 1.00166]	0.99999 [0.99978, 1.0002]
Financial Stress	0.99994 [0.99949, 1.00039]	1.00001 [0.99991, 1.00011]	1.00001 [0.99964, 1.00038]	1.00003 [0.99993, 1.00013]
Loneliness (Weekly)	1.00082 [0.99996, 1.00167]	0.99983 [0.99928, 1.00038]	1.00033 [0.99974, 1.00091]	0.99983 [0.99937, 1.00029]
Trading Alone (Weekly)	1.00029 [0.99814, 1.00243]	0.99896 [0.99732, 1.00061]	1.00048 [0.99885, 1.00211]	0.99911 [0.99768, 1.00054]

Note: each estimate corresponds to the interaction term of the moderator and either the grand-mean-centered (between-person effect) or person-mean-centered (within-person effect) trading time variable in a multilevel model with the corresponding outcome variable. *p<.05, **p<.01, ***p<.001.

Table 14

Interaction Effect Estimates (Trading Time Predictor Variable - Substance Use Dependent Variables)

	Alcohol Use (Between-Person)	**Alcohol Use (Within-Person)**	**Nicotine Use (Between-Person)**	**Nicotine Use (Within-Person)**
	Count Ratio [95% CI]	Count Ratio [95% CI]	Count Ratio [95% CI]	Count Ratio [95% CI]
Age	1.00008 [0.99874, 1.00142]	1.00000 [0.99966, 1.00034]	0.99966 [0.99779, 1.00153]	0.99971 [0.99883, 1.00061]
Attitudes Toward Trading	1.00103 [0.99969, 1.00236]	1.00015 [0.99975, 1.00055]	1.00123 [0.9987, 1.00376]	1.00001 [0.9995, 1.00051]
Injunctive Norms of Trading	0.99537 [0.99122, 0.99954]*	0.99953 [0.9984, 1.00065]	0.99705 [0.99107, 1.00307]	0.99914 [0.99752, 1.00077]
Descriptive Norms of Trading	0.99999 [0.99988, 1.00009]	1.00002 [0.99971, 1.00033]	1.00005 [0.99993, 1.00017]	0.99999 [0.9999, 1.00008]
Sensation Seeking	1.00033 [0.99956, 1.0011]	1.00007 [0.99985, 1.0003]	1.00102 [0.99968, 1.00237]	1.00009 [0.9995, 1.00069]
Impulsivity	0.9999 [0.99951, 1.00029]	0.9999 [0.99951, 1.00029]	0.99707 [0.99346, 1.00069]	1.00029 [0.99911, 1.00148]
Financial Stress	1.00044 [0.99947, 1.00141]	1.00003 [0.99988, 1.00017]	1.00008 [0.99885, 1.00132]	0.99992 [0.99953, 1.0003]
Loneliness (Weekly)	1.00153 [0.99979, 1.00327]	1.0006 [0.9995, 1.00171]	1.00063 [0.9984, 1.00287]	0.9986 [0.99628, 1.00093]
Trading Alone (Weekly)	0.99885 [0.99414, 1.00358]	1.00041 [0.99766, 1.00316]	0.99945 [0.99309, 1.00586]	1.00085 [0.99666, 1.00506]

Note: each estimate corresponds to the interaction term of the moderator and either the grand-mean-centered (between-person effect) or person-mean-centered (within-person effect) trading time variable in a multilevel model with the corresponding outcome variable. *p<.05, **p<.01, ***p<.001.

Table 15

Interaction Effect Estimates (Trading Frequency Predictor Variable - Behavioral Health Dependent Variables)

	Depression (PHQ-2) (Between-Person)	**Depression (PHQ-2) (Within-Person)**	**Anxiety (GAD-2) (Between-Person)**	**Anxiety (GAD-2) (Within-Person)**
	Count Ratio [95% CI]	Count Ratio [95% CI]	Count Ratio [95% CI]	Count Ratio [95% CI]
Age	1.00958 [0.9452, 1.07835]	0.98659 [0.96089, 1.01297]	1.02657 [0.96548, 1.09153]	0.9909 [0.96732, 1.01506]
Attitudes Toward Trading	1.04179 [0.98504, 1.10181]	1.00168 [0.98104, 1.02276]	1.01333 [0.9618, 1.06763]	1.00513 [0.9857, 1.02493]
Injunctive Norms of Trading	1.25355 [1.03419, 1.51943]*	0.9143 [0.84812, 0.98564]*	1.07635 [0.89836, 1.28961]	0.86932 [0.81001, 0.93298]***
Descriptive Norms of Trading	1.00056 [0.99742, 1.00371]	0.99954 [0.99618, 1.00291]	0.99957 [0.99653, 1.00262]	0.9998 [0.99667, 1.00294]
Sensation Seeking	1.00934 [0.97413, 1.04582]	0.99659 [0.98749, 1.00577]	1.02384 [0.9931, 1.05553]	0.99477 [0.98644, 1.00316]
Impulsivity	1.05954 [0.98928, 1.13479]	0.9958 [0.97273, 1.01943]	1.02739 [0.96445, 1.09443]	0.98598 [0.96311, 1.00939]
Financial Stress	1.00323 [0.97373, 1.03362]	0.99901 [0.99177, 1.00631]	1.00125 [0.97465, 1.02858]	0.999 [0.99207, 1.00599]
Loneliness (Weekly)	1.04935 [0.9747, 1.12972]	1.00223 [0.96349, 1.04253]	1.02666 [0.95875, 1.09939]	0.98899 [0.95394, 1.02531]
Trading Alone (Weekly)	1.0166 [0.80664, 1.28122]	0.92097 [0.76242, 1.1125]	1.02278 [0.81836, 1.27826]	0.90109 [0.75552, 1.0747]

Note: each estimate corresponds to the interaction term of the moderator and either the grand-mean-centered (between-person effect) or person-mean-centered (within-person effect) trading frequency variable in a multilevel model with the corresponding outcome variable. *p<.05, **p<.01, ***p<.001.

Table 16

Interaction Effect Estimates (Trading Frequency Predictor Variable - Substance Use Outcome Variables)

	Alcohol Use (Between-Person)	**Alcohol Use (Within-Person)**	**Nicotine Use (Between-Person)**	**Nicotine Use (Within-Person)**
	Count Ratio [95% CI]	Count Ratio [95% CI]	Count Ratio [95% CI]	Count Ratio [95% CI]
Age	1.04483 [0.89467, 1.22019]	1.00492 [0.9674, 1.0439]	1.25153 [1.05058, 1.49092]*	1.00638 [0.91659, 1.10497]
Attitudes Toward Trading	1.00298 [0.87476, 1.14998]	1.0183 [0.98971, 1.04772]	1.11826 [0.98972, 1.2635]	0.9784 [0.93212, 1.02698]
Injunctive Norms of Trading	0.94582 [0.57576, 1.55371]	0.93855 [0.85394, 1.03154]	2.00084 [1.0054, 3.98186]*	1.04283 [0.88776, 1.22499]
Descriptive Norms of Trading	0.99902 [0.99398, 1.00408]	1.00191 [0.99634, 1.00752]	1.00061 [0.99326, 1.00802]	0.99925 [0.99186, 1.0067]
Sensation Seeking	1.04064 [0.96287, 1.12469]	1.00937 [0.98905, 1.03011]	1.16563 [1.06394, 1.27703]**	0.99691 [0.95417, 1.04156]
Impulsivity	0.89512 [0.75744, 1.05782]	1.00204 [0.96135, 1.04445]	1.04579 [0.93181, 1.17371]	1.0249 [0.94837, 1.10761]
Financial Stress	1.03076 [0.96451, 1.10156]	1.00408 [0.99004, 1.01832]	1.11866 [1.02235, 1.22404]*	1.01197 [0.98254, 1.04227]
Loneliness (Weekly)	1.09862 [0.95223, 1.26751]	1.08938 [1.00368, 1.18239]*	1.15073 [0.91689, 1.4442]	0.90913 [0.74011, 1.11674]
Trading Alone (Weekly)	1.02317 [0.71269, 1.46889]	0.91458 [0.69434, 1.20469]	1.1565 [0.72775, 1.83785]	1.18385 [0.75122, 1.86566]

Note: each estimate corresponds to the interaction term of the moderator and either the grand-mean-centered (between-person effect) or person-mean-centered (within-person effect) trading frequency variable in a multilevel model with the corresponding outcome variable. *p<.05, **p<.01, ***p<.001.

Discussion

Discussion of Main and Interaction Effects

The present study was designed to investigate speculative trading activities' relationship to health indices, including behavioral health and substance use involvement. We sought to address three main aims: 1) investigate the between-person associations between speculative trading and health indices, 2) investigate the within-person associations between speculative trading and health indices, and 3) explore the interaction effects between speculative trading and selected covariates on health indices. The hypothesis for Aim 1 was partially supported, and the hypothesis for Aim 2 was not. Aim 3, which was exploratory in nature, identified several statistically significant interaction effects.

Among the between-person and within-person effects of trading frequency and, separately, time spent on trading on health indices evaluated using multilevel models, positive between-person association of trading frequency with nicotine use ($p<0.001$) was the sole significant link at alpha = 0.05. Each additional day of trading per week corresponded to a 146% increase in weekly ASSIST-Lite nicotine use score on average. This finding, highlighting the strong between-person link between the frequency of speculative trading and nicotine use, mirrors findings in problem gambling and nicotine use (McGrath et al., 2009).

There are several possible interpretations for this finding. First, consistent with the Problem Behavior Theory (Jessor & Jessor, 1977; Schlegel et al., 2008) discussed in the Introduction section (*Common Theories of Young Adult Problem Gambling*), speculative trading and nicotine use may have a shared function (e.g., relieving boredom or achieving a sense of excitement) in this cohort of young adults. Our findings also support the Problem Behavior

Theory's conceptualization of personality system and perceived environmental system as factors in psychosocial influences. Specifically, sensation seeking trait was positively associated with nicotine use in the same multilevel model, and it also moderated the relationship between the between-person effects of trading frequency and nicotine use involvement in a separate interaction model, making the case for sensation seeking as a personality trait associated with the two behaviors. In addition, perceived injunctive norms of trading moderated the association between the between-person effects of trading frequency and nicotine use involvement, suggesting that perceived social norms for a risk behavior can encourage engagement in another with a shared function.

Another possible explanation for associations between speculative trading and nicotine use is that increased nicotine use is a coping mechanism for those who report more frequent trading activities, as they seek to reduce the stress caused by increased involvement with the highly uncertain nature of financial markets. Supporting this explanation, financial stress moderated the link between between-person effects of trading frequency and nicotine use such that those who experienced higher financial stress reported a greater increase in nicotine use when they traded more frequently compared to those who experienced lower financial stress.

Among the covariates included in the analyses, sleep problems, financial stress, and sensation seeking consistently corresponded to higher depression and anxiety, consistent with past findings on the close association between poor sleep and emotional reactivity (Alvaro et al., 2013), the role of financial/economic strain in exacerbating persistent worry and depressive symptoms (Viseu et al., 2018), and the greater susceptibility to anxiety and depression among those higher in sensation seeking (Ortin et al. 2012, Teichman et al., 1989). Relatedly, in the multilevel model incorporating the between- and within-person effects of time spent on trading, positive attitudes toward trading were correlated with lower anxiety in the model. This finding suggests that among young adults who regularly engage in speculative trading, holding more positive attitudes toward trading may act as a "buffer" against anxiety as they find trading to be more enjoyable, controllable, or less problematic.

Meanwhile, and somewhat at odds with this finding, positive attitudes toward trading moderated the within-person effect of time spent on trading and anxiety. This suggests that for those with more positive attitudes toward trading, spending more time on trading was associated with higher anxiety than among those with less positive attitudes toward trading. A possible explanation is that those who hold more positive attitudes toward trading become more emotionally engaged in trading and thus experience greater anxiety from the increased exposure to financial market risks when they trade more. Another explanation is that they may experience anxiety from cognitive dissonance (Harmon-Jones et al., 2019), which forms as a result of both holding positive views of trading and experiencing less-positive-than-expected outcomes (e.g., financial losses, neglect of job or relationships) with more time spent on trading activity. They may also feel a greater sense of pressure from themselves or others to perform well in trading, leading to increased anxiety with more time spent on trading.

Perceived norms of trading moderated trading activity's links to key health indices at both between- and within-person levels in different ways. Injunctive norms weakened the within-person effects of trading frequency on anxiety and depression, suggesting that greater perceived social approval of trading could contribute to young adults being more "immune" to internalizing stress when they trade more frequently. In a similar fashion, descriptive norms weakened the within-person effects of trading time on anxiety, indicating a similar inoculation effect from believing trading is a popular activity among peers.

Greater injunctive norms, financial stress, and sensation seeking strengthened the between-person effects of trading frequency on nicotine use, supporting the Problem Behavior Theory (Jessor & Jessor, 1977)'s conceptualization of the role of personality system and perceived environment system in shaping psychosocial proneness to engage in risky behaviors. These findings also help to contextualize the between-person association identified between trading frequency and nicotine use.

Meanwhile, injunctive norms strengthened the link between depression and trading frequency at the between-person level. A possible explanation is that the belief that trading is a socially desirable skill could lead to a notion that trading carries beneficial outcomes. However, trading often leads to negative outcomes such as poorer work performance, losing control of finances, and relationship difficulties (Newall et al., 2022); in fact, in our own data we identified a modest positive correlation ($r = 0.21$, $p < 0.001$) between trading frequency and reporting being distracted or losing focus at work or school due to trading. Experiencing these results that stray away from the perceived norm could further intensify self-criticism and depressed mood. Taken together, perceived injunctive social norms' role in the trading-health connection may be complex, acting as a buffer against behavioral health harms within-person and both a buffer and a stressor depending on the assessed outcome between-person.

Discussion of Descriptive Statistics and Related Findings

Descriptive statistics yielded several notable insights into the trading behaviors and related harms among the study participants. Participants spent on average 154 minutes (over two and a half hours) per week on trading and related activities. A third of this time was spent on monitoring market data, followed by reading or listening to trading-related information, speaking to the participants' speculative, short-term mindset rather than a long term oriented approach.

Indeed, the average holding period for a trade was 9.7 days, an unlikely timeframe for material long-term changes in underlying companies or assets. These results also imply that trading is likely a significant cognitive and emotional commitment that takes attention away from other activities.

Our weekly survey of the functional consequences of trading supports this notion. Participants reported monitoring market data at work or school more than two thirds of the weekly periods (68%) and reading or exchanging information about trading while at work or school nearly as often (60%). They reported actually placing a trade while at work or school 44% of the weeks, and said they were distracted due to trading in these settings 32% of the time. Given trading and related activities require dedicated cognitive focus and decision-making abilities difficult to carry out alongside professional and academic responsibilities, it is quite possible that the actual rate of distraction is greater than reported. In addition, since making new trades is naturally followed by market monitoring behaviors, which can then lead to acting on additional trading opportunities, the continuous cycle of distraction from trading and related behaviors can be challenging to break. Another factor that may contribute to the widespread nature of trading-related distraction is the increasing availability of 24-hour trading; cryptocurrencies can be traded at all hours of the day, and popular stock trading platforms such as Robinhood have begun offering easy access to 24-hour trading (Robinhood Markets, 2025). Overall, these results suggest that trading and related activities are preoccupying activities for this cohort of young adults that can lead to lower concentration and lower performance in professional and academic settings.

The ubiquitous access of trading also raises concerns about the risks of trading alone, which can increase susceptibility to cognitive biases, making more emotionally driven financial decisions, and relying on trading as a substitute for social activities. Across the study period, participants reported trading while physically alone 78% of the weeks on average, and they were with people who were aware of their trading only 14% of the time. This is a concerning finding considering past research demonstrating that gambling alone is a risk factor for making more impulsive and larger bets, gambling more frequently, and experiencing more problem gambling harms (Bernhard et al., 2007; Lemoine et al. 2017), especially given the wide availability of trading on margin which can shift the financial risk-reward of trading more akin to high-stakes gambling.

Participants' mean Problem Gambling Severity Index - Speculative Trading score was 64% higher than their Problem Gambling Severity Index, and well within the moderate (3-7) problem gambling range at 4.1 out of 27. Considering the adapted measure assesses key aspects of problem gambling within the trading context such as developing tolerance, chasing loss, and experiencing financial problems, this result speaks to problem gambling-like consequences from trading activities among this cohort of young adults, which would have been overlooked had they only been assessed on traditional gambling activities.

Our study results also revealed that trading on margin (using borrowed money to trade with the aim of achieving larger profit) was popular among the young adults in the study. Average leverage for all stock trading was 1.5x, meaning the participants were on average taking on 50% more financial risk than the amount of money they are putting into each trade. On average, participants traded stocks on margin (using any borrowed money to trade) 37% of the time while trading stocks, and across the study period they reported trading stock derivatives (high-risk forms of trading on margin) 32% of the time. The appetite for trading on margin was even greater among cryptocurrency traders, with an average leverage of 2.5x. Participants traded on margin 48% of the time they traded cryptocurrency, while cryptocurrency derivatives were only traded 3% of the time, likely owing to lower availability. Alarmingly, across both stocks and cryptocurrencies, maximum leverage reached over 10x. At 10x margin, which is equal to borrowing $900 for every $100 in hand to trade with $1,000, a 10% trade loss leads to losing all of the money on hand.

The observed popularity of trading on margin can be explained by its nearly ubiquitous availability, high visibility through marketing, and easy access (Newall et al., 2022). It is of particular concern in the cryptocurrency trading domain since the cryptocurrency market is inherently more volatile than in stock markets and there are fewer financial regulations and consumer protection measures. Margin use can lead to larger profits as well as more detrimental losses, further enabling gambling-like behaviors in trading. The resulting high-reward, high-risk cycle can reinforce financial risk-taking behaviors and amplify the emotional stress and anxiety of trading.

Limitations and Future Directions

Several limitations of our study and its results must be noted.

First, the measures of speculative trading activity relied on self-reported responses from the participants without verifiable data from trading platforms, and it is possible that participants provided inaccurate or biased information especially as it relates to their trading activities. We sought to minimize this possibility of experimenter effects by conducting assessments online and explicitly ensuring confidentiality. We also screened for inconsistent or implausible data patterns and cross-referenced information through multiple questions throughout the assessment. Future studies can improve upon this limitation by incorporating objective trading data (e.g., from trading platforms) into the study design.

Second, our findings are limited by several issues caused by the relatively low sample size of 60. For one, small sample sizes are subject to a lower statistical power and a higher chance of false negatives. It is possible some of our findings (null or significant) resulted from as few as a single or a pair of data points, given the study's small sample size and the fact that we did not perform outlier or influential data analyses. In addition, although we optimized the multilevel model through the glmmTMB package's fine-tuning features and no model convergence warnings were generated during the modeling process, our models may suffer from inherent convergence and parameter estimation issues stemming from their complexity relative to the small sample size and the resulting elevated likelihood of false positives. Larger samples can address these problems in future studies.

Third, while we sought to recruit a representative sample of young adults who engage in speculative trading through targeted online advertisements, participant demographics exhibited a relatively high percentage of male participants (83%) and Asian participants (43%) and low percentage of White participants (40%), which raises questions about the generalizability of our findings. However, given the wide reach of our recruitment efforts, leading to participation from young adults in 16 different U.S. states, it is also possible that speculative trading is especially popular among these groups, mirroring the overrepresented groups in gambling participation (National Council on Problem Gambling, 2018). Future studies can continue efforts to recruit large, representative samples of young adults who engage in speculative trading to improve the understanding of their demographics.

Fourth, we must note the general lack of variability in our weekly assessment of substance use owing to reliance on a brief assessment measure, ASSIST-Lite. This limitation is demonstrated by the generally low reliability scores of ASSIST-Lite subscores items (see Table

18 from Appendix Section) as a result of two factors: they consisted of only three or four assessment items, and some questions assessed usage while others assessed problematic use. While we were able to identify several significant associations involving substance use, assessing substance use quantity and consequences 1) through a larger number of items and 2) separately for typical and peak use could have provided more variability, thus enabling more granular assessment of the associations between trading and substance use.

Fifth, our analysis did not account for time-specific economic or market conditions, which may have played a role in influencing the participants' trading activities and the associations between their trading activities and the covariates or health indices we assessed at different time points. Future studies can investigate the impact of these factors and ways to appropriately account for them through covariates and interaction effects if necessary.

Sixth, while our study design accounted for within-person variations in trading and health indices using longitudinal data, it was not able to discern directionality or causal links between these constructs. Future studies could aim to identify directionality of the relationship by using structural equation modeling techniques. Such a study would likely require a larger sample size and more frequent longitudinal assessments in order to ensure sufficient statistical power and granularity for capturing temporal dynamics.

Seventh, our study did not differentiate between participants' trading skill or experience level aside from screening out institutional traders, who are employed to trade on behalf of financial organizations. Even amongst retail traders, skill, experience, or sophistication could have been a significant confound variable influencing the main effects of our study, and future studies can consider the role of these factors in trading behaviors and related associations.

In conclusion, this study is the first of its kind known to assess the longitudinal links between speculative trading activities and health correlates in young adults. Our findings carry several implications for prevention, treatment, and policy efforts to reduce harm from speculative trading. Prevention programs for trading harms could focus on educating young adults prone to high financial stress, sensation seeking traits, and positive social norms of trading about the potential risks of trading. Similarly, treatment efforts for trading harms would benefit from considering these factors, and given trading's close link to nicotine use, substance use treatment providers could consider assessing risky trading behaviors in tandem. In terms of policy, efforts to promote responsible trading could focus on ensuring young adults' awareness of financial risks involved in margin and derivative trading given their popularity and consider the role of perceived social norms in shaping trading behaviors. Future research can build upon our findings to further explore these relationships and develop appropriate intervention strategies.

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Appendix

Table 17

Reliability Table for Baseline *Measures* (Omega and Alpha)

Measure	# of Items	Omega	Alpha
Brief Sensation Seeking Scale (BSSS)	8	0.82	0.81
Abbreviated Impulsiveness Scale (ABIS)	13	0.88	0.84
APR Financial Stress Scale (Affective Portion)	8	0.95	0.95
Problem Gambling Severity Index (PGSI)	9	0.93	0.92
Problem Gambling Severity Index - Speculative Trading (PGSI-ST)	9	0.89	0.89
Game Addiction Scale	7	0.92	0.92
Attitudes Towards Gambling Scale	8	0.71	0.69
Attitudes Towards Trading Scale	8	0.77	0.74

Table 18

Reliability Table for Weekly *Measures* (Omega and Alpha)

Measure	# of Items	Omega	Alpha
PHQ-2 (Depression)	2	0.86	0.86
GAD-2 (Anxiety)	2	0.87	0.87
Three-Item Loneliness Scale	3	0.84	0.84
Abbreviated B-PSQI (Sleep Quality)	4	0.67	0.65
ASSIST-Lite (Total)	22	0.84	0.78
ASSIST-Lite (Nicotine)	3	0.59	0.50
ASSIST-Lite (Alcohol)	4	0.58	0.52
ASSIST-Lite (Cannabis)	3	0.81	0.79
ASSIST-Lite (Stimulant)	3	0.62	0.61
ASSIST-Lite (Sedative)	3	0.54	0.51
ASSIST-Lite (Opioid)	3	0.48	0.39
ASSIST-Lite (Other)	3	0.52	0.37

Table 19

Comparison between random intercept and random linear slope model

	Random Intercept	Time (Linear Slope)	Error
Random Intercept Model	0.587	NA	0.652
Random Linear Slope Model	0.726	0.00032	0.652

Note: PHQ-2 was used as a dependent variable and trading frequency was used as the weekly trading variable. A negligible variance of random effect for time as a linear slope and a lack of meaningful difference in residual error were consistently found across dependent variables and trading variables.

Table 20

Correlation matrix for key variables

	Trading Frequency	Trading Time	Attitudes Toward Trading	Financial Stress	Sensation Seeking	Sleep Problems	Depression	Anxiety	Alcohol Use	Nicotine Use
Trading Frequency	1.00									
Trading Time	0.39	1.00								
Positive Attitudes Toward Trading	0.12	-0.06	1							
Financial Stress	-0.14	-0.20	0.18	1.00						
Sensation Seeking	0.21	-0.02	0.15	0.07	1.00					
Sleep Problems	0.03	-0.01	0.08	0.45	0.29	1.00				
Depression	0.04	0.04	0.27	0.58	0.29	0.20	1.00			
Anxiety	0.06	0.03	0.2	0.52	0.27	0.25	0.55	1.00		
Alcohol Use	0.16	0.05	-0.01	-0.02	0.18	0.01	0.04	0.00	1.00	
Nicotine Use	0.10	0.05	0.19	0.07	0.34	0.04	-0.03	-0.03	0.18	1.00

***Person-mean-centered values used for correlations between weekly measures, person-mean values used for correlations with baseline measures (positive attitudes toward trading, financial stress, sensation seeking).**

Table 21

Generalized Estimating Equations (GEE) Sensitivity Analysis Results

	Depression (PHQ-2) GEE with AR	**Depression (PHQ-2) GLMM**	**Nicotine Use GEE with AR**	**Nicotine Use GLMM**
	Count Ratio [95% CI]	Count Ratio [95% CI]	Count Ratio [95% CI]	Count Ratio [95% CI]
(Intercept)	5.290 [0.521, 49.891]	0.583 [0.064, 5.262]	0.0002 [0.000, 0.013]	0.000 [0.000, 0.020]***
Time	1.018 [0.985, 1.052]	1.000 [0.966, 1.036]	0.904 [0.809, 1.010]	0.903 [0.809, 1.009]
Age	0.917 [0.827, 1.014]	0.929 [0.845, 1.021]	0.725 [0.585, 0.897]**	0.726 [0.574, 0.919]**
Male Birth Sex (Yes/No)	1.107 [0.474, 2.578]	1.358 [0.671, 2.749]	3.456 [0.229, 52.300]	3.116 [0.443, 21.90]
Student (Yes/No)	0.583 [0.340, 1.004]	0.581 [0.305, 1.106]	0.114 [0.017, 0.752]*	0.119 [0.022, 0.641]*
Employed (Yes/No)	0.840 [0.574, 1.231]	0.879 [0.468, 1.652]	1.436 [0.079, 26.050]	1.252 [0.147, 10.64]
Household Income Above Area Median (Yes/No)	0.894 [0.531, 1.500]	0.707 [0.402, 1.246]	0.790 [0.252, 2.477]	0.823 [0.248, 2.727]
Sleep Problems	1.098 [1.044, 1.160]***	1.098 [1.041, 1.159]***	1.036 [0.876, 1.224]	1.035 [0.817, 1.311]
Positive Attitudes Toward Trading	0.589 [0.348, 0.980]*	0.988 [0.921, 1.060]	1.326 [0.390, 4.509]	1.065 [0.915, 1.238]
Financial Stress	1.265 [1.004, 1.598]	1.040 [1.007, 1.075]*	1.041 [0.599, 1.806]	1.002 [0.932, 1.077]
Sensation Seeking	1.552 [1.162, 2.072]**	1.051 [1.010, 1.094]*	2.399 [1.221, 4.711]*	1.117 [1.014, 1.231]*
Lost Money From Trading (Yes/No)	1.214 [0.983, 1.498]	1.137 [0.864, 1.496]	0.331 [0.053, 2.065]	0.325 [0.041, 2.556]
Trading Frequency (Between-Person, GMC)	0.809 [0.654, 1.004]	0.820 [0.655, 1.028]	2.474 [1.402, 4.371]**	2.462 [1.449, 4.183]***
Trading Frequency (Within-Person, PMC)	1.056 [0.967, 1.153]	1.028 [0.950, 1.112]	1.066 [0.954, 1.192]	1.067 [0.886, 1.284]

Note: GMC = grand-mean centered. PMC = person-mean centered. Models also adjusted for racial and ethnic identities, but estimates are not shown due to a priori decision not to interpret these effects. *p<.05, **p<.01, ***p<.001.