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Client Heart Rate Variability in Motivational Interviewing for Alcohol Use

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by

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THESIS

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ABSTRACT

Heart Rate Variability (HRV) is a useful tool for clinical practice and substance use research, as it may provide insight into liability for relapse or development of addiction, as well as provide indicators of recovery outcomes and response to treatment. Psychotherapy would benefit from an integrated understanding of physiological regulation systems such as what are measured by HRV, as HRV is linked to psychopathology and substance use disorders.

HRV was measured in non-treatment-seeking adult drinkers as they underwent a motivational interviewing (MI) session. Subjects' HRV from the interview was then regressed on therapist MI-consistent behaviors. The subjects' drinking at both baseline and follow-up was then regressed on their HRV from the MI interview.

HRV was significantly associated with baseline drinking; lower HRV was associated with higher scores on the Alcohol Use Disorder Identification Test (AUDIT), meaning diminished flexibility in physiological regulation systems was associated with more severe drinking behavior.

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1. Introduction:

1.1. The heart-brain connection:

The brain and body and its relations with the environment function as an interdependent and coordinated system (Critchley, 2009; Ingjaldsson, Laberg, & Thayer, 2003; Klimesch, 2018; Richardson & Chemro, 2014). This interdependence has been well established for the last century regarding physiology and emotion (Cannon, 1927; James, 1894; Lange 1885); even more, cognition, attention, memory and learning are all processes in coordination with the physiology of the body (Berntson & Cacioppo, 2000; Critchley & Harrison, 2013).

Of the viscera, the heart continuously propagates an electrical signal that is so powerful in amplitude, neurophysiological techniques such as magnetoencephalography (MEG) and electroencephalography (EEG), must account for it in order to interpret signals from the brain (Jousmaki & Hari, 1996). Electrocardiography (ECG) of the heart is often measured in such neurophysiological methods to distinguish cardiac and brain signals. As noted however, the brain is in constant coordination with the body, and in particular the heart. The heart is a major driver and coordinator in synchronism with whole body systems, including the brain (Fatisson et al., 2016; Klimesch, 2018). As such, how the heart is beating plays a prominent role in how the brain is functioning and should be considered when examining brain dynamics and behavior.

Heart rate variability (HRV) is one biological measure that has the potential to complement psychological research. HRV is the measure of variance in beat-to-beat changes in heart rate – the activity of which is directly modulated by the autonomic nervous system (ANS), including the sympathetic (SNS) and parasympathetic (PNS) nervous systems. As the name implies, the ANS is automatic and pervasive in everyday life, and is thus very influential in modulating behavior, often without conscious awareness (Bargh & Chartrand, 1999; Berntson et al., 1993; Chen & Bargh, 1999).

An important function of the ANS involves evaluating the environment in terms of valence – what to approach and avoid (Berntson, Boysen, & Cacioppo, 1993; Norman et al., 2011). Despite the nuance of this construct, it is at the root of the motivational system and is what allows us to navigate and regulate our lives in relation to the environment (Cacioppo & Gardner, 1999; Norman, Bernston, & Cacioppo, 2014; Thayer & Siegle, 2002). The functioning of this regulatory system is most ideal when it is adaptable and flexible. In other words, when it can adjust adaptively and appropriately to environmental demands (Thayer & Siegle, 2002; Thompson, 1994). Correspondingly, the heart functions best when it is appropriately adaptable and flexible to environmental demands. An optimal level of cardiac functioning is neither too rigid nor too chaotic (McCraty & Shaffer, 2015; Shaffer, McCraty, & Zerr, 2014). HRV provides a means to measure the activity of this evaluative and regulatory system (Thayer & Lane, 2000).

Considerations exist when characterizing HRV, as the heart rate is a rather complex phenomenon resulting out of various bodily systems operating at multiple temporal scales (McCarty & Shaffer, 2015; Quintana & Heathers, 2014). However, despite the difficulty in characterizing and quantifying such a complex signal, low variability is a pattern that has been consistently associated with pathological conditions. Low HRV, or diminished flexibility, is consistently associated with multiple psychopathologies including anxiety, post-traumatic stress disorder, bipolar, depression, substance use disorder (Berking & Wupperman, 2012; Friedman, 2007; Thayer & Siegle, 2002); as well as risk and mortality in physical health including cardiovascular disease, diabetes, and obesity (Chalmers et al., 2014; Kemp & Quintana, 2013; Stein & Kleiger, 1999).

1.2. Heart rate variability and substance use disorders:

HRV is relatively accessible and noninvasive to obtain, and could be valuable in clinical practice and research in providing insight into relapse liability and predispositions to the development of addiction; as well as provide indicators of recovery outcomes and response to treatment (Buckman et al., 2019; Karpyak et al., 2014). Low HRV is associated with alcohol dependence (Karpyak et al., 2014; Milivojevic & Sinha, 2018), and may be related to maladaptive coping mechanisms when dealing with alcohol cue exposures (Ingjaldsson et al., 2003). HRV reactivity to cue-exposure has also been shown to predict relapse in alcohol-dependent individuals (Garland et al., 2012).

In addition, Low HRV is associated with poor emotion regulation (Ingjaldsson et al., 2003), which is a consistent factor contributing to both use and relapse (Berking et al., 2011; Le Moal & Koob, 2007; Witkiewitz & Villaroel, 2009). In particular, the inability to tolerate negative affect, poor inhibitory control in response to cravings, and alleviation of withdrawal symptoms; though it should be noted, emotion regulation is complex in SUD, and both positive and negative affect play roles (Cheetham et al., 2010).

Furthermore, emotion dysregulation is proposed to be a transdiagnostic vulnerability of psychopathology more broadly (Beauchaine & Zisner, 2017). It may be of benefit to address a transdiagnostic factor such as emotion regulation (Berking & Wupperman, 2012), as SUD is more commonly comorbid among mental health disorders also characterized by emotion dysregulation, such as anxiety and mood disorders (Gross & Jazaieri, 2014; Kret & Ploeger, 2015). Consistent with this, alcohol relapse rates are higher among those with comorbid affective disorders, and alcohol treatment outcomes are improved by concomitant treatment for alcohol and depression and/or anxiety (Witkiewitz & Villaroel, 2009). Targeting regulation of stress and emotion could also improve relapse outcomes (Sinha et al., 2009). Additionally, using HRV as an index for functional attributes provides benefits towards clinical research in assessing functional based mechanisms rather than behavioral and symptomatic manifestations found in categorical nosology (van Praag et al., 1990).

1.3. Heart rate variability and substance use disorder treatment:

There are interventions that target HRV directly. For example, Heart Rate Variability Biofeedback (HRVB) is one such treatment that explicitly utilizes heart rate measures to target autonomic regulatory systems and has the potential to be utilized in the treatment of SUD (Eddie et al., 2015; Leyro, Buckman, & Bates, 2019). HRVB exploits resonance properties of the cardiovascular system by slowing breathing rate to match baroreflex cycles, and by doing so, greatly increases HRV. HRVB has also been used in stress and anxiety reduction (Goessl, Curtiss, & Hofmann, 2017) with promising results. It follows that increases in HRV via interpersonal biological mechanisms (e.g., psychotherapy) may also have a positive effect.

1.4. Heart rate variability and substance use disorder treatment; implications for psychotherapeutic interventions:

As considered here, psychotherapy is an interpersonal interaction through which an intervention or treatment is implemented by a clinician. The therapist, as the conduit of the intervention, is an interactive and variable component of the treatment (Saxon & Barkham, 2012; Wampold & Brown, 2005; Wampold & Imel, 2015; Zuroff et al., 2010). Even more, the interpersonal skills of the therapist are considered central to client improvement (Duncan, Miller, Wampold, & Hubble, 2010; Norcross & Wampold, 2011). Indeed, in recognizing this, there are effective approaches in addiction treatment that identify and specify relational factors within the method, such as motivational interviewing (MI) (Miller & Rollnick, 2013). MI has specified as a component of the effectiveness to its method, a necessary relational foundation (Miller & Rose, 2009; Moyers, 2014). However, when it comes to defining these relational constructs behaviorally, it can be difficult to discern for empirical and training purposes what exactly a therapist is doing to establish a positive therapeutic relationship, as how people relate to one another greatly varies by person and context (Duncan, Miller, Wampold, & Hubble, 2010). Given the significance of its contribution to client improvement however, it is important to find methods that can index the quality and mechanics of this process.

Therefore, psychotherapy research would benefit by having real-time, innovative ways of measuring and characterizing relational interactions. Biomarkers have the potential to provide such complementary and alternative ways of exploring such interactions (Bernston & Cacioppo, 2000), as well as to provide methods to empirically validate relational qualities within clinical practice (Coutinho, Silva, & Decety, 2014; Marci & Riess, 2005; Neumann et al., 2009; Neumann & Westbury, 2011; Riess, 2011). Indeed, much of the biobehavioral HRV literature has foundations in key theories (Porges, 1995; Thayer & Lane, 2000) that suggest HRV can be used to examine the relationship between autonomic regulation and interpersonal interaction (Quintana & Heathers, 2014). When psychotherapy is deemed effective, it is presumed there are associated biological changes (Grawe, 2007; Liggan & Kay, 1999). These change mechanisms are an important focus in addiction research (Mechanisms of Behavior Change Satellite Committee, 2018; Feldstein Ewing et al ., 2011; Longabaugh et al., 2013) and in psychotherapy research more broadly (Kazdin & Nock, 2003).

Furthermore, it has been shown that therapists can modulate client in-session behaviors, such as client speech (Glynn & Moyers, 2011; Moyers & Martin, 2006; Moyers et al., 2009; Moyers et al., 2017). It is proposed therapists also have the ability to modulate client physiology

(Geller & Porges, 2014; Kleinbub, 2017; Porges, 2009). Not only is this important as a potential treatment target/outcome in itself, but for client in-session behavior as well. Internal visceral states are incredibly influential and pervasive in driving motivational behaviors and motivational decisions (Critchley & Harrison, 2013). As a therapist, it is of critical importance to establish an environment that is constructive for therapeutic progress, including the modulatory role of the interpersonal engagement process. This includes establishing a context that fosters the neurobiological environments most conducive for behavior change (Grawe, 2007; Rossouw, 2013).

1.5. Hypotheses:

It is hypothesized that as the therapist engages with the client and conveys a positive therapeutic interaction through MI-adherent behaviors, the client's ANS will be more flexible and open, as interpreted by higher HRV. It is hypothesized that those with high HRV in-session will be associated with less drinking at baseline and follow up; and likewise, those with low HRV will be associated with more drinking.

2. Methods

2.1. Source of Data:

The data is from the Neuroimaging Assessment of Motivational Activity for Speech in Treatment Episodes (NAMASTE) project. This study used neuroimaging methods to elucidate brain areas and dynamics associated with behavior change in drinking behavior. The neuroimaging methods in this project make use of ECG measurements, which are the focus of the current analysis. Relevant recruitment criteria and methodology is described.

2.2. Participants:

An adult community sample (N = 57) of non-treatment seeking drinkers was recruited in a southwest metropolitan area. Participants were included if they drank above low-risk levels based on the Alcohol Use Disorders Identification Test (AUDIT). Those with self-reported comorbid mental health diagnoses were excluded, as well as those with polysubstance use (except for nicotine and marijuana). It is not known what medication participants may have been taking. Characteristics of the final sample at baseline (N = 31) are included in Table 1. Attrition resulted in smaller samples at 1-month (N = 24) and 3-month (N = 27).

Table 1
Demographic characteristics

	N (%)	Mean (SD)
Age	-	27.26 (9.54)
Sex		
Male	13 (41.9)	-
Female	18 (58.1)	-
Ethnicity		
Hispanic or Latino	17 (54.8)	-
Race		
White	26 (83.9)	-
American Indian or Alaska Native	2 (6.5)	-
Asian	0	-
Black or African American	1 (3.2)	-
Native Hawaiian or Other Pacific Islander	0	-
Other	3 (9.7)	-
Baseline drinking characteristics		
Age of Onset	-	15.68 (2.04)
AUDIT	-	13.06 (7.22)
Drinking days per month (of 30)	-	17.06 (16.05)
Drinks per drinking days (of 30)	-	6.84 (12.33)
Binge drinking days	-	8.37 (12.56)
Percent days abstinent	-	.431 (.535)

Note: Ethnicity and race counts do not sum to 100%. AUDIT = Alcohol Use Disorders Identification Test.

2.3. Collection of Electrocardiogram (ECG):

Heart rate data was obtained from participants during a MI session (session length (*m:s*)*;* M = 29:34, SD = 3:19) while undergoing a MEG scan. Participants then returned for a neuroimaging follow-up assessment at 1-month. An additional behavioral follow-up was conducted remotely at 3-months. During the MI interview, participants were conversing with a clinician, and so were alternating between speaking and listening. Clinicians were master's level counselors or clinical psychologists from the University of New Mexico. All participants were in a sitting position with electrodes (AgCl) in lead I position and were sampled at 1000 Hz, which was then down sampled to 333 Hz or 500 Hz. There was a 5-minute resting MEG scan before the heart recording/interview. In addition, the patient was sitting for about 30 minutes prior while being prepped for the MEG; meaning there was minimal body exertion before the heart recording, and so it is not likely the cardiac signal here is affected by strenuous physical activity.

The heart rate data consisted of 5-minute recordings. The 5-minute window was chosen to allow comparability with the literature as this has been the standard due to various HRV measures being related to recording length (Task Force; Malik et al., 1996). Where in the MI session the 5 minutes was recorded was chosen based on data quality (start time ranged (*m:s*); 00:47 – 22:18). For short-term recordings such as these, it is recommended (Task Force; Malik et al., 1996; Nunan et al., 2010) selections be free of artifacts. Due to this selection criteria, it is possible there is systematic bias in window start time. Additionally, quality of data acquisition with ECG can generally degrade as time passes; for instance, participants may shift and move around the longer they are in the scanner; sweat can also interfere with electrode attachment and data acquisition. This selection bias is not a concern for the current focus if the clinician's MI quality is consistent throughout regardless of window selection time. Analytical methods will be taken into consideration to verify MI quality throughout the session.

2.4. Processing of ECG data:

The ECG data was processed using Kubios HRV premium v3.3.0 (Tarvainen et al., 2014). Kubios uses an automatic artifact correction algorithm. Artifacts include missing, extra or misaligned beat detections, ectopic beats, and other arrhythmias. Kubios premium detects artifacts from a time series consisting of differences between successive RR intervals, and artifact beats are replaced by interpolated RR values (for full description see Kubios User Guide v3.3.0, 2019).

Raw ECG signals were analyzed, and as recommended (Task Force; Malik, 1996), all ECG data were manually inspected for artifacts. Those that were > %5 artifact correction for the entire sample, or those that were not possible to manually correct, were discarded (N = 24). There are various reasons these data were not able to be analyzed. Some had initial errors in data acquisition (e.g., electrode detachment during recording) and others had artifacts (e.g., movement, coughing) that did not allot for a continuous and clean 5-minute sample of data. Of the remaining sample (N = 31), all but three were satisfactorily processed by Kubios' algorithm, with < 5% artifact correction for the entire 5-minute sample. The other three were manually corrected. It is noted that the analysis of HRV was opportunistic; the ECG measures were obtained for the purpose of MEG analysis, and so were not necessarily the focus of data acquisition. In addition, the quality of ECG signal required for MEG analysis does not require as high a standard as HRV analysis. As such, many subjects were not included simply because the quality of data—for the purpose of HRV analysis—had too many artifacts.

2.5. Confounds and covariates affecting heart rate:

To the extent possible, confounding effects were taken into consideration.
All participants were measured between 8a- 6p. Regarding consumptives, all participants were asked to abstain from alcohol for at least 12 hours before their visit. Participants were also asked to abstain from any tobacco use at least one hour before their visit. Regarding caffeine, participants were not asked to abstain; participants were told to do/behave as they normally would with regard to caffeinated products. It is not known when they may have last ate. Regarding bladder and gastric distension, participants were reminded and provided several opportunities to use the restroom before the interview and recordings. All were verified through self-report. These effects are rarely considered and/or reported (Quintana & Heathers, 2014).

How respiration is taken into consideration in terms of methodology and analysis is still a topic of debate (Quintana & Heathers, 2014). Many individuals adjust for this effect depending on the goals of the study. Given the purpose of these measures was to reflect participants as they normally are, they were not instructed to breathe any different or mind their breath in any way. Respiration belts were not used; however, Kubios does approximate the respiration rate from the raw ECG data.

Finally, age is an effect worth extra consideration. It is important to consider as age is associated with both drinking severity (Rubinsky et al., 2013) and HRV (Umetani et al., 1998); however, it should be noted that the effect of age, while meaningful, does not afford insight into underlying mechanisms (Mann et al., 2015), and so was not included in the model.

2.6. Measures of Heart Rate Variability (HRV):

2.6.1. High Frequency HRV: There are various methods of assessing HRV with ECG measures**.** One method is to break down the signal into its constituent frequency contributions from the various systems that control the heart (e.g., SNS, PNS, baroreflex). High frequency (HF)-HRV (0.15—0.4 Hz) is a frequency-domain band figured through Fast Fourier Transform (FFT).

While the signal can be rather multifaceted in lower ranges where additional bodily systems can overlap, only the PNS operates at a high frequency (Raleski et al., 2019). Therefore, HF modulation of the heart signal can be used to infer modulation of the heart rate by parasympathetic nervous system specifically.

2.6.2. Baevsky's Stress Index: In addition, the SNS is often associated with distress, or fight-or-flight responses. One area of discipline that has sought to index the SNS stress response is space medicine. The Baevsky stress index (Baevsky et al., 1984) was originally developed to assess the stress level of astronauts in space, and has now been applied to various disciplines such as psychophysiology (Brugnera et al., 2018), medicine and applied physiology (Baevsky & Chernikova, 2017).

2.7. Measures of therapist behaviors:

Instruments have been developed to measure MI component fidelity during session, so as to ensure MI-adherent processes are present and to what quality (MITI; Moyers et al., 2014; Moyers et al., 2005); as well as to measure the sequential process of in-session therapist and client behaviors (MISC 2.5; Houck et al., 2010). With such an explicit emphasis on a relational foundation, as well as the instruments to discern its quality and process, the utilization of MI is well suited for assessing the relational engagement of therapist and client to potentially distinguish dynamics in relational quality, client HRV, and drinking behavior.

All interview sessions were coded with the Motivational Interviewing Skill Code (MISC 2.5) (Houck et al., 2010) before analysis of HRV. Relational ratings were scored with MITI 4.2.1 (Moyers et al., 2015), and all sessions were considered proficient in MI quality. Given a fundamental facet of MI is a relational foundation, the quality of the therapeutic interaction in the current model was determined through MI-consistent behaviors (MICO). It is a composite variable of behavior counts (all open questions + all reflections + affirm + emphasize control + support). All codes were coded from an experienced coder, with over 5 years of coding with MISC and MITI. Codes were acquired with the CASAA Application for Coding Treatment Interactions (CACTI) software (Glynn et al., 2012).

2.8. Measures of drinking:

Drinking severity was determined by the Alcohol Use Disorders Identification Test (AUDIT) (Saunders et al., 1993), which assesses alcohol consumption, drinking behaviors, and alcohol-related problems. Individuals were included in the study if they were drinking above low risk drinking levels and were not considered alcohol dependent to the extent they would need medically assisted detox.

Analyses were conducted in IBM SPSS Statistics Version 26.0. and R 4.0.2 (R Core Team, 2018); and the MASS (v7.3.53; Venables & Ripley, 2002) and the rrcov (v1.5.5; Todorov & Filzmoser, 2009) packages for negative binomial regression and principal component analysis, respectively.

3. Results:

Both heart variables, SI and HF-HRV, were log transformed to normalize the distributions. It is noted that Kubios software automatically square root transforms the SI score; however, for this sample a log transform was found to be more appropriate. Two outliers were present in the SI scores. These outliers were determined not to have resulted from erroneous origins but rather were extremes of the expected values in this sample. Given the sample size, removing outliers was especially not ideal. Winsorization was therefore used to address these extreme scores, and the two scores were replaced with the 5^{th} and 95^{th} percentile scores of the sample distribution.

3.1. Principal Component Analysis:

The heart rate measures, SI and HF-HRV, were highly correlated (r = -.911) (Figure 1). The SI and HF-HRV measures are considered to be measures of SNS and PNS activity, respectively. Therefore, it was expected these measures would be correlated due to their strong association in bodily systems. However, this raises the problem of multicollinearity in regression analysis, and so the two heart variables were reduced to a single component score using principal component analysis (PCA). The PCA was conducted on a correlation matrix and captured 95.5% of the variance in the heart measures. Bartlett's Test of Sphericity was significant, χ^2 (1, N = 31) = 50.37 , $p < .001$, indicating the appropriate use of PCA for this sample. The PC score was then used in the subsequent regression analyses.

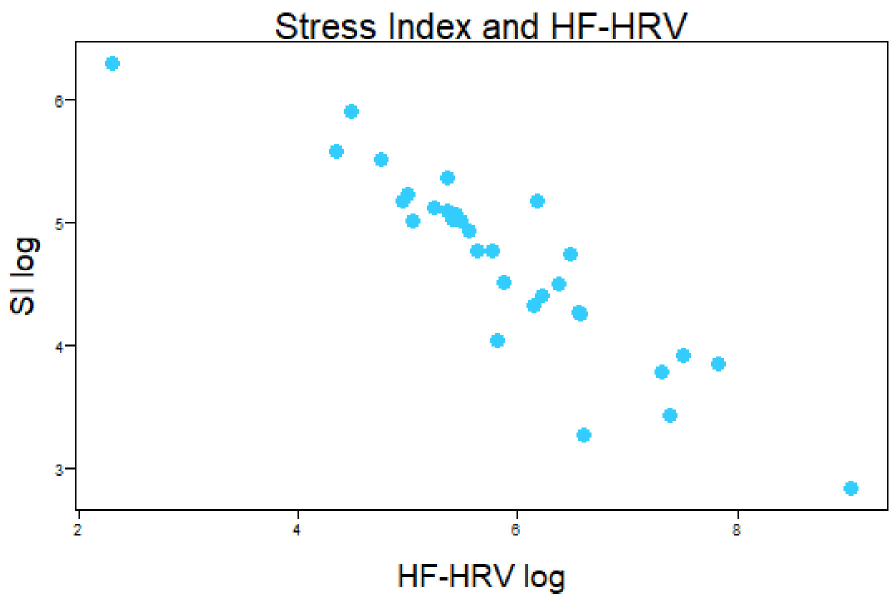

Fig. 1. Scatterplot of heart rate measures, SI and HF-HRV. The heart rate measures were highly correlated (r = -.911). HF-HRV = High Frequency Heart Rate Variability, SI = Stress Index.

3.2. Regression; Heart rate variability and therapist behaviors:

Separate regression paths were analyzed as the current sample was not large enough to detect a mediated effect. For the first path, regression using ordinary least squares was used to evaluate associations with therapist behavior (MICO) and client HRV from the same 5-minute segment. HRV was not significant (*b* = -.004, *t* = -.111, *p* = .912) when regressed on therapist MICO behaviors (Figure 2).

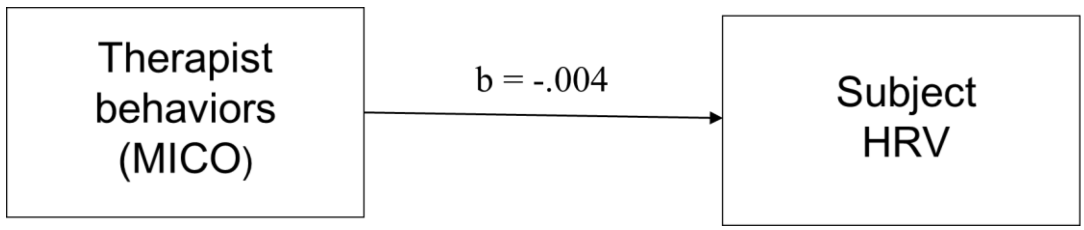

Fig. 2. Therapist MI-adherent behaviors were regressed on the client's HRV at baseline (*b* = -.004, *t* = -.111, *p* = .912). Therapist behaviors are counts. Subject HRV is a composite of HF-HRV and SI. As HRV increases, this is indicative of higher HF-HRV and lower SI. HF-HRV = High Frequency Heart Rate Variability. MICO = Motivational Interviewing Consistent behaviors. SI = Stress Index.

3.3. Negative binomial regression; Drinking and heart rate variability:

For the second path, negative binomial regression was used to evaluate client HRV and drinking AUDIT scores (See Figure 3 and Table 2). This model was chosen due to AUDIT scores being counts and the sample distributions being over-dispersed (Baseline ϴ = 6.04, SE = 2.26; 1-mo FU ϴ = 3.72, SE = 1.51; 3-mo FU ϴ = 2.90, SE = 1.05). Client HRV was significantly associated with baseline drinking, IRR = .854, 95% CI [.751, .968], *p* = .017. Meaning, with a one-unit increase in HRV, AUDIT scores are expected to be .854 times less. Follow-up drinking scores likewise were then regressed on client HRV using negative binomial regression. There were no significant associations with client HRV and follow-up drinking, either at 1-month follow-up (IRR = .873, 95% CI [.747, 1.016], *p* = .113) or 3-month follow-up (IRR = .863, 95% CI [.708, 1.055], *p* = .163).

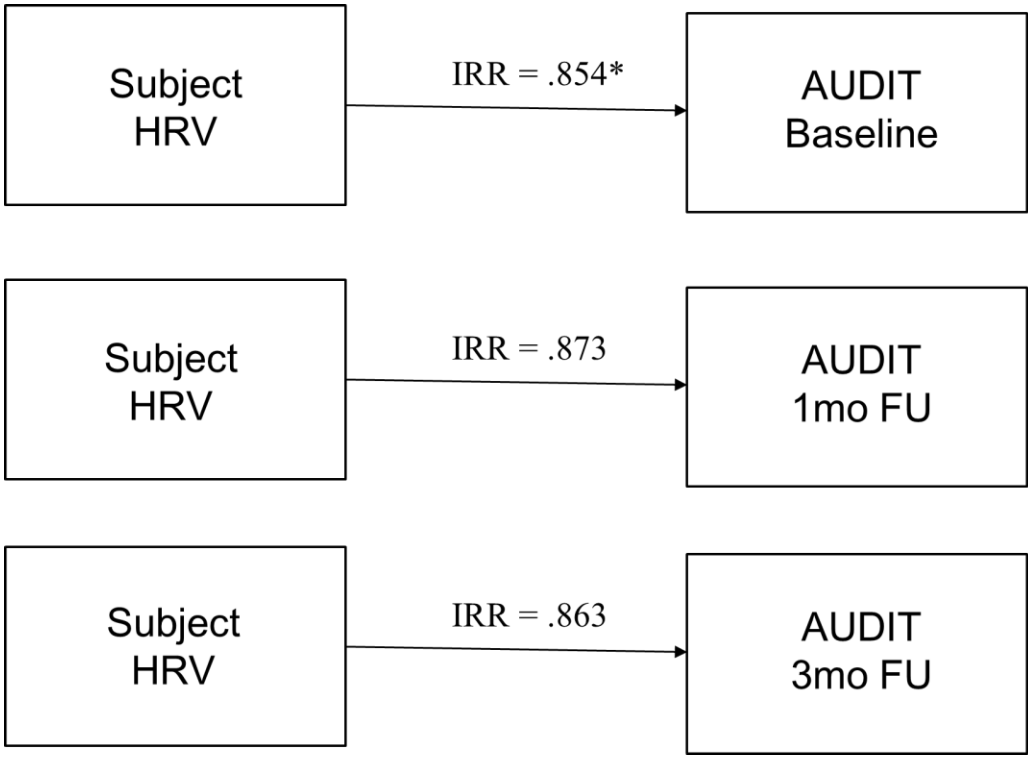

Fig. 3. Client HRV was regressed using negative binomial regression on baseline AUDIT scores, on 1-month follow-up AUDIT scores, and 3-month follow-up AUDIT scores. Subject HRV is a composite of HF-HRV and SI. As HRV increases, this is indicative of higher HF-HRV and lower SI. AUDIT = Alcohol Use Disorder Identification Test. 1mo FU = 1-month Follow-up. 3mo FU = 3-month Follow-up.HF-HRV = High Frequency Heart Rate Variability. SI = Stress Index.
* < .05

Table 2

Negative Binomial Regression of Heart Rate Variability on Baseline Drinking, on 1-month Follow-Up Drinking, and on 3-month Follow-Up Drinking

	b	SE	IRR / exp (*b*)	95% CI	*p*	ϴ	SE
Baseline AUDIT	-.158	.066	.854	.751, .968	.0165*	6.04	2.26
1-mo FU AUDIT	-.136	.086	.873	.747, 1.016	.113	3.72	1.51
3-mo FU AUDIT	-.147	.106	.863	.708, 1.055	.163	2.90	1.05

Note: AUDIT = Alcohol Use Disorder Identification Test. 1-mo FU = 1-month Follow-Up. 3-mo FU = 3-month Follow-Up.
* < .05

3.4. Motivational interviewing quality throughout session:

In addition, an analysis of variance (ANOVA) was conducted to check for systematic bias in MI quality based on the starting time within the session. Since the start time of the 5-minute window for HRV analysis was not randomly selected, it is important to check systematic bias of MI quality throughout the session. The 5-minute windows were classified as occurring in the beginning, middle, or end of the MI session based on the session length of each individual. For example, a 30-minute session would be divided into three equal 10-minute sections; beginning, middle, and end. The HRV analysis window was classified based on what grouping the majority of the window was in.

Group differences were compared on MI therapist variables to test consistency of MI quality depending on whether the window was in the beginning, middle, or end of the session. Therapist variables compared were MICO, Reflection:Question, Percent Complex Reflection, Percent Open Question, and Therapist:Client. One-way ANOVA for all therapist variables were not significant, meaning there were no significant differences in MI quality throughout the session.

4. Discussion:

Alcohol has substantial effects on the central and autonomic nervous system, which have profound influence on the ability to regulate emotions and stress, a major factor contributing to alcohol use and relapse (Seo & Sinha, 2015). It is hypothesized that chronic alcohol use contributes to a pathological state of allostasis which drives the addiction cycle as biological regulatory systems become dysregulated (Koob & Schulkin, 2019).

HRV is a useful measure in SUD research in potentially providing indicators of recovery outcomes and risk of relapse (Buckman et al., 2019; Karpyak et al., 2014). In the current study, HRV was associated with drinking severity at the time of the MI interview. Meaning, lower HRV was associated with higher scores on the AUDIT and vice versa. This is consistent with the literature in that lower HRV is associated with more severe pathology in alcohol and SUD more generally. Indeed, HF-HRV has been proposed to be a transdiagnostic biomarker of psychopathology more broadly (Beauchaine & Thayer, 2015), and furthermore, is of particular interest in emotion regulation research (Beauchaine, 2015). With the degree of comorbidity among SUDs (Gross & Jazaieri, 2014; Kret & Ploeger, 2015), it would be of benefit to address transdiagnostic factors such as poor emotion regulation (Berking & Wupperman, 2012). Comorbid conditions can be a barrier to effective treatment, as most of research is (at the expense of ecological validity) conducted at the exclusion of heterogenous populations.

Psychotherapy has the potential to modulate HRV which may have direct beneficial effects (such as in HRVB) and indirect effects, such as influencing motivational states in-session that may contribute to a more or less conducive therapeutic interaction (i.e., may increase or decrease the efficiency of therapeutic interventions) (Fiskum, 2019). Indeed, HRVB added to psychotherapy has shown to improve the treatment of major depressive order (Caldwell & Steffen, 2018). Additionally, a study with similar theoretical underpinnings found higher HF-HRV in-session was associated with higher client ratings of therapeutic alliance; as well as baseline HRV predicting depressive symptoms over the course of cognitive behavioral therapy (Blanck et al., 2019). It is argued that psychotherapy should be integrated with an understanding of physiological regulation systems such as what are measured by HRV, as not only is HRV linked to psychopathology but it is a potential target for interpersonal coregulation—similar to what has been studied in mother-infant dyads (Fiskum, 2019). Biomarkers may contribute to process research by shedding light on why—mechanistically— interpersonal skills have been established as integral for effective psychotherapeutic interventions such as MI. It is possible the relational foundations are considered important because they foster physiological states in the client that are most ideal when treating substance use disorders (and other conditions)— a state of “approach” rather than “avoid”.

Additionally, measures of HRV in the psychotherapeutic setting could potentially gauge therapist interpersonal skills, especially at the extremes (i.e., both highly effective and ineffective therapists) which may be useful in therapist quality screening, as well as stratifying patient care such that those with severe pathology—who may need the most effective care—can be referred to those therapists most effective. Indeed, variability among therapist effectiveness has been found to increase as patient severity increases, where greater effect sizes for therapist effects are found for more severe conditions; meaning, the more severe symptoms a patient has, the more it matters what therapist they interact with (Saxon & Barkman, 2012).

In addition, these sorts of physiological measures have an exciting and innovative future, as accessibility is continuously enhanced by technology. For instance, smart phones can measure heart rate by essentially operating as a plethysmograph. It may be possible to incorporate biological measures like HRV in “apps” people can download, which could potentially gauge treatment progress or be used as a stress indicator, which may help bring client awareness to visceral states in real-time such as in instances of high stress and intense emotions.

The current analyses did not detect significant effects here in relation to therapist behaviors and client within-session HRV. As noted, characterizing behavioral interactions in the psychotherapeutic setting can be difficult as specific, transversal behaviors are difficult to identify. Relational interactions are extremely complex and variable across context and interacting parties; one behavior with a particular client may elicit an entirely different reaction in a different client. It is still important however to identify behaviors and processes that characterize an effective therapeutic relationship, and biomarkers are objective measures that may aid in identifying such behaviors.

4.1. Limitations:

Limitations of the analysis include the sample size. Similar patterns were observed in the follow-up data but were likely underpowered as attrition resulted in an even lower number of subjects in follow-up analyses. The smaller sample size is also largely attributable to the nature of data collection; the parent study was using ECG measures for other purposes than HRV analysis, and so many subjects' data were excluded due to the length and quality of ECG data.

Another limitation is the one-sided quality of HRV analysis. Social interactions are necessarily interactional, and so it would be ideal to examine both interacting parties. Here, only HRV from the client was analyzed, which is a one-sided perspective of a phenomenon that is interdependently bidirectional. In addition, both the physiological and behavioral measures were summary measures of a 5-minute window, thus not capturing a temporally sensitive account of the reciprocal interaction of therapist and client.

The MI skill of the therapist also lacked variability, as all therapists were rated proficient. Therefore, it was not possible to compare therapist MI skills in quality as was intended. It is expected there would be differences in the physiology of the client depending on the quality of the therapeutic interaction; but with all sessions rated proficient in MI, there were no data on low quality relational skills.

4.2. Conclusions:

HRV is useful in alcohol research and treatment. A relationship was found here with drinking severity and HRV at baseline. It is possible HRV can be used to gauge alcohol use severity and treatment progress, as HRV improvement has shown concomitant associations with clinical improvement. Future research will assess dyadic data from both client and therapist, as well as employ analytic techniques with consideration for interdependent dynamics.

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