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Field Validity of Heart Rate Variability Metrics Produced by QRSTool and CMetX

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Interest in heart rate variability (HRV) metrics as markers of physiological and psychological health continues to grow beyond those with psychophysiological expertise, increasing the importance of developing suitable tools for researchers new to the field. Allen, Chambers, and Towers (2007) developed QRSTool and CMetX software as simple, user-friendly tools that can be used to compute metrics of HRV. In the present study, the authors examined the field validity of these software tools—that is, their validity when used by nonexperts. In a lab with extensive expertise in psychopathology but not psychophysiology, ECG data were obtained from 63 undergraduates at baseline and during a stressor and then processed using QRSTool and CMetX to produce the 10 HRV indices described in Allen et al. (2007). The indices displayed factor structures and patterns of changes from baseline to stressor that were similar to findings from Allen et al. and consistent with how indices of parasympathetic and sympathetic activity should behave. Results support the field validity of QRSTool and CMetX, suggesting that they are useful for nonexperts in psychophysiology interested in measuring HRV.

Keywords: heart rate variability, cardiac vagal control, field validity

Metrics of heart rate variability (HRV) are often used to index the influence of the autonomic nervous system on the heart and have been studied in relation to a wide variety of health issues—from the risk of cardiac events (Tsuji et al., 1996) to psychological disorders such as anxiety (Miu, Heilman, & Miclea, 2009) and depression (Lehofer et al., 1997). Interest in HRV metrics continues to increase; a search in PsycINFO using the term *heart rate variability* returned over 1,000 citations from the last 10 years alone.

As knowledge has grown about specific physiological influences on HRV and health, the field has increasingly come to focus on a particular aspect of HRV: respiratory sinus arrhythmia (RSA). Variability in heart rate (HR) is affected by both the sympathetic and the parasympathetic divisions of the autonomic nervous system, which act separately but typically have opposing effects: increasing and decreasing HR, respectively. The parasympathetic branch of the autonomic nervous system slows down HR through a branch of the vagus (the 10th cranial nerve), which synapses on the sinoatrial node of the heart. This parasympathetic influence on the heart, also referred to as the *vagal brake* and *cardiac vagal control*, is temporarily inhibited during normal respiration, creating RSA, a respiratory-linked fluctuation in HR. As such, RSA is often used as an index of vagal influence on the heart.

Despite the promise of HRV generally and RSA specifically for enhancing health research, three issues limit progress in this area. First, many metrics of HRV are differentially affected by the parasympathetic and sympathetic branches of the autonomic nervous system. Across studies, researchers have used different and nonequivalent metrics of HRV, making it difficult to compare and contrast findings across studies and to establish converging evidence around particular findings. Second, even if one chooses RSA for its ability to specifically index parasympathetic activity, there is no established gold standard for assessing RSA, and RSA can be and has been quantified in different ways (e.g., Grossman, van Beek, & Wientjes, 1990; Pomeranz et al., 1985; U.S. Patent No. 4,510,944, 1985; for an overview, see Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology, 1996). Third, given the technical complexity involved in assessing and quantifying HRV and RSA, it is quite difficult for researchers who lack psychophysiological expertise to incorporate these important metrics in their research. To

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A subset of these data were examined in Weinberg, Klonsky, and Hajcak (2009), where RSA and CSI were examined in relation to a measure of borderline personality disorder. We thank Greg Hajcak for his assistance in obtaining and setting up QRSTool and CMetX.

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increase the accessibility of these psychophysiological measures, researchers should develop, validate, and disseminate simple and user-friendly approaches to quantifying HRV data.

Allen, Chambers, and Towers (2007) addressed this issue in their accessible review of methodological considerations for assessing HRV. In this article, they introduced two tools for quantifying RSA and other measures of HRV: QRSTool and CMetX Cardiac Metric Software. These tools allow for the easy and simultaneous computation of some of the most popular indices of HRV, including RSA. QRSTool is a software program that provides a graphical interface with which users can extract and correct an interbeat-interval (IBI) series from electrocardiogram data. CMetX is a command-line-based program that uses IBI input to calculate many different metrics of HRV and cardiac vagal control. QRSTool and CMetX can be used together or individually with other compatible software; both are available for download at http://www.psychofizz.org. This freely available and user-friendly software suite has the potential to greatly aid researchers in incorporating measures of HRV into their studies, encouraging further research in the field.

CMetX calculates 10 metrics of HRV: (a) mean IBI, calculated by taking the average of IBIs; (b) the mean HR, calculated by averaging the rate-transformed IBIs; (c) HRV, calculated here by taking the natural log of the variance of the IBI time series; (d) standard deviation of normal-to-normal IBIs (SDNN), where *normal-to-normal* refers to the artifact-free IBI series; (e) root mean square of successive differences between IBIs (RMSSD); (f) mean of the absolute value of consecutive IBI differences (MSD); (g) proportion of consecutive IBI differences greater than 50 ms (pNN50); (h) RSA, calculated here by taking the natural log of the variance of filtered (0.12–0.40 Hz) IBI time series; (i) Toichi's cardiac vagal index (CVI); and (j) Toichi's cardiac sympathetic index (CSI; Toichi, Sugiura, Murai, & Sengoku, 1997). Allen et al. (2007) classified the 10 metrics into four categories: metrics of rate (mean IBI, mean HR), which are affected by both the parasympathetic and the sympathetic nervous systems (PNS and SNS, respectively); metrics of total HRV (HRV, SDNN, RMSSD), which are also influenced by both the PNS and the SNS; a metric of variability primarily influenced by the SNS (CSI); and metrics of variability primarily influenced by the PNS (MSD, pNN50, RSA, CVI).

To demonstrate the convergent and divergent validity of these indices as well as their covariation and structure, Allen et al. (2007) investigated the 10 metrics produced by CMetX in a college sample during both a resting baseline period and a serial paced arithmetic task. Covariation of the 10 metrics was examined both at rest and during the task, and the eight variability metrics (excluding the two HR metrics, mean HR and mean IBI) displayed a theoretically consistent structure when subjected to exploratory factor analysis. Two factors were extracted: one factor with high loadings for variability metrics most strongly associated with parasympathetic activity and a second factor with a high loading for a metric indexing sympathetic influence on the heart as well as smaller, inverse loadings on some of the parasympathetic metrics that loaded positively on the first factor. This structure replicated at rest, during the serial paced arithmetic task, and also on examining the intraindividual changes in metrics from baseline to stressor task. Also as expected, both for measurements at rest and during the stressor task, positive correlations were observed among measures associated with overall variability and those associated with parasympathetic influence (mean IBI, HRV, SDNN, RMSSD, MSD, pNN50, RSA, and CVI; *r*s ranged from .49 to .99), as well as between the sympathetic index (CSI) and mean HR ($r = .59$ at rest and $r = .75$ during the task).

In addition, the metrics demonstrated theoretically consistent changes from baseline to stressor. Specifically, Allen et al. (2007) found that from baseline to stressor task, mean HR, HRV, SDNN, and CSI increased, whereas mean IBI, RMSSD, MSD, pNN50, and RSA decreased, consistent with expectations regarding the response of parasympathetic and sympathetic activity to a stressor task. It is interesting that CVI was not found to significantly discriminate between baseline and stressor, possibly indicating that it should not be used interchangeably with RSA or other parasympathetic indices (Allen et al., 2007).

Since publication of Allen et al. (2007), QRSTool and CMetX have been adopted by researchers as valuable tools to examine cardiac vagal control. The programs are already being used in the context of diverse psychological constructs such depression (Gruber, Oveis, Keltner, & Johnson, 2011), power and compassion (van Kleef et al., 2008), and meditation (Lutz, Greischar, Perlman, & Davidson, 2009). Given their tremendous promise for facilitating psychophysiological research, it is important to demonstrate the validity of the programs' output metrics across laboratories and contexts.

More specifically, attention must be paid to the important distinction between a test's psychometric properties under ideal versus field conditions (McGrath et al., 2005; Wood, Nezworski, & Stejskal, 1996**8**). *Ideal properties* refers to the properties of a measure when administered and interpreted under ideal conditions, typically by the developers of the test and/or researchers directly trained by the developer in a research context. *Field properties* refers to the properties of the measure when administered and interpreted by consumers in applied contexts. Whereas ideal validity can be demonstrated by researchers involved in the development of a measure, field validity should be investigated in a practical context, because psychometric properties of a measure can vary greatly between ideal and field conditions.

The issue of ideal versus field validity has been applied to diverse areas of psychological assessment. For example, the field interrater reliability of the Hare Psychopathy Checklist—Revised when administered by state examiners was demonstrated to be much lower than the interrater reliability achieved and reported by the measure's developers (Edens, Boccaccini, & Johnson, 2010). Similarly, Lamb et al. (1997) found that, when applied to real-world interviews, criterion-based content analysis was less effective at distinguishing implausible accounts of child sexual abuse than had been previously assumed.

Although the validity of QRSTool and CMetX Cardiac Metric Software was supported by Allen et al. (2007), these data represent ideal validity. The data were obtained under ideal conditions: in the laboratory, supervised by the software's developers. However, these tools were specifically intended for use by researchers lacking in advanced psychophysiological expertise. Thus, it is important to verify the software's field validity, that is, to verify that validity of HRV indices is not compromised when QRSTool and

CMetX are used by nonexperts in psychophysiology. We designed the present study to address this aim.

Data were obtained and processed in a lab with advanced expertise in psychopathology and mental health but without advanced expertise in the measurement of HRV.[1] Paralleling the analyses in Allen et al. (2007), we examined the 10 metrics computed by QRSTool and CMetX in an Eastern U.S. undergraduate sample both at baseline and during an arithmetic stressor task. We hypothesized that the metrics would demonstrate intercorrelations, factor loadings, and task discrimination comparable to those of Allen et al., thus supporting the validity of metrics produced by QRSTool and CMetX in field conditions.

Method

Participants were 65 undergraduate students who received course credit in lower level psychology courses for participation in a larger study of emotion and psychophysiology. Two participants had HRs 2.5 standard deviations faster than the mean; therefore, they were regarded as outliers and excluded from further analyses. The final sample consisted of 63 participants (73.0% women) with a mean age of 19.0 years (SD = 1.5). Participants exhibited considerable ethnic diversity, including those who identified themselves as Caucasian (47.6%), Asian (38.1%), African American (3.2%), and other (11.1%).

After obtaining informed consent, we placed disposable Ag/AgCl electrodes connected to an MP100 BIOPAC system running Acq*Knowledge* (2005) on each participant's ankles and right forearm. The electrocardiogram was sampled at a rate of 1000 Hz. Following electrode placement, participants were asked to sit still and relax for 5 min while baseline recordings were taken. The 5-min baseline period was followed by a 5-min mental arithmetic stressor task. Participants were asked to count down from 1,258 in increments of 7 over a 5-min measurement period. To ensure the task was stressful in nature, we asked participants to restart each time they made an error, and participants also received frustrating feedback at several points during the task (e.g., "please try not to pause between responses" and "try to go faster").

Raw digitized electrocardiogram files (.acq) from Acq*Knowledge* (2005) were converted to text files (.txt) and imported into QRSTool. Artifacts in the IBI series were corrected by hand in QRSTool before being individually exported to CMetX to calculate the metrics of cardiac chronotropy reported in Allen et al. (2007): mean IBI, mean HR, HRV, SDNN, RMSSD, CSI, MSD, pNN50, CVI, and RSA. Data processing was performed according to instructions included with the software. The lab director (E. David Klonsky) received initial informal guidance from a colleague knowledgeable in psychophysiological measurement and subsequently trained two additional scorers—a graduate student and an undergraduate honors student—using several sample files. A subset of data files were double-checked to ensure procedures were accurately followed. Uncertainties that arose during the scoring process were discussed in lab meetings. Weekly readings on HRV, including the value and meaning of HRV metrics, complemented the technical training.

Results

Intercorrelations Among HRV Metrics

First, we used Pearson correlations to examine the interrelationships among the 10 metrics computed by CMetX (see Table 1). As expected, the metrics exhibited strong intercorrelations both at rest (median $|r|$ = .77) and during the mental arithmetic task (median $|r|$ = .78). Corresponding values reported by Allen et al. (2007) were .75 and .73. Also, as expected, those metrics commonly understood to measure the influence of the PNS correlated very strongly with each other, both at rest (median r = .90) and during the mental arithmetic task (median r = .91). Corresponding median intercorrelations reported by Allen et al. (2007) were .89 and .87. In addition, intercorrelations among the change scores (i.e., from baseline to stressor) of all metrics were strong (median $|r|$ = .69), with measures of parasympathetic influence on the heart again demonstrating especially strong correlations among their change scores (median r = .79). Corresponding median rs reported by Allen et al. (2007) were .45 and .61. Finally, consistent with Allen et al., Toichi's CSI (a measure of sympathetic influence on the heart) negatively correlated with measures of parasympathetic activity as well as all other metrics of HRV across time points (median r = −.59).

Factor Analysis

Mirroring the statistical approach from Allen et al. (2007), we conducted principle components analyses (with varimax rotation) to examine the structure of the 10 metrics at baseline and during the stressor task. Results were consistent with those of Allen et al. (2007), and a two-factor solution accounted for 94.3% of the variance in baseline measurement and 95.9% of the variance during the mental arithmetic task. As can be seen in Table 2, Factor 1 included high loadings for all measures of HRV except for Toichi's CSI. Conversely, Factor 2 included a high loading for Toichi's CSI and smaller, negative loadings for RMSSD, MSD, pNN50, RSA, and CVI. This pattern suggests that the metrics capturing overall HRV and those thought to measure parasympathetic influence on the heart loaded onto one factor, whereas a second factor reflected measures of sympathetic influence. Finally, we examined the structure of the change scores and found a two-factor solution that accounted for 90.0% of the variance of the change scores (see Table 2). Similar to the two-factor solution at baseline and during the stressor task, Factor 1 included high loadings for all measures of HRV except for Toichi's CSI, and Factor 2 included a high loading for Toichi's CSI and smaller, negative loadings for RMSSD, MSD, pNN50, RSA, and CVI.

Task Discrimination

Last, we examined the abilities of the 10 metrics to discriminate between the baseline and stressor task. As can be seen in Table 3,

[1] Data were obtained under the direction of E. David Klonsky. Although Klonsky and his lab members have since received advanced training and published several psychophysiological articles, data in the present article were collected and processed in 2008 before this training occurred.

Table 1
Intercorrelations Between Metrics at Rest and During Paced Arithmetic

Metric	IBI	HR	HRV	SDNN	RMSSD	CSI	MSD	pNN50	RSA	CVI
					Rest					
IBI	—									
HR	−.98	—								
HRV	.56	−.54	—							
SDNN	.59	−.54	.94	—						
RMSSD	.69	−.62	.82	.93	—					
CSI	−.59	.57	−.25	−.33	−.58	—				
MSD	.73	−.67	.80	.91	.99	−.62	—			
pNN50	.77	−.72	.78	.80	.89	−.67	.92	—		
RSA	.51	−.47	.90	.89	.86	−.49	.85	.82	—	
CVI	.69	−.66	.96	.93	.90	−.51	.90	.89	.93	—
					Arithmetic					
IBI	—									
HR	−.97	—								
HRV	.58	−.56	—							
SDNN	.62	−.58	.97	—						
RMSSD	.70	−.64	.84	.92	—					
CSI	−.68	.69	−.39	−.46	−.70	—				
MSD	.78	−.72	.82	.91	.98	−.69	—			
pNN50	.78	−.71	.83	.90	.95	−.67	.98	—		
RSA	.64	−.62	.91	.92	.91	−.64	.90	.90	—	
CVI	.71	−.69	.96	.96	.93	−.61	.91	.91	.95	—
					Change from rest to arithmetic					
IBI	—									
HR	−.91	—								
HRV	.30	−.33	—							
SDNN	.47	−.46	.93	—						
RMSSD	.78	−.68	.60	.78	—					
CSI	−.54	.61	.14	.00	−.48	—				
MSD	.82	−.72	.57	.76	.98	−.46	—			
pNN50	.78	−.71	.57	.69	.87	−.44	.91	—		
RSA	.51	−.54	.74	.77	.74	−.36	.72	.69	—	
CVI	.57	−.61	.90	.91	.82	−.29	.79	.79	.86	—

Note. $N = 63$; correlations greater in magnitude than .25 are significant at the $p < .05$ level. Each panel has measures of rate (IBI = mean interbeat interval; HR = mean heart rate), measures of total variability (HRV = natural log of the variance of the IBI time series; SDNN = standard deviation of IBIs; RMSSD = root mean square of differences between IBIs), an estimate of sympathetic-related variability (CSI = Toichi cardiac sympathetic index), and estimates of parasympathetically controlled variability (MSD = mean of the absolute value of consecutive IBI differences; pNN50 = proportion of consecutive IBI differences greater than 50 ms; RSA = natural log of the variance of filtered [0.12–0.40 Hz] IBI time series; CVI = Toichi cardiac vagal index).

seven of the 10 metrics discriminate between the two tasks, consistent with their performance in Allen et al. (2007). Also consistent with Allen et al. (2007), Toichi's CVI failed to significantly discriminate between baseline and the arithmetic stressor task. Two findings, however, were not consistent with Allen et al. (2007): Both RSA and RMSSD failed to significantly discriminate between the baseline and stressor tasks. Finally, although the overall pattern of task-discrimination findings was similar to that of Allen et al. (2007), the magnitudes of the task-discrimination effects in this study were generally lower than those found in Allen et al. (2007), ranging from .01 to .39 (median $\eta^2 = .08$) in this study as compared with .00 to .77 (median $\eta^2 = .27$) reported by Allen et al. (2007).

Discussion

This study sought to replicate findings by Allen et al. (2007) in a lab without advanced psychophysiological expertise and thus to provide evidence for the field validity of HRV metrics produced by QRSTool and CMetX. We examined the 10 metrics both at rest and during an arithmetic stressor task in an undergraduate sample in an Eastern U.S. university. Overall, results supported the robustness and validity of the 10 metrics produced by QRSTool and CMetX. In the present study, the metrics exhibited intercorrelations, factor structure, and task sensitivity consistent with findings reported in Allen et al. (2007). It is important to note that metrics provided by QRSTool and CMetX appear to reliably distinguish between measures of HRV that index PNS versus SNS activity. Findings suggest that QRSTool and CMetX can produce valid HRV metrics even in field conditions, such as laboratories without advanced psychophysiological expertise that desire to apply metrics of HRV to the study of psychopathology and other health conditions.

Only two findings contrasted with the data reported by Allen et al. (2007). In the present study, RSA and RMSSD failed to

Table 2
Factor Loadings for Metrics at Rest and During Arithmetic Stressor Task

	Rest		Arithmetic		Change from rest to arithmetic	
Metric	Factor 1	Factor 2	Factor 1	Factor 2	Factor 1	Factor 2
HRV	.98	—	.97	—	.97	—
SDNN	.97	—	.96	—	.98	—
RMSSD	.84	−.48	.80	−.57	.72	−.63
CSI	—	.97	—	.96	—	.94
MSD	.81	−.54	.79	−.58	.71	−.64
pNN50	.74	−.60	.79	−.55	.68	−.62
RSA	.88	−.33	.85	−.45	.79	−.38
CVI	.92	−.36	.90	−.40	.92	−.32

Note. $N = 63$. Dashes indicate loadings of a magnitude of .3 or less. Factor analysis included measures of total variability (HRV = natural log of the variance of the interbeat interval [IBI] time series; SDNN = standard deviation of IBIs; RMSSD = root mean square of differences between IBIs), an estimate of sympathetic-related variability (CSI = Toichi cardiac sympathetic index), and estimates of parasympathetically controlled variability (MSD = mean of the absolute value of consecutive IBI differences; pNN50 = proportion of consecutive IBI differences greater than 50 ms; RSA = natural log of the variance of filtered [0.12–0.40 Hz] IBI time series; CVI = Toichi cardiac vagal index).

significantly discriminate between baseline and stressor periods. The finding is difficult to interpret because other metrics purportedly measuring the same parasympathetic influence on the heart, such as MSD and pNN50, successfully discriminated between baseline and the stressor task. Given the many analyses performed in this study, the lack of support for just two predicted findings may be attributable to random error associated with the computation of numerous analyses. It is also possible that the presence of breathing rates outside of the 0.12–0.40 Hz range may have artificially decreased the level of RSA in our sample, as the software does not report modal breathing frequency. Another important possibility is that RSA and RMSSD are less robust with respect to distinguishing between resting and stressful states. In support of this, the effect size for RSA in Allen et al. was smaller than effect sizes for other measures of parasympathetic activity.

Table 3
Ability of Metrics to Discriminate Between Tasks

	Rest		Arithmetic				
Metric	*M*	*SE*	*M*	*SE*	*F*	*p*	η^2
IBI	789.89	16.51	720.34	15.20	36.78	<.001	.37
HR	78.41	1.61	86.29	1.86	39.09	<.001	.39
HRV	7.70	0.10	7.97	0.10	10.32	.002	.14
SDNN	54.53	3.28	60.37	3.12	5.03	.029	.08
RMSSD	44.61	3.73	41.42	3.13	1.22	.273	.02
CSI	2.49	0.09	3.09	0.11	23.86	<.001	.28
MSD	34.65	2.78	30.25	2.29	4.26	.043	.06
pNN50	21.40	2.44	17.03	2.04	6.02	.017	.09
RSA	6.31	0.13	6.37	0.13	0.37	.546	.01
CVI	4.44	0.05	4.47	0.05	0.48	.492	.01

Note. $N = 63$. Analyses included measures of rate (IBI = mean interbeat interval; HR = mean heart rate), measures of total variability (HRV = natural log of the variance of the IBI time series; SDNN = standard deviation of IBIs; RMSSD = root mean square of differences between IBIs), an estimate of sympathetic-related variability (CSI = Toichi cardiac sympathetic index), and estimates of parasympathetically controlled variability (MSD = mean of the absolute value of consecutive IBI differences; pNN50 = proportion of consecutive IBI differences greater than 50 ms; RSA = natural log of the variance of filtered [0.12–0.40 Hz] IBI time series; CVI = Toichi cardiac vagal index).

Limitations of the present study suggest directions for future research. Both the present study and Allen et al. (2007) used college samples. Therefore, it will be important for future researchers to examine the validity of QRSTool and CMetX in samples with diverse sociodemographic backgrounds, particularly as the likelihood of scoring challenges (e.g., ectopic beats) may be increased. Additionally, participants' medication status was not recorded. Given the nature of the sample, it is unlikely that medication status would have meaningfully influenced the group-level descriptive statistics or correlational patterns. However, researchers conducting future studies should take into account the influence of participants' medication status on HRV indices. In addition, psychometric properties that have not been examined in either the present study or Allen et al. (2007), such as interrater reliability, test–retest reliability, criterion validity, and convergent validity (i.e., correspondence between indices derived through QRSTool and CMetX and the same indices derived through other approaches), should be investigated.

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