## Letter to the Editor

## A Cross-cultural Examination of the Noise-sensitivity Scale-short Form: Measurement Invariance Testing between the US and Chinese Samples<sup>\*</sup>



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Unwanted sound that is unpleasant or disruptive to hear, often interpreted as noise, is a widespread environmental pollutant. Similar to other environmental pollutants, this noise incurs a variety of costs to society. Numerous negative health impacts are linked to increases in noise exposure, such as increased cardiovascular risk<sup>[1]</sup> and sleep disturbance<sup>[2]</sup>. Research suggests that noise impacts cognitive processes<sup>[3]</sup>, mood states<sup>[4]</sup>, and recreational experiences<sup>[5]</sup>. Collectively, this body of research demonstrates that noise interferes with human health and well-being.

Although noise levels may serve as a measure for understanding related human costs, they fail to account for the variations among individuals regarding their sensitivity to noise<sup>[6]</sup>. This variation, called noise sensitivity, is important for understanding annoyance among individuals, as it often predicts responses to noise exposure levels<sup>[6,7]</sup>. Furthermore, noise sensitivity uniquely predicts a variety of negative outcomes related to noise exposure, such as annoyance, health degradation, quality of life, and mental and cognitive performance<sup>[8]</sup>. Lastly, some studies suggest genetic mechanisms to influence noise sensitivity<sup>[9]</sup>.

To measure the concept of noise sensitivity, Weinstein developed a Noise Sensitivity Scale (NSS)<sup>[9]</sup>. However, the NSS was extremely burdensome for a significant number of studies and contained irrelevant items; therefore, a short form of the NSS (called NSS-SF) was developed in a US sample with national park visitors<sup>[10]</sup>. The NSS-SF was validated in Bulgarian<sup>[11]</sup> and Chinese samples<sup>[12]</sup>.

However, a major limitation of noise sensitivity research is a lack of cross-validation studies using the NSS-SF<sup>[6]</sup>. For instance, although a significant number of studies show sufficient psychometric properties within a single sample (i.e., within a cultural context), they do not compare how the scale functions across samples. One exception to this is a research that demonstrated configural and metric invariance among gender in a Chinese sample<sup>[6]</sup>. Even with this advancement, this body of research still lacks a comparison of how the NSS-SF functions across samples from different cultures. Furthermore, a significant number of the studies examining perceptions of sounds have been University/College laboratory-based, and the understanding of these concepts is based on fairly homogenous samples. Given the advancing global urbanization, and the link between parks, natural sounds, and human wellbeing, it is vital that we further the understanding of cultural perceptions of sounds. The purpose of this manuscript is to examine the psychometric properties of the NSS-SF in a cross-cultural context with visitors at an actual park. To do so, multi-group confirmatory factor analysis (CFA) is used to assess metric and configural invariance among a sample of Chinese and US visitors to urban parks.

Visitors to two similar urban parks were sampled for this study. The research was approved by a university Institutional Review Board (IRB) and informed consent was received prior to the subjects participating in the study. In China, visitors to an ecological park near the Tourism College of Jinan University in Shenzhen were intercepted (Jinan sample). In the US, visitors to the arboretum near

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the Pennsylvania State University (Penn State) in University Park were intercepted (UP sample). In both locations, trained university researchers intercepted visitors using a systematic *n*th technique (i.e., every fourth visitor intercepted). If a group of visitors was intercepted, the person in the group with the most recent birthday (not date of birth) was asked to participate in the research to randomize the selection and avoid self-selection bias. Both the *n*th and most recent birthday techniques are commonly used methods of intercepting surveys in parks<sup>[5,12]</sup>. The Jinan sample yielded 323 responses, and the UP sample yielded 414 responses.

A self-administered questionnaire was presented to respondents *via* a paper survey. The NSS-SF included five items (Table 1). Responses were recorded on a 6-point Likert-scale. The only anchor numbers that were labeled were 1 (strongly disagree) and 6 (strongly agree). The scale items were translated into Chinese (Mandarin) for administration to the Jinan sample. For Chinese translations, please contact the corresponding author.

We used AMOS and SPSS to analyze the data. Data cleaning established that some cases contained missing data points. An MCAR test indicated that there was no pattern in the missing data ( $\chi^2 = 7.755$ , df = 8, P = 0.458). Because maximum likelihood estimation commonly used in CFA procedures requires no missing data in AMOS, we deleted, listwise, any cases with missing data. This left a final sample size of n = 312 for the Jinan sample and n = 397 for the UP sample.

CFA with maximum likelihood estimation was used to examine the data. CFA is designed to confirm an explicitly specified measurement model. To assess how well the data fits the specified model, several fit statistics are used<sup>[6,13]</sup>. These included both relative and absolute fit statistics. Although  $\chi^2$ 

is reported, it is likely to be significant even with a good fitting model. Therefore, we relied on other fit statistics to assess the model. These include the compare fitting indices (CFI), Non-normed fitting indices (TLI), approximate root mean square error (RMSEA) (and the associated P-close test), and the SRMR. For CFI and TLI, values > 0.90 indicate an acceptable fit, with values > 0.95 indicating a good fit. For RMSEA, values should be < 0.10, with < 0.05 considered a good fit. Along with the RMSEA is an associated P-close test, where P-close > 0.05 indicates a close-fitting model. The SRMR value should also be < 0.08. In addition to satisfactory fit statistics, standardized factor loadings should be > 0.30, with > 0.60 considered 'high'. Lastly, reliability is assessed by Cronbach's  $\alpha$ , which should be > 0.65.

CFA analyses began with specifying and testing separate models from the UP and Jinan data. After confirming these initial models, configural invariance was tested using a multi-group model. Configural invariance tests if the structure of the model is similar among multiple groups, in this case, the samples from UP and Jinan. If configural invariance is confirmed through satisfactory fit indices, the next step is conducting metric invariance tests. Metric invariance is a multi-step process that examines the congruency of the measures among the groups<sup>[6]</sup>. First, an unconstrained model is compared to a model where the factor loadings are constrained to be equal among the groups. If there is no significant  $\chi^2$  difference, then the scale shows factor loading invariance among the two samples (i.e., the factor loadings are equal between the groups). If factor loading invariance is confirmed, additional constraints, such as covariance constraints, are placed on the model. If there is no significant  $\chi^2$  difference with these additional constraints, it can be said that the scale is invariant between the two samples.

ltam		ological Park = 312)	University Park Arboretum (N = 397)		
Item	$Mean \pm SD^1$	Standardized loading	$Mean \pm SD^1$	Standardized loading	
NOISE_SENS_1: I am sensitive to noise	4.41 ± 1.39	0.68	$4.11 \pm 1.45$	0.74	
NOISE_SENS_2: I find it hard to relax in places that are noisy	4.50 ± 1.37	0.85	4.67 ± 1.24	0.83	
NOISE_SENS_3: I get mad at people who make noise that keeps me from falling asleep or getting work done	4.42 ± 1.35	0.54	4.61 ± 1.34	0.57	
NOISE_SENS_4: I get annoyed when my neighbors are noisy	3.91 ± 1.37	0.43	$4.30 \pm 1.32$	0.56	
NOISE_SENS_5_RECO: I get used to most noises without difficulty	4.43 ± 1.34	0.32	3.74 ± 1.20	0.33	

Table 1. Descriptive Statistics for the NSS-SF

*Note.* <sup>1</sup>Measured on a Likert-type scale where 1 = strongly disagree and 6 = strongly agree. <sup>\*</sup>Item is reverse coded.

The descriptive statistics for items used in all CFA procedures are in Table 1. An initial CFA model was built and tested using the UP data. The fit statistics indicated that this initial model could be improved ( $\chi^2$  = 60.656, *df* = 5, *P* < 0.001; CFI = 0.898; TLI = 0.796; RMSEA = 0.168, P-close < 0.001; SRMR = 0.054). The modification indices suggested that covarying the disturbance terms of two measures (NOISE SENS 3: I get mad at people who make noise that keeps me from falling asleep or getting work done, NOISE\_SENS\_4: I get annoyed when my neighbors are noisy) could improve the model fit. When examining the two items, we observed that they both directly relate to a home environment. From this, we considered this covariance theoretically sound and re-specified the model with the covaried error terms (Figure 1). Fit statistics for this model, referred to as University Park unconstrained, indicated an excellent fit (Table 2). Subsequently, we ran the same model using only the data from the Jinan sample. This model, referred to as Jinan unconstrained, also indicated excellent fit (Table 2). Cronbach's  $\alpha$  was also sufficient (Jinan  $\alpha$  = 0.73; UP  $\alpha$  = 0.77).

To test configural invariance, a multi-group CFA was specified (Table 2, multi-group unconstrained)

using both Jinan and UP data. This model simultaneously compares the two groups<sup>[8]</sup>. The excellent fit statistics from this model indicated configural invariance between the two samples (Table 2).

Metric invariance was assessed in two additional multi-group models. The first model compares an unconstrained multi-group model (Table 2. multi-group unconstrained) to one where the factor loadings are constrained to be equal across the Jinan and UP models (Table 2, multi-group constrained factor loadings). An  $\chi^2$  difference test showed no significant differences between the constrained and unconstrained models ( $\chi^2$  = 5.72, *df* = 4, *P* < 0.221). Therefore, we can conclude that factor loadings are invariant between Jinan and UP samples. We also compared a model that constrained the covariance to be equal in addition to the equality of factor loadings constraint (Table 2, multi-group constrained covariances) against the unconstrained multi-group model (Table 2, multi-group unconstrained). An  $\chi^2$ difference test showed no significant differences between these models ( $\chi^2$  = 5.72, df = 5, P < 0.334). The interpretation of this is that there are no differences in factor loadings or covariances between the Jinan and UP samples.

Model	χ <sup>2</sup>	df	P-value	CFI	TLI	RMSEA	P-close	SRMR
1: University Park unconstrained	7.34	4	0.119	0.994	0.985	0.046	0.476	0.025
2: Jinan unconstrained	7.55	4	0.108	0.991	0.977	0.053	0.385	0.032
3: Multi-group unconstrained	14.90	8	0.061	0.993	0.981	0.035	0.796	0.032
4: Multi-group constrained factor loadings	20.62	12	0.056	0.991	0.985	0.032	0.899	0.039
5: Multi-group constrained covariances	20.62	13	0.081	0.992	0.987	0.029	0.939	0.039

Table 2. Model Fit and Measurement Invariance Testi	ng across Groups
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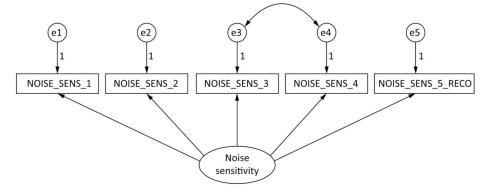


Figure 1. Re-specified CFA model for the noise sensitivity scale.

individual's Noise sensitivity, an unique response to noise, is a critical aspect for understanding the effects of sound pollution on human health and well-being. The NSS-SF emerged as a way to capture this individual variance, and was validated in several samples, including samples from the US<sup>[10]</sup>, Bulgaria<sup>[11]</sup>, and China<sup>[12]</sup>. Recent research applied configural and metric invariance testing of gender for the NSS-SF scale in a Chinese sample<sup>[6]</sup>. However, no cross-cultural comparisons of configural and metric invariance had ever been conducted for NSS-SF. The results from this current research provides further evidence that the NSS-SF is a robust and cross-culturally valid scale in that it demonstrated both configural and metrical invariance across samples from the US and China.

This is only the second study to implement configural and metric invariance testing for the NSS-SF. We encourage future use of these methods. For instance, a majority of research using the NSS-SF have been conducted in labs; however, this current research was conducted in the field. Examining if NSS-SF functions the same across lab and field samples is of critical importance. Evidence from this study indicates there may be some differences between field and lab samples. For instance, it was unique that the covariance of the two error terms associated more directly with a home environment. This indicates that perhaps there may be contextual differences of noise sensitivity as measured by the NSS-SF. As very few studies have examined configural and metric invariance in the NSS-SF, any new insights are welcome.

A few limitations and directions for future research should be noted. First, the samples in this study were obtained through local urban parks. It is unknown how these results would generalize to other populations, such as visitors to national parks. Further investigation of this is warranted. Additionally, the covariance between the two error terms in the models (e3 and e4) was a novel occurrence in the NSS-SF. In the future, researchers may wish to refine NSS-SF for different populations, such as urban park users, wilderness users, and those around homes. Lastly, the relatively low factor loading of NOISE SENS 5 RECO indicates that there may be some additional improvement needed in the NSS-SF. However, even with these limitations, we are of the opinion that the results from this study add meaningful contributions to our understanding of noise sensitivity.

This is the first study to use configural and metric invariance testing to assess how the NSS-SF functions across cultures. The research found that the NSS-SF demonstrated configural and metric invariance across a sample of Chinese and US visitors to urban parks. This adds to a greater body of evidence that the NSS-SF is a rigorous instrument for measuring noise sensitivity. Researchers should continue to use similar methods when exploring NSS-SF in a cross-cultural context.

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## REFERENCES

- Babisch W. Cardiovascular effects of noise. Noise Health, 2011; 13, 201-4.
- Frei P, Mohler E, Röösli M. Effect of nocturnal road traffic noise exposure and annoyance on objective and subjective sleep quality. Int J Hyg Environ Health, 2014; 217, 188-95.
- Benfield JA, Bell PA, Troup LJ, et al. Does anthropogenic noise in national parks impair memory? Environ Behav, 2010; 42, 693-706.
- Benfield JA, Taff BD, Newman P, et al. Natural sound facilitates mood recovery from stress. Ecopsychol, 2014; 6, 183-8.
- Miller ZD, Taff BD, Newman P. Visitor experiences of wilderness soundscapes in Denali National Park and Preserve. Int J Wilderness, 2018.
- Zhong T, Chung P, Liu JD. Short Form of Weinstein Noise Sensitivity Scale (NSS-SF): Reliability, Validity, and Gender Invariance among Chinese Individuals. Biomed Environ Sci, 2018; 31, 97-105.
- Weinstein ND. Individual differences in reactions to noise: A longitudinal study in a college dormitory. J Appl Psychol, 1978; 63, 458-66.
- Smith A. The concept of noise sensitivity: Implications for noise control. Noise Health, 2003; 5, 57-9.
- Heinonen-Guzejev M, Vuorinen HS, Mussalo-Rauhamaa H, et al. Genetic component of noise sensitivity. Twin Res Hum Genet, 2005; 8, 245-9.
- 10.Benfield JA, Nurse GA, Jakubowski R, et al. Testing noise in the field: A brief measure of individual noise sensitivity. Environ Beh, 2014; 46, 353-72.
- 11.Dzhambov AM, Dimitrova DD. Psychometric properties of the Bulgarian translation of Noise Sensitivity Scale Short Form (NSS-SF): Implementation in the field of noise control. Noise Health, 2014; 16, 361.
- Battaglia MP, Link MW, Frankel MR, et al. An evaluation of respondent selection methods for household mail surveys. Public Opinion Quarterly, 2008; 72, 459-69.
- 13.Kline RB. Principles and Practice of Structural Equation Modeling (3<sup>rd</sup> ed). New York, NY: The Guilford Press, 2011.