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A COMPARATIVE STUDY OF CB-SEM AND PLS-SEM METHODS USING ONLINE CASINO SURVEY DATA

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ABSTRACT

Structural equation modeling (SEM) is a multivariate statistical analysis technique for analyzing structural relationships. This technique is a combination of factor analysis and multiple regression analysis, and it is used to analyze the structural relationship between measured variables and latent constructs. Covariance-based SEM (CB-SEM) involves specifying a model and estimating the parameters so that the distance between the model's implied population covariance matrix and the sample covariance matrix S is minimized. In the Partial Least Squares approach to SEM (PLS-SEM), the explained variance of the endogenous latent variables is maximized. CB-SEM has been widely used by hospitality researchers, but not the soft-modeling approach of PLS-SEM. The CB-SEM method requires hard distributional assumptions on the data, whereas PLS-SEM is more flexible. This article compares the results of CB-SEM model with results derived from the PLS-SEM method to test the same hypothesis on a dataset from online casino gaming; the results show that PLS-SEM is more accurate than CB-SEM for this dataset. Literature also suggests the use of PLS-SEM over CB-SEM since multivariate normality of the sample is not required, and it generally works well even with smaller sample sizes.

Keywords: online gambling; atmospherics; servicescape; user experience; partial least squares; structural equation modeling, bootstrap

INTRODUCTION

SEM starts with specifying a path model showing relationships between observed variables and latent constructs. CB-SEM minimizes a distance function dist (Σ, S) where Σ is the true covariance matrix and S its sample estimate, whereas the PLS-SEM maximizes the explained variance of the endogenous latent variables. Multivariate normality is a required assumption for CB-SEM but not for PLS-SEM. The PLS approach "has its origins back in 1966 when Herman Wold presented two iterative procedures using least squares (LS) estimation for single and multicomponent models and for canonical correlation" (Mateos-Aparicio, 2011), which was further developed by Herman Wold as an alternative to the CB-SEM (Vinzi *et al.*, 2010), and also to address the issue of multicollinearity in regression problems (Wold, 1982; Wold, Wold, and Dunn, 1984). Partial Least Squares Regression (PLS-R) is a multivariate statistical method for dimension reduction utilized in multiple linear regression which eliminates multicollinearities among predictors in an optimal fashion; PLS-R was developed in 1980 by Svante Wold, the son of Herman Wold, as an improvement on Principal Components Regression (S. Wold *et al.*, 2001).

In a previous article (Abarbanel *et al.*, 2015), the CB-SEM method was used to test a stimulus–organism–response (S–O–R) structural model of the effects of servicescape/environmental cues of online casinos on gamblers' cognitive and affective states, which in turn affected their approach or avoidance behavioral intentions; results showed that atmospherics and functional qualities played a significant role in generating positive behaviors from online gamblers. This article compares the results of this CB-SEM model with results derived from the PLS-SEM method to test the same hypothesis on the same dataset.

LITERATURE REVIEW

CB-SEM and PLS-SEM

CB-SEM owes its popularity to the LISREL III computer program (Jöreskog & Sörbom, 1989) which uses the maximum likelihood (ML) estimation method and minimizes the distance between the sample covariance matrix S and the theoretically derived covariance matrix S imposed by the model. The independence and multivariate normality of the observations are required assumptions. The CB-SEM approach is fairly robust for non-multivariate normal samples, but small sample sizes can yield poor estimates and test statistics (Hu & Bentler, 1995). Two types of rules of thumb regarding the minimum number of samples exist in the CB-SEM literature (Wang & Wang, 2012): (i) minimum sample size N requirement, or (ii) minimum ratio of N to number of variables P. In the first type of rules, an approximate rating scale for N is available (MacCallum *et al.*, 1999):

100 = poor,

200 = fair,

300 = good,

500 = very good,

1,000 or more = excellent,

with a recommendation for 500 or more samples for CB-SEM analysis. In the second type of rules, the recommended ratio of N to P ranges from 3 to 10 (MacCallum *et al.*, 1999).

CB-SEM is widely used by researchers in marketing and social sciences (Abarbanel *et al.*, 2015; Bagozzi and Yi, 1988; Reisinger & Turner, 1999; Ruiz Molina *et al.*, 2010; Ali, 2016; Pawaskar & Goel, 2016), to name a few. The usage of CB-SEM in 209 articles published in nine tourism journals between 2000 and 2011 is reviewed by Nunkoo *et al.*, 2013.

PLS - SEM is an iterative approach for maximizing the explained variance of endogenous constructs (Fornell and Bookstein, 1982) not unlike the multiple regression analysis (Hair *et al.*, 2014). In the PLS step of PLS-SEM, factor scores are represented as sums of corresponding indicators, and optimal indicator weights are obtained for each latent variable using an iterative algorithm (Monecke and Leisch, 2012). PLS-SEM is computationally efficient since the computations for optimal weights are done in blocks.

Oom do Valle and Assaker (2016) reviewed a total of 44 articles published in 11 leading tourism journals during 2000 – 2014 and found a few issues with how PLS-SEM was applied in empirical research in tourism, and how its usage could be improved. Zhang, Dawson and Kline (2021) examined a total of 144 CB-SEM articles in management journals and suggested a systematic and standardized approach for using CB-SEM and reporting of results. Astrachan *et al.* (2014) compared the CB-SEM and PLS-SEM methods on a data set of 174 responses to an online survey that was designed to investigate the relationship between reputation and trustworthiness of family businesses. Their recommendation is to use PLS-SEM since PLS-SEM does not require multivariate normality of sample, and it can handle smaller sample sizes and greater numbers of constructs and indicators. Haenlein & Kaplan (2004) recommend the use of PLS-SEM over CB-SEM when CB-SEM method reaches its limit, viz., when the number of indicators per latent variable becomes excessively large and the high dimensionality of the sample covariance matrix creates computational difficulties.

CB-SEM appears to be the method of choice in gaming and hospitality research, even though PLS-SEM is known to have several advantages over the CB-SEM (Astrachan *et al.*, 2014). Mohajerani (2013) used CB-SEM to show that customer satisfaction has a significant and positive impact on customer loyalty in the Iranian hotel industry. Smith and Kumar (2014) used CB-SEM to study the impact of corporate social responsibility (CSR) on employee organizational commitment (EOC) within the gaming industry; results suggest that an employee with positive attitudes toward CSR will have a positive affective commitment (AC) and continuance commitment (CC) for the gaming company. Ali, Kim, Li, and Cobanoglu, (2018) used both CB-SEM and PLS-SEM on three different datasets from hospitality and tourism and found PLS-SEM to be advantageous for applying SEM in hospitality and tourism research. Sarstedt, *et al.* (2020) discuss the robustness of PLS-SEM. Manosuthi, Lee, & Han (2021) propose the use of a hybrid method based on PLS-SEM and generalized structured component analysis (GSCA) in hospitality research. The popularity of PLS-SEM is expected to grow with availability of statistical software: (i) the statistical software environment R has a semPLS package (Monecke and Leisch, 2012), and (ii) new, easy-to-use packages, like SmartPLS (Ringle, Wende & Becker, 2015), are making PLS-SEM analysis accessible to researchers (see full detail on this package in Garson, 2016). Wu, Zeng & Xie (2017) used the software SmartPLS to explore factors affecting Chinese travelers' behavioral intentions toward room-sharing platforms in the sharing economy. Their results suggest that utilitarian motivation, hedonic motivation and perceived trust positively impact tourists' behavioral intentions.

Online Gambling E-servicescape

The theoretical foundation of the online gambling e-servicescape was established in Bitner's (1992) seminal servicescape theory, describing a means of analyzing how a consumer interacts with a service setting. The servicescape concept is largely based on the stimulus-organism-response (S-O-R) paradigm, from the environmental psychology discipline (Mehrabian and Russell, 1974).

Drawing on prior applications of the servicescape model in the casino (Lucas, 2003, Suh and Erdem, 2009, Johnson *et al.*, 2004, Lam *et al.*, 2011) and online consumption (Eroglu *et al.*, 2003, Eroglu *et al.*, 2001, Lindgaard *et al.*, 2006, Williams and Dargel, 2004, Fiore and Kelly, 2007, Choi and Kim, 2004, Harris and Goode, 2010), Abarbanel *et al.* (2015) empirically examined an S-O-R model for the online gambling e-servicescape. The tested model is displayed in Figure 1 (Abarbanel, 2013).

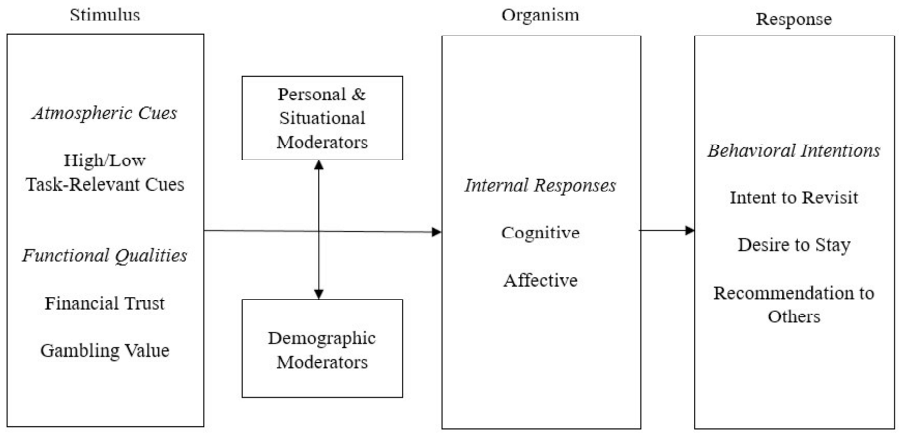

Figure 1: Conceptual SOR model

The CB-SEM and PLS-SEM procedures are compared along the hypotheses that describe the theoretical model; these hypotheses break down the major model S-O-R components to examine their individual effect (Abarbanel, 2013):

"H1: The online gambling site's task-relevant information is associated with the consumers' holistic satisfaction with the gambling environment, which then affects their behavioral intentions (revisitation intent, desire to stay, and recommendation to others).

H1a: The online gambling site's high task-relevant cues are associated with the consumers' holistic satisfaction with the gambling environment, which then affects their behavioral intentions. H1b: The online gambling site's low task-relevant cues (sound) are associated with the consumers' holistic satisfaction with the gambling environment, which then affects their behavioral intentions. H1c: The online gambling site's low task-relevant cues (image) are associated with the consumers' holistic satisfaction with the gambling environment, which then affects their behavioral intentions.

H2: Online gamblers' trust in financial transactions is associated with their holistic satisfaction with the gambling environment, which then affects their behavioral response (revisitation intent, desire to stay, and recommendation to others).

H3: Gambling value is associated with the consumers' holistic satisfaction with the gambling environment, which then affects their behavioral intentions (revisitation intent, desire to stay, and recommendation to others).

H4: The gamblers' internal responses mediate the relationship between the perceived environment and their behavioral intentions."

DATA AND METHODS

Data was collected in the online survey described in Abarbanel *et al.* (2015), from a population of adults older than of 18 with minimum of "one credit wager online during the three years preceding the survey". The specific construct measures from the survey are described in Appendix A. This analysis compares the CB-SEM and PLS-SEM models for the base theoretical model only, and not the group differences among moderating factors, as these factors are not considered when fitting the structural model. The theoretical model was operationalized for the SEM procedure as shown in Figure 2.

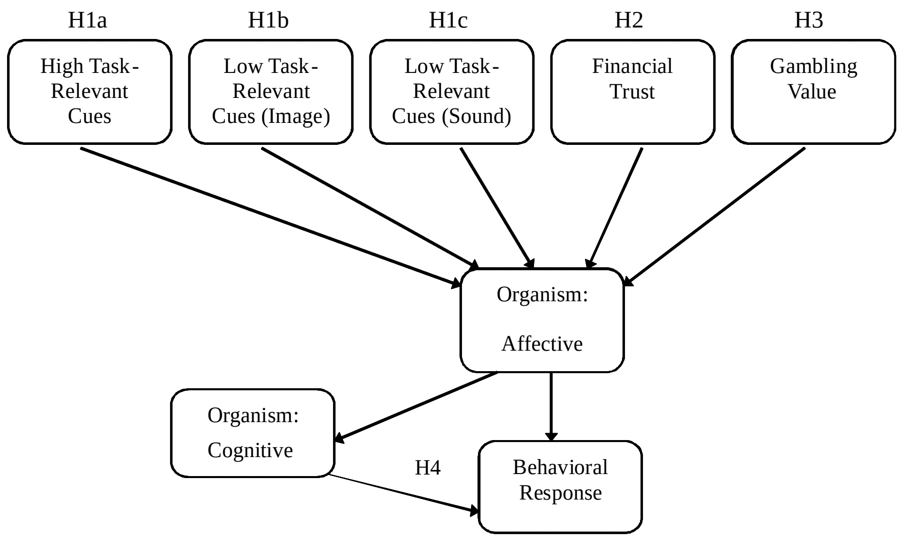

Figure 2: Empirically Operationalized Research Model

Note: Figure replicated from Abarbanel *et al.* (2015).

Assumptions testing was conducted on all measured variables, including skewness and kurtosis, univariate outliers, and multivariate outliers (Mahalnobis distance). One multivariate outlier was found and removed from the database. After accommodating for missing data and assumptions testing, a total N of 349 observations was available for analysis. In the CB-SEM the ML method is used to test H1–H4.

The SEM model was fitted to the data using SmartPLS (Ringle, Wende & Becker, 2015); the factor scores computed in the CB-SEM measurement model were used. The SmartPLS software uses a bootstrap procedure to calculate confidence intervals for path coefficients and also for several performance measures. The bootstrap procedure is an empirical method for statistical inference, in which a large number (B) of bootstrap samples with replacement are generated from the sample, and the statistic of interest is computed for each bootstrap sample; this gives rise to B values of the statistic of interest, from which one can conduct a hypothesis test or compute an approximate confidence interval (Efron and Tibshirani, 1998).

SEM Models and Findings

In Abarbanel *et al.* (2015), the low task-relevant cues measurement items were found to optimally load onto two separate constructs – one depicting the low cues of sound and one depicting the low cues of image. Hightask6, lowtask5, lowtask6, and fintrust5 had low loadings and were removed from analysis. The affective – arousal measures also displayed low loadings and were highly correlated with the affective – pleasure measures. As a result, affecta1, affecta2, and affecta3 were also removed from analysis and the affective construct was composed solely of the pleasure measures. Table 1 displays the factor loadings and z-values for the final measurement constructs; all P-values were significant (P-values < 0.0001). For all factors in the measurement model, the construct reliabilities and all Cronbach's alpha values exceeded the 0.70 rule of thumb and all AVE estimates were higher than the acceptable threshold of 0.50 (Hair *et al.*, 2010). Discriminant validity was confirmed, with all factors conforming to the requirement that the square root of factor AVE be higher than the construct correlations.

The CB-SEM model found that the paths from high task-relevant cues, low task-relevant cues (sound), financial trust, and gambling value to the affective construct were positive and significant (all p-values $< .05$); the path between affective and cognitive response was significant ($p < .001$), and the two paths from affective and cognitive response to behavioral response were both positive and significant (both p-values $< .01$). The path from low task-relevant cues (image) to affective response was not significant ($p > .05$). Chi square ($p = .001$), goodness-of-fit index (GFI, 0.98), adjusted goodness-of fit index (AGFI, .92), normed fit index (NFI, .98), root-mean-square residual (RMSR, .02), and root-mean-square error approximation (RMSEA, .08) were used to assess the fit between model and data (Abarbanel *et al.*, 2015).

The results from PLS-SEM (see Table 3 and Figure 3) show that all path coefficients are highly significant ($p < 0.01$), with the exception of organism (affective) to behavioral response, which is significant at the $p = 0.10$ level.

Table 1: Item Loadings and z-values

Factor	*Measurement Item*	*Factor Loading*	*z-Value*
Stimulus			
High Task-Relevant Cues	hightask1	0.648	20.57
	hightask2	0.708	21.87
	hightask3	0.736	22.98
	hightask4	0.669	18.59
	hightask5	0.591	17.07
Low Task-Relevant Cues - Image	lowtask1	0.705	18.65
	lowtask2	0.682	20.21
	lowtask3	0.673	20.94
	lowtask4	0.673	16.88
Low Task-Relevant Cues - Sound	lowtask7	0.869	14.58
	lowtask8	0.668	11.75
Financial Trust	fintrust1	0.692	17.96
	fintrust2	0.745	17.62
	fintrust3	0.619	15.45
	fintrust4	0.638	17.87
	fintrust6	0.563	15.12
Gambling Value	gamval1	0.555	15.48
	gamval2	0.598	16.24
	gamval3	0.608	15.70
	gamval4	0.556	16.10
Organism			
Affective	affectp1	0.683	18.37
	affectp2	0.835	20.56
	affectp3	0.777	19.42
Cognitive	cog1	0.882	21.67
	cog2	0.977	24.22
	cog3	0.949	23.00
Response			
	response1	0.790	19.52
	response2	0.815	20.75
	response3	0.680	20.85
	response4	0.812	22.92
	response5	0.818	22.69

*All tests were significant, $p < 0.0001$
Note: Source: Abarbanel *et al.* 2015

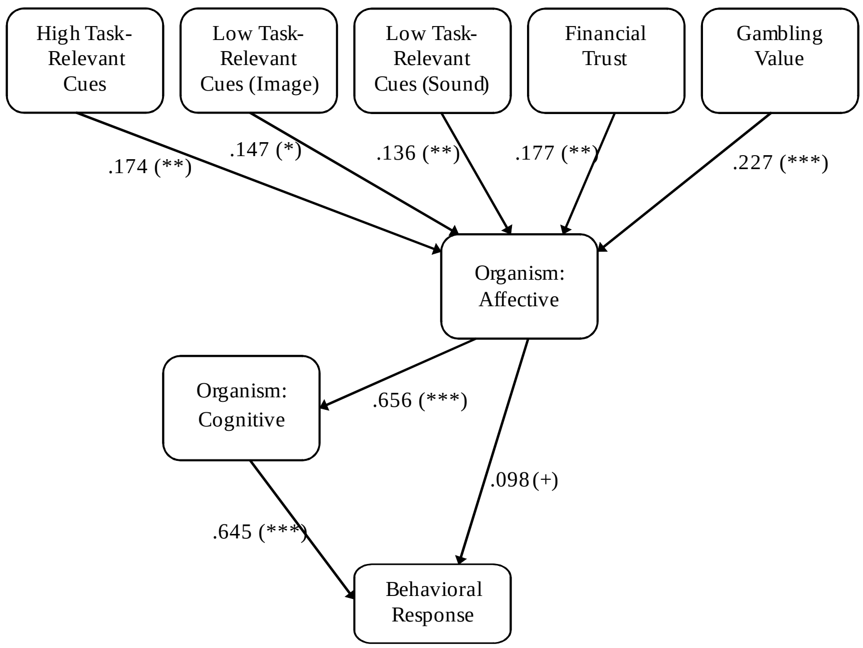

Figure 3: Structural model results for PLS-SEM analysis.

Note: +p < .10, *p < .05, **p < .01, ***p < .001

Table 3: Summary of Test Results for the PLS-SEM Structural Model

Hypothesis	*Path*	*Standardized Path Coefficient*	*p-Value*
H1	High Task-Relevant Cues ® Affective	0.174	0.009
	Low Task-Relevant Cues (Image) ® Affective	0.147	0.013
	Low Task-Relevant Cues (Sound) ® Affective	0.136	0.003
H2	Financial Trust ® Affective	0.177	0.003
H3	Gambling Value ® Affective	0.227	< 0.001
H4	Affective ® Cognitive	0.656	< 0.001
	Affective ® Behavioral Response	0.098	0.081
	Cognitive ® Behavioral Response	0.645	< 0.001

The values of goodness of fit measures from PLS-SEM are: SRMR = 0.089, chi-square p < 0.001, NFI = 0.85, and rms Theta = 0.249. The sample size in this analysis, N = 349, is within appropriate range to fit a model based on chi-square tests (Gatignon, 2009); the goodness-of-fit from the other measures verifies that this model is a good fit for the dataset.

It should be noted that the results from PLS-SEM do not require the normality assumption of CB-SEM and hence can be considered to be robust.

Comparison of Path Model Results

The primary differences in path significance between the CB-SEM and PLS-SEM models exist on the two Low Task-Relevant Cues – Affective paths, and the Affective-Behavioral Response path. Use of CB-SEM resulted in non-significant path coefficients for the Low-Task Relevant Cues functional qualities in the general model (significant in the moderated model), while the more robust PLS-SEM analysis resulted in significant path coefficients for all the theorized stimuli for the online casino e-servicescape environment.

DISCUSSION AND CONCLUSIONS

Analytical Implications

The package mvnormtest of the statistical software environment R (2016) was used to test multivariate normality; the data was found to be highly non-multivariate normal, with P-value of 0.000. The test of significance of skewness showed that, with the exceptions of lowtask1 and lowtask4, all indicators were very highly skewed. The z-values for skewness, except for lowtask1 and lowtask4, were all above 2, suggesting the data to have substantial non-normality (Kim, 2013). Non-normality of data does not affect the parameter estimates, but tends to lower the standard deviations of the estimates, and also results in overestimation of the likelihood-ration chi-square test statistic (Kaplan, 2001). This might explain higher GOF measures using CB-SEM when compared to PLS-SEM.

The non-significant path from affective to behavioral response in the PLS-SEM results is also of note. The theoretical background for the model indicates that the indirect path from affective to cognitive to behavioral response should carry a higher weight than the direct path. Several prior S-O-R studies with application in servicescape analysis suggest that the affective ’! cognitive sequence of constructs that is used in this model is a more accurate representation of the Organism relationship (Cohen and Areni, 1991, Eroglu *et al.*, 2003).

Practical Implications

Based on the theoretical model in (Abarbanel, 2013), the PLS-SEM results for all the stimuli (atmospherics and functional qualities) are more reflective of the literature support for these constructs. Further, because PLS is a more robust analytical method, we turn to the resulting values from this analysis to consider the practical value of the results. The PLS-SEM demonstrates robust significant results for Low Task-Relevant Cues for the full model, not just when accommodating for moderating effects (as was the result with CB-SEM). Both Image and Sound Low Task-Relevant Cues – such as graphics and music – can be used in a virtual gambling environment to improve the gambler's experience through implicit suggestion that the site is of higher quality, as well as contribute to the perceived ease-of-use and perceived usefulness of the gambling technology. While it is the High Task-Relevant Cues (which display significant paths in both PLS- and CB-SEM analyses) that actively facilitate the gambling activity in an online casino, the Low Task-Relevant Cues provide the visual and auditory context that can make the gambling experience more enjoyable.

The significance of Low Task-Relevant Cues in affecting player response to the servicescape also offers implications for responsible gambling programs in online casino operations. Operators should consider the look and feel of a responsible gambling program, beyond the basic requirements set forth by regulators (e.g., a self-exclusion program or limit-setting tools). Having these tools available addresses the High Task-Relevant component of online gambling site design, but consumer preference for Low Task-Relevant atmospherics suggests that these tools are more likely to be utilized if they are promoted to consumers with richer media.

In relation to broader gambling servicescape, the casino e-servicescape has the benefit of existing in a virtual space. As Abarbanel *et al.* (2015) note, site operators have the options to constantly research and reassess their site design, then make improvements and changes on the back-end of the website/software while still maintaining the current user interface for interim use. This permits online gambling sites to take advantage of evidence-based digital marketing tools, such as A/B testing, to manipulate the conditions of High and Low Task-Relevant Cues to optimize use of these cues, with respect to the behavioral responses of customers.

Limitations and Future Research

As noted in Abarbanel *et al.* (2015), the sample used for this analysis skews to a higher age range than other studies of an online gambling population, and has a large proportion of US-based respondents. Replication of the study would be valuable to determine if the results are generalizable to a broader online population.

The data collection process did not investigate specific High and Low Task-Relevant Cues, but rather the general concept of images and sound. Additional research that manipulates types of High and Low Task-Relevant Cues, such as specific signage and navigation (High) or specific colors, background patterns, font styles, and music (Low), would provide valuable detail to more comprehensive academic literature.

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Appendix A: Survey Scale Measures for Latent Variable Construction

Factor	*Survey Scale Measure Statement*	*Code for Analysis*
Stimulus		
High Task-Relevant Cues	The layout of this online gaming site allows a person to quickly get to the game they want to play.	hightask1
	This online gaming site is user-friendly.	hightask2
	It is easy to navigate this online gaming site to find what you are looking for.	hightask3
	On this site, I can easily find important information I need.	hightask4
	The links on this site are obvious in their intent and destination.	hightask5
	There is a great deal of irrelevant information.*	hightask6
Low Task-Relevant Cues	The use of color in this site's graphic design adds excitement to the gambling.	lowtask1
	The site's overall graphic design is attractive.	lowtask2
	The site's individual images are appealing.	lowtask3
	The site's images make gambling more fun.	lowtask4
	The site's images are useful for gambling.	lowtask5
	The site's sounds are annoying.*	lowtask6
	The site's sounds make gambling more fun.	lowtask7
	The site's sounds are useful when I gamble.	lowtask8
Financial Trust	When I deposit money on this online gaming site, I feel my transaction is secure.	fintrust1
	When I make a withdrawal from this online gaming site, I feel confident I will receive my money.	fintrust2
	The security systems of this online gaming site seem rigorous.	fintrust3

	When I place bets on this site, I am reassured by the security procedures.	fintrust4
	I think some of the online gaming site's claims about winning percentages are exaggerated.*	fintrust5
	The site has a reputation for running an honest game.	fintrust6
Gambling Value	I am able to play for a reasonable amount of time on the site, given my investment.	gamval1
	The payout/rake for the games on this site is reasonable.	gamval2
	You can win by playing at this site.	gamval3
	The games offered by this online casino are fair.	gamval4
Organism		
Affective	This online gambling site makes me feel…	
Pleasure	Unhappy/Happy	affectp1
	Annoyed/Pleased	affectp2
	Unsatisfied/Satisfied	affectp3
Arousal	Relaxed/Stimulated	affecta1
	Calm/Excited	affecta2
	Not aroused/Aroused	affecta3
Cognitive	My view of this online gambling site is…	
	Unfavorable/Favorable	cog1
	Negative/Positive	cog2
	Bad/Good	cog3
Response		
Revisit Intention	I will gamble at this online site in the future.	response1
	The next time I gamble online, I would like to go back to the same site.	response2
Desire to Stay	I enjoy spending time at this online gaming site.	response3
Recommend to Others	This is an online gaming site I would recommend to other people.	response4
	If asked, I would say positive things about this casino.	response5
Moderator		
Atmospheric Responsiveness	When I gamble online, I notice the site's "feel."	atmoresp1
	Background music makes a difference to me in deciding where I gamble.	atmoresp2
	Background colors make a difference to me in deciding where I gamble.	atmoresp3
	I find myself making decisions on where to gamble based on how the site looks.	atmoresp4
	A site's graphic design influences my decision about where I gamble.	atmoresp5