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Table 1: Assessment of compositional invariance

	PLS-PM		**GSCA**		**PLS$_C$**		**GSCA$_M$**		
	H_0: Compositional measurement invariance of the constructs								
Composite	**C = 1**	**95% CI**	**C = 1**	**95% CI**	**C = 1**	**95% CI**	**C = 1**	**95% CI**	**Result**
BI	0.9991	[0.9961, 1]	0.9984	[0.9938, 1]	0.9991	[0.9961, 1]	0.9988	[0.9978, 1]	FTR
SAT	1.0000	[0.9997, 1]	0.9994	[0.9944, 1]	1	[0.9997, 1]	1	[1, 1]	FTR
WTW	0.9998	[0.9996, 1]	0.9976	[0.9967, 1]	0.9998	[0.9996, 1]	0.9999	[0.9998, 1]	FTR

FTR = Fail to reject the null hypothesis

Table 2: Assessment of mean and variance invariances

	PLS-PM		GSCA		PLS_C		$GSCA_M$		
	H_0: Difference between group mean is zero								
Composite	**Test stat**	**95% CI**	**Test stat**	**95% CI**	**Test stat**	**95% CI**	**Test stat**	**95% CI**	**Result**
BI	0.0184	[−0.3396, 0.3318]	0.0169	[−0.3339, 0.3355]	0.0184	[−0.3410, 0.3352]	0.0189	[−0.3252, 0.3149]	FTR
SAT	−0.1019	[−0.3371, 0.3351]	−0.1051	[−0.3292, 0.3362]	−0.1019	[−0.3391, 0.3365]	−0.1011	[−0.3284, 0.3251]	FTR
WTW	−0.2045	[−0.3380, 0.3396]	−0.2046	[−0.3324, 0.3327]	−0.2045	[−0.3440, 0.3362]	−0.2043	[−0.3112, 0.3280]	FTR
	H_0: Log of the ratio of the group variances is zero								
Composite	**Test stat**	**95% CI**	**Test stat**	**95% CI**	**Test stat**	**95% CI**	**Test stat**	**95% CI**	**Result**
BI	0.1579	[−0.4640, 0.4928]	0.1698	[−0.4764, 0.4834]	0.1579	[−0.4684, 0.4862]	0.1581	[−0.4292, 0.4905]	FTR
SAT	0.1420	[−0.4670, 0.4797]	0.1422	[−0.4559, 0.4820]	0.1420	[−0.4673, 0.4842]	0.1417	[−0.4506, 0.5162]	FTR
WTW	0.2391	[−0.5534, 0.5696]	0.2404	[−0.5555, 0.5824]	0.2391	[−0.5650, 0.5725]	0.2393	[−0.5365, 0.5973]	FTR

Note: FTR = Fail to reject the null hypothesis

Table 3: Assessment of structural invariance using an MGA procedure

Method		PLS-PM		GSCA		PLS_C		$GSCA_M$	
Klesel et al. (2019)	H_0: Model-implied indicator covariance matrix is equal across groups								
	Distance measure:	Test stat	*p* value	Test stat	*p* value	Test stat	*p* value	Test stat	*p* value
	d_G	0.1624	0.5025	0.1732	0.4824	0.4697	0.1759	0.2372	0.3970
	d_L	0.3004	0.5729	0.3152	0.5377	0.4991	0.6382	0.4826	0.5427
Chin & Dibbern (2010)	H_0: Parameter *k* is equal across two groups								
	BI→SAT	0.1272	0.1357	0.1299	0.1508	0.1091	0.1910	0.1164	0.1960
	BI→WTW	−0.2600	0.1357	−0.2726	0.1658	−0.3126	0.2915	−0.3023	0.2161
	SAT→WTW	0.2047	0.2563	0.2264	0.2613	0.2461	0.4121	0.2349	0.4171
Keil et al. (2000)	H_0: Parameter *k* is equal across two groups								
	BI→SAT	1.4828	0.1405	1.4843	0.1401	1.2552	0.2116	1.2154	0.2263
	BI→WTW	−1.5683	0.1192	−1.5874	0.1148	−1.1398	0.2564	−1.2540	0.2120
	SAT→WTW	1.3168	0.1901	1.3958	0.1651	0.9403	0.3488	1.0422	0.2992
Nitzl (2010)	H_0: Parameter *k* is equal across two groups								
	BI→SAT	1.4309	0.1557	1.4274	0.1569	1.2076	0.2303	1.1613	0.2488
	BI→WTW	−1.5732	0.1181	−1.5873	0.1149	−1.1433	0.2550	−1.2579	0.2107
	SAT→WTW	1.2997	0.1962	1.3747	0.1719	0.9336	0.3523	1.0322	0.3040
Henseler (2009)	H_0: Parameter *k* of Group 1 is smaller/larger than that of Group 2								
	BI→SAT	-	0.0689	-	0.0686	-	0.1067	-	0.1109
	BI→WTW	-	0.9411	-	0.9433	-	0.8762	-	0.8956
	SAT→WTW	-	0.0982	-	0.0856	-	0.1759	-	0.1525
Admissible per 10,000 permutation		10,000		10,000		9,719		10,000	

Note: d_G = geodesic distance, d_L = squared Euclidean distance

Table 4: Assessment of internal consistency reliability and convergent validity

	PLS-PM[a]		GSCA[b]		PLS_C[c]		$GSCA_M$[d]		ρ_a	AVE
Item	$\hat{\lambda}_i$	95% CI ($\hat{\lambda}_i$)	$\hat{\lambda}_i$	95% CI ($\hat{\lambda}_i$)	$\hat{\lambda}_i$	95% CI ($\hat{\lambda}_i$)	$\hat{\lambda}_i$	95% CI ($\hat{\lambda}_i$)		
Benefit from international Muslim tourists (BI)									0.922[a] 0.925[b] 0.892[c] 0.894[d]	0.739[a] 0.738[b] 0.658[c] 0.661[d]
BI1	0.8506	[0.7775; 0.9042]	0.8482	[0.7799; 0.9012]	0.7839	[0.6593; 0.8880]	0.8044	[0.7088; 0.8875]		
BI2	0.9249	[0.8990; 0.9480]	0.9315	[0.9027; 0.9541]	0.9360	[0.8509; 0.9919]	0.9387	[0.8849; 0.9849]		
BI3	0.8180	[0.7162; 0.8834]	0.8134	[0.7175; 0.8811]	0.7374	[0.5731; 0.8625]	0.7384	[0.6026; 0.8415]		
BI4	0.8420	[0.7432; 0.9070]	0.8402	[0.7406; 0.9073]	0.7745	[0.6105; 0.9069]	0.7566	[0.6213; 0.8661]		
Satisfaction (SAT)									0.961[a] 0.963[b] 0.922[c] 0.922[d]	0.925[a] 0.923[b] 0.852[c] 0.855[d]
SAT1	0.9590	[0.9371; 0.9743]	0.9487	[0.9164; 0.9714]	0.8897	[0.8252; 0.9414]	0.9202	[0.8823; 0.9504]		
SAT2	0.9646	[0.9497; 0.9762]	0.9730	[0.9559; 0.9853]	0.9557	[0.9131; 0.9897]	0.9297	[0.9003; 0.9546]		
Willingness to welcome (WTW)									0.969[a] 0.958[b] 0.960[c] 0.961[d]	0.862[a] 0.862[b] 0.828[c] 0.830[d]
WTW1	0.9209	[0.8752; 0.9522]	0.9192	[0.8727; 0.9516]	0.8886	[0.8134; 0.9439]	0.8980	[0.8343; 0.9454]		
WTW2	0.9415	[0.9122; 0.9621]	0.9424	[0.9117; 0.9628]	0.9355	[0.8850; 0.9737]	0.9337	[0.8911; 0.9628]		
WTW3	0.9434	[0.9145; 0.9647]	0.9447	[0.9124; 0.9668]	0.9387	[0.8845; 0.9809]	0.9356	[0.8909; 0.9666]		
WTW4	0.9202	[0.8653; 0.9577]	0.9213	[0.8690; 0.9577]	0.9084	[0.8295; 0.9707]	0.8950	[0.8157; 0.9545]		
WTW5	0.9174	[0.8699; 0.9488]	0.9154	[0.8671; 0.9492]	0.8784	[0.7895; 0.9438]	0.8933	[0.8327; 0.9388]		

Note 1: $\hat{\lambda}_i$ = estimated composite loadings; 95% CI ($\hat{\lambda}_i$) = 95% confidence intervals from bootstrapping with 10,000 samples of estimated composite loadings;
ρ_a = Dijkstra–Henselers rho to assess internal consistency (α); AVE = average variance extracted; VIF = variance inflation factor. Note 2: a, b, c, and d refer to PLS, GSCA, PLS_C, and $GSCA_M$ estimators, respectively.

Table 5: Assessment of discriminant (HTMT ratio), nomological, and concurrent validities

	PLS			GSCA		
	BI	**SAT**	**WTW**	**BI**	**SAT**	**WTW**
BI	**0.7392972**			**0.7386908**		
SAT	0.7928694	**0.9250426**		0.7928694	**0.9234515**	
WTW	0.7663558	0.8750092	**0.8625715**	0.7663558	0.8750092	**0.8624702**
	PLS_C			**$GSCA_M$**		
	BI	**SAT**	**WTW**	**BI**	**SAT**	**WTW**
BI	**0.6585109**			**0.6614684**		
SAT	0.7928694	**0.8524442**		0.7928694	**0.8555703**	
WTW	0.7663558	0.8750092	**0.8285319**	0.7663558	0.8750092	**0.8305057**

The bold diagonal values are the AVEs of different estimators. The lower triangle elements are the HTMT ratio.

Concurrent validity					
Exogenous composite	**Endogenous composite**	**PLS**	**GSCA**	**PLS_C**	**$GSCA_M$**
BI	**SAT**	0.701***	0.712***	0.707***	0.706***
BI	**WTW**	0.265***	0.256***	0.262***	0.263***
SAT	**WTW**	0.638***	0.644***	0.639***	0.637***
Nomological validity					
Correlation between composite scores		**PLS**	**GSCA**	**PLS_C**	**$GSCA_M$**
Cor(BI, SAT)		0.700***	0.711***	0.706***	0.705***
Cor(BI, WTW)		0.711***	0.714***	0.713***	0.712***
Cor(SAT, WTW)		0.823***	0.826***	0.823***	0.822***

***** Significant at 0.01**

Table 6: Assessment of structural model

Algorithm	Endogenous	Predictor	$\hat{\beta}$	95% CI ($\hat{\beta}$)	VIF	F^2	R^2
PLS-PM	WTW						0.7062
		BI	0.2420	[0.0734; 0.4210]	2.0652	0.0965	
		SAT	0.6495	[0.4704; 0.8064]	2.0652	0.6954	
	SAT						0.5158
		BI	0.7182	[0.6281; 0.7945]		1.0652	
GSCA	WTW						0.7096
		BI	0.2391	[0.0627; 0.4265]	2.0976	0.0939	
		SAT	0.6531	[0.4681; 0.8188]	2.0976	0.7002	
	SAT						0.5233
		BI	0.7234	[0.6363; 0.8040]		1.0976	
PLS_C	WTW						0.7790
		BI	0.1951	[−0.0793; 0.4624]	2.6758	0.0644	
		SAT	0.7202	[0.4568; 0.9799]	2.6758	0.8771	
	SAT						0.6263
		BI	0.7914	[0.7003; 0.8709]		1.6758	
$GSCA_M$	WTW						0.7747
		BI	0.1990	[−0.0610; 0.4507]	2.6342	0.0667	
		SAT	0.7149	[0.4676; 0.9541]	2.6342	0.8612	
	SAT						0.6204
		BI	0.7876	[0.6919; 0.8590]		1.6342	

Note: $\hat{\beta}$ = estimated standardized beta coefficients; VIF = variance inflation factor; F^2= Cohen's effect size; R^2 = in-sample predictive power

95% BCa CI = 95% bias-corrected and accelerated confidence intervals from bootstrapping with 10,000 samples

Table 7: Assessment of overall model fit indices

Discrepancy	PLS-PM	GSCA	PLS_C	$GSCA_M$
Geodesic distance (d_G)	0.1881628	0.1796125	0.1191982	0.1167121
Squared Euclidian distance (d_L)	0.1401212	0.1288794	0.04393462	0.05639506
ML distance	1.22395	1.16728	0.6264954	0.6195391
CFI	0.9100418	0.9150205	0.9625306	0.9631418
GFI	0.9953748	0.9957459	0.9985498	0.9981385
IFI	0.9116516	0.9165412	0.9632012	0.9638014
NFI	0.8961867	0.9009933	0.9468618	0.9474518
NNFI	0.8167518	0.8268936	0.9236735	0.9249184
RMSEA	0.194741	0.1892754	0.1256826	0.1246535
RMS_θ	0.0418407	0.04125384	0.05606688	0.05501129
SRMR	0.04607654	0.04418957	0.0258007	0.02923133
Tested for overall model fit based on Beran and Srivastava (1985)	**H_0: Population indicator covariance matrix is equal to model-implied indicator covariance matrix**			
Critical value 95% d_G	0.1882	0.1920	0.1880	0.1340
Critical value 95% SRMR	0.0461	0.0497	0.0368	0.0462
Critical value 95% d_L	0.1401	0.1631	0.0892	0.1411
Result of overall model fit test	FTR	FTR	FTR	FTR

Note: CFI, GFI, IFI, NFI, NNFI, RMSE, and SRMR indices are interpreted similar to the traditional factor-based SEM. RMS_θ is the root mean square of the measurement model residual covariance. Distance measures for composite-based SEM: geodesic distance (d_G), squared Euclidean distance (d_L), and ML distance (d_{ML}) are presented in the first three rows. FTR = Fail to reject the null hypothesis

Table 8: Assessment of out-of-sample predictive power based on the indicator level

Procedure	Item	$Q^2_{Predict}$	Normality	$RMSE_{target}$	$RMSE_{Benchmark}$	SSD
PLS-PM	SAT1	0.4247	No	1.2364	1.2978	0.00376996
	SAT2	0.5075	No	1.1433	1.1742	0.00095481
	WTW1	0.3898	No	1.2237	1.3421	0.01401856
	WTW2	0.4079	No	1.2151	1.3211	0.011236
	WTW3	0.4230	Yes*	0.9185*	0.9211*	6.76E-06
	WTW4	0.4678	No	1.0946	1.1727	0.00609961
	WTW5	0.4244	No	1.1377	1.2227	0.007225
						0.0433107
GSCA	SAT1	0.4239	No	1.236	1.3014	0.00427716
	SAT2	0.5082	No	1.1434	1.185	0.00173056
	WTW1	0.3866	No	1.2273	1.3438	0.01357225
	WTW2	0.4086	No	1.2125	1.3272	0.01315609
	WTW3	0.4278	No	1.1808	1.254	0.00535824
	WTW4	0.4680	No	1.0954	1.1728	0.00599076
	WTW5	0.4258	No	1.137	1.2247	0.00769129
						0.05177635
PLSc	SAT1	0.4195	No	1.2408	1.3111	0.004942
	SAT2	0.5035	No	1.1491	1.1915	0.001798
	WTW1	0.3818	No	1.2311	1.3544	0.015203
	WTW2	0.4005	No	1.2211	1.3342	0.012792
	WTW3	0.4181	No	1.1899	1.2576	0.004583
	WTW4	0.4643	No	1.0977	1.1775	0.006368
	WTW5	0.4231	No	1.1381	1.2277	0.008028
						0.053714
$GSCA_M$	SAT1	0.4214	Yes*	0.9727	0.9825	9.6E-05
	SAT2	0.5099	No	1.1401	1.183	0.00184
	WTW1	0.3840	No	1.2288	1.3459	0.013712
	WTW2	0.4038	No	1.2176	1.3298	0.012589
	WTW3	0.4210	No	1.1881	1.2623	0.005506
	WTW4	0.4688	No	1.095	1.1786	0.006989
	WTW5	0.4241	No	1.1376	1.2289	0.008336
						0.049068

Note: $Q^2_{predict}$ is the predictive test for out-of-sample analysis; Normality = distribution test for error terms; SSD = sum of squared differences; SSD in bold font is the total sum of square errors; * = use MAE instead of RMSE to evaluate out-of-sample predictive power for the normality case of a residual

Table 9: Assessment of out-of-sample predictive power based on the composite level

Model	Procedure	Composite	$Q^2_{Predict}$	Normality	$RMSE_{target}$	$RMSE_{Benchmark}$	SSD
I	PLS-PM	SAT	0.4832	No	1.1264	1.155	0.00081796
		WTW	0.4956	No	1.0162	1.0967	0.00648025
							0.00729821
I	GSCA	SAT	0.4985	No	1.1102	1.1346	0.00059536
		WTW	0.4994	No	1.0133	1.093	0.00635209
							0.00694745
I	PLSc	SAT	0.4913	No	1.1169	1.1427	0.000666
		WTW	0.4972	No	1.0142	1.0924	0.006115
							0.006781
I	**$GSCA_M$**	**SAT**	**0.4903**	**No**	**1.1183**	**1.1442**	**0.000671**
		WTW	**0.4970**	**No**	**1.0149**	**1.0926**	**0.006037**
							0.006708
II	PLS-PM	SAT	0.4831	No	1.1265	1.1547	0.00079524
		WTW	0.4958	No	1.0162	1.0965	0.00644809
							0.00724333
II	GSCA	SAT	0.4991	No	1.11	1.1346	0.00060516
		WTW	0.4860	No	1.02	1.0927	0.00528529
							0.00589045
II	PLSc	SAT	0.4920	No	1.1168	1.1424	0.000655
		WTW	0.4826	No	1.0294	1.0922	0.003944
							0.004599
II	**$GSCA_M$**	**SAT**	**0.4907**	**No**	**1.1179**	**1.1439**	**0.000676**
		WTW	**0.4817**	**No**	**1.0301**	**1.0923**	**0.003869**
							0.004545

Note: $Q^2_{predict}$ is the predictive test for out-of-sample analysis; Normality = distribution test for error terms; SSD = sum of squared differences; SSD in bold font is the total sum of squared differences

Table 10: Assessment of predictors' importance and their performance

			Importance		Performance of predictor
Algorithm	**Endogenous variable**	**Predictor**	$\hat{\beta}$	**95% BCa CI ($\hat{\beta}$)**	**Mean**
PLS-PM	**WTW**				
		SAT	0.8235	[0.7373; 0.8903]	4.561964
		BI	0.5915	[0.4790; 0.6952]	5.099231
	SAT				
		BI	0.8235	[0.7373; 0.8903]	
GSCA	**WTW**				
		SAT	0.7235	[0.6369; 0.8039]	4.547779
		BI	0.5981	[0.4808; 0.7051]	4.417815
	SAT				
		BI	0.7235	[0.6369; 0.8039]	
PLS_C	**WTW**				
		SAT	0.8745	[0.7851; 0.9409]	4.561964
		BI	0.6923	[0.5666; 0.8007]	4.423546
	SAT				
		BI	0.7916	[0.7023; 0.8702]	
$GSCA_M$	**WTW**				
		SAT	0.8716	[0.7775; 0.9351]	4.565577
		BI	0.6865	[0.5521; 0.7879]	4.429045
	SAT				
		BI	0.7876	[0.6893; 0.8599]	

Note: Importance of predictor (construct's level) is the total effect calculated using 95% bias-corrected and accelerated CIs from bootstrapping with 10,000 samples

Table 11: Guidelines for choosing between composite-based and factor-based SEM

Issue	Detail	Suggestion	Note
DGP	Dataset is assumed to originate from a population of a common factor model.	Factor-based SEM	PLS_C or $GSCA_M$ can be used as alternative methods.
	Dataset is assumed to originate from a population of a composite model.	Composite-based SEM	
	Unsure whether dataset originates from a population of common factor or composite model	Composite-based SEM (Hair & Sarstedt, 2019)	
Research objective	Focuses on confirming theory in general	Factor-based SEM	PLS_C or $GSCA_M$ can be used as alternative methods.
	Focuses on prediction and theoretical testing	Composite-based SEM (Hair & Sarstedt, 2019)	
	Focuses on exploration and theory development	Composite-based SEM	
Small sample size	Small sample size but acceptable statistical power level	Both	
	Small sample size but factor-based SEM produces an inappropriate solution or a non-convergence issue	Composite-based SEM	
Subsequent analysis	Researchers require a determinate form of composite scores to perform subsequent analysis (e.g., IPMA)	Composite-based SEM	
Measurement model	Measurement model incorporates reflective indicators	Both	
	Measurement model incorporates causal–formative indicators	Factor-based SEM	Identification issue should be verified. If not, then the MIMIC model can be used.
	Measurement model incorporates composite–formative indicators	Composite-based SEM	
Data type	Dataset includes artifacts (e.g., financial ratios or secondary data)	Composite-based SEM	
Distribution assumptions	Dataset violates multivariate normality distribution	Both	Robust version of ML (MLR) or other techniques (MIIV-2SLS or MIIV-GMM) in factor-based SEM or bootstrapping can be used.
Estimation	Inappropriate solutions generated from factor-based SEM	Composite-based SEM	
	Non-convergence issue arising from factor-based SEM	Composite-based SEM	

Table 12: Guidelines for assessing a reflective measurement model in accordance with CCA

Step	Suggestion	Threshold	Reference
Evaluation of loadings and their significance	Standardized loadings	Greater than or equal to 0.708 and significant at 0.05	Benitez, Henseler, Castillo, & Schuberth (2020)
Evaluation of indicator reliability	Squaring the standardized loadings	Greater than or equal to 0.5	Hair, Howard, & Nitzl (2020)
Evaluation of composite reliability	Composite reliability	Above 0.7 but less than 0.95	Hair et al. (2020)
Evaluation of convergent validity	AVE	Higher than 0.5	Hair et al. (2020)
Evaluation of discriminant validity	HTMT ratio of correlation	Not higher than 0.85 (conservative case) Not higher than 0.9 (liberal case) Or use null hypothesis significance testing	Benitez et al. (2020) (Henseler, Ringle, & Sarstedt, 2015)
Nomological validity	Correlation between composite scores	Check whether it is consistent with the theoretical direction. Correlation coefficients should be significant.	Hair et al. (2020)
Predictive validity*	Data are collected at a later time, and the composite score is recalculated and regressed again.	Check whether it is consistent with the theoretical direction. Path coefficient should be significant.	Hair et al. (2020)

Note: * This analysis is not officially required. We suggest using concurrent validity instead for simplicity.

Table 13: Guidelines for assessing a structural model

Step	Suggestion	Threshold	Reference
Evaluation of collinearity	VIF	Less than or equal to 3.3 (conservative case) Less than or equal to 5 (liberal case)	Diamantopoulos & Siguaw (2006) Hair et al. (2020)
Evaluation of path coefficients	Significance test (or bootstrapping) of path coefficients	Level of significance test should be at 0.05 Bootstrapping procedure with 5,000 to 10,000 samples	Hair et al. (2020) Hair et al. (2020)
Evaluation of in-sample prediction	Effect size (f^2) Coefficient of determination (R^2)	Small effect size if $f^2 \in [0.02, 0.15)$ Medium effect size if $f^2 \in [0.15, 0.35)$ Large effect size if $f^2 \in [0.35, 0.5)$ Very large effect size if $f^2 \geq 0.5$ R^2 can be either high or low and is recommended to be compared with the previous literature.	Cohen (1992) Hair et al. (2020) Benitez et al. (2020)
Evaluation of out-of-sample prediction*	$Q^2_{predict}$ and $PLS_{predict}$ with other datasets	If the same dataset is used, then 10-fold and 10-repetition cross-validations are recommended.	Hair et al. (2020) Benitez et al. (2020)
Evaluation of model fit**	SRMR Geodesic distance (d_G) Squared Euclidean distance (d_L)	SRMR < 0.08 or use a significance test 95% quantile of d_G and d_L reference distribution (HI_{95})	Benitez et al. (2020) Benitez et al. (2020)

Note: * for PLS and GSCA. ** for PLS_C and $GSCA_M$ only, and the results should be compared with factor-based SEM.