Appendix B: Measurement model assessment for first order LVs

Table 8 shows loading and cross-loadings for the first order LVs that make up ACAP, with the latter being a second order LV. As we can see, all loadings are greater than 0.5, suggesting good convergent validity (Amora, 2021; Kock, 2014). That is, they suggest that respondents understood the question-statements associated with each of the LVs in the same way as the designer of the questionnaire did.

Table 8: Loading and cross-loadings for first order LVs that make up ACAP

	AQU	ASS	TRA	EXP
AQU1	(0.836)	0.013	0.108	0.088
AQU2	(0.838)	0.113	-0.097	0.069
AQU3	(0.685)	-0.155	-0.014	-0.192
ASS1	0.051	(0.857)	-0.018	-0.090
ASS2	0.013	(0.844)	-0.091	0.032
ASS3	0.004	(0.820)	-0.030	0.116
ASS4	-0.072	(0.806)	0.145	-0.055
TRA1	0.087	-0.009	(0.833)	-0.041
TRA2	0.024	-0.025	(0.873)	-0.083
TRA3	-0.002	0.080	(0.844)	0.064
TRA4	-0.111	-0.046	(0.820)	0.064
EXP1	0.064	-0.133	-0.029	(0.819)
EXP2	-0.016	0.040	-0.008	(0.923)
EXP3	-0.044	0.083	0.036	(0.876)

Notes: Loadings are unrotated and cross-loadings are oblique-rotated. Loadings shown within parentheses. Loadings > 0.5 suggest good convergent validity.

Table 9 shows correlations and square roots for AVEs for the first order LVs that make up ACAP, with the latter being a second order LV. As we can see, all square roots of AVEs were greater than the correlations in the same columns, suggest good discriminant validity (Kock, 2014; Rasoolimanesh, 2022). That is, respondents did not mistake question-statements as associated with the wrong LVs.

Table 9: Correlations and square roots for AVEs for first order LVs that make up ACAP

	AQU	ASS	TRA	EXP
AQU	(0.789)	0.537	0.552	0.545
ASS	0.537	(0.832)	0.532	0.556
TRA	0.552	0.532	(0.843)	0.645
EXP	0.545	0.556	0.645	(0.874)

Notes: Square roots of AVEs show along diagonal within parentheses. Square roots of AVEs greater than the correlations the same column suggest good discriminant validity.

Table 10 shows various LV coefficients for the first order LVs that make up ACAP, with the latter being a second order LV. The composite reliabilities and Cronbach's alphas

are all greater than 0.6, suggesting good reliability (Kock, 2014). That is, the respondents appeared to have understood the question-statements used to measure each LV in the same way among themselves. This was further validated through the calculation of HTMT and HTMT2 ratios, with the highest ratios being 0.755 and 0.756 respective, and thus lower than the 0.85 threshold, further suggesting good discriminant validity (Kock, 2022; Rasoolimanesh, 2022).

Table 10: LV coefficients for first order LVs that make up ACAP

	AQU	**ASS**	**TRA**	**EXP**
Composite reliability	0.831	0.900	0.907	0.906
Cronbach's alpha	0.693	0.852	0.864	0.844
Full collinearity VIF	1.705	1.692	1.968	2.006
Jarque-Bera test of normality	No	No	No	Yes
Robust Jarque-Bera test of normality	No	No	No	Yes

Notes: Composite reliabilities and Cronbach's alphas > 0.6 suggest good reliability. FCVIFs < 3.3 suggest no common method bias. Multivariate non-normality, indicated by the Jarque-Bera test and its robust variation provide support for the use of the non-parametric PLS-SEM method.

All full collinearity VIFs were lower than 3.3, suggesting no common method bias (Kock, 2015; Kock & Lynn, 2012). This was further validated by a Harman's single factor test, which yielded as single factor with an AVE of 0.473, lower than the 0.5 threshold, also suggesting no common method bias (Kock, 2021b). Multivariate non-normality was indicated, by the Jarque-Bera test and its robust variation, as existing in 3 out of the 4 first-order LVs, which provides support for our use of PLS-SEM, a non-parametric SEM method that does not assume multivariate normality (Kock, 2016b; Ma & Zhang, 2023).

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