Show me the money: the magic of the marketing and finance interface to drive financial performance in hospitality operations

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Curriculum Vitae

Ganna is a profitability consultant and a Lecturer in Management Accounting and Controlling at Bremerhaven University of Applied Science, Germany. She has a lifelong background as an international entrepreneur and a consultant. She was born in Ukraine, where in 1996 she graduated with a master's degree in enterprise economics and ran her own business involved in international trade and industry supply. As Ukraine transitioned from ex-Soviet to international accounting standards, pushing the country into the learning process, she obtained a qualification of chief accountant, analogical to a CPA. She has been actively following burgeoning developments in Ukrainian audit and reporting standards, which she has personally implemented in her company. Later, Ganna joined an executive MBA program offered in Ukraine by a German institution and, in 2006, successfully graduated with distinction. After graduation, she served as a tutor in financial management and information systems. She also joined the international teaching team and co-lectured in residential periods on financial management, where she initiated and took an active part in redesigning the FM course and realigning the entire program with the new content. Ganna independently consulted several leading Ukrainian retail chains in operational profit maximization issues and gave seminars to Ukrainian startups for business planning, financial management, and general taxation principles. Her academic work mainly focused on a cost-benefit analysis to evaluate strategic choices in for-profit firms. She decided to pursue an academic path and applied for an executive DBA in Zürich, Switzerland.

In 2008, Ganna extended her company's supply chain by founding a German entity and living between two countries. She obtained her third master's diploma in public administration with distinction, with her thesis on the institutionalization of Ukrainian society. She underwent several preparatory trainings and graduate teaching assistantships in executive MBA classes offered by the Swiss business school. However, this private school was sold and the DBA program was discontinued. Ganna received an option to transition to Leiden University as an external part-time PhD student, and was accepted in 2016. Her preparatory work resulted in two academic publications about focused financial metrics, based on the airline and restaurant industries, one of which received an outstanding research award in 2010. By this time, she had moved from Ukraine to Germany, where she had been managing several businesses.

Ganna's doctoral research is dedicated to customer-centric accounting information for managerial decision-making applied to the lodging and cruise industries in a collection of articles. As a part-time external PhD candidate, she published eight peer-reviewed articles and successfully presented her work to multiple international audiences, both academic and professional, with one featuring the best paper award. Ganna developed a solid collaborative network and co-authored with ten other academics from nine countries and three continents. During her part-time PhD, Ganna founded and managed a chain of ice cream and coffee shops, where she gained rich industry experience and combined it with her previous controlling tactics. Her current teaching covers management accounting and control at the undergraduate level for international tourism and hotel management studies in Germany. She integrates her research and experience into the teaching materials and trains future industry leaders to think holistically and beyond numbers.

Ganna serves as Executive Secretary for the International Association of Hospitality Financial Management Education (iAHFME). She is an active member of the American Accounting Association (AAA), the International Association for Tourism Economics (IATE), and the International Council on Hotel and Restaurant Education (ICHRIE).

Appendices

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Figure A1. The relationship between aim, objectives, and research questions

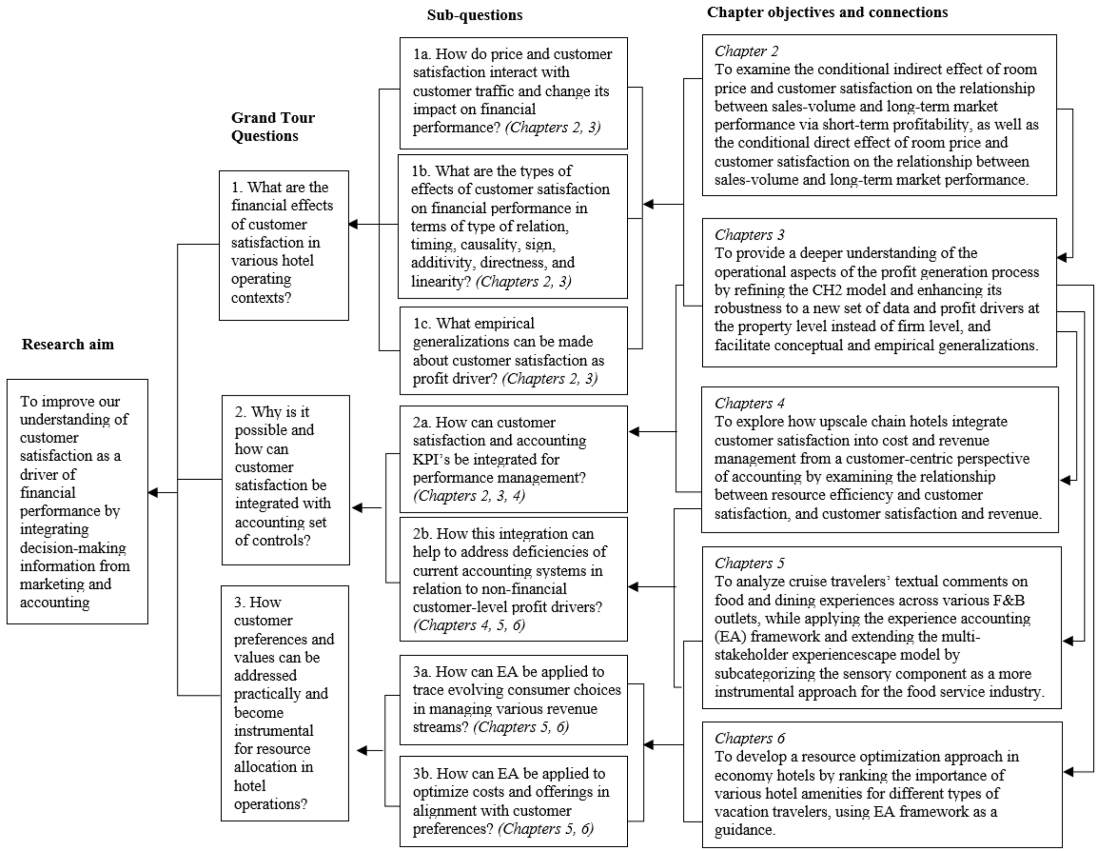

Table A1. Main effects based on a model without interaction terms

First step moderated mediation. Outcome variable operating profitability GPNIGHTSS (Y)

Path		B	t	Sig.	R-sq
$X_1 \rightarrow Y$	Sales quantity NIGHTSS	**1.311*** **	5.028	< 0.001	0.640
$X_2 \rightarrow Y$	Room price ADR	**0.896*** **	7.868	< 0.001	
$X_3 \rightarrow Y$	Customer satisfaction ACSI	**-0.231** **	-2.974	0.004	
$X_4 \rightarrow Y$	Company size NHOTEL	**-1.113*** **	-4.465	< 0.001	
$X_5 \rightarrow Y$	Property size RPP	**-0.545*** **	-4.029	< 0.001	

Note: N=78.
** p < 0.05. ** p < 0.01. *** p<0.001 (two-tailed)*

First step moderated mediation. Outcome variable accounting profitability NPM (Y)

Path		B	t	Sig.	R-sq
$X_1 \rightarrow Y$	Sales quantity NIGHTSS	0.630	1.721	0.090	0.290
$X_2 \rightarrow Y$	Room price ADR	-0.067	-0.419	0.677	
$X_3 \rightarrow Y$	Customer satisfaction ACSI	0.125	1.143	0.257	
$X_4 \rightarrow Y$	Company size NHOTEL	-0.124	-0.355	0.724	
$X_5 \rightarrow Y$	Property size RPP	-0.251	-1.319	0.191	

Note: N=78.
** p < 0.05. ** p < 0.01. *** p<0.001 (two-tailed)*

First step moderated mediation. Outcome variable accounting profitability ROA (Y)

Path		B	t	Sig.	R-sq
$X_1 \rightarrow Y$	Sales quantity NIGHTSS	0.499	1.335	1.335	0.260
$X_2 \rightarrow Y$	Room price ADR	0.108	0.660	0.660	
$X_3 \rightarrow Y$	Customer satisfaction ACSI	0.308	2.764	2.764	
$X_4 \rightarrow Y$	Company size NHOTEL	-0.130	-0.363	-0.363	
$X_5 \rightarrow Y$	Property size RPP	-0.379	-1.952	-1.952	

Note: N=78.
** p < 0.05. ** p < 0.01. *** p<0.001 (two-tailed)*

First step moderated mediation. Outcome variable accounting profitability ROE (Y)

Path		B	t	Sig.	R-sq
$X_1 \rightarrow Y$	Sales quantity NIGHTSS	0.187	0.437	0.663	0.037
$X_2 \rightarrow Y$	Room price ADR	0.185	0.993	0.324	
$X_3 \rightarrow Y$	Customer satisfaction ACSI	-0.083	-0.655	0.514	
$X_4 \rightarrow Y$	Company size NHOTEL	-0.232	-0.569	0.571	
$X_5 \rightarrow Y$	Property size RPP	-0.124	-0.559	0.578	

Note: N=78.
** p < 0.05. ** p < 0.01. *** p<0.001 (two-tailed)*

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Table A2. Main effects based on a model without interaction terms

Second step moderated mediation. Outcome variable stock market performance RA10 (Y)

Path		B	t	Sig.	R-sq
$X_1 \rightarrow Y$	Sales quantity NIGHTSS	**0.828****	3.245	0.002	0.753
$X_2 \rightarrow Y$	Room price ADR	**0.287***	2.069	0.042	
$X_3 \rightarrow Y$	Customer satisfaction ACSI	**0.386*****	5.353	< 0.001	
$X_4 \rightarrow Y$	Operating prof. GPNIGHTSS	**-0.510*****	-4.675	< 0.001	
$X_5 \rightarrow Y$	Accounting prof. **NPM**	**0.367*****	4.728	< 0.001	
$X_6 \rightarrow Y$	Company size NHOTEL	-0.478	-1.988	0.051	
$X_7 \rightarrow Y$	Property size RPP	**-0.393****	-3.117	0.003	

Note: N=78.
** p < 0.05. ** p < 0.01. *** p<0.001 (two-tailed)*

Second step moderated mediation. Outcome variable stock market performance RA10 (Y)

Path		B	t	Sig.	R-sq
$X_1 \rightarrow Y$	Sales quantity NIGHTSS	**0.860*****	3.446	<0.001	0.764
$X_2 \rightarrow Y$	Room price ADR	0.214	1.637	0.106	
$X_3 \rightarrow Y$	Customer satisfaction ACSI	**0.317*****	4.247	<0.001	
$X_4 \rightarrow Y$	Operating prof. GPNIGHTSS	**-0.502*****	-4.788	<0.001	
$X_5 \rightarrow Y$	Accounting prof. **ROA**	**0.378*****	5.175	<0.001	
$X_6 \rightarrow Y$	Company size NHOTEL	-0.465	-1.988	0.051	
$X_7 \rightarrow Y$	Property size RPP	**-0.337****	-2.738	0.008	

Note: N=78.
** p < 0.05. ** p < 0.01. *** p<0.001 (two-tailed)*

Second step moderated mediation. Outcome variable stock market performance RA10 (Y)

Path		B	t	Sig.	R-sq
$X_1 \rightarrow Y$	Sales quantity NIGHTSS	**0.806****	2.760	0.007	0.679
$X_2 \rightarrow Y$	Room price ADR	0.093	0.616	0.540	
$X_3 \rightarrow Y$	Customer satisfaction ACSI	**0.473*****	5.959	<0.001	
$X_4 \rightarrow Y$	Operating prof. GPNIGHTSS	**-0.306****	-2.698	0.009	
$X_5 \rightarrow Y$	Accounting prof. **ROE**	-0.072	-1.039	0.303	
$X_6 \rightarrow Y$	Company size NHOTEL	-0.314	-1.155	0.252	
$X_7 \rightarrow Y$	Property size RPP	**-0.383****	-2.653	0.010	

Note: N=78.
** p < 0.05. ** p < 0.01. *** p<0.001 (two-tailed)*

Table A3. Main effects based on a model without interaction terms

Second step moderated mediation. Outcome variable stock market performance TQ (Y)

Path		B	t	Sig.	R-sq
$X_1 \rightarrow Y$	Sales quantity NIGHTSS	0.510	1.377	0.173	0.479
$X_2 \rightarrow Y$	Room price ADR	**0.671****	3.337	0.001	
$X_3 \rightarrow Y$	Customer satisfaction ACSI	**0.415*****	3.967	<0.001	
$X_4 \rightarrow Y$	Operating prof. GPNIGHTSS	-0.282	-1.780	0.079	
$X_5 \rightarrow Y$	Accounting prof. **NPM**	**0.330****	2.924	0.005	
$X_6 \rightarrow Y$	Company size NHOTEL	-0.368	-1.056	0.295	
$X_7 \rightarrow Y$	Property size RPP	**-0.718*****	-3.926	<0.001	

Note: N=78.
** p < 0.05. ** p < 0.01. *** p<0.001 (two-tailed)*

Second step moderated mediation. Outcome variable stock market performance TQ (Y)

Path		B	t	Sig.	R-sq
$X_1 \rightarrow Y$	Sales quantity NIGHTSS	0.564	1.630	0.108	0.546
$X_2 \rightarrow Y$	Room price ADR	**0.650*****	3.586	<0.001	
$X_3 \rightarrow Y$	Customer satisfaction ACSI	**0.304****	2.928	0.005	
$X_4 \rightarrow Y$	Operating prof. GPNIGHTSS	**-0.338***	-2.323	0.023	
$X_5 \rightarrow Y$	Accounting prof. **ROA**	**0.455*****	4.485	<0.001	
$X_6 \rightarrow Y$	Company size NHOTEL	-0.412	-1.271	0.208	
$X_7 \rightarrow Y$	Property size RPP	**-0.659*****	-3.858	<0.001	

Note: N=78.
** p < 0.05. ** p < 0.01. *** p<0.001 (two-tailed)*

Second step moderated mediation. Outcome variable stock market performance TQ (Y)

Path		B	t	Sig.	R-sq
$X_1 \rightarrow Y$	Sales quantity NIGHTSS	0.475	1.206	0.232	0.416
$X_2 \rightarrow Y$	Room price ADR	**0.484***	2.383	0.020	
$X_3 \rightarrow Y$	Customer satisfaction ACSI	**0.498*****	4.654	<0.001	
$X_4 \rightarrow Y$	Operating prof. GPNIGHTSS	-0.093	-0.605	0.547	
$X_5 \rightarrow Y$	Accounting prof. **ROE**	-0.027	-0.285	0.777	
$X_6 \rightarrow Y$	Company size NHOTEL	-0.205	-0.560	0.577	
$X_7 \rightarrow Y$	Property size RPP	**-0.701*****	-3.603	<.001	

Note: N=78.
** p < 0.05. ** p < 0.01. *** p<0.001 (two-tailed)*

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Table A4. Main effects based on a model without interaction terms

Full sample: Outcome variable operating profitability GOPPS (Y)

Path		B	t	Sig.	R-sq
$X_1 \rightarrow Y$	Sales volume driver OCC	**0.648*****	26.869	< 0.001	0.483
$X_2 \rightarrow Y$	Room price ADR	**0.121***	2.281	0.023	
$X_3 \rightarrow Y$	Customer satisfaction TRATE	**0.100*****	3.944	< 0.001	
$X_4 \rightarrow Y$	Room-Nights sold NIGHTSS	-0.036	-0.958	0.338	

Note: N=813.
** p < 0.05. ** p < 0.01. *** p<0.001 (two-tailed)*

Table A4 presents the results without the interaction terms. When the interaction term X*W is excluded from the model specification, the ADR is also positively related to customer profitability (GOPPS). In this case, additional analyses revealed that a one standard deviation increase in ADR was related to a 0.121 standard deviation (SD) increase in GOPPS. Similar to room price (ADR), customer satisfaction (TRATE) is positively associated with GOPPS, which can potentially be related to more receptive customer booking behaviors towards higher ADR for hotels with higher review ratings. A model specification without interaction terms revealed that a one-SD increase in TRATE was associated with a 0.100 SDs increase in GOPPS. Sales volume driver (OCC) has a significantly positive direct effect on the customer-level operating profitability (GOPPS), in models with and without interaction terms. Further, Tables A4.1 and A4.2 present same analysis without interaction terms for full- and limited-service subsamples separately. The model including interaction terms corresponds to the Table 20 in the main document.

A4.1 Full-service hotels only: Outcome variable accounting profitability EBITDAPS (Y)

Path		B	t	Sig.	R-sq
$X_1 \rightarrow Y$	Sales volume driver OCC	**0.614*****	20.140	< 0.001	0.442
$X_2 \rightarrow Y$	Room price ADR	0.024	0.420	0.674	
$X_3 \rightarrow Y$	Customer satisfaction TRATE	**0.135*****	4.071	< 0.001	
$X_4 \rightarrow Y$	Room-Nights sold NIGHTSS	0.025	0.626	0.532	

Note: N=548.
** p < 0.05. ** p < 0.01. *** p<0.001 (two-tailed)*

A4.2 Limited-service hotels only: Outcome variable accounting profitability EBITDAPS (Y)

Path		B	t	Sig.	R-sq
$X_1 \rightarrow Y$	Sales volume driver OCC	**0.494*****	13.286	< 0.001	0.697
$X_2 \rightarrow Y$	Room price ADR	**0.880*****	6.281	< 0.001	
$X_3 \rightarrow Y$	Customer satisfaction TRATE	0.043	1.318	0.189	
$X_4 \rightarrow Y$	Room-Nights sold NIGHTSS	**1.852*****	5.259	< 0.001	

Note: N=263.
** p < 0.05. ** p < 0.01. *** p<0.001 (two-tailed)*

Table A5. Main effects based on a model without interaction terms

Full sample: Full and Limited Service mixed. Outcome variable accounting profitability EBITDAPS (Y)

Path		B	t	Sig.	R-sq
$X_1 \rightarrow Y$	Sales volume driver OCC	**0.194*** **	7.250	< 0.001	0.622
$X_2 \rightarrow Y$	Operating profit GOPPS	**0.563*** **	19.777	< 0.001	
$X_3 \rightarrow Y$	Room price ADR	**0.137** **	3.183	0.002	
$X_4 \rightarrow Y$	Customer satisfaction TRATE	-0.006	-0.300	0.764	
$X_5 \rightarrow Y$	Room-Nights sold NIGHTSS	**0.117*** **	3.805	< 0.001	

Note: N=813.
** p < 0.05. ** p < 0.01. *** p<0.001 (two-tailed)*

Table A5 presents the results of the second-stage mediation analysis (accounting performance) without interaction terms. The results are different as for the model with interaction terms (Table 17 in the main document). The coefficient for ADR increases as compared to GOPPS path, but the coefficients for OCC remain higher, which was not the case in the model with interaction terms. In the model without interaction terms, a one SD increase in NIGHTSS is related to a 0.117 SDs increase in EBITDAPS.

Further, Tables A5.1 and A5.2 present same analysis without interaction terms for full- and limited-service subsamples separately. The model including interaction terms corresponds to the Table 21 in the main document.

A5.1 Full-service hotels only: Outcome variable accounting profitability EBITDAPS (Y)

Path		B	t	Sig.	R-sq
$X_1 \rightarrow Y$	Sales volume driver OCC	0.035	1.548	0.122	0.703
$X_2 \rightarrow Y$	Operating profit GOPPS	**0.615*** **	25.341	< 0.001	
$X_3 \rightarrow Y$	Room price ADR	0.030	0.925	0.356	
$X_4 \rightarrow Y$	Customer satisfaction TRATE	0.023	1.191	0.234	
$X_5 \rightarrow Y$	Room-Nights sold NIGHTSS	**0.048***	2.141	0.033	

Note: N=548.
** p < 0.05. ** p < 0.01. *** p<0.001 (two-tailed)*

A5.2 Limited-service hotels only: Outcome variable accounting profitability EBITDAPS (Y)

Path		B	t	Sig.	R-sq
$X_1 \rightarrow Y$	Sales volume driver OCC	**0.454*** **	8.106	< 0.001	0.707
$X_2 \rightarrow Y$	Operating profit GOPPS	**0.618*** **	8.572	< 0.001	
$X_3 \rightarrow Y$	Room price ADR	0.060	0.345	0.731	
$X_4 \rightarrow Y$	Customer satisfaction TRATE	-0.004	-0.093	0.926	
$X_5 \rightarrow Y$	Room-Nights sold NIGHTSS	-0.707	-1.643	0.102	

Note: N=263.
** p < 0.05. ** p < 0.01. *** p<0.001 (two-tailed)*

Table A6. Moderation probing. Full-service subsample

Conditional effects of the focal predictor (OCC → GOPPS) at values of the moderator(s):

	ADR	TRATE	Effect	se	t	p	LLCI	ULCI
Low price & Low satisfaction:	-.6200	-.9975	**.7195**	.0547	13.1446	**.0000**	.6120	.8270
Low price & Mean satisfaction:	-.6200	-.2126	.7180	.0449	15.9860	.0000	.6298	.8063
Low price & High satisfaction:	-.6200	.8863	.7160	.0519	13.7960	.0000	.6141	.8180
Mean price & Low satisfaction:	-.1848	-.9975	.6498	.0450	14.4431	.0000	.5614	.7382
Mean price & Mean satisfaction:	-.1848	-.2126	**.6484**	.0328	19.7714	**.0000**	.5839	.7128
Mean price & High satisfaction:	-.1848	.8863	.6463	.0423	15.2631	.0000	.5631	.7295
High price & Low satisfaction:	.4580	-.9975	.5469	.0481	11.3582	.0000	.4523	.6414
High price & Mean satisfaction:	.4580	-.2126	.5454	.0376	14.5080	.0000	.4716	.6193
High price & High satisfaction:	.4580	.8863	**.5434**	.0468	11.6043	**.0000**	.4514	.6354

Conditional direct effects of X on Y (OCC → EBITDAPS)

	ADR	TRATE	Effect	se	t	p	LLCI	ULCI
Low price & Low satisfaction:	-.6200	-.9975	.0539	.0356	1.5157	.1302	-.0160	.1239
Low price & Mean satisfaction:	**-.6200**	**-.2126**	**.0797**	**.0309**	**2.5839**	**.0100**	**.0191**	**.1403**
Low price & High satisfaction:	**-.6200**	**.8863**	**.1158**	**.0342**	**3.3899**	**.0008**	**.0487**	**.1829**
Mean price & Low satisfaction:	-.1848	-.9975	.0229	.0300	.7640	.4452	-.0360	.0818
Mean price & Mean satisfaction:	**-.1848**	**-.2126**	**.0487**	**.0244**	**1.9982**	**.0462**	**.0008**	**.0965**
Mean price & High satisfaction:	**-.1848**	**.8863**	**.0848**	**.0287**	**2.9561**	**.0033**	**.0284**	**.1411**
High price & Low satisfaction:	.4580	-.9975	-.0229	.0303	-.7565	.4497	-.0825	.0366
High price & Mean satisfaction:	.4580	-.2126	.0028	.0251	.1126	.9104	-.0464	.0521
High price & High satisfaction:	.4580	.8863	.0389	.0296	1.3132	.1897	-.0193	.0971

Table A7. Moderation probing. Limited-service subsample

Conditional effects of the focal predictor (OCC → GOPPS) at values of the moderator(s):

	ADR	TRATE	Effect	se	t	p	LLCI	ULCI
Low price & Low satisfaction:	-.6881	-.9766	**.6501**	.0516	12.5949	**.0000**	.5485	.7518
Low price & Mean satisfaction:	-.6881	-.0556	.6334	.0427	14.8395	.0000	.5493	.7174
Low price & High satisfaction:	-.6881	1.0433	.6133	.0493	12.4371	.0000	.5162	.7105
Mean price & Low satisfaction:	-.4497	-.9766	.5047	.0452	11.1761	.0000	.4158	.5937
Mean price & Mean satisfaction:	-.4497	-.0556	**.4879**	.0353	13.8075	**.0000**	.4184	.5575
Mean price & High satisfaction:	-.4497	1.0433	.4679	.0438	10.6746	.0000	.3816	.5542
High price & Low satisfaction:	-.1090	-.9766	.2969	.0581	5.1126	.0000	.1825	.4112
High price & Mean satisfaction:	-.1090	-.0556	.2801	.0515	5.4352	.0000	.1786	.3816
High price & High satisfaction:	-.1090	1.0433	**.2601**	.0585	4.4488	**.0000**	.1450	.3752

Conditional direct effects of X on Y (OCC → EBITDAPS)

	ADR	TRATE	Effect	se	t	p	LLCI	ULCI
Low price & Low satisfaction:	-.6881	-.9766	**.5729**	.0802	7.1393	**.0000**	.4149	.7310
Low price & Mean satisfaction:	-.6881	-.0556	.5147	.0711	7.2387	.0000	.3746	.6547
Low price & High satisfaction:	-.6881	1.0433	.4451	.0763	5.8339	.0000	.2949	.5954
Mean price & Low satisfaction:	-.4497	-.9766	.5347	.0673	7.9454	.0000	.4022	.6673
Mean price & Mean satisfaction:	-.4497	-.0556	**.4765**	.0570	8.3566	**.0000**	.3642	.5887
Mean price & High satisfaction:	-.4497	1.0433	.4069	.0644	6.3209	.0000	.2802	.5337
High price & Low satisfaction:	-.1090	-.9766	.4801	.0745	6.4442	.0000	.3334	.6268
High price & Mean satisfaction:	-.1090	-.0556	.4219	.0665	6.3421	.0000	.2909	.5529
High price & High satisfaction:	-.1090	1.0433	**.3523**	.0742	4.7509	**.0000**	.2063	.4984

Remark A8. Discussion of the replication results by driver

Sales volume driver. In general, the replication and focal results agree that sales volume drivers reflecting activity levels are significant positive predictors of operating and accounting performance. In addition, in the full samples of both studies, the positive effects of sales drivers were stronger in terms of coefficients than those of price. The replication regression coefficients were lower in the full sample, which can be attributed to differences in aggregation levels and measurements (detailed information in Table 28). Further analysis indicated that full-service properties are more sensitive to OCC for GOPPS, whereas for EBITDAPS, the effect is reversed. In turn, limited-service properties were less sensitive to OCC than to NIGHTSS, which is similar to the focal study at the operating level. At the accounting level, the effect was reversed compared to the operating level and the full-service subsample. Owing to these distinctions, neither the positive effects of OCC nor NIGHTSS are generalizable for full- and limited-service properties.

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Price. Similar to sales volume, price (ADR) predicted operating and accounting profitability consistently positively in replication and focal studies. In the replication, its effects on profits were stronger in terms of statistical significance, which can be attributed to differences in the measurements and datasets. However, the patterns change with further disaggregation. Thus, in the full-service subsample, the direct effects of ADR on GOPPS and EBITDA were not significant. In the limited-service subsample, ADR only predicted GOPPS, and its effect was much stronger than in the full sample. Therefore, it is safe to generalize that ADR is a positive profit driver based on mixed property-type datasets, which cannot be extended to full- and limited-service properties.

Customer satisfaction. This comparison has the potential to be the most interesting one, owing to the basic distinctions between ACSI and TRATE as measurements, with ACSI measuring nationwide satisfaction with hotel brands and TRATE measuring satisfaction with a specific property. Formally, the replication results failed to confirm the findings of the focal study, as they only demonstrated a significant positive effect of TRATE on GOPPS in the full sample and in the full-service subsample. GOPPS is on at the operating performance level, while the effects of ACSI in the focal study were observed on capital market level for RA10 and TQ, which this study did not test. Because of the absence of any effects at the accounting level, it is possible to assume that ACSI captures the performance of a corporation better, while TRATE is more of an operational hands-on number for properties. Thus, in general, replication results testified that customer satisfaction is a positive profit driver; however, an empirical generalization for ACSI and TRATE is not possible.

Remark A9. Discussion of the replication results by service model

Thanks to the expanded replication analyses, it was possible to observe distinctions between datasets with and without customer satisfaction, testifying to several cases when the main relationships changed in the presence of TRATE. It was also possible to observe hidden effects of customer satisfaction in the full-service subsample (Table 22 in the main document), as well as the distinct roles in different subsamples, such as direct positive effect of TRATE on GOPPS. Based on the empirical results of this expanded replication, integrating TRATE with an accounting set of controls can provide more informative results for regular operational planning and monitoring.

Full- versus Limited-service properties. To summarize the replication results, in the full-service subsample, occupancy (OCC) and customer satisfaction (TRATE) appeared as positive drivers of operating performance, with OCC indicating a higher weight. Price (ADR) was not associated with either operating or accounting profit; however, ADR had a negative moderating effect on the OCC – profit relationship at both performance levels. The effect of OCC on EBITDAPS was not significant at low TRATE and high ADR values. NIGHTSS proxying property size was not important for gross operating margin generation, but gained importance later for EBITDAPS. In contrast, in the limited-service subsample, operating profit was driven by NIGHTSS and much less by OCC, underlying the importance of property size. Furthermore, ADR was strongly positively associated with GOPPS but not with EBITDAPS. However, a negative moderating effect of ADR was mainly observed at an operating performance level similar to that of the full-service subsample, and it was stronger. Customer satisfaction TRATE has no significant effect on the limited-service subsample.

Table A8. Definition of variables

Inputs in Stage-1 (X):	
Rooms Expenses	Total Rooms Department Expenses including payroll
F&B Expenses	Total Food & Beverage Department Expenses, incl. payroll
Amenities Expenses	Cost of all other Amenities in Total and including payroll (Parking, SPA, Golf course, Sky lift, Telecom)
Intermediate Product (Z):	
Review Rating	Overall Satisfaction Rating for a Hotel ranging from one to five stars collected from Tripadvisor website and estimated as mean value of all ratings within a given year for a specific property
Outputs of Stage-2 (Y):	
Rooms Revenue	Total Revenue Rooms Department
F&B Revenue	Total Revenue Food & Beverage Department
Amenities Revenue	Total Revenue from all other Amenities
Other variables:	
POM Expenses	Total Property, Operation, and Maintenance Expenses
Room-Nights Sold	Number of room-nights sold by the property within a given year

Remark A10. Selection of variables

Revenues and costs: When deciding what revenue and cost variables to use we chose to include cost and revenue streams that (i) managers were able to manage in a short-term horizon; and (ii) were associated with the core services that generates customer experience (Campo et al., 2014; Cui et al., 2024; Yin et al., 2020). In our full-service hotel context these were rooms, food and beverage, and amenities. We recognize that fixed assets are a common measure in hotel DEA analysis (e.g. Kim & Chung, 2022). However, fixed assets cannot be changed in the short term, which restricts managerial ability to manage these tactically. Our choice of operational revenues and costs means our analysis relates to practices where management have greater control. Miscellaneous costs and revenues were excluded due to their undefined nature and because these categories often had missing values.

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Kim, C., & Chung, K. (2022). Measuring Customer Satisfaction and Hotel Efficiency Analysis: An Approach Based on Data Envelopment Analysis. *Cornell Hospitality Quarterly 63*(2), 257–266.

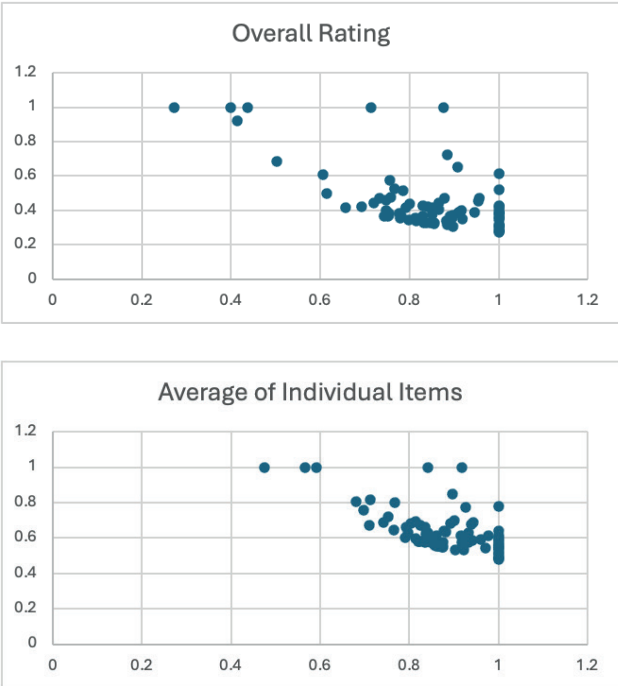
Remark A11. Measurement of customer satisfaction

Customer satisfaction is a challenging construct for hotels to capture. Prior research has used proprietary information such as the American Customer Satisfaction Index (Assaf and Magnini, 2012) or J.D. Power's Hotel Guest Satisfaction Index Study (Kim and Chung, 2022). This use of proprietary information has historically been a hurdle in strategic management accounting research as it increases the cost of obtaining this information and is available for only select hotels. Following Boccali et al. (2022), our approach to capture customer satisfaction is to use customer review website scores. Customer review website scores are an indicator of customer satisfaction; customers who enjoy the stay (i.e. who are satisfied) will post higher scores and those less satisfied, lower scores. Customer review website scores do have limitations as a measure of customer satisfaction, such as by customer subjectivity, idiosyncrasies of customers, potential manipulation, bias towards extremes, and that not all customers leave reviews (Kim, 2021). However, we argue that customer reviews are a practically relevant metric for hotels. As a publicly visible measure, they have become a key factor in the customer booking process. Customers tend to take review scores at face-value, rather than choosing to question and disregard the scores. Accordingly, hotels must manage their operations using these scores; they are not able to 'choose' to disregard these scores. Hence, we chose to use customer review scores as our measure of customer satisfaction.

We also tested the use of the overall review score versus taking the mean of individual scores into an average rating. Figure 1(A11) compares the two charts; the Overall Rating shows a wider spread of scores than the average of individual items but with similar patterns. The scores for the average of individual items are higher than the overall scores. For example, in 2019 the Overall rating mean C-S is 0.833 (SD is 0.16) and mean S-R is 0.453 (SD is 0.18). The average of individual items mean C-S is 0.875 (SD is 0.11) and mean S-R is 0.638 (SD is 0.12). The pattern of DEA results were substantially similar across the two approaches and so we took the overall score for parsimony.

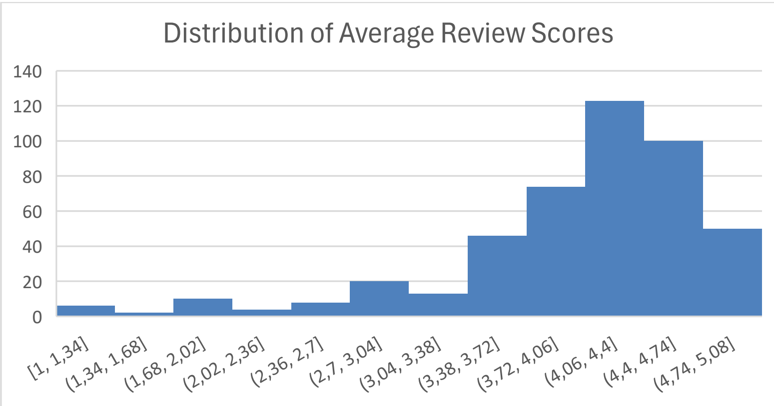
Customer review scores are measured on a 1-5 ordinal scale. This raises two considerations. First, this means that our customer satisfaction measure does not recognize the scale of the hotel. Hotels of various sizes are still evaluated on a 1-5 scale, whereas their revenues and costs may differ considerably. The options for treatment are to either scale up the review scores by a measure of size or to scale down the revenue and cost scores (Dyson, 2001). Our focus was to keep the customer review scores as-is, as the measure that management needs to face. Moreover, scaling revenue and cost figures, such as by cost per room-night or relative to overall expenses, we view as more common in practice as accounting ratios are often used for performance. Consider RevPAR as an example where revenue metrics are scaled. Further details about our scaling approaches are outlined below.

Figure 1(A11). Comparison of Overall and Average of Individual Items



Second, the use of ordinal scores risks the measure not recognizing incremental differences across hotels. Individual reviews can only pick from a 1-5 scale, typically needing to leave an integer score. Our data combines reviews across customers to obtain our customer review scores. This is similar to survey research where respondents indicate their answers on a 1-5 Likert scale and the outcome is the combination of scores (Frazer & Lawley, 2000). Figure 2(A11) shows how these scores are distributed. Note that the x-axis lists bands of scores (0.34 wide, generated by Excel automatically). The graph (Figure 2(A11)) shows a roughly normal distribution of scores from 3.38 to 5.00, with tail of scores showing the minimum score of 1. Our sample also includes hotels with the maximum and minimum scores, with hotels having differences in the number of reviews included. This variability is helpful from the perspective that hotels in practice do face differences in the number of scores they receive.

Figure 2(A11). Distribution of Average Review Scores



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Kim R. Y. (2021). Using Online Reviews for Customer Sentiment Analysis. *IEEE Engineering Management Review, 49*(4): 162-168.

Remark A12. Selection of non-negative data

We reviewed the hotels in the sample to identify those with missing information or negative values and removed those hotels. DEA models require that the data exclude zeros and negative values. A potential remedy for these hotels is to add a small value to all hotels such that none have missing or negative values (Bowlin, 1999; Charnes et al., 1983; Seiford & Zhu, 1999). We did not take this approach for several reasons. First is the mechanical effect. In the case of costs, adding a small value to all hotels means that we will have hotels with very low costs meaning they will look efficient. A very large value could be applied to these firms to avoid affecting the frontier but this would mean intentionally including artificially inefficient hotels, skewing the evaluation of efficiency. Second is our focus on full-service hotels. Hotels that do not have values in one of the categories are not a full-service hotel and so not be a relevant competitor in the analysis. Third, our overarching approach of practical managerial information meant that manipulating revenue and cost data for performance evaluation was inappropriate as this is not what managers would seek to do.

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Seiford, L. M., & Zhu, J. (1999). Profitability and Marketability of the Top 55 U.S. Commercial Banks. *Management Science*, *45*(9): 1270–1288.

Remark A13. Assessment of outliers and data errors

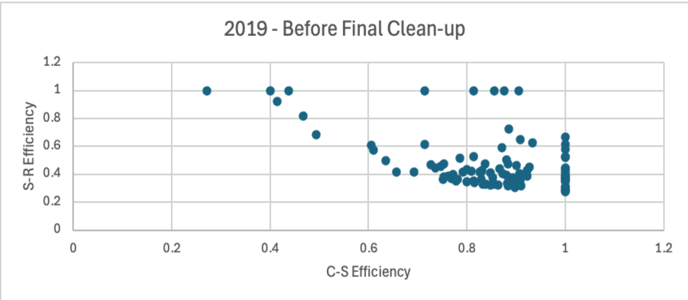
DEA analyses are sensitive to outliers as they affect the frontier of performance (Dyson et al., 2001). Outliers can arise because of errors in the data (e.g. additional zeros) or when a hotel's performance far exceeds industry standards.

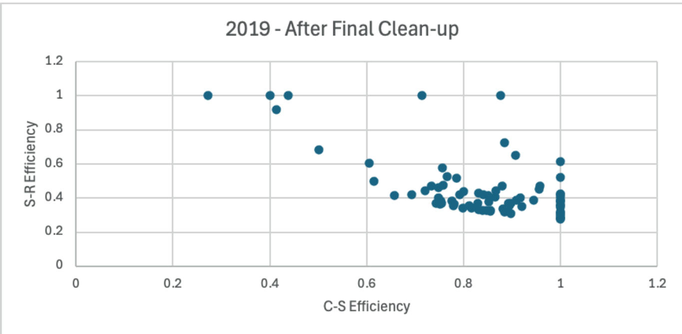
We examined hotel ratios to identify whether each hotel has plausible data with respect to its own information, helping detect possible data entry issues. We assessed ratios of revenues, costs, and scale across the variables. This includes cost-revenue ratios for rooms, food and beverage, and amenities, and ratios among categories including food-to-rooms, amenities-to-rooms, and comparing to our measures of size. We next identified outliers using the interquartile range (the difference between the first and third quartile). The upper fence uses the third quartile plus 1.5 times the interquartile range; the lower fence uses the first quartile minus 1.5 times the interquartile range (Dekking et al., 2005). The upper fence was applied to revenues as very high revenues alter the frontier and the lower fence was applied to costs as very low costs affect the frontier. We applied this outlier identification for each of the revenue and cost variables and hotels were identified as outliers if they exceeded the fences for at least one variable. We also conducted outlier identification to the variables that capture the scale of the hotel (Total POM and Room Nights) using the same quartile and interquartile range definition. This was to further ensure that very large and very small hotels were excluded from the hotel to have a comparable sample. Hotels were marked as outliers or having potential data entry errors if they had very high or very low values that were not a consistent pattern for the hotel.

Second, we considered two approaches for handling the outliers. This considered winsorising (imputing) scores for outlier hotels or to remove them from the sample (Sullivan et al., 2021). Following our overarching approach to take actual observations, we elected to remove potential outliers from the sample. In practice, hotels would remove competitors from their analysis on the basis that they are not appropriate comparisons. They would not alter competitor information in their analysis. We recognize that removal of outliers, rather than imputing, reduces the sample size, for example in 2019 there was a reduction in firms from 97 hotels to 76 hotels. Our principle was to take variation as given and take an approach that managers would do (so not imputing but discarding irrelevant competitors).

Figure 1(A13) compares the results before and after the clean-up to remove potential outliers and potential data entry errors. It was reassuring to see that the patterns before and after removing the cases were similar. Our closer inspection identified this is associated with the range of room revenue scores observed; this variable had the highest interquartile range and so there were some hotels with very large revenues. The results before and after were similar, but with lower averages. The 2019 averages before removing the cases were C-S 0.842 and S-R 0.479. The 2019 averages after removing the cases were C-S 0.833, S-R 0.453. Our final clean-up for outliers, potential data entry issues, and non-comparable firms saw a decrease from 586 to 456 firms.

Figure 1(A13). 2019 Example Results Before and After Clean-up





We ensured that our sample size follows the sample size "rule of thumb" in DEA to meet the minimum number of observations necessary for DEA to have sufficient discriminatory power on a year-by-year basis. Guidelines vary in defining the minimum number of observations. The largest recommendation for minimum size is that the number of DMUs exceed three times the total number of inputs and outputs, or the product of the number of inputs and outputs, whichever is greater (Banker et al., 1989; W. W. Cooper et al., 2007). For our model, 3 (1) inputs and 1 (3) output, this result in a minimum of 12 DMUs because 12 (3×(3+1) is greater than 3 (3×1). Each year in our sample exceeds this minimum standard.

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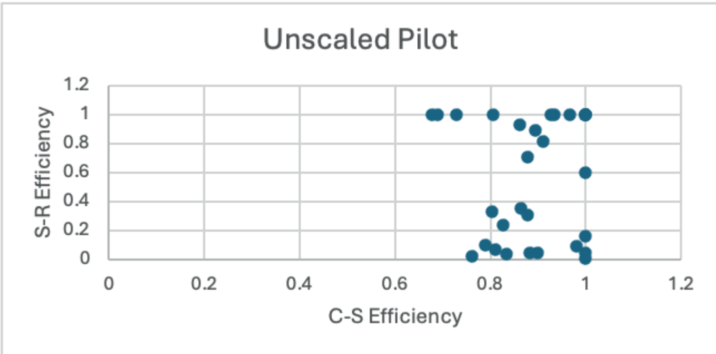
Remark A14. Scaling approach

As noted in Remark 13 above, our decision to use customer review scores as-is requires that revenues and costs be scaled to facilitate meaningful comparisons. We tested alternative approaches: unscaled, scaled by room nights, and scaled by total property, operations, and maintenance expense (Total POM). Unscaled data were confirmed to be inappropriate. Consider a hotel could be twice the size of another hotel, but still have the same customer review score. This would mean the larger hotel would appear extremely inefficient in C-S efficiency (using twice times the cost to produce the same review score) but extremely efficient in S-R efficiency (using the same review score to produce twice the revenue). This is shown in Figure 1(A14). The analysis shows two groups. One, with high S-R scores (above 0.6) with a clear set of hotels with S-R efficiency of 1. Another, with low S-R scores (below 0.4), with many hotels showing low S-R efficiency near 0. This indicates that hotel scale is overriding a lot of the results, driving a split in results.

Figure 1(A14). Unscaled data in pilot analysis



Scaling by room nights is practically appealing as it produces cost-per-room and revenue-per room, being practical managerial measures. Scaling by room nights addresses scale issues. However, scaling purely by room nights disregards other factors that typically affect review scores. Higher quality hotels generate higher revenues per customer but also incur greater costs. Hotels with special features, such as heritage buildings, unique locations, or a wider set of customer amenities also attract higher revenues but also higher costs.

We sought to capture these characteristics using Total POM as our scaling variable. Total POM expense recognizes scale as larger hotels have higher expenses. It recognizes quality as higher quality hotels require more activities and supplies to be maintained to a higher standard. It recognizes special features as these incur their own maintenance requirements. Additionally, Total POM helps to recognize that hotels in different locations may face different input prices (e.g. labor costs), affecting prices that can be charged, which reduces comparability across hotel sites. A hotel's Total POM expense is likely to face similar input prices for its operational expenses and its maintenance expense. Scaling by total POM therefore allows us to reduce the effect of different input prices, increasing comparability. The benefits offered by scaling using Total POM thus drove us to pick this over Room Nights.

***Alternative Scaling using Room Nights*.** As an unexpected result we discovered that scaling by Room Nights revealed a strong pattern of consistent cost and revenue per room night, which we term an "industry plateau" effect. This arose as many hotels appeared to largely follow a set of industry-markups, where hotels at any particular price point have similar costs-per-room, and therefore similar mark-up. This effect appeared to dominate the assessment of revenue and cost capabilities in some of the years. We describe this further below, *Additional analysis - Industry Plateau*. This supports discarding scaling by Room Nights.

***Scaled and unscaled descriptive statistics*:** Table 3 in the main manuscript reports descriptive statistics for scaled data that were used in the reported analysis. Descriptive statistics for unscaled data are reported here to convey the practical sense of the hotels (Table 1(A14)). The hotels exhibit an extremely wide range of values when unscaled, such as food and beverage revenue, even after assessing for outliers and data entry errors. The scaled data show a much narrow band of variation relative to the review scores. In particular, the median and quartile scores show that a lot of the variation is within a reasonable band.

Table 1(A14). Descriptive Statistics of Variables (unscaled data)

	Mean	Standard Deviation	Range	Minimum	Q1	Median	Q3	Maximum
Rooms Expenses, USD	2,850,298.72	2,584,823.10	14,475,848.00	322,480.00	1,124,319.00	1,771,653.00	3,501,425.50	14,798,328.00
F&B Expenses, USD	2,639,260.34	4,104,924.61	21,317,343.00	1,975.00	99,868.50	604,646.00	3,143,131.50	21,319,318.00
Amenities Expenses, USD	238,738.01	507,808.56	4,533,711.00	8.00	12,393.50	37,419.00	236,876.50	4,533,719.00
POM Expenses, USD	703,062.12	660,740.33	3,323,630.00	108,401.00	187,546.00	439,721.00	1,080,466.50	3,432,031.00
Review Rating (stars)	4.03	0.76	4.00	1.00	3.75	4.21	4.52	5.00
Rooms Revenue, USD	10,698,754.22	9,930,505.20	50,231,919.00	765,998.00	3,800,525.50	6,502,774.00	14,598,093.50	50,997,917.00
F&B Revenue, USD	3,630,101.56	5,917,758.25	31,904,946.00	12,532.00	160,182.00	632,010.00	3,970,377.50	31,917,478.00
Amenities Revenue, USD	360,147.81	629,447.61	5,766,323.00	85.00	24,739.00	65,575.00	475,214.00	5,766,408.00

N = 455
USD – United States Dollar
Q1 – 25th percentile; Median – 50th percentile; Q3 – 75th percentile

Remark A15. Model specifications: VRS and CRS

Due to the variation in input and output variables, we tested both the variable returns to scale (VRS) and constant returns to scales (CRS) models (Banker et al., 1984; Charnes et al., 1978). CRS models assume proportional-change relationships in how a firm uses its inputs to produce outputs (Charnes et al., 1978). For this analysis, it suggests that the cost and revenue associated with a review score of, for example, 3.0 has a linear relationship to that with a score of 4.0. The practical nature of customer review scores is that higher levels of score become harder to achieve beyond a certain point, incurring greater and greater cost, and that the revenue increases beyond a certain standard also taper. VRS models recognize these relationships vary and so accommodates different relationships at different scales (Banker et al., 1984). This, in tandem with use of Total POM, provides further treatment for hotels of different sizes. Additionally, the range of review scores (where a small number of hotels having extreme scores) reinforced the use of VRS. The majority of our sample includes hotels with a high number of reviews that group around a similar review score (between 4.0 and 4.5 satisfaction). The hotels with high and low scores (max of 5 and min of 1) meant that DEA would consider our hotels to be different in the 'scale' of customer review scores. VRS allowed these hotels to be included in our analysis without penalizing other hotels.

Figure 1(A15). Comparison of CRS and VRS models in 2019

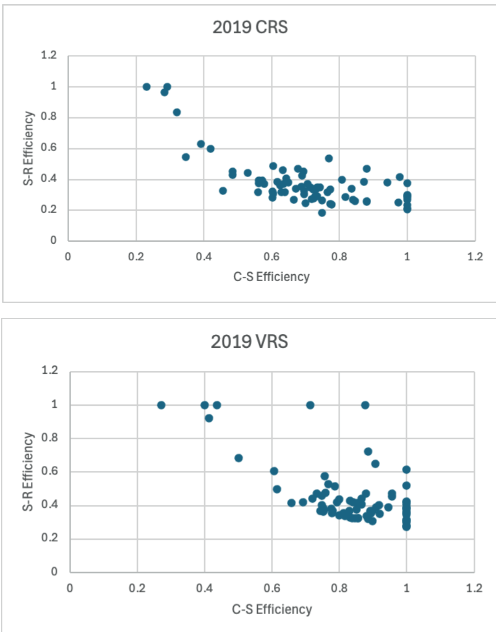


Figure 1(A15) illustrates the results for 2019, comparing the CRS and VRS scores. The 2019 results followed a similar pattern to other years. When comparing the two charts, the 2019 scores show a curved relationship, indicating a trade-off between S-R and C-S efficiency. A similar curved relationship was identified when analyzing results when scaling by room nights, which we term an industry plateau (see below for further discussion). A key result is that firms are either efficient in C-S or S-R revenue, but not both. In contrast, the VRS model produces a greater variety of efficiency scores and we see more hotels with high S-R efficiency. These differences are key as otherwise hotel results fail to recognize that hotels of different scales can be efficient.

References

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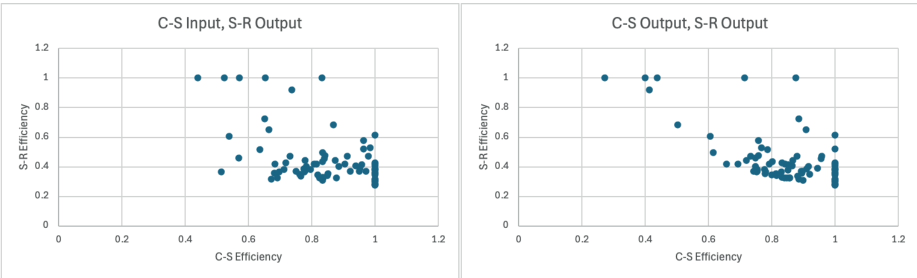
Charnes, A., Cooper, W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *Company European Journal of Operational Research*, *2:* 429–444.

Remark A16. Alternative model specifications: Input and Output models

We further considered DEA's sensitivity to model specification by testing input and output models for the C-S efficiency. It considers how a hotel uses cost inputs to produce customer review scores. This can be interpreted from an input perspective, where a hotel improves performance by reducing its costs to produce a given customer review score, or an output perspective, where a hotel improves performance by increasing its customer review score for the costs it spends. We tested both approaches. Figure 1(A16) illustrates the results for 2019, which follow patterns similar to those of the other years.

Figure 1(A16). VRS and CRS models in 2019



The S-R efficiency scores are identical across the two graphs, both being output-oriented. Differences arise in the C-S scores, being either an input orientation or an output orientation. The two graphs show similar patterns in terms of the strongest performers (the group of hotels with high S-R efficiency but differences in C-S efficiency) and clustering of hotels with similar levels of performance.

We decided to use the output model, as is common in hotel DEA research (for example, Dong et al. 2020). Hotels already appear competitive in terms of cost management, which is reflected in their high C-S efficiency scores. Signaling hotels to further reduce costs is a challenging recommendation. The output perspective indicates that hotels should consider how they can better spend their resources to increase customer satisfaction. For your current level of spending, how can you increase your review score? Conceptually, a hotel's customer review scores are produced by the activities it conducts rather than customer review scores being fixed. This supports an output production model.

References

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Remark A17. Additional analysis. One stage Cost-to-Revenue Efficiency

Our focus in the manuscript is to assess hotel cost and revenue capabilities and the integration of customer metrics into accounting analysis, captured by C-S and S-R scores. To show the additional insight from compared to an accounting-only model, we showed C-R (cost-revenue) efficiency scores. C-R efficiency follows the approach in prior research, which considers how a hotel uses its resources (costs) to produce outcomes (revenue). Prior hotel DEA research typically includes fixed assets rather than operational costs only. The manuscript emphasizes how the C-S and S-R results contrast with the C-R scores. Here, we provide further details about C-R scores and associations.

The model for C-R scores followed parameters similar to those of C-S and SR. The inputs were the three cost categories (rooms, food and beverage, and amenities), and the outputs were the revenues for the same three categories. The model was run using data scaled by Total POM using a VRS model under an output orientation. The analysis was run separately for each year.

Our comparison of CR, CS, and S-R is important because it identifies that differences in performance appear to be driven from the revenue side. Overall, hotels have a similar ability across the industry to manage costs in relation to review scores.

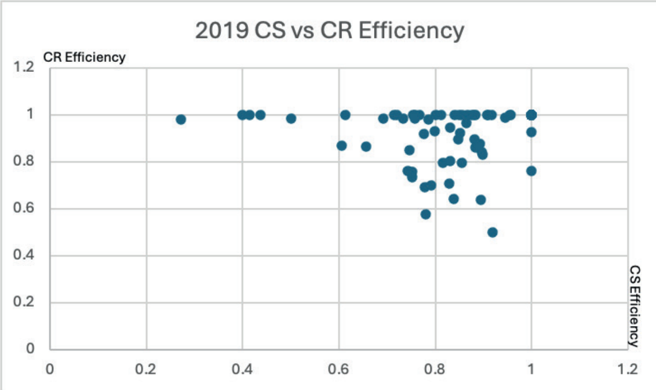
Table 1(A17). One-stage DEA scores: C-R Cost to Revenue Efficiency

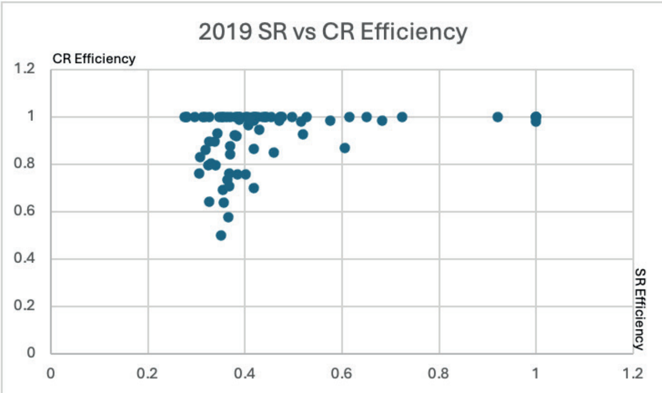
Year	Mean	SD	Range	Min	Q1	Median	Q3	99%	100%
2015	0.91	0.10	0.42	0.58	0.86	0.94	1.00	43.33%	41.67%
2016	0.92	0.10	0.34	0.66	0.86	0.97	1.00	47.22%	45.83%
2017	0.93	0.09	0.32	0.68	0.87	0.97	1.00	47.89%	46.48%
2018	0.95	0.11	0.47	0.53	0.96	1.00	1.00	72.50%	72.50%
2019	0.92	0.12	0.50	0.50	0.86	1.00	1.00	52.63%	51.32%
2020	0.86	0.16	0.63	0.37	0.75	0.91	1.00	38.24%	38.24%
2021	0.91	0.13	0.55	0.45	0.84	0.99	1.00	50.72%	49.28%

The results showed high average efficiency scores for CR. This indicates that the overall performance across the industry is consistent each year, where the best performers do not significantly outperform the rest of the industry.

We considered the relationship between C-S and S-R to the overall C-R score. Figure 1(A17) shows the scatter plots of the relationships.

Figure 1(A17). CS-CR and SR-CR Efficiency Plots





Both tables show that many hotels are regarded as fully efficient or near-full under C-R efficiency. C-R efficiency is on the Y-axis on both charts, and there are many observations at 1. The pattern shows many hotels with high C-S scores (clustering on the right-hand side, around a C-S score of 0.8) and many hotels with low S-R scores (clustering on the left-hand side, around an S-R score of 0.35). These clusters support our main discussion that most hotels have good C-S scores and weaker S-R scores.

We see tails of high C-R performance in both graphs. For the CS-CR graph, there is a tail of hotels with high C-R performance but low CS. This indicates that these fewer hotels have achieved high C-R scores because of their high revenue performance (high SR). For the SR-CR graph, there is a tail of hotels with high C-S and C-R performance. This indicates that there are few hotels with high C-R and S-R scores. In both graphs, the tails indicate that hotels stand out in performance due to their S-R scores.

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Remark A18. Additional analysis. Industry Plateau Effect

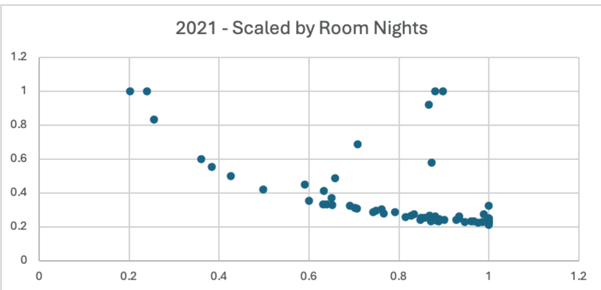
As an additional analysis, we scaled the cost and revenue amounts by room nights sold. This produces an average variable cost and revenue per room. Compared to scaling by Total Property, Operating, and Maintenance Expense, scaling by room nights sold only controls for the size of the hotel.

The mechanical nature of DEA means that hotels will systematically vary in their relative cost-satisfaction and satisfaction-revenue rating if they run at an industry-average mark-up. For example, in 2021, the data show a very close correlation between cost and revenue per room night (and F&B per room night). For example, hotels earning $140 per night have costs around $40 per night. Hotels earning $350 per room night have costs around $70 per night.

Consider two hotels. Hotel A is a typical low-price-point hotel that has $40 variable costs per room night, a satisfaction score of 4.0, and $140 total revenue per room night. Hotel B is a typical high-price-point hotel that has $70 variable cost per room night, satisfaction score is also 4.0, and $350 total revenue per room night. Hotel A will look cost efficient compared to Hotel B because with only $40 cost, able to achieve the same satisfaction as Hotel B spending $70. By contrast, Hotel B will look revenue efficient compared to Hotel A. With the same satisfaction of 4.0, they can earn $70 whereas Hotel A only earns $40.

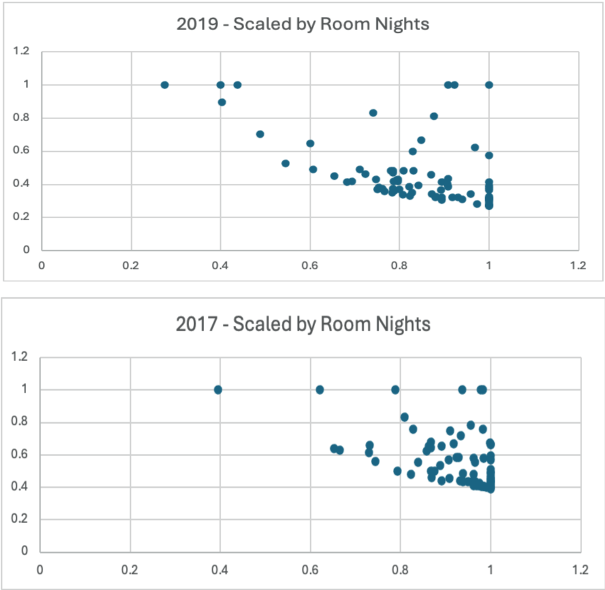
This mechanical trade-off in the DEA is shown in the 2021 graph. Most hotels fall on a very neat curve. This indicates that these hotels exhibit an industry-standard markup. There are, however, a few hotels off-curve. This demonstrates hotels that can perform beyond the typical industry standard markup, thereby achieving higher revenue and cost performance. Figure 1(A18) shows the cost-satisfaction-revenue chart for 2021 scaled by room night.

Figure 1(A18). C-S-R Efficiency Plot (scaled by room nights). 2021



This mechanical relationship provides a baseline standard for the amount of information provided by the analysis. Thus, when a given DEA analysis shows a spread of efficiency scores beyond this curve, it can identify differences in performance exceeding an industry-average markup. For example, consider the cost-satisfaction-performance charts for 2019 and 2017. In 2019, most hotels were on an industry-averaged markup curve. However, when compared to 2021, there is a spread of hotels beyond this curve. The 2017 chart shows an even greater range of dispersion.

Figure 2(A18). C-S-R Efficiency Plots (scaled by room nights). 2019, 2017



We posit that the cost-satisfaction-revenue charts show the presence of an industry standard markup, as seen by the curve relationship. Any spread beyond the curve identifies hotels that exceed this baseline performance.

We can return to considering the analysis when scaling by Total Property, Operations, and Maintenance expense (Figure 6 in the main manuscript). We see evidence of the curve, but largely see spread in hotels away from this curve. This supports that scaling by Total Property, Operations, and Maintenance expense helps to control for size, quality, and condition of facilities. That is, it provides evidence that hotels perform beyond the industry average. That said, we observed in 2019 that there is a clearer industry average curve, as there are few hotels beyond this. This suggests that, in 2019, hotels were not able to achieve markups beyond the industry average, suggesting high competition.

A

Remark A19. Quadrants over time

Figure 1(A19) shows how the distribution of hotels across these quadrants evolved from 2015 to 2021, following the industry challenges. For managers and analysts, this tool offers a quick snapshot of strategic positioning over time and signals where shifts in customer value delivery or pricing effectiveness may be required.

Figure 1(A19). Distribution of hotels across performance quadrants (2015-2021)

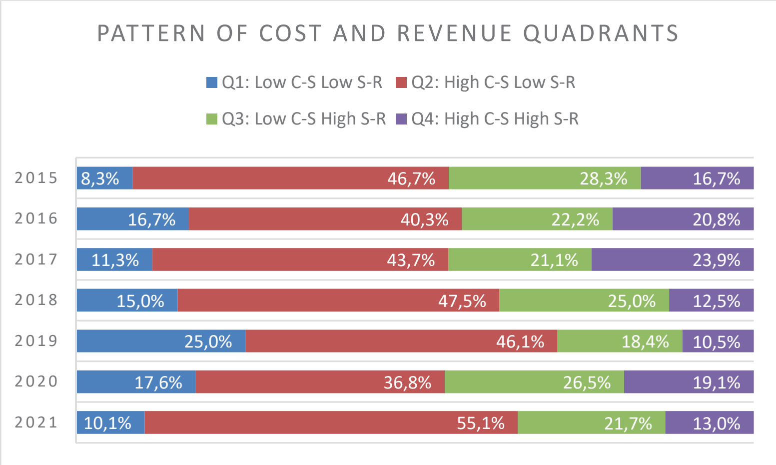


Table 6 in the main manuscript indicates that Quadrant 2 (High C-S, Low S-R) always contains the greatest proportion of hotels. These results further reinforce that most hotels are successful in maintaining a good service standard while keeping costs under control. However, most hotels have the potential to utilize more revenue given their customer satisfaction. The distributions among the other quadrants vary from year to year, signalling the relative challenges facing the hotel industry. For example, Quadrant 1 was at its largest in 2019, identifying that while the hotel industry as a whole performed well, many firms achieved poor C-S results and poor S-R, given their satisfaction scores. Such quadrant categorization can be useful for hotels to understand the roots of their performance relative to the industry and to guide their focus towards improving C-S efficiency, S-R efficiency, or both.

Table 1(A19) illustrates how the sample of hotels changed in quadrants from 2018 to 2021. This provides a practical way for hotels to evaluate their revenue and cost management capabilities relative to their competitors. In this example, we show two hotels exhibiting a stable pattern, two showing improvement in their quadrants (all demonstrating an increase in S-R), two with fluctuating quadrants (suggesting that these hotels are close to the mean), and two hotels demonstrating a declining trend (one deteriorating in C-S and the other in S-R).

Table 1(A19). Illustration of quadrants over time from 2018 to 2021

DMU	2018	2019	2020	2021	Comment	Notes
10053574	4	4	4	2	Stable	S-R decreasing
3014094	3	3	3	3	Stable	
82665	4	4	4	4	Stable	
118829	2	2	4	4	Growth	S-R increasing
5999884	1	2	2	4	Growth	C-S and S-R increasing
6274762	1	1	3	3	Growth	S-R increasing
6691599	1	3	4	3	Growth	S-R increasing
958451	2	2	4	4	Growth	S-R increasing
10050643	1	3	1	2	Fluctuating	
238338	3	3	4	1	Fluctuating	
2584763	3	3	1	2	Fluctuating	
2902572	3	2	4	3	Fluctuating	
3905763	3	2	4	4	Fluctuating	
4900408	2	2	3	2	Fluctuating	Relatively stable
7755309	3	2	1	3	Fluctuating	
8079184	1	2	2	1	Fluctuating	Generally poor
8233561	2	2	3	2	Fluctuating	Relatively stable
8930298	2	3	3	3	Fluctuating	Relatively stable
9434859	2	1	3	3	Fluctuating	
9823821	2	2	1	3	Fluctuating	
3948027	2	2	1	1	Decline	C-S decreasing
7307341	4	1	2	2	Decline	S-R decreasing

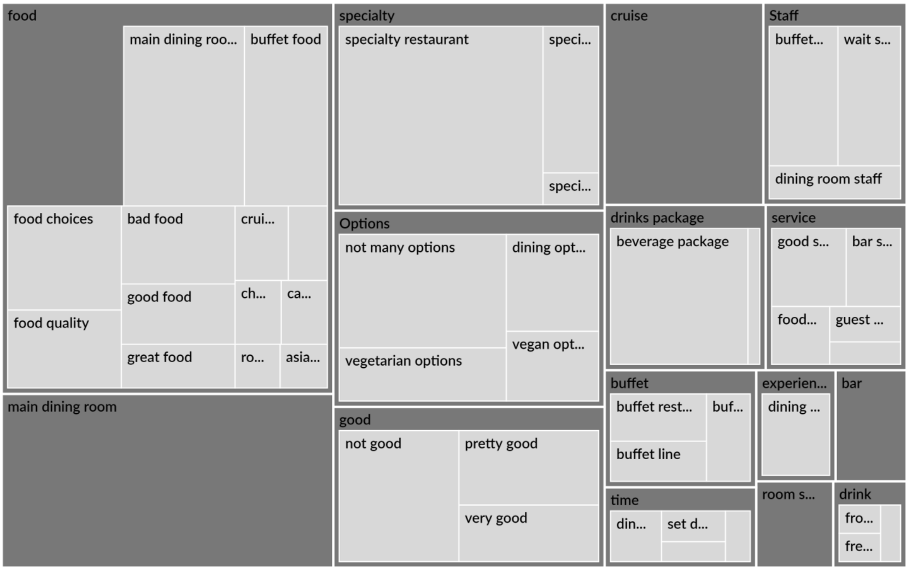
A

Figure A2: Word Cloud analysis of pre-pandemic and post-pandemic samples

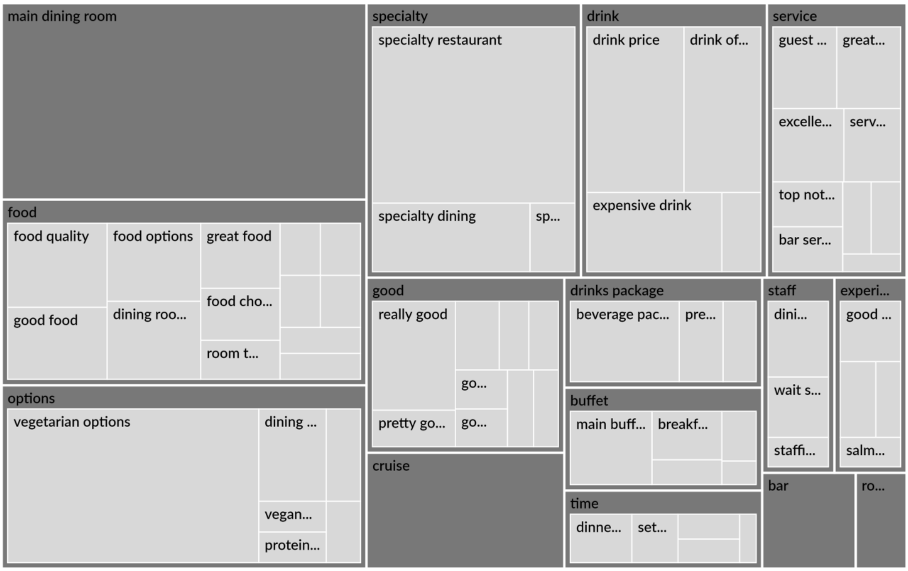
Pre-pandemic period (2018-2019) total of 23441 reviews worldwide (100%)

Post-pandemic period (2021-2022) total of 15637 reviews worldwide (100%)

Figure A3: Thematic analysis based on pre-pandemic and post-pandemic samples



Pre-pandemic period (2018-2019) total of 23441 reviews worldwide (100%)



Post-pandemic period (2021-2022) total of 15637 reviews worldwide (100%)

Figure A3 presents thematic maps depicting the hierarchical structure of the themes and subthemes related to cruise dining before and after the pandemic. The maps revealed that *food* was a central theme, with subthemes related to *food quality*, followed by the *main dining room*. After the restart of cruising in 2021, the *main dining room* takes a central place, and *food* now shares centricity with *options*).

Appendix A20. Questionnaire “LOW-COST HOTEL” [31]

1. Age

(_) < 18 years-old (_) 18 to 25 years-old (_) 26 to 34 years-old (_) 35 to 50 years-old (_) > 50 years-old

2. Gender: (_) male (_) female

3. Monthly wage (MW = Minimum wage = U$ 250.00)

(_) < 4 MW (_) 4 to 8 MW (_) 9 to 15 MW (_) 15 to 20 MW (_) more than 20 MW

4. Marital status: (_) single (_) married (_) other

5. Choosing a tourist destination, in terms of expenses, assign from 1 (not important) to 5 (very important) the following variables:

__ 1 __2 __3 __4 __5 – Accommodation
__ 1 __2 __3 __4 __5 – Transport (origin-destination)
__ 1 __2 __3 __4 __5 – Transport (in the destination)
__ 1 __2 __3 __4 __5 – Food
__ 1 __2 __3 __4 __5 – Ticket´s prices in the tourist attractions

6. **If you are traveling for pleasure, rate from 1 (I do not like) to 5 (I like much) the types of destinations below.**

__ 1 __2 __3 __4 __5 – Beach
__ 1 __2 __3 __4 __5 – Farm and/or field
__ 1 __2 __3 __4 __5 – Historical cities
__ 1 __2 __3 __4 __5 – Big cities
__ 1 __2 __3 __4 __5 – Entertainment and leisure cities (ex: Orlando, USA)

7. In your leisure travel, on average, what is your length of stay at the destination?

(_) < 2 days (_) 3 to 4 days (_) 5 to 7 days (_) 8 to 10 days (_) more than 10 days

8. Suppose you stay in a low-cost hotel with a daily rate of $ 40.00, located in a **BEACH** destination. However, some products and services can be purchased on an optional basis. **Assign the maximum $-amount you would be willing to pay for them, daily**.

Internet	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more
Swimming pool	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more
Gym	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more
Telephone in the room	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more
Mini-fridge	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more
Breakfast	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more
TV in the room	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more
Bath Items	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more
Pillow	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more

9. Suppose you stay in a low-cost hotel with a daily rate of $ 40.00, located in a **GREAT CITY/ METROPOLE**. However, some products and services can be purchased on an optional basis. **Assign the maximum $-amount you would be willing to pay for them, daily**

Internet	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more
Swimming pool	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more
Gym	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more
Telephone in the room	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more
Mini-fridge	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more
Breakfast	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more
TV in the room	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more
Bath Items	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more
Pillow	__ 0.00	__ 1.00	__2.00	__3.00	__4.00	__5.00 or more

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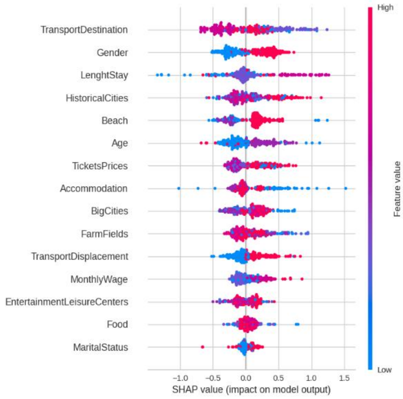
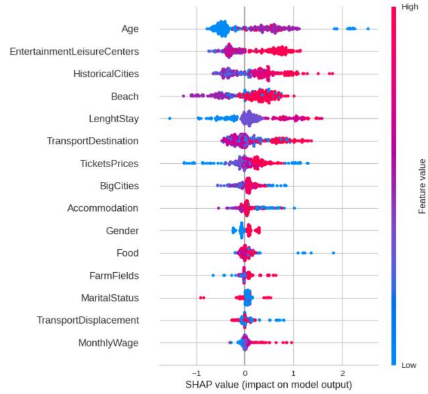
[31] The original language of the Questionnaire was Portuguese.

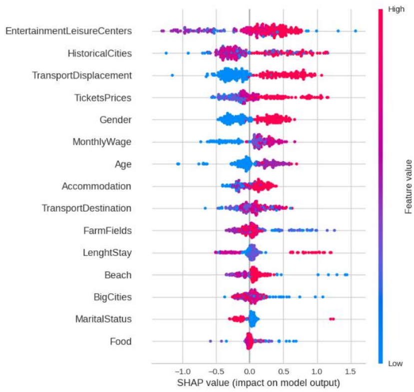
Figure A4: Shapley Values for comfort elements at beach destinations



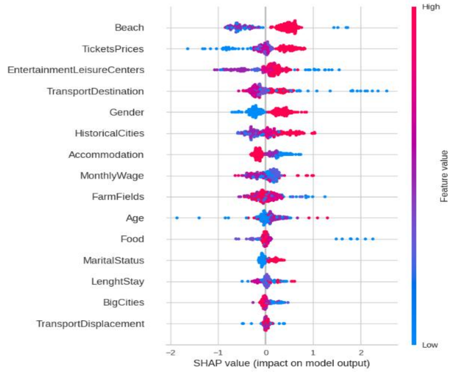
2.1. Swimming pool



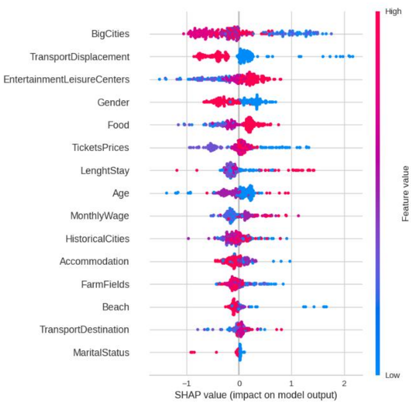
2.2 Gym



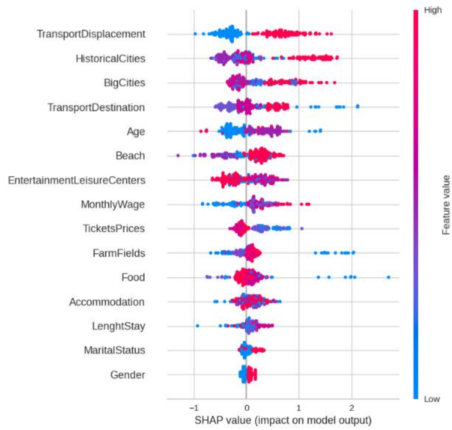
2.3. Pillow



2.4. Minibar

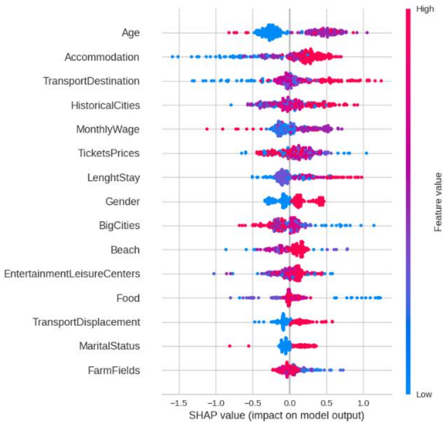


2.5. Breakfast

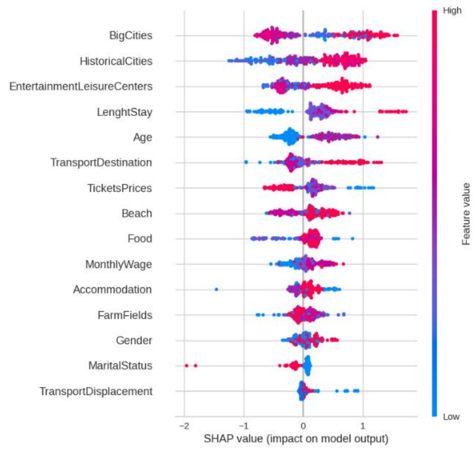


2.6. TV in the Room

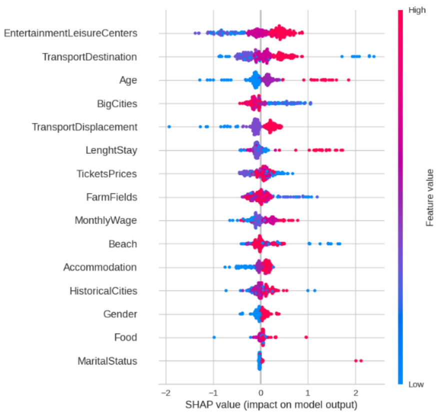
Figure A5: Shapley Values for comfort elements at city destinations



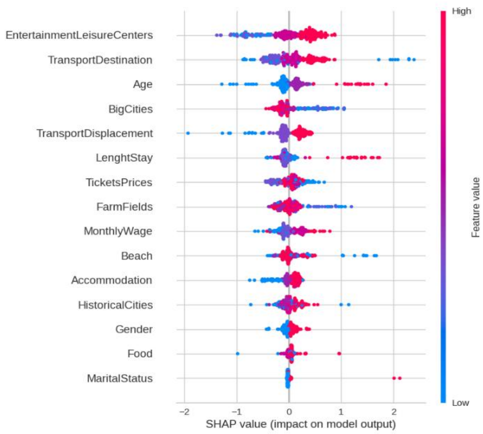
3.1 Swimming pool



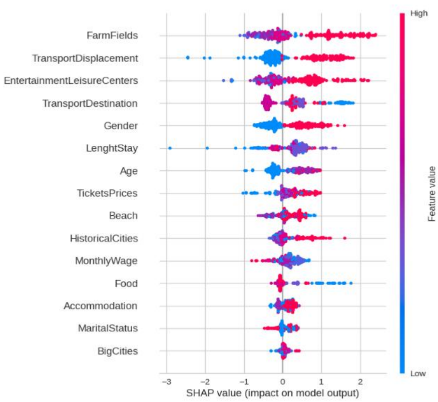
3.2 Gym



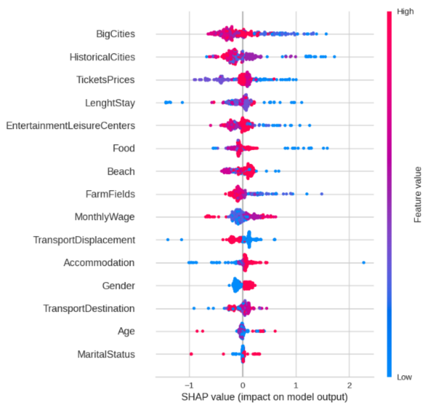
3.3 Pillow



3.4 Minibar

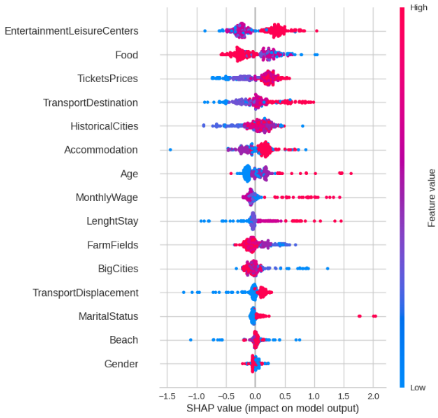


3.5 Telephone

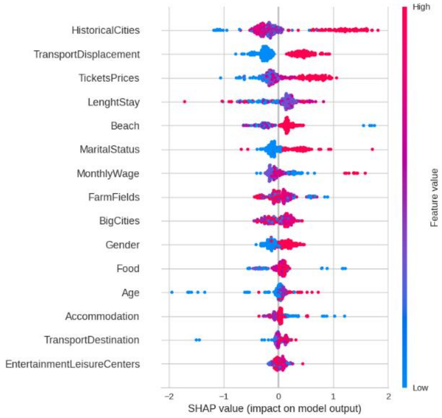


3.6 Breakfast

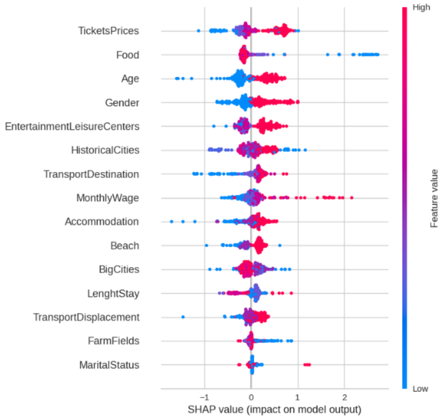
Figure A5 (continued): Shapley Values for comfort elements at city destinations



3.7 Toiletries



3.8 TV in the room



3.9 Internet

A

Appendix A21. Author contribution chapters

Chapter 2

Title chapter: Customer Satisfaction as a Profit Driver in Upscale Hotel Chains: A Cross-Level Analysis of Financial Performance

Title published article: Balancing Short-Term Gains and Long-Term Success in Lodging: The Role of Customer Satisfaction and Price in Hotel Profitability Model

Researchers involved: Ganna Demydyuk (GD), Mats Carlbäck (MC), Jean Pierre van der Rest (JR), Peter van der Zwan (PZ)

	Limited contribution	**Substantial contribution**
Conceptualization		GD, MC (coauthor published article, parts of which have been included in this chapter)
Methodology		GD
Analysis		GD
Writing (original draft)	MC	GD
Writing (review and editing)	JR, PZ, GD	
Visualization		GD

Chapter 3

Title chapter: Extending the Sales-Volume-Driver Hotel Profitability Model: An analysis of Full- and Limited-Service Upscale Chain Hotels

Researchers involved: Ganna Demydyuk (GD), Jean Pierre van der Rest (JR), Peter van der Zwan (PZ)

	Limited contribution	**Substantial contribution**
Conceptualization		GD
Methodology		GD
Analysis		GD
Writing (original draft)		GD
Writing (review and editing)	JR, PZ, GD	
Visualization		GD

Chapter 4

Title chapter: Integrating Customer Satisfaction into Cost and Revenue Management: A Two-Stage DEA of Upscale Chain Hotels

Title conference paper: Maximizing Revenue from Satisfaction: Unveiling the efficiency of guest delight in hotels

Researchers involved: Frederick Ng (FN), Ganna Demydyuk (GD), Claire Cui (CC), Jean Pierre van der Rest (JR), Peter van der Zwan (PZ)

	Limited contribution	**Substantial contribution**
Conceptualization	CC (first author conf. paper, parts of which have been included in this chapter)	GD, FN (coauthor)
Methodology		FN, CC, GD
Analysis	FN	CC, GD
Writing (original draft)		GD, FN, CC
Writing (review and editing)	JR, PZ, GD	
Visualization		GD, FN

Chapter 5

Title chapter: Navigating the Evolving Dining Choices: Practical Insights into Analysis of Cruise Passengers' Expectations Using Experience Accounting (EA) Framework

Title published article: From the Galley to Gourmet: The Evolving Dining Choices of Cruise Passengers since the Return of Cruising

Researchers involved: Ganna Demydyuk (GD), Rahul Kaurav (RK), Mats Carlbäck (MC), Henrik Vejlgaard (HV), Jean Pierre van der Rest (JR), Peter van der Zwan (PZ)

	Limited contribution	**Substantial contribution**
Conceptualization	RK, MC (coauthors published article, parts of which have been included in this chapter)	GD
Methodology	RK	GD
Analysis		RK, GD
Writing (original draft)	RK, MC, HV (coauthor)	GD
Writing (review and editing)	JR, PZ, GD	
Visualization		GD, RK

Chapter 6

Title chapter: Surviving Competition: Practical Insights from Experience Accounting (EA) and Machine Learning for Optimizing Profitability in Economy Hotels

Title conference paper: Optimizing Resource Allocation to Sustain the Airbnb Battle: An Experience Accounting Perspective on Modelling Low-Cost Hotel Experience Profiles using Machine Learning

Researchers involved: Ganna Demydyuk (GD), Jean Tavares (JT), Giancarlo Fedeli (GF), Jean Pierre van der Rest (JR), Peter van der Zwan (PZ)

	Limited contribution	**Substantial contribution**
Conceptualization	GF (coauthor conf. paper, parts of which have been included in this chapter)	JT (first author), GD
Methodology		JT, GD
Analysis		JT, GD
Writing (original draft)	GF	GD, JT
Writing (review and editing)	JR, PZ, GD	
Visualization		GD, JT