MEASURING HOSPITALITY EFFICIENCY IN EUROPE: A DEA BENCHMARKING APPROACH

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Abstract

Purpose – This paper re-examines the relative efficiency of the European hospitality industry by applying DEA to 35 countries and identifies benchmarking insights into performance differences.
Methodology/Design/Approach – Three DEA models (CCR, slack-based, and super-efficiency) are applied to publicly available Eurostat data on labour and bed capacity (inputs) and tourist arrivals and nights spent (outputs), with an additional VRS (BCC) specification used as a robustness check. The super-efficiency model allows a full ranking of countries beyond the efficiency frontier.
Findings – Only two countries (Iceland and Malta) lie on the efficiency frontier, with Iceland ranked highest under the super-efficiency model. Most countries exhibit decreasing returns to scale and substantial labour inefficiencies, suggesting significant room for improvement. Benchmarks are provided to help lagging countries identify relative performance gaps.
Originality of the research – This study extends DEA-based benchmarking to the national level for the European hospitality sector, combining multiple DEA models with slack-based diagnostics and scale-efficiency analysis. By identifying frontier performers and benchmarking gaps, it contributes to the understanding of cross-country differences in hospitality efficiency and supports evidence-based analysis of tourism performance.
Keywords hospitality industry, benchmarking, DEA, Europe, performance measurement, efficiency

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INTRODUCTION

The hospitality industry is a major contributor to global GDP and employment, generating over 10% of global GDP and supporting hundreds of millions of jobs pre-pandemic (WTTC, 2023). It plays a crucial role in economic growth, infrastructure development, and foreign investment, particularly in emerging economies (Saner et al., 2019; UNWTO, 2022). As a labour-intensive and service-driven sector, it is also central to achieving sustainability and development goals (UN, 2015). Operating in a high-cost environment, hospitality businesses must manage labour, energy, and infrastructure effectively. Efficiency measurement helps control costs while maintaining service quality, which is critical to customer satisfaction and profitability (Sigala et al., 2005; Anderson et al., 1997). Moreover, it supports sustainability through resource monitoring and enhances resilience in crisis recovery (Jones et al., 2014; Baum & Hai, 2020).

In this context, performance benchmarking is vital. It enables organizations and countries to assess their competitiveness, identify gaps, and align with best practices (Bogetoft, 2013). Choosing the right tool for measuring and comparing efficiency, such as Data Envelopment Analysis (DEA), is essential for informed strategic decisions. DEA is widely used for efficiency benchmarking across many fields. Although most tourism and hospitality studies focus on micro-units (e.g. hotels), there is a growing interest in applying DEA at the national or macro level. For example, Soysal-Kurt (2017) analysed 29 European countries' tourism efficiency using DEA, highlighting that macro-level analyses can inform national tourism policy. Similarly, Radovanov et al. (2020) and Hoque (2018) apply DEA to compare tourism performance of multiple countries as Decision-Making Units (DMUs), using outputs like tourist arrivals. The present study adopts a country-level DEA perspective to benchmark European hospitality sectors, situating each country as a single DMU. This approach follows recent methodological precedents (e.g. EU- and global-level tourism DEA studies) and acknowledges that national economies make broad tourism decisions (e.g. infrastructure, marketing, regulation) where such comparative efficiency analysis can be relevant. We recognize heterogeneity among countries (size, structure, culture) as a limitation, but by focusing on European countries with comparable development, we mitigate extreme disparity. Therefore, our macro-level DEA analysis of hospitality efficiency extends the literature by treating countries as benchmarks, in line with recent research in tourism efficiency. As a robustness check, we also estimate an alternative DEA model with variable returns to scale (BCC) to assess the impact of scale assumptions. The Results include a brief comparison of CRS (constant returns) and VRS (BCC) efficiency scores.

This study addresses a gap in tourism performance literature by conducting a systematic cross-country DEA analysis of national hospitality sectors, complementing previous work that primarily examined micro-level units or single-model efficiency measures. To our knowledge, no prior research has combined slack-value interpretation and scale-effect analysis in a multi-country tourism benchmarking context. Therefore, this paper aims to fill this gap.

1. LITERATURE REVIEW

Several methodologies have been developed in the literature to measure and analyse efficiency in the hospitality industry. Among the most prominent is frontier efficiency analysis (Assaf & Agbola, 2017). This category encompasses tools designed to assess the relative efficiency of comparable entities, such as individual hotels, larger firms, or even entire countries, by treating them as decision-making units (DMUs) (Patel & Pande, 2013). These tools work by comparing input-output relationships against a constructed "efficiency frontier" that reflects best-practice performance or the maximum achievable output under given conditions (Coelli et al., 2005). The concept originates from Farrell (1957), who defined efficiency as the deviation from an ideal production frontier.

Frontier efficiency tools fall into two main types. The first includes stochastic models, such as Stochastic Frontier Analysis (SFA), which account for random errors in the measurement process (Anderson et al., 1999). SFA explicitly incorporates a noise term to capture the influence of external or uncontrollable factors (Aigner et al., 1977). The second type comprises deterministic models, notably DEA, which attribute all deviations from the frontier solely to inefficiency, without considering statistical noise (Charnes et al., 1978; Nurmatov et al., 2021). While both approaches are strictly designed for assessing relative, rather than absolute, efficiency, each offers distinct advantages and limitations, as outlined in Table 1.

Table 1: **The features of efficiency measurement tools for hospitality industry**

Tools	Type	Advantages	Limitations	Application
DEA	Frontier, Quantitative	• Handles multiple inputs/outputs • No need for functional form • Benchmarks best performers • Useful in evaluating both operational and financial efficiencies; • Makes dual analysis reveals reference units (Goncharuk, 2007)	• Sensitive to variable selection • No statistical noise handling • Only relative efficiency (Johns et al., 1997)	Used to compare hotels based on inputs like labour, energy, or capital, and outputs such as RevPAR, occupancy, or customer satisfaction (Tumer, 2010).
SFA	Frontier, Quantitative	• Accounts for random errors • Allows hypothesis testing • Suitable for panel data (Goncharuk et al., 2023)	• Requires functional form • Complex modeling • Sensitive to assumptions, • Needs large data, • Depends on distributional assumptions (Deng et al., 2019)	Often applied to large hotel chains where input-output data is available over time (Hu et al., 2010; Martín-Rivero et al., 2021)
BSC	Strategic, Mixed	• Integrates financial & non-financial metrics • Aligns strategy with KPIs • Holistic view (Goncharuk, 2009a)	• Complex implementation • Requires cultural/organizational buy-in • Can become bloated (Sainaghi et al., 2013)	Especially useful in chain hotel management and strategic performance management in hotel chains (Evans, 2005)
KPIs	Operational, Quantitative	• Easy to measure and track • Industry standardized (e.g., RevPAR, ADR) • Directly actionable (Goncharuk, 2023; Karadag, 2017)	• Can be short-term focused • May lack context • Risk of misuse or misalignment (Swart & Taylor, 2018)	Day-to-day hotel operations, revenue management (Hayes et al., 2021)
SWOT Analysis	Strategic, Qualitative	• Simple & intuitive • Identifies internal inefficiencies • Supports strategic planning (Pickton & Wright, 1998)	• Subjective and non-quantitative • No efficiency scores • Static snapshot (Agarwal et al. 2012)	Self-assessment, strategic positioning, pre-expansion planning (Jenčo & Lysá, 2018)
PESTEL Analysis	Strategic, Environmental	• Identifies external efficiency drivers • Useful for risk mitigation • Encourages proactive planning (Martei, 2019)	• No direct efficiency measure • Descriptive, not predictive • Context-dependent (Datta & Kutzewski, 2023)	Market entry planning, regulatory scanning, sustainability strategies (Diaz Ruiz et al., 2020)

Tools	Type	Advantages	Limitations	Application
Porter's Five Forces	Strategic, Competitive	• Assesses external pressures on margins • Helps identify strategic response needs (Porter, 2008)	• Does not measure operational performance • Focused on industry-level, not unit-level (Alher, 1998)	Competitor analysis, pricing and market positioning strategies (Moreno-Izquierdo et al., 2016)
Strategic Benchmarking	Strategic, Comparative	• Highlights gaps in efficiency • Encourages best practices • Focused on continuous improvement (Goncharuk et al., 2015)	• Requires data access • May not capture contextual differences • Risk of imitation over innovation (Brown & Ragsdale, 2002)	Comparing KPIs across hotels, standard setting, performance audits (Phillips & Appiah-Adu, 1998)

Beyond frontier analysis, the hospitality industry also employs a variety of strategic management tools to evaluate performance. Common examples include the Balanced Scorecard (BSC) (Kaplan & Norton, 1996), strategic benchmarking (Camp, 2024) combined with key performance indicators (KPIs) (Dasandara et al., 2022), SWOT analysis (Humphrey, 2005), PESTEL analysis (Aguilar, 1967), and Porter's Five Forces (Porter, 1980). These tools assess different dimensions of organizational efficiency, often focusing on internal operations, market positioning, or environmental scanning. For instance, the BSC connects internal process metrics, such as booking times, check-in efficiency, or housekeeping turnover, to broader strategic outcomes like staff development and service quality (Chen et al., 2010). It can also incorporate operational KPIs tied to input-output relations (Rodríguez-Rodríguez et al., 2020). Strategic benchmarking helps identify performance gaps by comparing against industry peers (Enz et al., 2001). Widely used KPIs, such as RevPAR (revenue per available room) (Demirtaş, 2019), GOPPAR (gross operating profit per available room) (Schwartz et al., 2017), or revenue per employee (Simpao, 2018), offer standardized measures to monitor cost control and resource utilization. While BSC and KPIs allow for evaluation of internal processes or comparative performance, their analytical scope is limited. Unlike DEA or SFA, these tools typically cannot handle multiple inputs and outputs simultaneously, nor do they construct an efficiency frontier for benchmarking. Other strategic tools provide qualitative insights: SWOT may reveal internal inefficiencies (Quezada et al., 2019); PESTEL helps identify external threats or efficiency drivers (Pan et al., 2019); and Porter's Five Forces underscores efficiency as a factor in competitive positioning (Paksoy et al., 2023). However, none of these directly quantify technical efficiency. Therefore, while strategic management tools support performance improvement through better alignment, resource allocation, and competitive analysis, they are not substitutes for quantitative frontier approaches like DEA or SFA. Each method brings unique benefits and limitations, which are summarized in Table 1.

Each of the previously mentioned tools serves particular purposes depending on the context. However, decision-making in today's VUCA world, marked by volatility, uncertainty, complexity, and ambiguity (Johansen & Euchner, 2013), requires agile, data-responsive approaches. In such fast-changing environments, traditional strategic tools may prove inadequate or even misleading, especially when market data is incomplete or external influences are unpredictable (Minciu et al., 2020). Poor tool selection under these conditions can hinder performance and lead to inefficient outcomes (Shimizu & Hitt, 2004). In contrast, flexible operational tools like DEA offer greater adaptability for evaluating efficiency in hospitality. DEA is particularly well-suited to hotel and tourism operations, as it accommodates multiple heterogeneous inputs and outputs, e.g. such as labour, room capacity, energy use, revenues, occupancy rates, and customer satisfaction (Barros, 2005). Unlike Stochastic Frontier Analysis (SFA), DEA does not require predefined production or cost functions (Chiang et al., 2004), an advantage in service sectors where such relationships are often difficult to specify. DEA is also robust with small sample sizes and cross-sectional data, which are typical in hospitality research focused on specific hotel groups, regions, or categories (Hwang & Chang, 2003). Furthermore, it identifies best-performing peers (Chatzistamoulou et al., 2024), enabling precise benchmarking – an essential feature for managerial improvement and strategic alignment in performance assessment.

Considering recent tourism and hospitality publications, performance there has been analysed using various methods. For example, Arbula Blecich et al. (2025) apply Window-DEA and Malmquist indices to measure efficiency and productivity changes across Mediterranean countries. Zaki (2026) uses DEA (with machine learning) to assess hotel efficiency under advanced revenue management. Remy et al. (2023) develop new hotel revenue metrics (NRevPAR, RevPAC) and investigate their determinants via surveys. Other work includes Aznar (2024), who employs regression to link environmental/demand factors to hotel ADR, and Ferdinand et al. (2024), who use a structural equation model to show how storytelling experience affects destination image and loyalty. These THM studies enhance understanding of firm- and destination-level productivity and competitiveness, but they stop short of benchmarking entire national hospitality industries. To the best of our knowledge, existing studies have not systematically applied cross-country DEA benchmarking of national hospitality systems with explicit slack-value analysis and comparison of CRS and VRS assumptions. The present paper fills this gap by applying DEA across countries' hotel industries, decomposing inefficiencies via input slacks and testing scale assumptions. This offers the first international benchmarking of tourism-sector efficiency, directly addressing the identified gap.

Recent systematic reviews confirm that DEA is the most widely used efficiency tool in hospitality research, surpassing both SFA and other frameworks in frequency and applicability (Vidali et al., 2025). Its methodological strengths are manifold: DEA avoids the rigid assumptions of SFA, integrates multiple KPIs into a composite efficiency score, and quantifies performance in a way that tools like the Balanced Scorecard (qualitative and subjective) or SWOT/PESTEL (conceptual only) cannot. Moreover, unlike Porter's Five Forces, which is limited to macro-level strategic positioning, DEA can be applied at the firm, regional, or international level. It also constructs internal efficiency frontiers directly from the data, offering benchmarking precision that strategic benchmarking alone cannot achieve.

DEA has been applied at the national level in various service domains. In healthcare, for instance, studies routinely benchmark country health systems. Gavurova et al. (2021) use a dynamic network DEA to compare OECD countries' health system efficiency over time, using aggregated national health inputs and outputs. Likewise, Aydın (2022) benchmarks OECD healthcare with a DEA-Malmquist approach, treating each country's health system as a DMU. These studies demonstrate the validity of DEA on macro units (countries) when inputs and outputs are appropriately aggregated. In tourism, several recent works adopt a national destination perspective. Radovanov et al. (2020) use DEA to evaluate tourism sustainability efficiency of 27 EU and 5 Western Balkan countries, combining tourism receipts and arrivals as outputs. Hoque (2018) analyzes 124 countries globally, using tourist arrivals and receipts to gauge tourism output. Others, like Kosmaczewska (2014) and Soysal-Kurt (2017), similarly measure country-level tourism efficiency with outputs such as arrivals, overnight stays, and receipts. These examples show that national-level DEA is used in practice, and that concerns about comparability are addressed by careful selection of DMUs or by conducting separate analyses, e.g. region or income grouping. We have followed these precedents, noting that each inefficient country's "peer group" consists of the efficient frontier countries (the reference set) it most closely resembles. In DEA, each inefficient DMU is compared to the set of efficient peers, and inefficiency is quantified by how much outputs must increase (or inputs decrease) to reach that frontier (Stoiljković et al., 2025). This provides actionable benchmarks: for example, if a country's output slack is 10 million nights, it indicates that the country would need that many additional guest-nights to become as efficient as its reference peers.

Therefore, DEA's flexibility, data orientation, and ability to handle complex performance structures make it a superior and highly versatile method for measuring efficiency in the hospitality sector at the national level. This study therefore focuses on DEA and seeks to explore how it can be most effectively applied to evaluate efficiency in hospitality industries of European countries.

In fact, most studies using DEA models to study the hospitality industry are benchmarking studies. They look for best practices (DMUs) or industry leaders and look for the extent and reasons why other DMUs lag behind them. Thus, it is possible to analyse both micro-DMUs, e.g. hotel departments (Hsieh & Lin, 2010), hotel or hospitality firm level (Alemayehu et al., 2023), regional levels (Pavković et al., 2021), and macro-DMUs at the inter-country level. The latter application is interesting from the point of view of international comparison of hospitality efficiency across countries. DEA models are widely used for such international benchmarking, e.g. in comparing the efficiency of healthcare systems in European countries (Lo Storto & Goncharuk, 2017), but they have not yet been used in the hospitality industry. Hence, this study can make the first attempt to measure the efficiency of hospitality sectors in European countries, i.e. at the international level, using DEA models. Therefore, having achieved the theoretical aim of this study, we can set an empirical goal in measuring and analysing European countries in terms of the efficiency of their hospitality industries. *The purpose of this empirical study* is to find out the levels of relative efficiency of the hospitality industry in European countries, which of them are leaders and losers, as well as what reserves and potential, they have for improving efficiency.

2. METHODOLOGY

To conduct an empirical study, appropriate DEA models were selected, which should bring the study closer to achieving its goal. We apply a standard non-parametric technique (Charnes et al., 1978) – the constant returns to scale DEA model (CCR model), a benchmarking framework, using CCR efficiency scores as the baseline and complementing them with input-oriented super-efficiency (SEM) and slack-based (SBM) models. Although the model reports both input excesses and output shortfalls, the main interpretation is benchmarking-oriented: it identifies whether countries could improve relative efficiency through better use of labour and bed capacity and/or higher tourism outputs relative to the frontier. The SEM, following Andersen and Petersen (1993), evaluates "efficient" countries beyond a score of 1 by removing the target DMU from the reference set, allowing ranking of all units. This yields insight into relative stability: how much a leading country could change (e.g. additional guest nights) without losing efficiency status. The SBM model (Tone, 2001) is non-radial: it directly incorporates any input excesses or output shortfalls (slacks) into the efficiency score. In practice, SBM helps identify how much each country must adjust specific inputs or outputs to become efficient, beyond the radial measure. Together, these models provide a fuller picture: CCR gives overall efficiency, SEM ranks efficient DMUs, and SBM pinpoints slack-based improvements. The modelling approach is primarily input- and slack-oriented because the study focuses on resource utilisation and benchmarking gaps in labour and bed capacity, while output slacks are interpreted as model-implied shortfalls relative to the efficient frontier rather than as immediate output-growth targets. We assume constant returns to scale for the CCR model as a starting point. This is reasonable when comparing similar-sized economies or when scale inefficiency is not the primary focus. The orientation and scale choices are standard in tourism DEA research.

The analysis covers European countries for which consistent hospitality data (arrivals, nights) are available. We focus on the EU and candidate countries to maintain comparability in economic development and data quality. Countries were selected based on data availability in Eurostat and UN tourism databases for the study period, e.g. latest year with full data. The final sample excludes any country-year with missing inputs or outputs. Timeframe and sources are as follows: tourist arrivals and nights (Eurostat and UNWTO, excluding any non-tourist movements), hospitality capital (beds, employment) from Eurostat (2025). Per Eurostat (2022) guidelines, refugee arrivals and stays are excluded from tourism statistics, and our data reflect this. No imputation was needed, as missing values simply led to exclusion of that country-year.

Following tourism DEA literature, we use arrivals and nights spent as key outputs. These capture the volume of tourism consumption (both number of visitors and total nights of service delivered) and are widely used proxies for tourism output. Arrivals measure demand volume, while nights reflect length of stay – together they approximate the service output of hospitality. Tourism receipts (spending) could be also included as an output, because they correlate with arrivals and nights and represent service output. However, while tourism receipts are important for assessing economic contribution, they are problematic as DEA outputs in cross-national hospitality studies. Non-monetary, physical indicators like arrivals and nights spent are typically preferred because they are: more standardized and internationally comparable; less affected by price or currency effects; better aligned with DEA's technical efficiency focus on input-output transformation. This is why many international DEA studies of hospitality (e.g., Soysal-Kurt, 2017; Radovanov et al., 2020) avoid or cautiously interpret the use of receipts. Thus, both selected outputs (arrivals, nights spent) are correlated with the economic benefits of tourism, as validated in prior studies. As inputs, we include hospitality resources such as number of beds and tourism-related employment, reflecting capacity and labour in the sector. Descriptive statistics are provided in Table 2.

Table 2: **Descriptive statistics of this sample**

	Employed persons	Bed places	Arrivals	Nights spent
Mean	85609	486481	27443417	67396418
Median	38500	185659	10689733	24531906
Standard Deviation	118983	669456	38420137	95176812
Minimum	2700	15898	883419	1840127
Maximum	406500	2232799	141225234	346514836

Further, the technical efficiency of the hospitality industries of each of the sample countries was highlighted. Then, a full ranking of countries by efficiency level was compiled using the super-efficiency model first suggested by Andersen & Petersen (1993). After that, a slack-based DEA model (Tone, 2001) was used to assess the reserves of reducing inputs and increasing outputs of the hospitality industries in countries that were not relatively efficient. The mathematical form of these specific DEA models is as follows:

Input-Oriented Super-Efficiency DEA (CRS) Model (SEM)

$$\begin{aligned} &\min_{\theta,\lambda} \quad \theta \\ &\text{subject to:} \quad \sum_{j\neq o} \lambda_j x_{ij} \leq \theta x_{io}, \quad \forall i \\ &\qquad\qquad\quad \sum_{j\neq o} \lambda_j y_{rj} \geq y_{ro}, \quad \forall r \\ &\qquad\qquad\quad \lambda_j \geq 0, \quad \forall j \neq o \end{aligned} \tag{4}$$

If $\boldsymbol{\theta} < \mathbf{1}$ → inefficient
If $\boldsymbol{\theta} > \mathbf{1}$ → super-efficient (better than the frontier)

Input-Oriented Slack-Based DEA (CRS) Model (SBM)

$$\begin{aligned} &\rho = \min \left(\frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{io}}}{1 + \frac{1}{s}\sum_{r=1}^{s} \frac{s_r^+}{y_{ro}}} \right) \\ &\text{subject to:} \quad x_{io} = \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- \\ &\qquad\qquad\quad y_{ro} = \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ \\ &\qquad\qquad\quad \lambda_j \geq 0, \quad s_i^-, s_r^+ \geq 0 \end{aligned} \tag{5}$$

where s_i^-: Input slack (extra input)

s_r^+: Output slack (missed output)

x_{ij}, y_{rj}: Inputs/outputs of DMU j

x_{io}, y_{ro}: Inputs/outputs of DMU_0

It should be noted here that this combination of DEA models (CCR+SEM+SBM) used is not entirely original, because it has previously been used to analyse efficiency in certain industries, e.g. brewing (Goncharuk, 2009b) or winemaking (Goncharuk & Figurek, 2017). Although it seems that it is applied for the hospitality industry for the first time.

In DEA, each inefficient country's reference set consists of the efficient countries that form its benchmarking peers. By solving the linear programs, the DEA model yields weight (λ) variables that show how each inefficient country can be represented as a convex combination of efficient ones. This effectively groups each country with "closest" efficient peers. We review these weights to see which efficient countries serve as benchmarks for each inefficient country; this informs realistic targets. For example, if an Eastern European country's references are mainly older EU members, this suggests that raising performance to those standards may require infrastructure or policy shifts. Such peer grouping follows standard DEA practice and was also observed in Soysal-Kurt's (2017) European country study.

Finally, having the results of the analysis according to the three DEA models, the conclusions regarding the efficiency of the hospitality industries of European countries and the opportunities for its improvement can be drawn.

In this study, the decision-making unit (DMU) is defined as each country's national accommodation/hospitality system, i.e., the aggregate production system that transforms accommodation capacity and labour into realised accommodation demand. This macro-level definition is consistent with the general DEA framework, which was originally developed to assess efficiency of decision-making units in public and non-profit program settings and is not restricted to firms (Charnes et al., 1978). It can be acknowledged the standard concern that DEA requires a reasonable degree of homogeneity among DMUs and that environmental differences can be confounded with inefficiency if not addressed (Dyson et al., 2001). To maximise cross-country comparability, we use harmonised Eurostat tourism accommodation statistics: tourist accommodation establishments in the Eurostat scope are classified under NACE Rev. 2 Section I55, and the study relies on Eurostat definitions of bed places (capacity), arrivals, and nights spent in tourist accommodation establishments (Eurostat, 2023).

As methodological mitigations for heterogeneity and scale, we implement a VRS (BCC) DEA model as a robustness check to separate pure technical efficiency from scale effects (Banker et al., 1984), and we outline peer-group restrictions via clustering/categorical DEA to construct more comparable reference sets (Banker & Morey, 1986). Where suitable contextual data are available, we recommend a second-stage approach with proper statistical inference for examining environmental drivers (Simar & Wilson, 2007). We implement both CCR (CRS) and BCC (VRS) DEA models using the same input-output data. The BCC results (efficiency scores and scale-efficiency factors) will be reported alongside the CRS results. This allows us to decompose inefficiency into pure technical vs. scale inefficiency.

3. THE RESULTS

Measuring technical efficiency revealed only two countries on the efficiency frontier out of thirty-five, namely Malta and Iceland, which have the highest efficiency score of 1. Further application of SEM enabled to identify the best of them, namely Iceland, which has a super-efficiency score of 1.203. The full ranking of the sample countries (Table 3) looks like this: 1st place is Iceland with a super-efficiency score of 1.203, second place is Malta with a score of 1.024, third place (already outside the efficiency frontier) is occupied by the Netherlands with a score of 0.997, fourth – Cyprus (0.944), followed by Spain (0.873), Portugal (0.864), France (0.836), etc. The lowest efficiency among the thirty-five countries considered found in Montenegro (0.354), North Macedonia (0.375) and Bulgaria (0.419).

Table 3: **The results of applying DEA models**

Country	CCR TE	BCC TE	Scale Efficiency	RTS	SEM	Input slacks		Output slacks	
						Employed persons	Bed places	Arrivals	Nights spent
Belgium	0.72099	0.73539	0.98042	Decreasing	0.72099	19253	0	6433765	7848583
Bulgaria	0.41787	0.50935	0.82040	Decreasing	0.41787	2661	0	28199853	32976045
Czechia	0.59150	0.77373	0.76448	Decreasing	0.59150	0	6672	25771262	27313106
Denmark	0.81106	0.84618	0.95849	Decreasing	0.81106	9047	0	8312387	3987186
Germany	0.78472	1.00000	0.78472	Decreasing	0.78472	127090	0	91443994	76989409
Estonia	0.72196	0.78140	0.92393	Increasing	0.72196	1994	0	1447002	1897156
Ireland	0.73305	0.73854	0.99256	Decreasing	0.73305	28454	0	11815188	8477124
Greece	0.63285	1.00000	0.63285	Decreasing	0.63285	0	291990	45006496	4691017
Spain	0.87247	1.00000	0.87247	Decreasing	0.87247	135822	0	132049476	42602794
France	0.83622	1.00000	0.83622	Decreasing	0.83622	58036	0	41558483	41339005
Croatia	0.72745	0.75072	0.96900	Decreasing	0.72745	16744	0	13387412	8523913
Italy	0.62911	1.00000	0.62911	Decreasing	0.62911	0	82599	165622499	138084213
Cyprus	0.94358	1.00000	0.94358	Decreasing	0.94358	4545	0	6950021	494229
Latvia	0.67128	0.83017	0.80861	Increasing	0.67128	4405	0	1209864	1642776
Lithuania	0.53109	0.58350	0.91018	Increasing	0.53109	1341	0	2996774	4172010
Luxembourg	0.61801	1.00000	0.61801	Increasing	0.61801	699	0	876737	1157656
Hungary	0.64596	0.64801	0.99684	Decreasing	0.64596	23635	0	12329264	12332482
Malta	**1.00000**	**1.00000**	**1.00000**	**Constant**	**1.02350**	**0**	**0**	**0**	**0**
Netherlands	0.99651	1.00000	0.99651	Decreasing	0.99651	37503	0	3237272	0
Austria	0.75503	1.00000	0.75503	Decreasing	0.75503	0	29104	38208094	21525076
Poland	0.75009	0.75338	0.99563	Decreasing	0.75009	59470	0	18841635	18506126
Portugal	0.86435	0.91234	0.94740	Decreasing	0.86435	39479	0	22255143	8600752
Romania	0.43500	0.53197	0.81772	Decreasing	0.43500	1663	0	23607760	31004300
Slovenia	0.65758	0.65774	0.99976	Increasing	0.65758	6848	0	4148618	3944160
Slovakia	0.49498	0.49542	0.99912	Decreasing	0.49498	15222	0	8642905	10332531
Finland	0.65800	1.00000	0.65800	Decreasing	0.65800	0	30837	3492160	3756408
Sweden	0.75216	1.00000	0.75216	Decreasing	0.75216	3103	0	10108539	13522431
Iceland	**1.00000**	**1.00000**	**1.00000**	**Constant**	**1.20332**	**0**	**0**	**0**	**0**
Norway	0.62839	0.90628	0.69338	Decreasing	0.62839	0	10553	8877620	12865289
Switzerland	0.74913	0.85840	0.87271	Decreasing	0.74913	14130	0	13855684	13505127
United Kingdom	0.49831	0.60953	0.81752	Decreasing	0.49831	71234	0	163419572	184997995
Montenegro	0.35389	0.53036	0.66726	Increasing	0.35389	0	1139	4961821	5858508
North Macedonia	0.37499	0.62781	0.59729	Increasing	0.37499	4213	0	2113610	3029035
Serbia	0.71546	0.75490	0.94776	Increasing	0.71546	17221	0	2411615	2136588
Türkiye	0.73890	0.84906	0.87026	Decreasing	0.73890	195469	0	107575932	80377025
Average or Total	**0.6730406**	**0.79980**	**0.84151**	**0.8415105**	**0.6770585**	**899280**	**452894**	**1031168457**	**828490055**

In the slack-based model, the reported slack values quantify the distance between an observed country (DMU) and its DEA frontier projection. Specifically, input slack indicates an excess amount of an input (e.g., employees, bed places) that could be reduced if the DMU operated efficiently, whereas output slack indicates an output shortfall (e.g., arrivals, nights spent) that would need to be produced to reach the efficient frontier with the given resources. These values are expressed in the original measurement units (persons, bed places, arrivals, nights) and therefore can look numerically large for large countries even when the underlying efficiency gap is moderate in percentage terms (Tone, 2001). Importantly, output slacks should be interpreted as benchmarking gaps rather than forecasts. Under CRS, the frontier permits proportional scaling of efficient benchmark countries. Hence a large country may be projected onto a frontier point implied by scaled-up efficient peers, which can generate sizeable absolute output shortfalls (Banker et al., 1984). For example, Italy's output slacks indicate a substantial relative shortfall versus the frontier in arrivals and nights per employee/bed, and should be read as a signal of underutilized capacity/productivity relative to the benchmark set — not as an operationally feasible one-year increase of that magnitude.

Analysis of the sum of lambda coefficients indicates the returns to scale (RTS) for each country, which on average turned out to be decreasing (0.842). This means that the sample as a whole is dominated by the decreasing RTS, that is, a physical increase in the industry will not bring an increase in its efficiency. Therefore, this suggests that efficiency improvements may require adjustments in the scale and utilization of existing capacities rather than simple expansion. All countries considered were grouped into four groups based on their technical efficiency scores: efficient leaders (bold green), followers (green), medium-performing hospitality industries (brown), and outliers (red). They are highlighted in the appropriate colour in Table 3.

As a robustness check, we re-estimated the DEA using the BCC (variable returns to scale) model. Table 3 compares CRS and VRS efficiency scores for each country. Most countries have VRS ≥ CRS, implying scale inefficiency. For example, Germany has CRS score = 0.78472, VRS score = 1.00000 (Scale Efficiency = 0.78472) that, having decreasing returns to scale (RTS), indicates excess capacity. The table also lists the slack in Labour and Beds from the CRS model. These benchmarks suggest which resources are under-utilized in each system. The comparison between CRS and VRS efficiency scores reveals that a substantial share of inefficiency observed under the CRS model is attributable to scale effects rather than pure technical inefficiency. Several countries (e.g., Germany, Italy, Spain, France) appear fully efficient under the VRS specification but remain inefficient under CRS, indicating that their performance is influenced by suboptimal scale rather than inefficient use of resources. This suggests that CRS-based efficiency rankings may overstate inefficiency in larger hospitality systems and should therefore be interpreted with caution.

Applying the SBM indicated substantial potential input inefficiencies, which on average for the sample amounted to almost 900 thousand employees and over 450 thousand bed places. These correspond to approximately 30% and 2.7% of total inputs, respectively, and should be interpreted as relative benchmarking gaps rather than directly achievable reductions. That is, if there are not so many excess beds, only in 7 countries out of 35, then excess labour exists in most European countries (26 out of 35). Thus, labour adjustment appears to offer the greatest potential for efficiency improvement across the sample. However, applying the performance benchmarking and improvements to current resources suggest that there exist substantial output gaps relative to the efficiency frontier, particularly in terms of arrivals and nights spent. However, these values should be interpreted as model-implied benchmarking gaps rather than feasible short-term increases. In a cross-country context, such magnitudes partly reflect differences in scale, demand conditions, and structural characteristics of national hospitality systems.

The efficiency scores and peer sets should be interpreted as policy benchmarking diagnostics for national accommodation systems, not as direct operational prescriptions for individual hotels. This interpretation aligns with existing tourism literature that benchmarks countries as DMUs using DEA to identify best-practice peers and relative performance gaps (Soysal-Kurt, 2017; Radovanov et al., 2020; Stoiljković et al., 2025).

At the national level, the implicit “decision makers” are ministries and public authorities responsible for tourism and labour policy, national tourism boards, and industry associations — actors that influence demand management, capacity utilisation and workforce productivity through coordinated destination management and tourism policy measures. Accordingly, we focus on comparative signals such as utilisation and productivity intensity (e.g., nights per bed place; arrivals per employee) derived from Eurostat-defined capacity and demand indicators (Eurostat, 2023).

4. DISCUSSION

The results reveal a lot about the efficiency of the European hospitality market. First, they identify two clear leaders in efficiency in the European hospitality market, the best of which is Iceland. This country serves significantly more guests in terms of arrivals number and nights spent per employee and bed place than any of the other 35 countries on the continent. This is the first time that such a result has been obtained. In other pan-European comparisons using DEA, Iceland has either not been included in the sample, e.g. in the tourism efficiency study by Stoiljković et al. (2025), or has also emerged among the leaders, e.g. in the higher education efficiency study by Tóth (2009). This provides some evidence of the high efficiency of this country in various service areas and confirms the value of using SEM and DEA.

Second, a large group of followers was identified, whose efficiency is higher than most other countries in the sample but does not reach the leaders. Among them are mainly large countries with a well-known hospitality background, e.g. the Netherlands, France, Spain, Germany, and Portugal. However, they all have a decreasing effect of scale, which indicates an overheating of their hospitality market, which should reduce the inputs, mostly human one, for efficient development. Countries of this group were found to be efficient in Stoiljković et al. (2025), who assessed the tourism efficiency of European countries using DEA.

Third, a group of efficiency losers has been identified, whose hospitality is the worst among European countries. Some of these countries have a decreasing RTS (Great Britain, Romania, Slovakia, Bulgaria) and the rest have an increasing RTS (Montenegro, North Macedonia and Lithuania). They are extremely far from achieving high relative efficiency, but to improve it they need to reduce and increase their hospitality industries accordingly. These results are partially (for Lithuania, Bulgaria, and North Macedonia) confirmed by Stoiljković et al. (2025) low efficiency scores for the tourism market, but are the opposite for Romania, which there was among the efficient touristic countries.

Our findings align with and extend recent hospitality efficiency research. For instance, Radovanov et al. (2020) found that older EU members (EU15) had higher tourism efficiency than new members and Western Balkans. If our analysis similarly identifies

Western Balkans or new member states as relatively inefficient compared to EU15 benchmarks, this reinforces that pattern. Soysal-Kurt (2017) also found Luxembourg, France, and some other Western European countries at the efficient frontier, while smaller or newer EU countries trailed. Our results echo these high-level patterns, suggesting consistency. Conversely, if any findings diverge (e.g. some new member outperforms an EU15 peer), this would be noteworthy and suggest new competitiveness.

Slack values quantify the model-implied gap between observed performance and a DEA frontier projection, not an immediately achievable operational plan. In country-level hospitality benchmarking, large absolute output slacks can arise for two structural reasons. First, countries differ substantially in scale: because slacks are reported in original units, a large country can show a very large absolute shortfall even when the efficiency gap is moderate in proportional terms. Second, under the CRS assumption, efficient DMUs can be proportionally scaled to form benchmarks for larger DMUs. Thus, a large country may be compared to a frontier point implied by scaled-up "high-output-density" peers (Banker et al., 1984). For example, for Italy, the DEA result does not claim that Italy could "simply handle" 165 million additional arrivals and 138 million additional nights in the next year. Rather, it indicates that, given Italy's labour and bed capacity, its observed arrivals and nights are far below what would be implied if it achieved the frontier's output-per-input performance with a similar output mix. In practice, these benchmarking gaps are influenced by demand constraints, seasonality, destination composition, and measurement aggregation at the national level. Therefore, policy interpretation should focus on relative productivity and utilization (e.g., arrivals per employee, nights per bed, implied occupancy improvements) rather than literal absolute slack magnitudes (Soysal-Kurt, 2017). DEA frontiers can be sensitive to extreme observations. To ensure that large slack values are not artifacts of a single influential DMU, standard practice is to: (i) inspect reference sets (λ-weights), (ii) apply influence/outlier diagnostics and robust frontier methods, and (iii) compare CRS results with VRS/BCC estimates that separate pure technical inefficiency from scale effects (Cazals et al., 2002). In the analysis, we complement absolute slack reporting with relative measures and include robustness checks that constrain peer comparability. This substantially improves the logical interpretability of the slack magnitudes while preserving the main qualitative ranking patterns.

From a capacity perspective, bed places measure accommodation capacity (persons who can stay overnight), and utilization is inherently less than 100% due to seasonality and market conditions. Eurostat occupancy statistics show wide cross-country differences in bed-place occupancy, reinforcing that large "unused capacity" gaps can exist in large markets. The huge reserves of staff reduction and increasing arrivals revealed indicate that in 2023 the European hospitality market had excellent growth prospects and high efficiency potential. However, certain negative phenomena, such as the influx of migrants from the East, e.g. millions of asylum seekers from Ukraine (Goncharuk and Kereziev, 2025), may affect the official statistics of arrivals and nights spent, and unnaturally increase them. Nevertheless, shelter and care for disadvantaged people are also an element of hospitality and an integral part of the European mentality. Thus, during the refugee crisis, ordinary citizens, e.g., across Nordic countries (Koefoed et al., 2021), South Europe (Quagliariello, 2021) took personal responsibility like offering homes, meals, language cafés, and social support as expressions of hospitality grounded in ethical action and shared humanity. However, in practice, certain tensions and conflicting expectations (Challinor, 2018) regarding hospitality sometimes arise. In any case, Eurostat has issued clear guidelines instructing member states to exclude refugees and other humanitarian arrivals from official tourism statistics (Eurostat, 2022). While this is an important step toward ensuring accuracy in tourism benchmarking, its consistent application and verification remain essential, particularly in countries that have experienced sudden surges in arrivals due to crisis events.

The results of this study align with earlier hospitality DEA research showing substantial inefficiencies in resource utilization, particularly labour (Assaf & Agbola, 2017; Vidali et al., 2025). However, while most prior DEA studies focus on hotels or chains at the micro level, our country-level analysis reveals structural inefficiencies on a macro scale, echoing findings in national tourism benchmarking (Barros & Dieke, 2008; Stoiljković et al., 2025). The identification of decreasing returns to scale in most countries suggests that growth alone does not yield proportional efficiency gains, a finding that resonates with recent tourism sustainability studies (Zhang et al., 2023). Moreover, our slack analysis offers quantified performance gaps and policy-relevant benchmarks, contributing to the call for evidence-based tourism governance (Lozano-Ramírez et al., 2023). This study thus extends the literature by demonstrating how DEA can inform national strategies and support sectoral resilience, especially in the post-COVID recovery context. While aggregation has limitations, country-level DEA provides a valuable lens to complement micro-level diagnostics and support cross-national comparisons in hospitality performance.

These results have clear implications for tourism policy and destination management: they identify which resources (labour or beds) are under- or over-utilized in each country, guiding targeted interventions (investment and regulation strategies). For example, a high labour slack suggests workforce adjustments to improve competitiveness. Our findings thus inform policymakers on resource allocation strategies for destination competitiveness. These findings extend previous studies on competitiveness by quantifying efficiency differences at the national level, thus providing a quantitative complement to qualitative destination development research.

Beyond confirming general patterns identified in prior tourism efficiency studies, the present results also reveal important differences. In particular, the finding that several large European countries are efficient under VRS but not under CRS suggests that earlier studies relying solely on CRS assumptions may have overstated inefficiency in large-scale destinations. This highlights the sensitivity of efficiency rankings to model specification and scale assumptions. Furthermore, the integration of slack-based analysis provides more detailed insights into the sources of inefficiency, extending existing approaches that rely primarily on radial efficiency measures. These findings imply that efficiency improvement strategies should distinguish between scale adjustments and productivity enhancements, rather than focusing solely on input reduction.

5. LIMITATIONS AND FUTURE RESEARCH

While this study provides valuable benchmarking insights, several limitations should be acknowledged. We recognise that defining DMUs at the country level introduces heterogeneity in market structure, product mix, accessibility and seasonality. DEA applications should explicitly acknowledge that such environmental variation can bias efficiency estimates if treated as purely discretionary inefficiency (Dyson et al., 2001). For this reason, results are interpreted as relative benchmarking of national accommodation systems built on harmonised Eurostat tourism accommodation measures, rather than as causal statements about managerial quality (Eurostat, 2023). To mitigate comparability and scale concerns, we recommend/implement robustness checks standard in DEA: variable returns to scale and scale decomposition to distinguish pure technical from scale efficiency (Banker et al., 1984), and restricted peer sets via clustering/categorical DEA (Banker & Morey, 1986). To better account for exogenous context, future work can incorporate non-discretionary/environmental variables or apply two-stage DEA with appropriate bootstrap inference (Simar & Wilson, 2007). Finally, Eurostat provides tourism indicators at regional (NUTS) level, enabling future disaggregation from national to regional DMUs to improve homogeneity and managerial relevance (Eurostat, 2026).

CONCLUSION

This study applied DEA to benchmark the efficiency of the hospitality sector across 35 European countries, using bed-place capacity and employment as inputs and tourist arrivals and nights spent as outputs. The approach identified just two countries (Iceland and Malta) on the efficiency frontier, with Iceland achieving the highest score under the super-efficiency model. Most countries exhibited decreasing returns to scale, suggesting that simply expanding labour or bed capacity does not proportionately increase tourism output. DEA slack analysis further revealed substantial benchmarking gaps in both input utilization and output generation. In particular, the results indicate significant relative inefficiencies in labour use and capacity utilization across countries. However, these magnitudes should be interpreted as model-implied gaps with respect to the efficiency frontier rather than as directly achievable operational adjustments.

The findings underscore the value of DEA as a strategic benchmarking tool and highlight the need for smarter resource management and workforce optimization in the sector. While the macro-level perspective offers useful policy insights, it also has limitations: aggregating diverse regional and operational contexts into national DMUs may mask important nuances. Future research should therefore incorporate panel data, multi-stage DEA models, or additional sustainability indicators to capture dynamic and qualitative dimensions of performance. Despite these caveats, the present analysis demonstrates that country-level DEA can illuminate significant efficiency gaps and inform targeted strategies for improving hospitality competitiveness across Europe.

Importantly, the reported slack values should be interpreted as benchmarking gaps relative to the DEA frontier rather than as immediate operational targets. The differences between CRS and VRS efficiencies indicate the role of scale effects in shaping performance, but translating these insights into policy requires additional feasibility and context-specific analysis.

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