Decoding Hotel Ratings: A Cultural and Developmental Lens on Traveler Behavior

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Abstract

Using a large dataset of 545,000 reviews from 27,000 hotels, this study investigates how travelers' nationalities influence hotel review ratings and their relationship with cultural dimensions and human development indicators. The presented analysis shows that hotel ratings can serve as predictors of components of the Human Development Index, with the Education Index showing the strongest association (adjusted R^2 is 42.6%). The predictive power of hotel ratings was also compared to Hofstede's dimensions in the context of predicting Human Development Index components.

In terms of Hofstede's dimensions we discovered that "Individualism vs Collectivism" and "Long-Term Orientation" dimensions exhibit the strongest associations with hotel ratings (adjusted R^2 is 44.9% and 30.1% correspondingly), though the study's focus on European hotels may limit generalizability.

In terms of rating patterns, English-speaking countries and Israel use narrower score ranges with higher means (8.66 ± 1.46), while predominantly Muslim countries employ wider ranges, resulting in lower means (7.96 ± 1.79). European and Asian countries generally fall between these extremes.

The paper concludes with practical implications of the presented findings to the tourist recommender systems.

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1 Introduction

In an increasingly interconnected world, online reviews have become a critical component in shaping travelers' decisions and perceptions, particularly in the hospitality sector. Platforms such as Booking.com, TripAdvisor and Agoda changed how travelers choose accommodation, with hotel ratings and reviews often serving as the main determinants of reservations Chrysanthos Dellarocas (2007); Ye, Law, and Gu (2009); Öğüt and Tas (2012).

Although service quality traditionally drives hotel ratings, research increasingly shows that cultural factors, particularly reviewer nationality and background, significantly influence these ratings. Despite this recognition, there has been limited comprehensive analysis that examines how cultural dimensions and human development indicators collectively impact hotel ratings.

Understanding these relationships has practical implications for the hospitality industry. Firstly, it can help platforms develop more nuanced rating systems that account for cultural variations. Secondly, it can help hoteliers tailor their services to diverse international guests. Finally, it can improve the accuracy of recommendation systems by considering cultural and developmental factors in their algorithms. These insights are particularly valuable as global tourism continues to grow and diversify.

1. *How does the nationality influence hotel ratings*?
2. *What is the relationship between hotel ratings and the components of Human Development Index*?
3. *How do hotel ratings compare to Hofstede dimensions in predicting Human Development Index*?
4. *Can hotel ratings predict Hofstede's cultural dimensions*?
5. *How does controlling for socioeconomic factors (e.g. HDI) affect the predictive relationship between hotel ratings and Hofstede's cultural dimensions?*

We address these questions using Booking.com hotel ratings data, Hofstede's cultural dimensions data, and `HDI` data. The analysis employs clustering analysis, Principal Component Analysis, and regression analysis. However, since the study focuses primarily on hotels in European countries, the generalizability of our findings to other regions may be limited.

2 Literature Review

Several studies have explored the relationship between cultural traits and online hotel ratings. Mariani and Predvoditeleva (2019) demonstrated that the cultural traits of online reviewers could influence hotel ratings, particularly in the Muscovite hotel sector. Similarly, Phillips, Antonio, de Almeida, and Nunes (2020) found that geographic and psychic distances between the travelers' home countries and the hotel location can influence their satisfaction levels and ratings. In addition, Ayeh, Au, and Law (2016) and Tseng (2017) have investigated the cross-national heterogeneity and the role of seller ratings in shaping tourist satisfaction, highlighting the complex interaction between cultural background and perceived service quality. Antonio, de Almeida, Nunes, Batista, and Ribeiro (2018) conducted a comprehensive analysis of hotel reviews in Portugal and found that English-speaking guests consistently gave higher ratings compared to Spanish and Portuguese reviewers, while also revealing distinct preferences in their textual feedback about hotel amenities and services. Further evidence of cultural differences in hospitality experiences is provided by Fam, Cheng, Cham, Yi, and Ting (2021), who found significant variations between Asian and Western tourists in how relationship marketing efforts influence perceived service quality and how satisfaction translates into loyalty. However, most existing studies focus on single country analyses or specific cultural contexts, leaving a gap in understanding how these factors influence hotel ratings across multiple countries.

To understand cultural influences on hotel ratings, we use cultural dimensions provided by Hofstede (2011), a widely recognized framework in cross-cultural research. Hofstede's model identifies six dimensions or indexes: power distance `PDI`, individualism versus collectivism `IDV`, masculinity versus femininity `MAS`, uncertainty avoidance `UAI`, long-term versus short-term orientation `LTO`, and indulgence versus restraint `IND`, which describe the effects of a society's culture on the values of its members. These dimensions have been used extensively to analyze cultural differences in various fields, including consumer behavior and service evaluations. Although the model has faced criticism for its simplicity and reliance on outdated data Hampden-Turner and Trompenaars (1997); Orr and Hauser (2008), it remains a relevant tool for understanding the cultural basis of tourist behavior.

In addition to cultural factors, socioeconomic factors have been extensively studied in the context of tourism. Previous research has primarily examined how the socioeconomic development of a destination country influences tourism growth and satisfaction Cárdenas-García, Brida, Alcalá-Ordóñez, and Segarra (2024); Chattopadhyay, Kumar, Ali, and Mitra (2021). In contrast, our study shifts the focus to the tourists themselves, specifically exploring how the `HDI` (Human Development Index) of a tourist's home country relates to their perceptions and evaluations of destinations. Tourists from countries with higher `HDI` may have different standards for accommodation, service quality, and overall travel experience due to their exposure to higher living standards, better education, and potentially more travel experience. In contrast, tourists from countries with lower `HDI` might have different baseline expectations or may be more appreciative of certain amenities. By exploring this relationship, we aim to understand how a traveler's home country development level might influence their evaluation of hotel experiences abroad.

Based on the literature review, we propose four research hypotheses:

H1: The nationality of hotel guests significantly influences the overall ratings they give to hotels. Gao et al. (2018); Mariani and Predvoditeleva (2019); Phillips et al. (2020) demonstrated this effect in single-country studies; we extend this to a multi-country analysis.

H2: There is a significant relationship between hotel ratings and the components of `HDI`. While Cárdenas-García et al. (2024); Chattopadhyay et al. (2021) examined tourism's impact on destination development, we uniquely investigate how tourists' home country development levels influence their rating behavior.

H3: Hotel ratings are as effective as, or more effective than, Hofstede's cultural dimensions in predicting the `HDI` of a country. Building on connection of cultural dimensions to satisfaction made by Reisinger and Turner (2002) and work of Rivera (2017) on development-tourism synergies, we compare the predictive power of behavioral data (ratings) versus cultural frameworks.

H4: Hotel ratings can predict Hofstede's cultural dimensions for different countries. Findings on cultural influences made by Leon (2019); Nath et al. (2016); Songshan (Sam) Huang (2019) suggest rating patterns might serve as proxies for underlying cultural dimensions.

Table 1: Hofstede's cultural dimensions' impact on hotel ratings

Dim.	**Definition**	**Expected Impact on Ratings**	**Key Studies**
`PDI`	Acceptance of unequal power distribution in institutions and organizations	Higher PDI leads to more moderate ratings and less detailed feedback due to reluctance to criticize authority	Gao, Li, Liu, and Fang (2018); Mariani and Predvoditeleva (2019); Reisinger and Turner (2002)
`IDV`	Degree to which people are integrated into groups vs. emphasis on individual achievement	Higher IDV associated with more generous ratings when personal expectations are met; greater emphasis on individual experience	Sauer, Sonderegger, and Álvarez (2017); Torres, Fu, and Lehto (2014)
`MAS`	Preference for achievement and assertiveness vs. cooperation and quality of life	Higher MAS linked to lower ratings due to higher expectations and more critical evaluation standards	Nath, Devlin, and Reid (2016); Song, Moon, Chen, and Houston (2017)
`UAI`	Society's tolerance for ambiguity and uncertainty	Higher UAI correlates with greater deviation from average ratings and more detailed critical feedback	Leon (2019); Reisinger and Turner (2002)
`LTO`	Focus on future rewards vs. immediate gratification	Higher LTO associated with more critical ratings focusing on long-term improvement potential	Chen, Cheung, and Law (2012); Mariani and Predvoditeleva (2019)
`IND`	Allowing relatively free gratification vs. controlling gratification through strict social norms	Higher indulgence leads to greater rating variance and more extreme ratings	Songshan (Sam) Huang (2019)

H5: Controlling for socioeconomic factors (e.g., HDI) will alter the predictive relationship between hotel ratings and Hofstede's cultural dimensions, indicating that some cultural dimensions are influenced by socioeconomic development while others are independent of it.

3 Methods

3.1 Data

This study utilizes four primary datasets:

Hotel ratings Dataset 1 is *"515k Hotel Reviews Data in Europe"* and consists of hotel ratings on Booking.com. The dataset is obtained from Kaggle and contains 515,000 ratings of 1493 hotels across Austria, France, Italy, The Netherlands, Spain, the UK. The ratings were collected during the period of 2015/08/04 to 2017/08/03. In total, travelers of 226 nationalities booked hotels within this period.

Hotel ratings Dataset 2 is *"marketing sample for booking.com"* also sourced from Kaggle and consists of hotel ratings on Booking.com. The dataset contains 30,000 ratings of 26,212 hotels. Overall, travelers of 10 nationalities across 110 countries booked hotels within the period of 2019/05/01 to 2019/06/30. It is worth mentioning that no explicit country of hotels nor the nationality of travelers that booked the hotels was provided. The details on the preprocessing steps to extract this information are given in the next subsection. In total, hotel guests of 106 nationalities booked hotels within this period. The use of this dataset was limited due to rating sparsity.

Human Development Index Dataset was retrieved from humdata.org and includes Human Development Index (`HDI`), Life expectancy at birth (`LEaB`), Expected years of schooling (`EYoS`), Mean years of schooling(`MYoS`), Gross national income per capita (`GNI`), GNI per capita rank minus `HDI` rank. Using this information Life Expectancy Index (`LEI`), Education Index (`EI`), and Income Index (`II`) were computed as follows

$$
\begin{aligned}
\texttt{LEI} &= \frac{\texttt{LEaB} - 20}{65} \\
\texttt{EI} &= \frac{\texttt{MYoS}}{15} + \frac{1}{2}\frac{\texttt{EYoS}}{18} \\
\texttt{II} &= \frac{\log(\texttt{GNI}) - \log(100)}{\log(750)} \\
\texttt{HDI} &= \sqrt[3]{\texttt{LEI} \cdot \texttt{EI} \cdot \texttt{II}}
\end{aligned}
$$

Hofstede's Cultural Dimensions Theory Cultural dimensions data was obtained from theculturefactor.com.

3.2 Preprocessing

Both datasets are sparse, and many pairs (Nationality, Hotel-Country) either have zero hotel ratings or the number is insufficient for conducting any analysis. To exclude pairs with a small number of ratings in dataset #1, the threshold value of 32 was chosen, and hence a pair with fewer ratings was zeroed. For dataset #2, which gives a much smaller overall number of ratings, the threshold value was set to 16. In addition, nationalities and countries that had more than 3 missing pairs with insufficient ratings were completely excluded.

Dataset #1 does not need any additional preprocessing as it contains both *"Hotel Address"* column, which was used to extract the country, and *"Reviewer Nationality"*. Dataset #2 does not explicitly provide this information, but it contains such columns as *"HotelUrlFromSource"*, and *"ReviewUrl"*. The URLs in both columns implicitly contains country codes that allowed us to extract the reviewer's country which was assumed to be the tourist's nationality and the hotel's country. Furthermore, because the records had missing fields, only 8694 ratings were successfully extracted.

3.3 Analytical Methods

Our analysis employed four main techniques: (a) Spectral clustering to identify patterns in rating behavior across nationalities. (b) Principal Component Analysis for dimensionality reduction.(c) Multiple regression analysis with ANOVA testing for relationship validation. (d) t-SNE visualization for high-dimensional data representation.

4 Results

We analyzed cultural biases in hotel ratings through visualization and statistical analysis of ratings across different nationalities and hotel locations. Fig. 1 presents average ratings, rating variability, and rating frequency across different nationality-hotel country pairs.

4.1 Cultural Bias

4.1.1 Clustering Analysis of Hotel Ratings

Preliminary analysis of the hotel ratings (Fig. 1-left pane) revealed distinct rating patterns across cultural groups: English-speaking countries and Western European nations (e.g., USA, Australia, Israel, France, Germany) tend to give higher ratings with less variance, while predominantly Muslim countries (e.g., Oman, Egypt, Iran, UAE) utilize the full rating spectrum, resulting in lower average ratings (Fig. 2).

To further investigate whether hotel scoring behavior varies across countries and whether some nationalities form clusters in terms of scoring behavior, we performed spectral clustering. This method was introduced by Von Luxburg (2007). In addition to discovering similarities between scoring behavior of different nationalities, this would also allow us to investigate the cultural commonalities of the discovered groups.

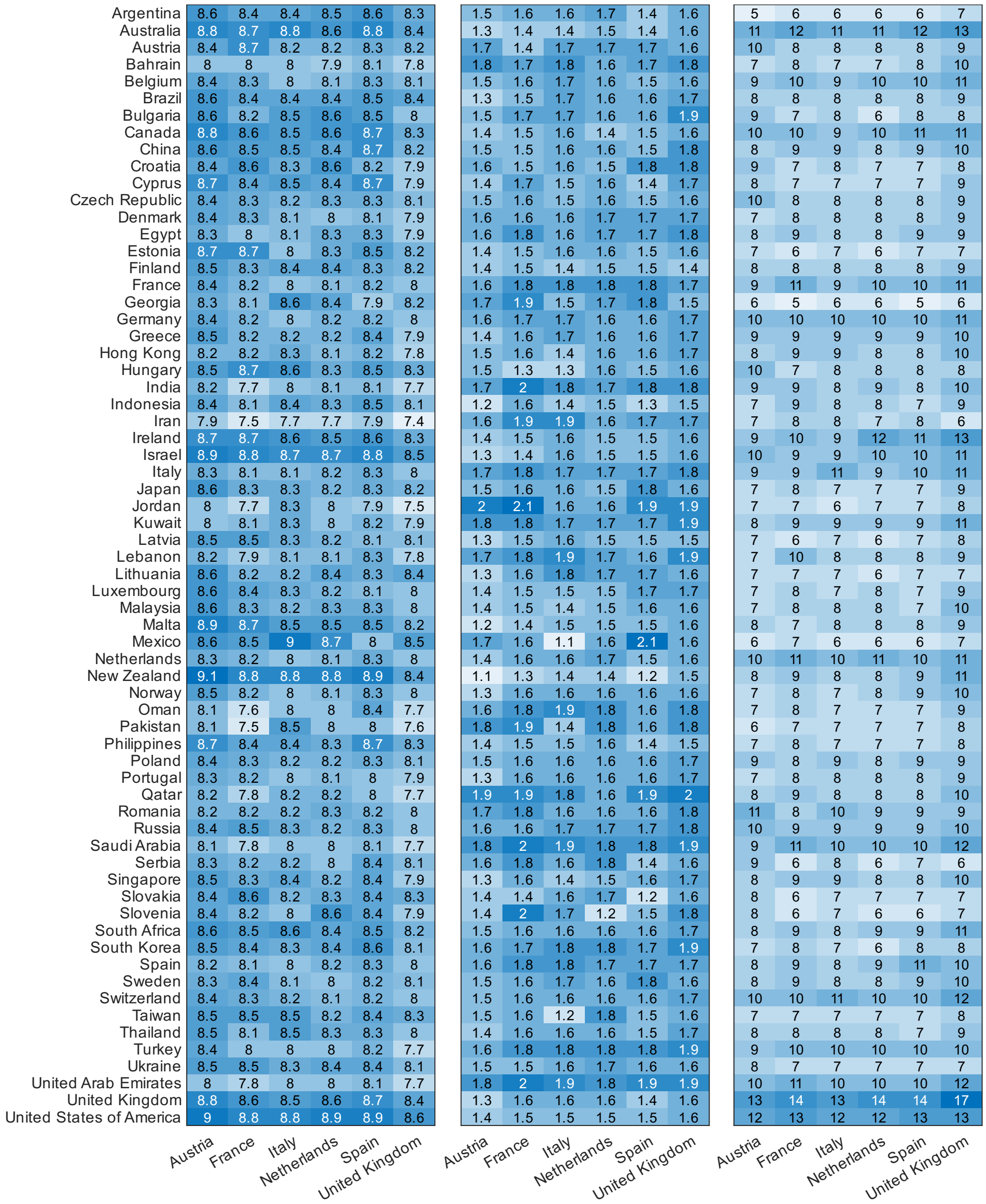
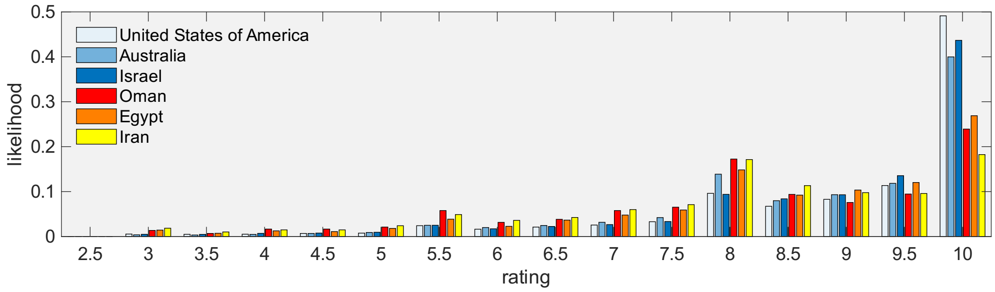
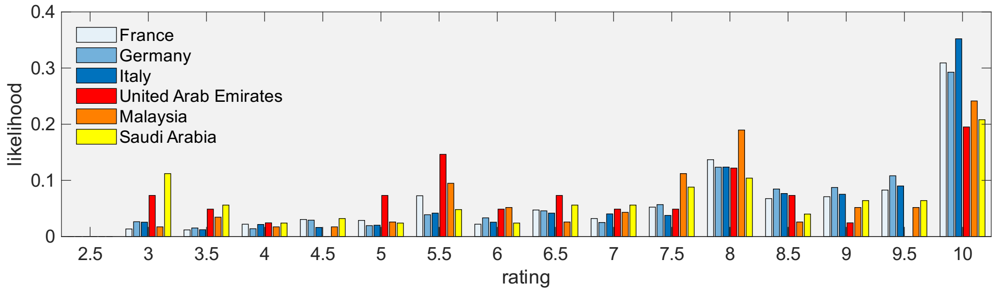


Fig. 1: x-axis represents a nationality and y-axis a hotel's country for dataset #1. Left: average ratings. Middle: ratings standard deviations. Right: number of ratings in `log` base 2.



(a) Dataset 1



(b) Dataset 2

Fig. 2: Normalised histogram of total ratings for selected nationalities

The clustering was performed on vectors that constitute average ratings by tourists of each nationality, represented by rows in Fig. 1-left pane. We used a standardised Euclidean distance as a similarity measure. The resultant clusters of hotel ratings are shown in Fig. 3-top. The countries that fell in each of the four clusters are listed in the Tab. 4.

Cluster 1 contains 29 home countries, of which 9 are in Asia. This cluster encapsulates all Asian countries presented in the dataset, except Hong Kong, which fell into Cluster 3. Of the remaining 20 countries in this cluster, 16 are European, 3 are in South America, and the last one is South Africa. Given the dominance of European and Asian countries in this cluster, it is labeled `E. & A.` in Tab. 6.

Cluster 2 contains 12 countries, all except India are Arab countries or predominantly Muslim. We label this cluster `M.` for Muslim.

Cluster 3 contains 17 countries, of which 15 are European and the remaining two are Egypt and Hong Kong. We label this cluster `E.` for European. The last cluster consists of 8 countries and all of them are English speaking except Israel, and so we label this cluster `Eng.`

Clusters 1 and 3 have significant overlap in terms of European nations, however, Cluster 1 also strongly emphasizes on Asian countries. Clusters 2 and 4 have a very different cultural background.

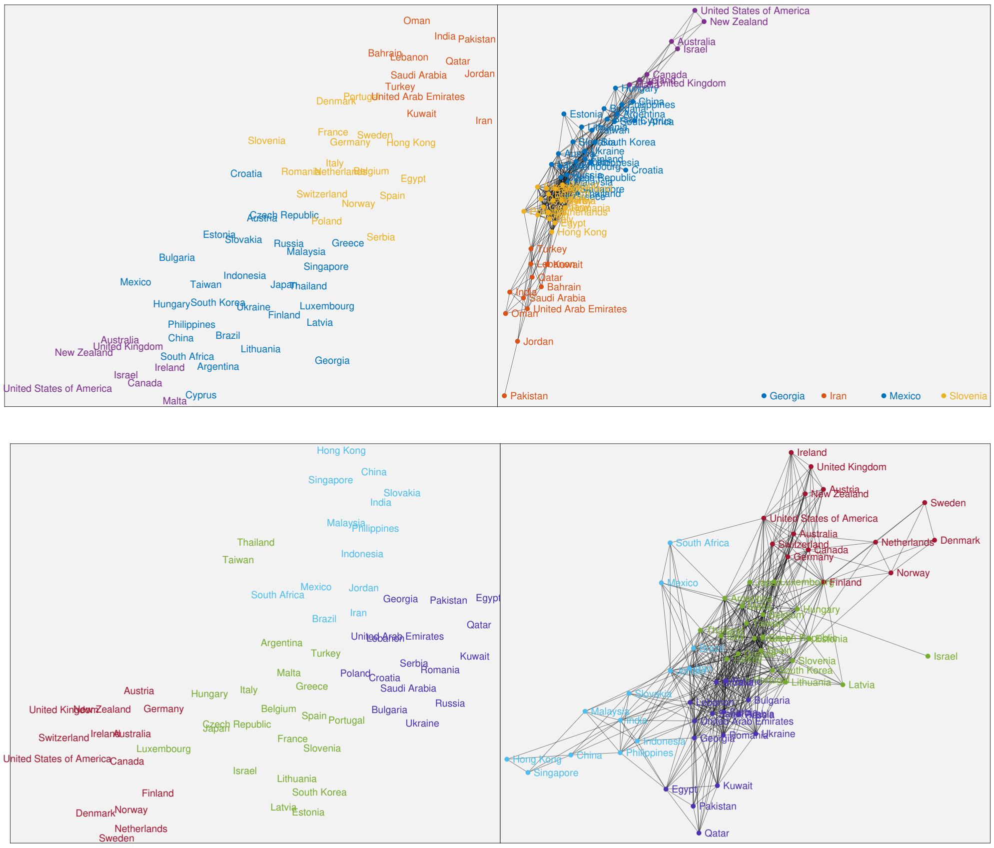


Fig. 3: tSNE visualisation: (top row) Clustering of hotel ratings' provided by travelers of different nationalities. (bottom row) Clustering of 6-dimensional Hofstede score vectors representing different nationalities.

Clearly, Fig. 3-top illustrates and supports the hypothesis that hotel ratings reflect cultural background, while socioeconomic component needs to be studied separately and discussed blow.

4.1.2 Comparison of Means and Standard Deviations

However, the scoring bias does not tell the full story, since it could be a result of not just having a different mean but also a different standard deviation. In other words, travelers from some countries might be more critical and take advantage of a wider range of ratings, rather than scoring all hotels on a narrow range of ratings with the same or a higher mean, the latter was already evident in Fig. 2. To further confirm this, for all countries in each of the discovered clusters, we take the mean ratings (Fig. 1-left pane) and the standard deviation (Fig. 1-middle pane) and plot these values on a 2D coordinate plane (Fig. 4). The means and standard deviations are plotted separately

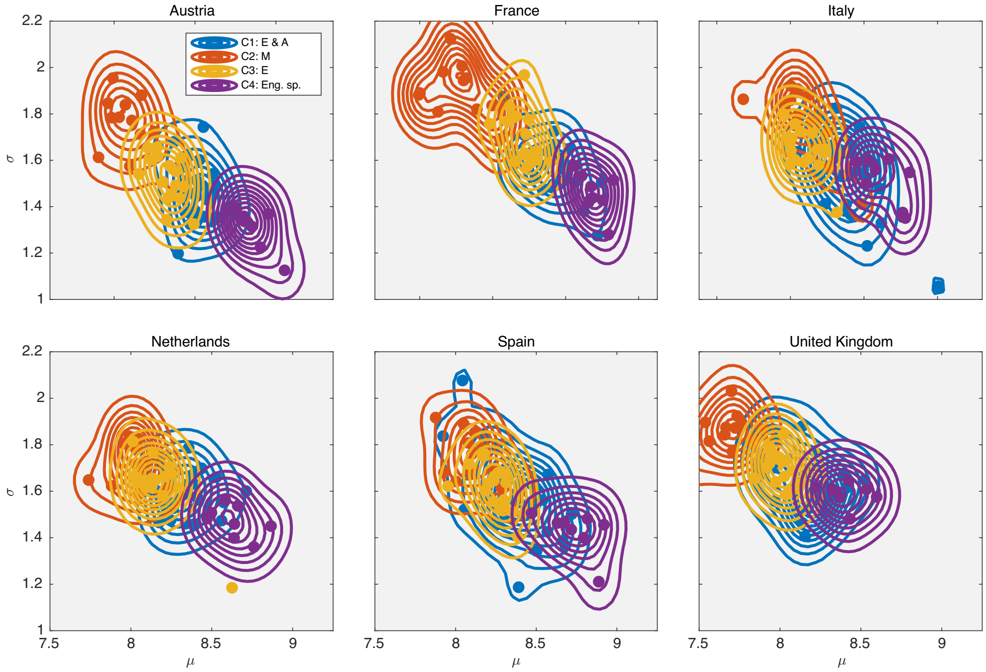


Fig. 4: x and y axis are the mean μ and standard deviation σ of hotel ratings given by travelers of certain nationality, while colours encode the clusters (see text) and each of the six panes correspond to the destination country. The colours represent the earlier discovered clusters and consistent with Fig. 3-top. Each cluster denoted by letter `C` followed by letters: `A` for Asia, `M` for Muslim, `Eng.` for English speaking countries and `E.` for broadly European, which represent the most dominant common cultural factor of a given cluster.

for each destination country. Table 2 reports the mans and standard deviations for each cluster per each destination country. From a visual inspection, it is easy to see that each cluster is categorized not only by its own mean, but also by its own value of standard deviation. For example, English-speaking countries tend to have a higher mean and less variability and, since they are also associated with a higher score, less critical (8.66 ± 1.46). However, countries with a predominantly Muslim population exhibit greater variability in ratings, implying that they are more critical (7.96 ± 1.79).

This observation further supports the hypothesis of the existence of cultural bias in hotel ratings.

4.2 Normalization Analysis

To isolate different effects in rating patterns, we performed three types of normalization: *Nationality bias normalization*, removes systematic rating tendencies of different nationalities (Fig. 6-left pane). *Country attractiveness normalization*, accounts for overall popularity or quality differences between destination countries

Table 2: Mean (μ) and standard deviation (σ) of hotel ratings by clusters for each destination Country

Country	C1 (E & A)	C2 (M)	C3 (E)	C4 (Eng.)
Austria	8.53 ± 1.46	8.09 ± 1.75	8.33 ± 1.52	8.86 ± 1.31
France	8.40 ± 1.56	7.78 ± 1.90	8.20 ± 1.69	8.69 ± 1.46
Italy	8.38 ± 1.54	8.09 ± 1.77	8.09 ± 1.64	8.64 ± 1.51
Netherlands	8.34 ± 1.60	8.00 ± 1.72	8.17 ± 1.63	8.64 ± 1.47
Spain	8.37 ± 1.58	8.11 ± 1.75	8.24 ± 1.61	8.74 ± 1.43
United Kingdom	8.14 ± 1.64	7.68 ± 1.86	8.0 ± 1.70	8.40 ± 1.60
Average per cluster	8.36 ± 1.56	7.96 ± 1.79	8.17 ± 1.63	8.66 ± 1.46

(Fig. 6-middle). Lastly, *combined normalization*, addresses both nationality bias and country attractiveness simultaneously (Fig. 6-right pane).

The normalizations revealed three key patterns. Firstly, general destination preferences, for example, the UK consistently received lower ratings across nationalities compared to Austria and Spain, possibly due to factors such as hospitality standards, language barriers, or weather conditions. Secondly, persistent cultural biases, as certain nationalities maintained consistent rating patterns even after normalization. Travelers from Iran, Egypt, and Oman consistently provided more critical ratings, while those from Israel, USA, and Australia tended toward more positive ratings. Lastly, political-cultural sentiment, for example, the combined normalization (Fig. 6-right pane) revealed rating patterns that may reflect international relations. Iranian travelers rated Spanish hotels significantly higher than other destinations, aligning with the documented friendly diplomatic relations between these countries ("Spain is considered in Iran as a friendly country and one of the countries of the European Union with a better image").

Furthermore, such normalizations allow us to account for the perception of ratings that might vary from country to country where hotels are located. For example, a score of 8 out of 10, considered excellent by reviewers of some nationalities, while among the travelers of other nationalities, an 8 might be just an average.

4.3 Hotel ratings and Hofstede's 6-dimensional model

4.3.1 Matching Hotel Score Clusters with Cultural Dimension Clusters

To investigate the connection between hotel ratings and Hofstede's 6-dimensional model, we performed clustering analysis on countries of origin represented by 6-dimensional vectors.

This analysis serves two primary purposes: first, it allows us to examine whether countries that cluster similarly based on hotel ratings also share similar cultural characteristics as defined by Hofstede's dimensions. Second, it helps us assess whether hotel rating patterns could potentially serve as a proxy for deeper cultural traits. By comparing these two clustering results, we aim to uncover potential links between observable tourist behaviors (as reflected in hotel ratings) and the underlying cultural values.

It is important to note that of all 66 countries available in Dataset #1, we were able to obtain Hofstede's dimensions for 63 countries from theculturefactor.com, with Bahrain, Oman, and Cyprus being missing. The results of clustering are shown in Fig. 3-bottom and Tab. 5. The clustering resulted in the following four clusters.

Cluster 1 consists of 21 countries, of which 15 are in Europe. We label this cluster `E.` in Tab. 6.

Cluster 2 consists of 13 countries, of which 7 are in Asia. Given that most are in Asia, we label this cluster `A`.

Of the 14 countries in cluster 3, all are Central / North European or English speaking countries, so we label this cluster with `Eng. & N.E.`

Finally, in cluster 4 out of 15 countries, 8 are Eastern European and 7 are predominantly Muslim countries, hence we label it as `M & E.E.`

To compare whether hotel ratings and Hofstede dimensions-based clustering reflect similar cultural traits, we counted the number of matched pairs of countries between all pairs of clusters in the Tab. 4 (Fig. 3)-top and the clusters in Tab. 5 (Fig.3)-right. The number of countries in the intersected set was divided by the number of countries in the smallest cluster of the two intersecting clusters. Table 6 presents the corresponding intersection ratios and the number of countries present in both clusters. The largest intersection (69 %) for cluster 1 based on hotel ratings with clusters based on Hofstede's dimensions is cluster 2. The countries that appeared in both clusters are China, Indonesia, Malaysia, Philippines, Singapore, Slovakia, South Africa, Mexico, and Brazil. The largest intersection for hotel score-based cluster 2 is Hofstede dimension-based cluster 4, with the countries appearing in both clusters being Kuwait, Lebanon, Pakistan, Qatar, Saudi Arabia and United Arab Emirates. The largest intersection for rating-based Cluster 3 is Hofstede dimension-based Cluster 1 with the countries appearing in both cluster being Belgium, France, Italy, Portugal, Slovenia, Spain. The highest intersection for cluster 4 based on the hotel score is the Hofstede dimension-based cluster 3, which includes Australia, Canada, Ireland, New Zealand, the United Kingdom and the United States of America. In total, 27 countries out of 63 countries for which Hofstede's dimensions were available were matched across the hotel score-based clustering and Hofstede's dimensions clustering. The aforementioned groups of countries, represent the countries that are both similar from cultural perspective and in terms of hotel scoring behaviour. The intersection of score-based cluster 1 consists of mostly Asian countries. Score-based cluster 2 contains countries with the majority of Muslim population, and score-based cluster 3 consists of central Europe. Finally cluster 4, consists of English-speaking countries that have historical ties to the British Empire. This illustrates a connection between the hotels' ratings left by hotel guests of certain nationalities and their countries' Hofstede's dimensions.

4.3.2 Hotel Ratings as a Proxy for Cultural Dimensions

Another approach to investigate the relationship between hotel ratings and cultural dimensions is to test whether all six or at least some of the Hofstede's dimensions

Indexes	Adjusted R^2	F-statistic	p-value
`PDI`	9.2%	2.2	6.1×10^{-2}
`IDV`	44.9%	11.1	$\mathbf{1.7 \times 10^{-7}}$
`MAS`	13.9%	1.8	1.2×10^{-1}
`UAI`	0.0%	1.0	4.4×10^{-1}
`LTO`	30.1%	6.3	$\mathbf{9.6 \times 10^{-5}}$
`IND`	16.1%	3.3	$\mathbf{9.7 \times 10^{-3}}$

Table 3: The linear relationship between PCs of hotel ratings and the Hofstede's dimensions. Columns adjusted R^2, F-statistic and p-value are ANOVA factor values.

can be predicted by hotel ratings. Prior to fitting predictive models, we explore the relationship between hotel ratings left by hotel guests from each country. To do so, we apply Principal Component Analysis (PCA) to the hotel ratings, which allows us to measure the linear dependence of each column (hotel's country). PCA results in `77.9, 9.3, 5.9, 3.0, 2.6, 1.9` that is the percentage of the total variance explained by each of the corresponding principal component (`PC`). As can be seen, the first principal component ($\mathtt{PC}_1$) explains 78% of variance. One possible explanation for such high value is the fact that all six countries are located in Europe. For further analysis, we selected the first five principal Components (PCs) ($\mathtt{PC}_1, \mathtt{PC}_2, \mathtt{PC}_3, \mathtt{PC}_4, \mathtt{PC}_5$) of hotel ratings, and fit a linear regression model of the following form

$$y \sim w_0 \cdot 1 + w_1 \cdot \mathtt{PC}_1 + w_2 \cdot \mathtt{PC}_2 + w_3 \cdot \mathtt{PC}_3 + w_4 \cdot \mathtt{PC}_4 + w_5 \cdot \mathtt{PC}_5$$

Of six models (Fig. 5), three models (`IDV`, `LTO`, and `IND`) are significant (Tab. 6), while three models (`PDI`, `MAS`, and `UAI`) failed the test. The models predicting `IDV` and `LTO` reached the highest explainability of 44.9% and 30.1% correspondingly, illustrating that hotel ratings could be used as proxy for at least some cultural dimensions. However, at this point, it is also important to reiterate that hotel ratings for only 6 destination countries in Europe might not be enough to draw the conclusion and more variability in countries and a higher number of countries is required.

4.4 Hotels Ratings and Education, Life Expectancy and Income Indexes

Finally, we turn our attention to investigating whether there is a relationship between hotel ratings and the development of the guest's home country. In other words, our aim is to study the impact of hotel score on the level of country's prosperity if the ratings are treated as a proxy for culture. Travelers from wealthier countries with better education and healthcare might give higher ratings because they may feel more satisfied and happier in life. `HDI` serves as a summary measure of average achievement in key dimensions of human development, i.e. a long and healthy life, being knowledgeable and having a decent standard of living and hence serves as a measure the countries' "wealthiness" that we use to related to hotels' ratings. `HDI` as mentioned earlier consists of three factors: `LEI`, `EI`, and `II` that is computed directly from

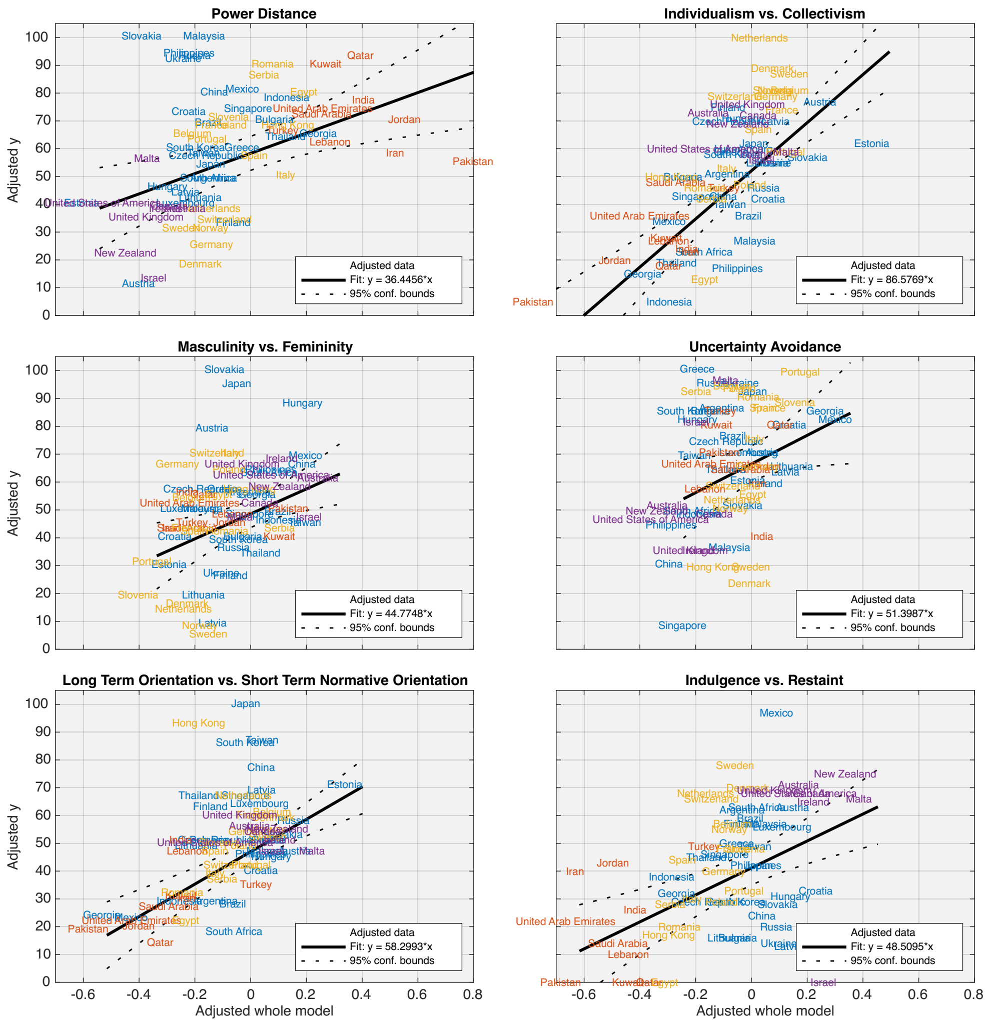


Fig. 5: Added variable plot for whole model based on PCs of values of hotels ratings for Hofstede dimensions: `PDI` (top-left), `IDV` (top-right), `MAS` (mid-left), `UAI` (mid-right), `LTO` (bottom-left), `IND` (bottom-right). y-axis is in the range of [0, 100] in all four panes. The colours represent the earlier discovered clusters and consistent with Fig. 3-bottom.

the the gross national income, whereas `HDI` is the geometric mean of these three factors as described in section Methods. Fig. 7 presents a chart of `HDI` and its constituents in 2014.

Similarly to earlier regression analysis, we selected the first five PCs ($\mathtt{PC}_1, \mathtt{PC}_2, \mathtt{PC}_3, \mathtt{PC}_4, \mathtt{PC}_5$) of hotel ratings, and fit a linear regression model of the following form

$$y \sim w_0 \cdot 1 + w_1 \cdot \mathtt{PC}_1 + w_2 \cdot \mathtt{PC}_2 + w_3 \cdot \mathtt{PC}_3 + w_4 \cdot \mathtt{PC}_4 + w_5 \cdot \mathtt{PC}_5$$

The models' parameters $w_0, w_1, w_2, w_3, w_4, w_5$ are solved for, in fitting for `LEI`, `EI`, `II`, and `HDI`. The resultant ANOVA statistics are shown in Tab. 7 (top four rows).

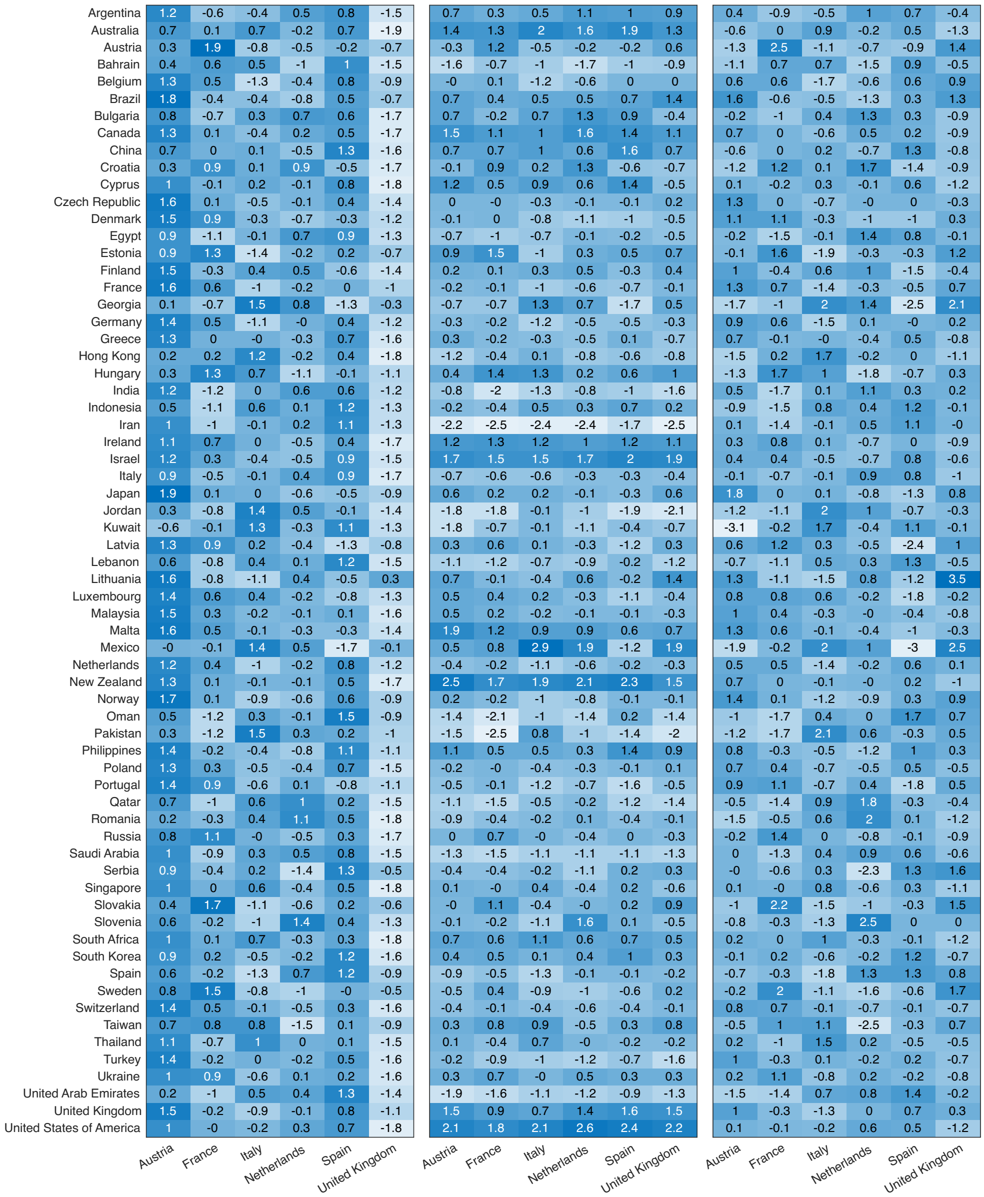


Fig. 6: Average ratings acquired from dataset #1. x-axis represents a nationality and y-axis a hotel's country. Left: normalised w.r.t guest's nationality. Middle: normalised w.r.t hotel's country. Right: normalised both w.r.t nationality and w.r.t hotel's country.

Cluster 1	Cluster 2	Cluster 3	Cluster 4
Argentina	Bahrain	Belgium	Australia
Austria	India	Denmark	Canada
Brazil	Iran	Egypt	Ireland
Bulgaria	Jordan	France	Israel
China	Kuwait	Germany	Malta
Croatia	Lebanon	Hong Kong	New Zealand
Cyprus	Oman	Italy	United Kingdom
Czech Republic	Pakistan	Netherlands	United States of America
Estonia	Qatar	Norway	
Finland	Saudi Arabia	Poland	
Georgia	Turkey	Portugal	
Greece	United Arab Emirates	Romania	
Hungary		Serbia	
Indonesia		Slovenia	
Japan		Spain	
Latvia		Sweden	
Lithuania		Switzerland	
Luxembourg			
Malaysia			
Mexico			
Philippines			
Russia			
Singapore			
Slovakia			
South Africa			
South Korea			
Taiwan			
Thailand			
Ukraine			

Table 4: Hotel ratings based clustering w.r.t guests' nationality.

All four linear regression models are overall statistically significant (Fig. 9), suggesting that these PCs collectively explain a significant portion of the variability in `HDI` as well as in each of its constituents. Of the four indexes, `EI` explains 42.6% of variability, demonstrating a strong connection between hotel ratings left by travelers and the `EI` associated with their nation. `HDI`, being second best index, only explaining 24.0%.

The above modeling is repeated for ratings normalised with respect to home country (Fig. 6 (left)). The normalisation aims to remove the nationality-related bias. Similarly, to mitigate the collinearity of the ratings in these 6 countries, a PCA is applied that resulted in the following percentage of the total variance explained by each principal component: `39.41, 25.53, 16.47, 9.89, 8.69, 0.00`. The first five PCs were selected. Surprisingly, even after compensating for the differences in scoring bias (mean) and criticality (standard deviation), the four models (Fig. 9) still remained significant (Tab. 7 (bottom four rows)). Similarly, among the four indexes, `EI` still explained the most variability (35.5%), with `HDI` explaining 23.8%.

Cluster 1	Cluster 2	Cluster 3	Cluster 4
Argentina	Brazil	Australia	Bulgaria
Belgium	China	Austria	Croatia
Czech Republic	Hong Kong	Canada	Egypt
Estonia	India	Denmark	Georgia
France	Indonesia	Finland	Kuwait
Greece	Iran	Germany	Lebanon
Hungary	Jordan	Ireland	Pakistan
Israel	Malaysia	Netherlands	Poland
Italy	Mexico	New Zealand	Qatar
Japan	Philippines	Norway	Romania
Latvia	Singapore	Sweden	Russia
Lithuania	Slovakia	Switzerland	Saudi Arabia
Luxembourg	South Africa	United Kingdom	Serbia
Malta		United States of America	Ukraine
Portugal			United Arab Emirates
Slovenia			
South Korea			
Spain			
Taiwan			
Thailand			
Turkey			

Table 5: Hofstede based clustering.

Ratings \ Hofstede	C1: `E.`	C2: `A.`	C3: `Eng. & N.E.`	C4: `M. & E.E.`
C1: `E. & A.`	57.1% (12)	**69.2**% (9)	14.3% (2)	33.3% (5)
C2: `M.`	8.3% (1)	25.0% (3)	0% (0)	**50.0**% (6)
C3: `E.`	**35.3**% (6)	7.7% (1)	42.8% (6)	26.7% (4)
C4: `Eng.`	25.0% (2)	0.0% (0)	**75.0**% (6)	0.0% (0)

Table 6: Intersection between the countries in each pair of clusters shown in relative percentage, and in parenthesis the number of countries that present in both cluster. Each cluster denoted by letter C followed a cluster number and by abbreviation discussed in text that aim to represent the most dominant common cultural factor of a given cluster.

4.5 Cultural Dimensions and Education, Life Expectancy and Income Indexes

We further investigate whether there is a relationship between the values of Hofstede dimensions with each of the four indexes. This also allows us to compare the impact of culture on the home country's level of prosperity with the aforementioned impact of hotel score on level of prosperity if the ratings serve a proxy role for culture. In contrast to the above analysis, PCA is applied to the values of Hofstede dimensions instead of hotel ratings. The percentage of the total variance explained by each of the corresponding principal components is `41.1, 18.5, 15.3, 12.1, 9.4, 3.6`. Similarly, the first five PCs were selected to fit the models (Fig. 10). All four models are significant (Tab. 8), and as expected, the dimensions resulted in a better explanation of the indexes than the hotel ratings. Among the three constituents

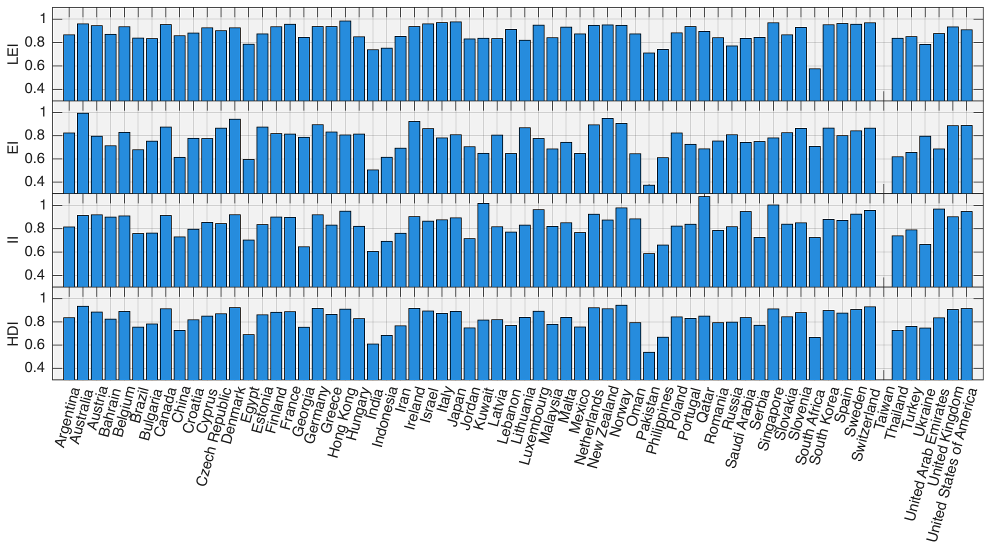


Fig. 7: Life Expectancy Index, Education Index, Income Index, Human Development Index and Gross National Income

Indexes	Adjusted R^2	F-statistic	p-value
`LEI`	10.5%	2.0	$\mathbf{4.0 \times 10^{-2}}$
`EI`	42.6%	10.5	$\mathbf{3.1 \times 10^{-7}}$
`II`	11.1%	2.6	$\mathbf{3.4 \times 10^{-2}}$
`HDI`	24.0%	5.0	$\mathbf{6.4 \times 10^{-4}}$
`LEI` (norm. ratings)	13.9%	3.0	$\mathbf{1.6 \times 10^{-2}}$
`EI` (norm. ratings)	35.5%	8.0	$\mathbf{7.6 \times 10^{-6}}$
`II` (norm. ratings)	12.2%	2.8	$\mathbf{2.6 \times 10^{-2}}$
`HDI` (norm. ratings)	23.8%	5.0	$\mathbf{6.9 \times 10^{-4}}$

Table 7: The linear relationship between PCs of hotels ratings/normalised ratings and the indexes. Columns adjusted R^2, F-statistic and p-value are ANOVA factor values.

of `HDI`, `EI` is predicted better than the other two constituents that match the results of predicting `EI` with hotel ratings. However, `HDI` this time is better explained (64.5%) than any of the indexes taken separately. This reinforces the deserved recognition of Hofstede dimensions in studying cultural impact in different settings.

4.6 Are Hotel Ratings a Proxy for Socioeconomic Factors in Predicting Cultural Dimensions

Another important question to investigate is whether the predictive power of cultural dimensions using hotel ratings come solely from the ratings acting as proxies for socioeconomic

Indexes	Adjusted R^2	F-statistic	p-value
`LEI`	50.0%	13.2	$\mathbf{1.7 \times 10^{-8}}$
`EI`	56.7%	17.0	$\mathbf{3.4 \times 10^{-10}}$
`II`	48.8%	12.6	$\mathbf{3.2 \times 10^{-8}}$
`HDI`	63.4%	22.1	$\mathbf{3.6 \times 10^{-12}}$

Table 8: The linear relationship between PCs of Hofstede's dimensions and the socioeconomic indexes. Columns adjusted R^2, F-statistic and p-value are ANOVA factor values.

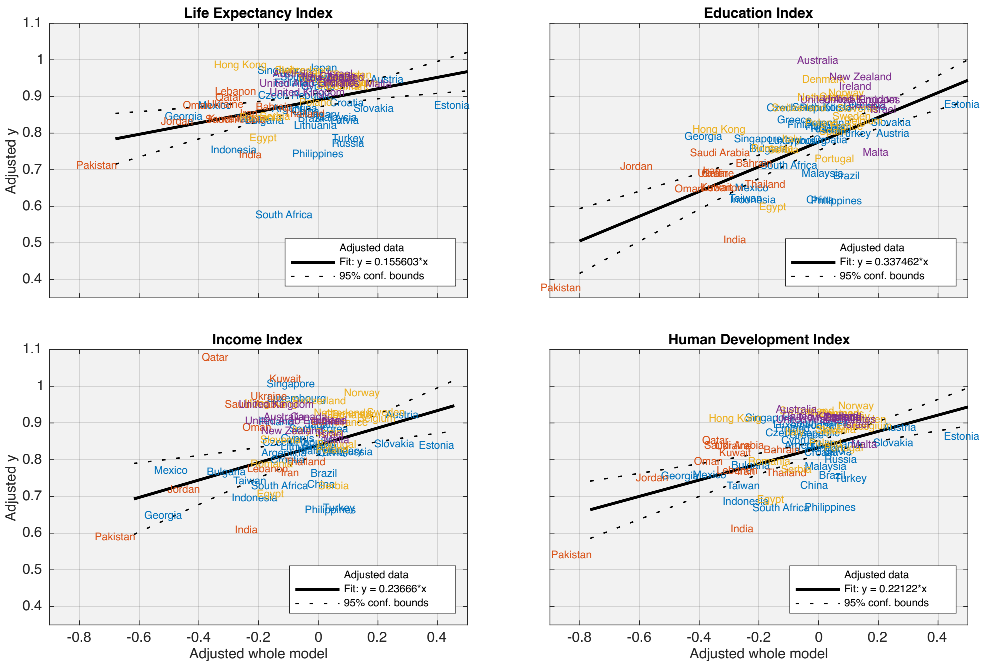


Fig. 8: Added variable plot for whole model. LEI (top-left), Education Index (top-right), II (bottom-left), HDI (bottom-right). y-axis is in the range of [0.35, 1.1] in all four panes. The colours represent the earlier discovered score-based clusters and consistent with Fig. 3-top.

indexes (Table 7). In order to control for the impact of socioeconomic factors we included HDI values alongside with principal components of hotel ratings. Table 9 presents an extension of Table 6 that reports the prediction performance of Hofstede's dimensions solely using hotel ratings.

As it is seen from Table 9, including HDI significantly improves the models for `PDI` and `IDV` prediction, indicating that socioeconomic development plays a crucial role in these cultural dimensions. For `IDV`, both HDI and hotel ratings remain significant, suggesting that hotel ratings capture cultural nuances beyond socioeconomic status. The interesting finding

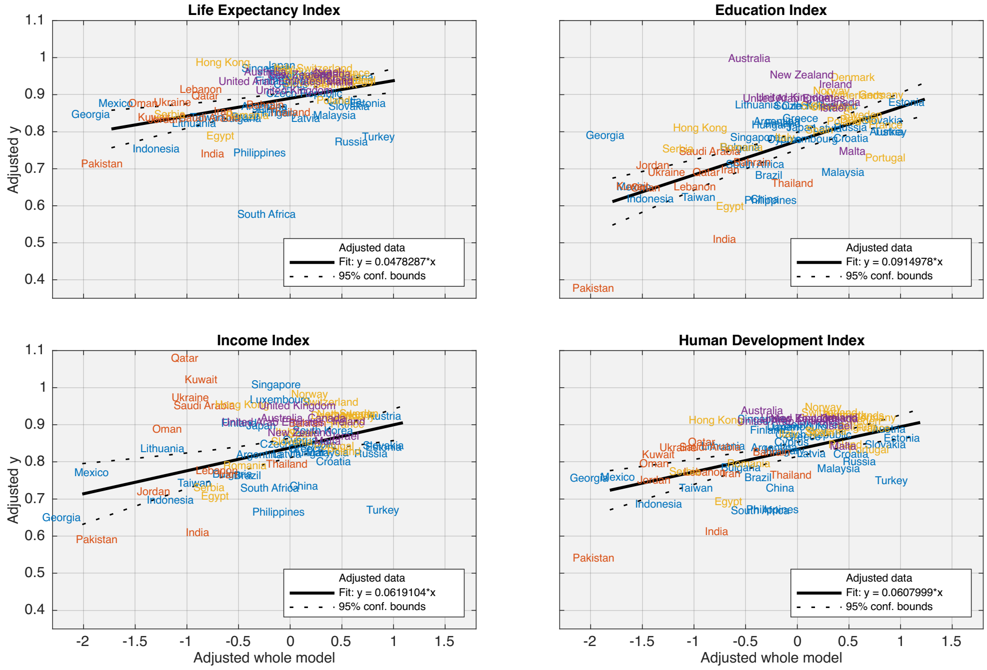


Fig. 9: Added variable plot for whole model based on normalised w.r.t country of origin, ratings: `LEI` (top-left), `EI` (top-right), `II` (bottom-left), `HDI` (bottom-right). y-axis is in the range of [0.35, 1.1] in all four panes. The colours represent the earlier discovered score-based clusters and consistent with Fig. 3-bottom.

is that hotel ratings capture cultural values related to individualism, long-term orientation, and indulgence that are not fully explained by socioeconomic factors. This suggests that hotel rating behaviors are influenced by deeper cultural norms and values.

For `PDI`, the initial relationship with hotel ratings appears to be confounded by socioeconomic factors. Hotel ratings do not significantly predict `MAS` and `UAI`, indicating that these dimensions may not be reflected in rating behaviors or require different measurement approaches. Hence, some cultural dimensions are more closely tied to economic development, while others are embedded in societal norms independent of economic status. While others do not depend neither on socioeconomic factors nor on customer behavior presented in the form of hotel ratings.

5 Discussion

Our analysis revealed several key findings that both support and challenge existing theories about cultural influences on hotel ratings. These findings span three main areas: cultural rating patterns, relationships with development indicators, and connections to established cultural frameworks. Before delving into detailed analysis, Table 10 summarizes our findings regarding the four research hypotheses:

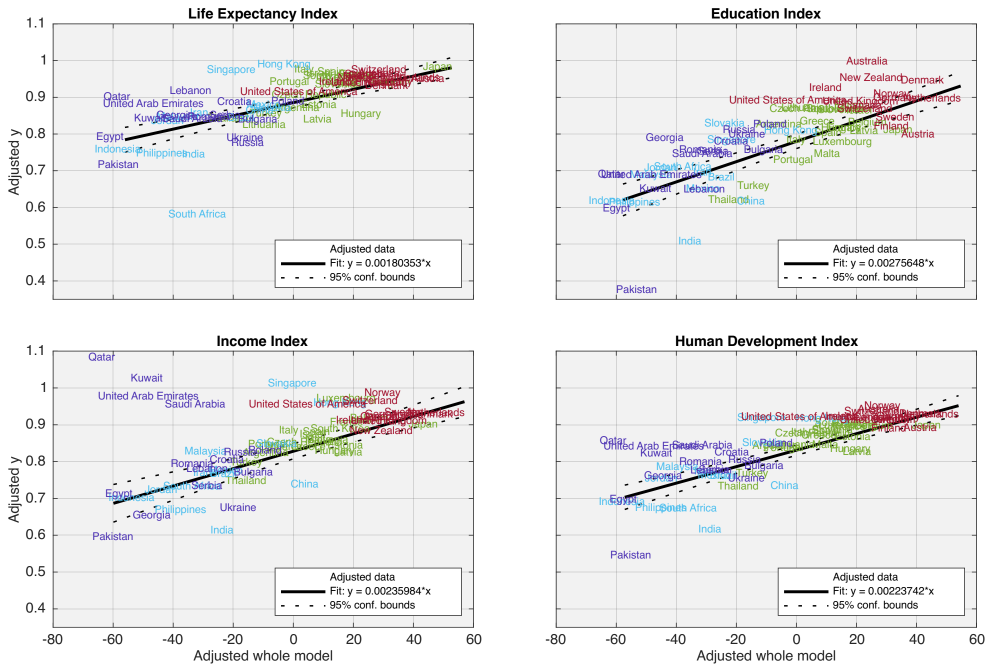


Fig. 10: Added variable plot for whole model based on PCs computed for Hofstede dimensions: `LEI` (top-left), `EI` (top-right), `II` (bottom-left), `HDI` (bottom-right). y-axis is in the range of [0.35, 1.1] in all four panes. The colours represent the earlier discovered Hofstede's dimensions-based clusters and consistent with Fig. 3-bottom.

5.1 Contextualising Results

In terms of cultural bias in hotel ratings, our analysis showed that hotel ratings depend on the nationality of the reviewer. Hotel guests from predominantly English-speaking countries and Israel tend to use a narrower range of ratings with higher means, while guests from Arab countries or countries with predominantly Muslim populations use a wider range of ratings, resulting in lower mean ratings. This finding aligns with previous research by Leon (2019); Mariani and Predvoditeleva (2019), who found that cultural traits significantly impact online hotel reviews. However, our results challenge some aspects of the High-Context vs. Low-Context Communication (HC/LC) theory of Hall (1976). According to this theory, we might expect high-context cultures (like many Arab countries) to use more moderate ratings and avoid extremes, while low-context cultures (like English-speaking countries) would use more direct and potentially extreme ratings. Our findings suggest the opposite, indicating that the application of communication theories to online rating behaviors may require a more nuanced interpretation. Our finding is also supported by a more recent survey of the literature conducted by Kittler, Rygl, and Mackinnon (2011), which relied on Hall's theory. The authors showed that "*most previous research that utilized HC/LC country classifications is based on seemingly less-than-adequate evidence. Mixed and often contradictory findings reveal inconsistencies in the conventional country classifications and show that they are flawed or, at best, very limited.*"

Dim.	Tot. Adjusted R^2	Tot. F-statistic	HDI p-value	Top PC p-value
PDI	26.0%	4.6	$\mathbf{6.3 \times 10^{-4}}$	1.6×10^{-1}(PC1)
IDV	73.6%	29.3	$\mathbf{9.3 \times 10^{-10}}$	$\mathbf{7.7 \times 10^{-5}}$(PC2)
MAS	5.8%	1.6	1.0×10^{0}	1.6×10^{-1}(PC1)
UAI	0.0%	0.9	6.2×10^{-1}	1.0×10^{-1}(PC4)
LTO	34.4%	6.3	5.2×10^{-2}	$\mathbf{6.7 \times 10^{-3}}$(PC2)
IND	17.6%	3.17	5.8×10^{-2}	$\mathbf{1.2 \times 10^{-3}}$(PC1)

Table 9: The linear relationship between PCs of hotel ratings supplemented by HDI and the Hofstede's dimensions. Columns adjusted R^2, F-statistic are ANOVA factor values whereas HDI p-value and top PC p-value demonstrate the significance of socioeconomic or hotel ratings contribution in predicting Hofstede dimensions.

Table 10: Evaluation of research hypotheses

Hypothesis	Key Finding
H1: Cultural Impact	*Confirmed*: Distinct rating patterns between English-speaking (narrow, high mean) and Muslim-majority countries (wide range, lower mean)
H2: HDI Relationship	*Confirmed*: Strong correlation with Education Index (42.6%) while weaker with HDI (24.0%)
H3: Predictive Power	*Partially Rejected*: Hofstede dimensions turned out to be better in predicting HDI (63.4%) and EI (56.7%) than hotel ratings (see H2 above).
H4: Cultural Dimensions	*Partially Confirmed*: Strong prediction of IDV (44.9%) and LTO (30.1%); weak for PDI, MAS, UAI
H5: Control for Socioeconomics	*Confirmed*: Some cultural dimensions are more tied to economic development. In particular, including HDI improves models for PDI (26%) and IDV(73%); For IDV, LTO(34.4%), and IND(17.6%) hotel ratings capture cultural values beyond socioeconomic status;

This discrepancy might be explained by the concept of psychic distance Phillips et al. (2020), which refers to the perceived differences between the home and host country. The greater psychic distance experienced by Arab tourists in European countries could lead to more varied experiences and thus a wider range of ratings. In contrast, English-speaking tourists may find European countries more familiar, resulting in more consistently positive experiences.

In addition, a significant relationship is observed between hotel ratings and the HDI of guests' home countries, particularly with the EI. This novel finding suggests that the level of education in a tourist's home country may influence their perception and evaluation of hotel experiences. This relationship persisted even after normalizing for cultural biases in rating behavior, indicating a robust connection between a country's educational development and its citizens' tourism experiences.

This finding extends the existing literature (Cárdenas-García et al. (2024); Chattopadhyay et al. (2021); Rivera (2017)), which has primarily focused on how tourism impacts the HDI of host countries, by demonstrating a reverse relationship: how the HDI of tourists' home countries influences their evaluation of tourism experiences.

Furthermore, while both hotel ratings and Hofstede's cultural dimensions demonstrated significant relationships with `HDI`, our analysis shows that Hofstede's dimensions have a greater overall predictive power. Hofstede's dimensions explained 63.4% of the variance in `HDI`, compared to 24.0% for hotel ratings. However, it should be noted that hotel ratings were particularly effective in predicting the `EI` component of `HDI`, explaining 42.6% of its variance. This suggests that while Hofstede's dimensions remain a more comprehensive predictor of overall human development, hotel ratings could serve as a valuable proxy for educational development in particular.

In terms of the relationship between cultural dimensions and hotel ratings, contrary to our initial hypotheses, we found that hotel ratings were most predictive of the `IDV` dimension ($R^2 = 44.9\%$) and the `LTO` dimension ($R^2 = 30.1\%$). This suggests that these cultural aspects have a stronger influence on hotel rating behavior than previously thought.

The strong relationship with `IDV` aligns with the findings of Sauer et al. (2017), who noted that individualistic tourists often provide more generous ratings reflecting their levels of personal satisfaction. Our results extend this understanding, suggesting that the individualism-collectivism spectrum significantly shapes how tourists approach the rating process itself.

The relationship between hotel ratings and `LTO` is a novel finding that warrants further investigation. It suggests that cultures with a more long-term orientation might approach hotel ratings differently, perhaps considering factors beyond immediate satisfaction. This aligns with observation reported by Mariani and Predvoditeleva (2019) that long-term-oriented tourists are more critical in their evaluations, focusing on long-term improvements and sustainability in service quality.

Interestingly, the linear relationship between hotel ratings and `PDI`, `MAS`, or `UAI` failed the ANOVA test. This contradicts earlier findings by Gao et al. (2018) and Leon Leon (2019), who suggested significant influences of these dimensions on review behavior. This discrepancy highlights the complexity of cultural influences on tourism experiences and the need for continued research in this area.

Lastly, controlling for `HDI` allows us to show that hotel ratings still significantly predict certain cultural dimensions (`LTO`, `IND` and partially `IDV`), while `PDI` is completely determined by `HDI`. Cultural values often change more slowly than economic conditions, resulting in persistent cultural behaviors despite changes in socioeconomic status. Further, hotel ratings are a form of consumer behavior that reflects individuals' expectations, satisfaction levels, and value judgments influenced by their cultural backgrounds , that might not directly be tied to a country's level of development. Hence, economic growth and improved human development do not automatically lead to shifts in cultural orientations related to time perception and indulgence.

To summarise, our findings challenge established theories while presenting novel findings:

1. Contrary to Hall's theory, high-context cultures showed more extreme ratings. This aligns with Kittler et al. (2011) critique and suggests psychic distance Phillips et al. (2020) may better explain rating behavior.
2. The strong correlation between Education Index and ratings (42.6%) suggests educational development shapes tourism evaluation practices.
3. The strong predictive power of IDV and LTO, combined with weak relationships to PDI, MAS, and UAI, suggests a need to revise current understanding of cultural influences on rating behavior.
4. While socioeconomic development (as measured by HDI) accounts for certain cultural dimensions like `PDI`, our findings show that hotel ratings independently reflect

cultural values related to IDV, LTO, and IND. This suggests that hotel rating behaviors are influenced by deeper cultural norms and values that are not solely tied to economic development.

5.2 Recommender System Implications

From a more practical perspective, the recommendation system could benefit from adjusting ratings based on the cultural background of both the reviewer and the potential guest, similar to how Sem-Fit adapts to user preferences over time described by García-Crespo, López-Cuadrado, Colomo-Palacios, González-Carrasco, and Ruiz-Mezcua (2011). For example, if a potential guest is from a country that tends to give higher ratings (e.g., English-speaking countries), the system could slightly deflate displayed ratings from reviewers of similar backgrounds, or inflate ratings from cultures that tend to rate more critically, e.g., some Middle Eastern countries. Further, given the strong correlation found between hotel ratings and the HDI, and in particularly EI, the system could use the HDI of a user's home country to tailor recommendations. For example, for users from countries with lower HDI/EI, the system could emphasize hotels with high ratings for basic amenities, value for money, or staff helpfulness. The recommendation system could also account for Hofstede's cultural dimensions. For users of high IDV cultures, the system could prioritize hotels with high ratings for privacy, personal space, or unique experiences, while for users from high LTO cultures, the system could emphasize hotels with good ratings for sustainability practices or those with a long history of consistent service.

Future research could explore the application of recommender systems to mitigate the cultural and socioeconomic biases identified in this study. One promising approach is the Variational Anchoring Effect Encoder model presented by Xiao, Zhang, and Li (2024), originally developed to address anchoring bias in e-commerce recommendations. This model could be adapted to learn representations of cultural and socioeconomic biases in hotel ratings.

The cold-start problem for new users could also be aided by the findings in this paper. For example, the system could implement an approach similar to ColdU presented by Dong, Wu, Wang, and Jingbo Zhou (2024). ColdU uses user-specific modulation to quickly adapt to new users with limited interaction histories. This approach could be enhanced by incorporating the cultural and socioeconomic factors, by including information about the user's country of origin, its HDI/EI score, and relevant Hofstede dimensions in the initial task context embedding in ColdU.

Similar to Bayesian approach used in movie genre prediction by Lensky and Makita (2017), future research could infer tourists' nationalities, cultural dimensions, or home country socioeconomic indices based on tourists hotel ratings. This approach could help mitigate self-reporting biases and fill in missing data, potentially providing a more accurate representation of a user's cultural and socioeconomic background. Furthermore, by basing recommendations on inferred rather than declared characteristics, this method might reduce the direct impact of cultural stereotypes on recommendations.

6 Limitations and Future Research

This study's primary limitation is its focus on European hotels, which may not capture global rating patterns. The study can be extended by including hotels in Asia, Americas, and Africa that could reveal different cultural interaction patterns and validate our findings' generalizability. Further deeper cultural analysis should be performed by exploring (a) qualitative studies of rating decision processes across cultures, (b) sentiment analysis of textual reviews with the help of Large Language Models and (c) analyzing the impact of destination country's cultural relationship with reviewer's home country. Lastly, in this work, the focus was mostly on using hotel ratings to predict socioeconomic factors and cultural dimensions while in the coming study the focus is made more on developing culturally-aware recommendation systems that incorporate: nationality-based rating normalization, `HDI` and cultural dimension weightings, as well as sentiment analysis of textual reviewers to predict hotel ratings.

7 Conclusion

This study reveals the complex interaction between cultural background, development indicators, and hotel rating behavior. In particular, the study contributed by identifying different rating behaviors between English-speaking and Muslim-majority countries, challenging existing communication theories. Furthermore, the study discovered a strong correlation between EI and rating behavior (42.6% explanatory power), suggesting the role of education in shaping tourism expectations. Lastly, novel findings about Individualism (44.9%) and Long-Term Orientation (30.1%) as key predictors of rating behavior were identified.

These findings have immediate practical applications for the hospitality industry by development of culturally-sensitive service delivery, creation of more accurate recommendation systems and providing better interpretation of guest feedback across cultural contexts.

Our results suggest that effective cross-cultural hospitality requires understanding not just cultural differences, but also the socioeconomic context of travelers' home countries.

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