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A Reproducible Framework for Tourism Pressure Assessment and Demand-Balancing Analysis in the United Arab Emirates

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ABSTRACT

Timely evidence on visitor pressure, spatial concentration, and recovery asymmetries is becoming increasingly demanded in destination management, but public agencies may not have full, cleaned, daily mobility databases. This paper formulates a replicable analytical system that can be functional even in the case of publicly visible summary mobility statistics. United Arab Emirates (UAE) retail and recreation indicators and transit-station indicators at the emirate level based on the history of Google Community Mobility Reports reflected via CEIC public pages are converted into understandable recovery, volatility and composite pressure measures. Clustering is then standardized in order to determine destination profiles and an exemplary demand-balancing scenario is implemented to emirates with high recovery scores. The findings indicate that there is evident heterogeneity within the federation. Abu Dhabi has a contained-recovery profile, and the middle-recovery group with moderate-high volatility includes Ajman, Fujairah, Ras Al Khaimah, and Sharjah, with the outlier of high pressure at Umm Al Quwain. In the observed configuration, the average recovery score is 21.67 and in the balancing scenario, it is 19.73 across the six emirates with full retail summaries, which is equivalent to an 8.94% drop. The paper will add a clear methodological process of transforming public summary indicators into destination-level diagnostics which can be used to facilitate prioritization, intervention screening and policy communication in conditions of limited data-access.

Keywords: Tourism Pressure, Mobility Analytics, Destination Management, Visitor Concentration, United Arab Emirates
JEL Classifications: L83

1. INTRODUCTION

Tourism governance has ceased to focus on destination promotion to congestion, liveability, infrastructure loading and environmental stress management. Such issues are particularly acute in fast growing urban and peri-urban tourist destinations, where demand may rise rapidly with traditional tourism statistics being published on broader time frames. In this situation, destination managers are almost completely on digital traces and mobility indicators to supplement visitor numbers, accommodation metrics, and evidence from surveys.

Smart tourism and urban analytics studies have demonstrated that mobility data can be used to identify spatial and temporal demand patterns that cannot be easily monitored using conventional monitoring systems (Buhalis and Amaranggana, 2014; Gretzel et al., 2015; Li et al., 2018; Xiang and Fesenmaier, 2017). Local authorities might not have complete access to curated raw series in operational settings, however. Rather, they can be provided with dashboards, re-flected public summaries, or headline mobility indicators. This disconnect between the visibility and the usability of data is significant to tourism policy, as the design of interventions is often based on understandable and transparent measures, and not obscure predictive models.

A good example of this limitation is historical Google Community Mobility Reports. The data is the percentage change compared to a pr1e-pandemic baseline in categories like retail and recreation, parks, transit stations, workplaces, and residential locations (Google, 2022a; 2022b). On one hand, the historical archive is in open access; however, according to Google, the reports have not been updated after mid-October 2022 and recommends cautious consideration of the data in the context of the region (Google, 2022a; 2022b). On the one hand, the historical archive is open access, but according to Google, the reports have not been updated since the middle of October 2022 and encourages a careful interpretation of the These properties render the mobility series especially appropriate to within-country profiling and intervention screening instead of naive cross-country ranking to destination management purposes.

United Arab Emirates is a suitable empirical context to conduct this analysis since the country has several destination geographies that have dissimilar urban structure, transport structures and tourism functions. The publicly visible CEIC pages reflect the summary statistics of the historical Google mobility series at the emirate level with the latest observed value, period means, all-time maximum, all-time minimum, and the number of observations of retail and recreation, and in some cases, transit stations as well (CEIC Data, 2025a; 2025b). Even though such summaries cannot substitute the entire daily archive, they may still be useful to the intensive analytical arguments provided that they are transformed into logical and clear policy signals.

Against this background, the paper is answering the following research question: To what extent can publicly visible summary mobility statistics support a reproducible framework for tourism pressure assessment and demand-balancing analysis? To answer this question, the paper provides three contributions. First, it builds a summary-based analytical workflow to build destination-level measures of recovery, volatility and composite pressure. Second, it uses standardized clustering to determine interpretable emirates profiles. Third, it considers an exemplary demand-balancing case of destinations with high recovery scores. The remainder of the paper is organized as follows. Section 2 reviews the literature and clarifies the analytical gap. Section 3 describes the study context and data structure. Section 4 presents the analytical framework. Section 5 reports the empirical results. Section 6 discusses the implications and limitations. Section 7 concludes the paper.

2. RELATED LITERATURE AND ANALYTICAL POSITIONING

2.1. Tourism Governance, Sustainability, and Visitor Pressure

Tourism planning has long been treated as a policy process shaped by institutional relationships, development priorities, and the need to balance economic gains with social and environmental costs. Hall (2008) frames tourism planning as a political and relational process rather than a purely technical exercise. Goodwin (2011) similarly argues that responsible tourism requires measurable

Figure 1: Average and latest retail and recreation mobility by emirate

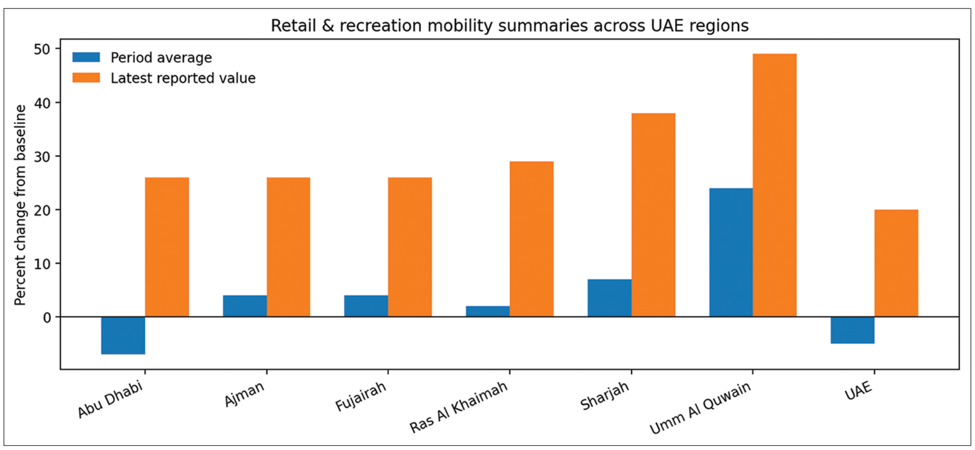
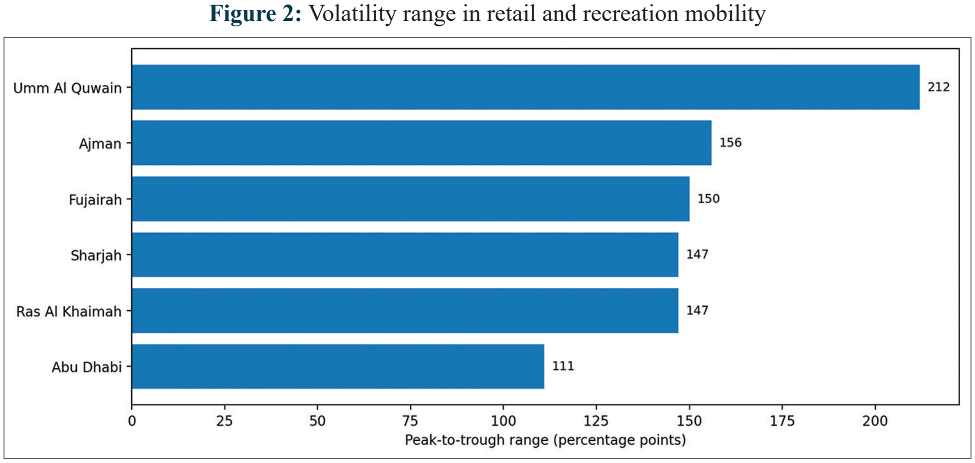


Figure 2: Volatility range in retail and recreation mobility



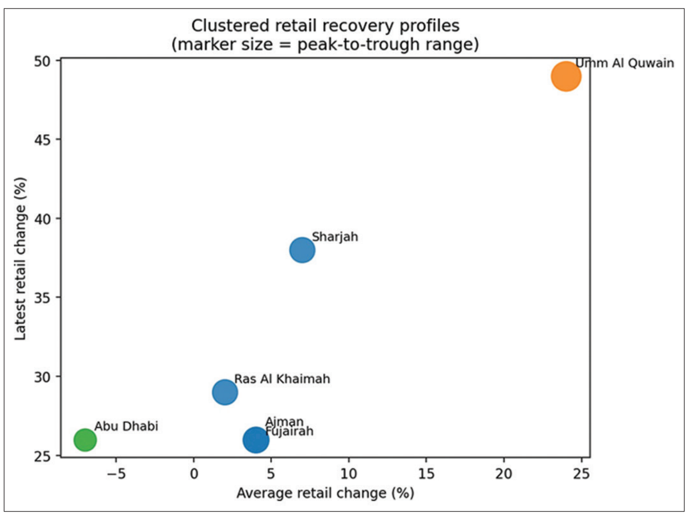
attention to local impacts, resource use, and resident welfare. These perspectives remain central to current debates on carrying capacity, concentration effects, and destination pressure.

The overtourism literature sharpens this concern by emphasizing that the core problem is not tourism growth alone but its uneven spatial and temporal distribution (Peeters et al., 2018; World Tourism Organization, 2018). Koens et al. (2018) show that tourism pressure in city contexts is multidimensional, historically contingent, and often oversimplified in public debate. In policy terms, this implies that pressure-management measures should be differentiated by local conditions rather than applied uniformly.

2.2. Smart Tourism, Mobility Evidence, and Public-Data Analytics

Research on smart tourism highlights the role of digitally connected ecosystems in improving destination intelligence and decision support. Buhalis and Amaranggana (2014) conceptualize smart tourism destinations as environments where data, infrastructure, and stakeholders are increasingly integrated. Gretzel et al. (2015) similarly position smart tourism as a field grounded in data infrastructures, connectivity, and value co-creation. More recent work extends this perspective by arguing that smart destinations should be understood holistically, incorporating technology, infrastructure, governance, quality of life, and the perspectives of both tourists and residents (Cerd´a-Mansilla et al., 2024). The broader literature on big data in tourism then demonstrates how digital traces can support forecasting, segmentation, and destination monitoring (Li et al., 2018; Xiang and Fesenmaier, 2017).

Figure 3: Clustered destination profiles based on retail recovery and volatility; marker size reflects volatility range



Mobility evidence occupies a particularly important place within this analytical shift. Shoval and Ahas (2016) show that tracking technologies reveal movement structures that are difficult to observe through conventional surveys. Batty (2013) reaches a parallel conclusion in urban analytics, arguing that digitally generated traces can support dynamic monitoring of city sys- tems and infrastructure loading. More recent work has also shown that tourists' sustainable mobility choices at city destinations are shaped both by destination conditions and by travel habits carried from home, reinforcing the policy relevance of destination-level transport environments (Zientara et al., 2024). Mobility indicators have also been linked to policy conditions and recovery trajectories in the UAE context (Shanableh et al., 2022). Collectively, these studies support the relevance of mobility evidence for destination management while also underscoring the value of transparent analytical workflows.

2.3. Analytical Gap

Despite these advances, two limitations remain prominent. First, many studies assume access to complete raw datasets and advanced processing pipelines that may not be available to local public institutions. Second, relatively limited attention has been given to analytical designs that remain defensible when only public summary statistics are accessible. The present study addresses this gap by proposing a reproducible framework that begins with summary-level mobility indicators and converts them into transparent diagnostics, cluster-based destination profiles, and intervention-oriented scenario analysis. Table 1 positions

Table 1: Representative studies and the analytical contribution of the present paper

Study	Data basis	Primary contribution	Limitation addressed in this study
Hall (2008)	Conceptual/policy	Tourism planning as a governance process	Does not provide an operational mobility-based diagnostic framework
Goodwin (2011)	Conceptual/policy	Responsible tourism and measurable local impact	Does not operationalize destination pressure from public digital traces
Buhalis and Ama- ranggana (2014)	Conceptual/systems	Smart destination architecture and data- enabled management	Does not specify a summary-data workflow for constrained institutional settings
Gretzel et al. (2015)	Conceptual/systems	Foundations of smart tourism and data ecosystems	Focuses on conceptual foundations rather than applied public-summary analytics
Li et al. (2018)	Literature review	Big-data uses in tourism research	Assumes richer data access than many destination authorities possess
Shoval and Ahas (2016)	Tracking studies	Mobility evidence for tourist movement research	Reviews tracking methods but does not develop summary-based pressure indicators
Koens et al. (2018)	Qualitative city evidence	Multidimensional under- standing of over tourism	Does not build a re- producible destination- profiling framework from mobility summaries
Shanableh et al. (2022)	UAE mobility and air- quality evidence	Links mobility patterns with pandemic-era environmental change	Does not extend summary mobility evidence into destination clustering and pol- icy screening
This study	Public summary mobility indicators	Recovery, volatility, pressure scoring, clustering, and balancing scenario design	Provides an explainable workflow for tourism-pressure assessment under constrained data access

Figure 4: Average and latest transit-station mobility in observable regions

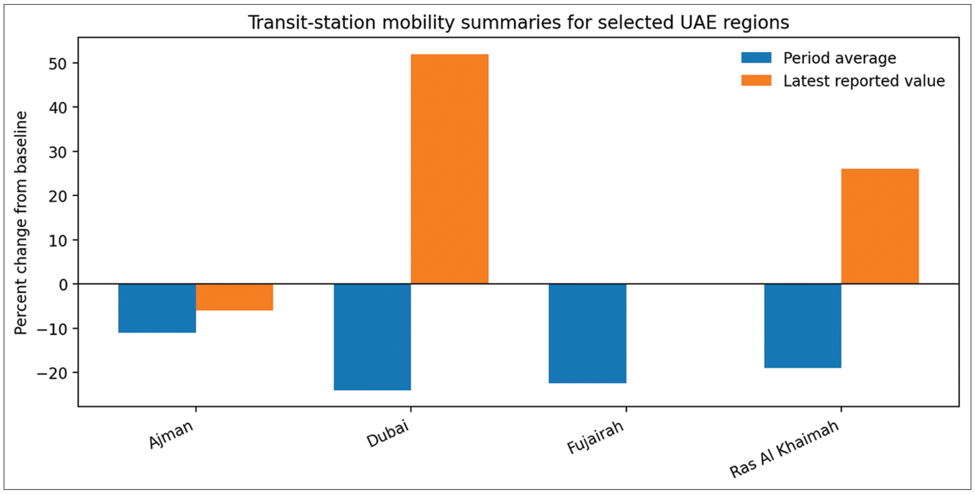
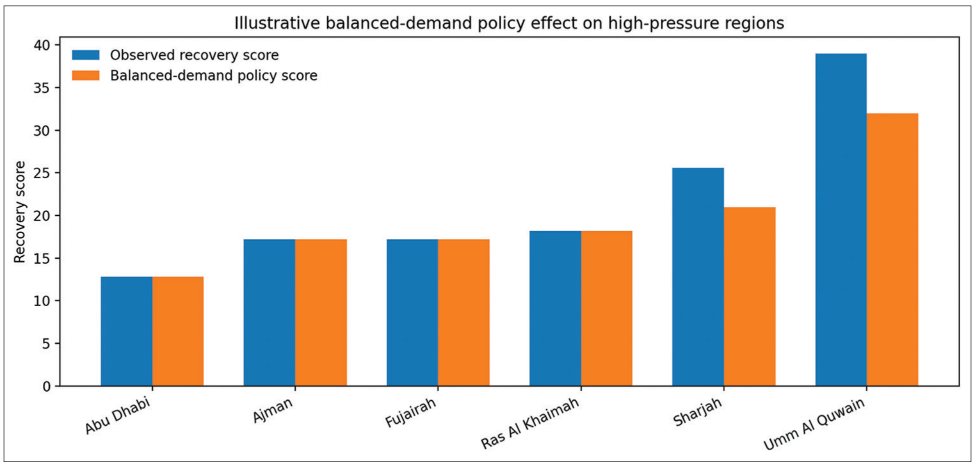


Figure 5: Illustrative demand-balancing scenario for high-recovery emirates



the present study relative to representative contributions in the literature.

3. STUDY CONTEXT, DATA SOURCES, AND OBSERVED VARIABLES

3.1. Empirical Setting

The empirical analysis is conducted at the emirate level in the UAE. This scale is appropriate because tourism activity, retail concentration, and transport intensity vary across emirates and because public summary mobility indicators are exposed at that geographic level. The UAE also offers a relevant multi-destination setting in which federation-wide tourism dynamics coexist with substantial subnational heterogeneity.

3.2. Data Sources

The analysis uses publicly visible CEIC pages that mirror Google Community Mobility Reports for the UAE (CEIC data, 2025a; 2025b). According to Google's documentation, mobility indicators are reported as percentage changes relative to a baseline defined as the median value for the corresponding day of the week during 3 January-6 February 2020 (Google, 2022b). The mirrored public pages report the latest observed value, period average, all-time maximum, all-time minimum, and the number of observations.

Retail and recreation summaries with sufficient fields for full indicator construction were available for Abu Dhabi, Ajman, Fujairah, Ras Al Khaimah, Sharjah, and Umm Al Quwain. A UAE aggregate was also visible but did not provide all range fields required for the derived metrics developed here and was therefore excluded from cluster estimation. Transit-station summaries were visible for Ajman, Dubai, Fujairah, and Ras Al Khaimah. Because transit coverage is incomplete across emirates, transit data are used as a diagnostic layer rather than merged directly into the retail clustering matrix.

3.3. Observed Inputs

Retail and recreation mobility is treated as the primary visitor-facing indicator because it is the mobility category most closely aligned with tourism-related commercial activity and destination pressure. For each emirate *r*, four observed quantities are extracted from the public summaries: The latest observed value (L_r), the period average ($\bar{M}$ r), the all-time maximum (M^{max}), and the all-time minimum (M^{min}). The number of observations is retained to document the underlying reporting coverage. Table 2 reports the retail and recreation summaries used in the analysis.

4. ANALYTICAL FRAMEWORK

4.1. Indicator Construction

Three derived measures are computed to convert the public summaries into policy-interpretable destination diagnostics.

Recovery score. Current recovery is represented through a weighted combination of the latest observed value and the longer-run period average:

$$RS_r = \omega L_r + (1-\omega)\bar{M}r \tag{1}$$

Where $\omega = 0.6$ in the baseline specification. This weighting scheme places greater emphasis on the most recent condition while preventing the indicator from being driven by a single point- in-time observation.

Volatility range. Historical instability is represented by the peak-to-trough spread:

$$VR_r = M_r^{\max} - M_r^{\min} \tag{2}$$

The measure captures the amplitude of mobility swings and helps distinguish relatively stable recovery from highly fluctuating trajectories.

Composite pressure score. To prioritize destinations for management attention, a trans- parent composite pressure score is defined as:

$$PS_r = L_r + 0.15M_r^{\max} - 0.10\bar{M}r \tag{3}$$

The score emphasizes current activity, recognizes the destination's potential to reach high peaks, and includes a modest offset for sustained average elevation. The objective is interpretability rather than aggressive parameter tuning.

4.2. Feature Matrix and Standardization

Destination profiling is based on the feature vector

$$\mathrm{x}_r = [\bar{M}r, L_r, VR_r]. \tag{4}$$

Because these features operate on different scales, each variable is standardized using a z-score transformation

$$zrj\,\frac{\mathrm{xrj}-\mu j}{\sigma_j} \tag{5}$$

Where μ_j and σ_j denote the sample mean and standard deviation of feature j, respectively. Standardization prevents the volatility range from dominating clustering purely because of scale.

4.3. Cluster Profiling

K-means clustering with $k = 3$ is applied to the standardized feature matrix. The clustering objective is

$$\{C_k\}_{k=1k=1\mathbf{z}_r\in C_k}^{\mathrm{Min}^3} \quad \mathbf{z}_r - \mu k \quad 2, \tag{6}$$

Where C_k denotes cluster k and μk its centroid. The three-cluster design is theory-led and intended to distinguish contained-recovery destinations, intermediate destinations, and high- pressure outliers. Given the small number of emirates, clustering is used here as an interpretable profiling device rather than as evidence of stable latent population structure.

4.4. Demand-Balancing Scenario

To illustrate how the framework can support intervention screening, a balancing scenario is applied to emirates with recovery scores of at least 20. The post-intervention recovery score is defined as:

$$RS_r^{'} = \frac{RSr, \quad RSr < 20,}{(1-\alpha)RSr, \quad RSr > 20,} \tag{7}$$

Where the baseline scenario uses $\alpha = 0.18$. This scenario is not interpreted as a causal estimate of policy effectiveness. Instead, it represents a stylized intervention package that could combine temporal dispersion, selective event redistribution, targeted promotion of alternative destina - tions, and load-management measures. Two outputs are examined: The emirate-level difference $\Delta RS_r = RSr' - RS_r$ for affected destinations and the percentage change in the cross-emirate mean recovery score.

4.5. Sensitivity Assessment

A limited robustness assessment is conducted in two ways. First, the recovery weighting pa- rameter ω is varied from 0.5 to 0.7 in order to test whether moderate changes in the emphasis placed on the latest observation alter the substantive ordering of emirates. Second, balancing intensities of $\alpha = 0.15$ and $\alpha = 0.20$ are compared with the baseline $\alpha = 0.18$ configuration to examine whether the direction and scale of the scenario result remain stable under nearby intervention strengths.

5. RESULTS

5.1. Retail-Mobility Differentiation across Emirates

The retail and recreation summaries reveal pronounced cross-emirate differentiation (Figure 1). Period averages range from −7% in Abu Dhabi to 24% in Umm Al Quwain, while the latest observed values range from 26% in Abu Dhabi, Ajman, and Fujairah to 49% in Umm Al Quwain. These differences indicate that visitor-facing recovery is not distributed uniformly across the federation.

Two empirical patterns stand out. First, Umm Al Quwain is clearly separated from the remainder of the sample because both its average and latest values are substantially higher than those of the other emirates. Second, Sharjah occupies an intermediate but distinctly elevated position relative to Ajman, Fujairah, and Ras Al Khaimah. Abu Dhabi combines the lowest period average with a moderate latest value, suggesting a more contained recovery profile.

5.2. Recovery, Volatility, and Composite Pressure

The volatility range adds a second analytical dimension (Figure 2). Abu Dhabi records the narrowest peak-to-trough spread at 111% points, while Umm Al Quwain exhibits the widest range at 212% points. Ajman, Fujairah, Ras Al Khaimah, and Sharjah all lie between 147% and 156% points.

Table 3 reports the derived metrics. Abu Dhabi has the lowest recovery score at 12.8, while Umm Al Quwain reaches 39.0. Sharjah follows at 25.6, while Ajman and Fujairah each record 17.2 and Ras Al Khaimah records 18.2. The composite pressure score yields the same broad ranking, with Umm Al Quwain remaining the clear outlier.

Taken together, the indicators distinguish between strong but relatively contained recovery and potentially unbalanced pressure. Umm Al Quwain scores highly on both recovery and volatility, while Sharjah shows elevated recovery without the extreme historical amplitude observed in Umm Al Quwain. Abu Dhabi remains the least pressure-intensive destination under the present indicator set.

5.3. Cluster-Based Destination Profiles

The standardized k-means procedure yields three interpretable profiles. Abu Dhabi forms a contained-recovery cluster characterized by the lowest period average and the narrowest volatility range. Ajman, Fujairah, Ras Al Khaimah, and Sharjah form a middle-recovery cluster, al-though Sharjah lies at its upper boundary because of a stronger latest value (Figure 3). Umm Al Quwain forms a high-pressure outlier cluster because it simultaneously combines the highest average, highest latest value, and widest volatility range.

The cluster structure highlights a central management finding: Tourism pressure in the UAE is spatially differentiated. A single federation-wide response would therefore obscure material subnational asymmetries. The evidence instead supports differentiated management intensity, with the strongest balancing attention directed to Umm Al Quwain, a lighter but still active pressure-management posture for Sharjah, and comparatively limited urgency for Abu Dhabi under the observed metrics.

5.4. Transit-Station Diagnostics

Transit-station summaries provide a complementary transport perspective (Figure 4). All four observable regions have negative period averages over the reporting window, ranging from −11% in Ajman to −24% in Dubai, indicating that the broader period still incorporates substantial disruption. Latest transit values, however, differ sharply: Dubai reaches 52%, Ras Al Khaimah 26%, Fujairah 0%, and Ajman −6% (CEIC Data, 2025b).

These transport diagnostics suggest that retail-facing recovery and transport recovery do not necessarily move in lockstep. Dubai, which is not part of the retail cluster analysis because the mirrored retail summary used here did not expose all range fields required for the derived metrics, nonetheless exhibits strong recent transit recovery. This divergence reinforces the need to interpret tourism pressure using multiple analytical lenses.

Table 2: Retail and recreation public summaries used in the analysis

Region	Latest	Average	Max	Min	Observations
Abu Dhabi	26	−7	35	−76	959
Ajman	26	4	82	−74	957
Fujairah	26	4	80	−70	934
Ras Al Khaimah	29	2	74	−73	974
Sharjah	38	7	70	−77	974
Umm Al Quwain	49	24	141	−71	934
UAE (aggregate)	20	−5	–	–	959

Table 3: Derived recovery, volatility, and pressure measures

Region	Recovery score (RS_r)	Volatility range (VR_r)	Pressure score (PS_r)
Abu Dhabi	12.8	111	31.95
Ajman	17.2	156	37.90
Fujairah	17.2	150	37.60
Ras Al Khaimah	18.2	147	39.90
Sharjah	25.6	147	47.80
Umm Al Quwain	39.0	212	67.75

5.5. Demand-Balancing Scenario and Sensitivity Assessment

An illustrative balancing scenario is applied to emirates with recovery scores of at least 20, namely Sharjah and Umm Al Quwain (Figure 5). Across the six emirates with complete retail summaries, the baseline mean recovery score is 21.67. Under the balancing scenario, the post-intervention mean declines to 19.73, corresponding to an 8.94% reduction.

The limited sensitivity assessment indicates that the substantive ranking of emirates remains stable when the recovery-weighting parameter ω is varied between 0.5 and 0.7: Abu Dhabi remains the lowest-recovery emirate, Umm Al Quwain remains the highest, and Sharjah remains the second-highest. Likewise, balancing intensities of 0.15 and 0.20 yield mean-recovery reductions of 7.45% and 9.94%, respectively, preserving the same directional conclusion as the baseline 0.18 scenario.

6. DISCUSSION

There are three major implications of the results. To start, meaningful tourism-pressure diagnostics can be supported by public summary statistics in the case of unavailable complete raw mobility data. This is not in lieu of more comprehensive time-series analysis, but it offers a viable and analytically transparent alternative when subject to realistically constrained institutions.

Second, the UAE results show why subnational differentiation is important in destination governance. The pressure on retails is not balanced throughout emirates and the recovery of transport does not develop with commercial destination activity. This is in line with the overtourism literature that focuses on distribution as opposed to aggregate volume alone (Koens et al., 2018; Peeters et al., 2018; World Tourism Organization, 2018). It is also consistent with recent evidence that destination managers are increasingly expected to align sustainability goals with efforts to reduce perceived crowding rather than rely on promotion alone (Fierro-Rubio et al., 2025). Operationally, high recovery and high volatility destinations demand varying policy combinations as compared to contained-recovery destinations.

Third, the framework can be explicably explained. The indicators are computationally light and replicable and can be interpreted in policy language. It particularly comes in handy during the context of a decision-making in the public where the concepts of legitimacy, transparency, and communicability can be prioritized in importance as methodological complexity.

The research however has limitations. The empirical layer uses publicly available summary values instead of the entire daily series, eliminating seasonal decomposition, causal inference and formal time-series validation. Retail and recreation mobility is a proxy that faces visitors instead of a direct number of tourists. Transit coverage is not full across the emirates, thus the evidence of transport has not yet been integrated into the clustering stage, but has been diagnostic. Future activity ought to incorporate past data on daily mobility with accommodation occupancy, visitor arrivals, event schedules and local capacity indicators with the aim of testing whether the same profile structure can be maintained under more data-rich conditions.

7. CONCLUSION

The research has created a repeatable model of analyzing tourism pressure and demand-balancing in the form of publicly visible mobility summaries of the UAE. The analysis is able to convert retail and transit summary indicators into recovery, volatility, and composite pressure measures to demonstrate that even at the summary level, the evidence can be used to support destination profiling and pre-implementation policy screening. Empirical findings determine that there is a contained-recovery profile i n Abu Dhabi, a middle-recovery group in Ajman, Fujairah, R as Al Khaimah, and Sharjah, and high pressure outlier in Umm Al Quwain. The exemplary balancing scenario lowers the average recovery score among the six complete emirates by 8.94%.

The key value added by the paper is the design of a clear analytical workflow that can be used in the limited data-access conditions. To tourism boards, municipal governments and destination managers, the framework provides a viable path between the summaries of public mobility and evidence of policy that can be understood.

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