Research Papers Review

**Predictivity of Tourism Demand Data, *Annals of Tourism Research (2021)*  
Yishuo Zhang, Gang Li, Birgit Muskat, Huy Quan Vu, Rob Law**

| **Aspect** | **Strengths** | **Weaknesses** |
| --- | --- | --- |
| **Theoretical Significance** | - Introduces the concept of maximum predictivity to tourism forecasting using entropy-based evaluation - Fills a gap in understanding data characteristics | - Limited theoretical connection to broader fields beyond tourism - Heavily focused on entropy without discussing potential other measures |
| **Methodology** | - Applies sample and multi-scale entropy with Fano’s inequality to estimate predictivity - Demonstrates generalizable entropy framework | - Entropy estimation may vary based on parameter choices (e.g., embedding dimension) |
| **Practical Implications** | - Offers a diagnostic tool to assess the quality of tourism data before modeling - Helps determine when more data or different preprocessing is needed | - The method does not offer direct model improvements, only a diagnostic lens - Requires computational and technical literacy |

**Tourism Demand Forecasting: A Decomposed Deep Learning Approach, Journal of Travel Research (2021)  
 Yishuo Zhang, Gang Li, Birgit Muskat, Rob Law**

| **Aspect** | **Strengths** | **Weaknesses** |
| --- | --- | --- |
| **Theoretical Significance** | - Extends AI forecasting by combining STL decomposition with a novel duo attention deep learning model (STL-DADLM) |  |
| **Methodology** | - Addresses overfitting in AI-based forecasting with decomposition and automated feature selection - Proposes a multi-layer attention model | - Performance highly depends on tuning and data quality - The proposed method assumes access to clean and structured data |
| **Practical Implications** | - Can improve short- and long-term forecast accuracy without requiring extra explanatory variables - Reduces model complexity | - Implementation of the DADLM may be inaccessible to practitioners unfamiliar with deep learning |

**Limits of Predictability in Human Mobility, Science (2010)  
Authors: Chaoming Song, Zehui Qu, Nicholas Blumm, Albert-Laszlo Barabasi**

| **Aspect** | **Strengths** | **Weaknesses** |
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| **Theoretical Significance** | - Establishes upper bounds for human mobility predictability using entropy measures - Provides a foundational concept of intrinsic predictability |  |
| **Methodology** | - Uses entropy-based modeling over large mobile phone datasets - Introduces a novel way to quantify movement predictability | - Assumes consistent behavior over time, which may not generalize |
| **Practical Implications** | - Framework useful for applications in urban planning, epidemiology, or demand forecasting | - Data collection at this scale is not feasible for most tourism contexts, limiting direct application |

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| **Annals of Tourism Research**  **Ai-based counterfactual reasoning for tourism research**  **Haiyang Xia, Birgit Muskat, Gang Li, Girish Prayag** | | | |
| **Aspect** | | **Strengths** | **Weaknesses** |
| **Theoretical Significance** | | - Introduces a novel method by applying AI-based counterfactual reasoning to tourism research  - Addresses the key limitation of the reasoning approaches in AI tourism research |  |
| **Methodology** | | - Counterfactual reasoning AI algorithms capture causal effects by constructing a counterfactual optimization problem | - AI-based methods heavily rely on the quality and representativeness of the big data, therefore, the method might be susceptible to biases or limitations inherent in the data sources |
| **Practical Implications** | | - Counterfactual reasoning aims to understand "what if" scenarios and identify potential causal links | - Implementing AI-based counterfactual reasoning might require specialized skills, potentially limiting its immediate practical adoption by tourism researchers and industry practitioners |
| **Annals of Tourism Research**  ***Forecasting international tourism demand: a local spatiotemporal model***  ***Xiaoying Jiao, Gang Li, Jason Li Chen*** | | | |
| **Aspect** | | **Strengths** | **Weaknesses** |
| **Theoretical Significance** | | - Integrates spatial dependence and spatial heterogeneity into tourism forecasting, areas previously underexplored  - The development and application of local spatiotemporal autoregressive models advance beyond traditional global models  - The modeling approach has implications for other fields | - The findings may not generalize to non-European contexts where spatial interdependencies are structured differently |
| **Methodology** | | - Application to 37 European countries over time strengthens empirical relevance and robustness  - Compares the spatial model against standard benchmarks (ARIMA, Naive) across multiple forecasting horizons  - Demonstrates how the localized model improves accuracy by capturing heterogeneity | - Spatiotemporal model can be difficult to interpret and implement for practitioners without technical expertise  - Does not explore how shocks (e.g., pandemics) could impact model performance |
| **Practical Implications** | | - Shows that the spatiotemporal model provides more accurate predictions | - The complexity of the spatiotemporal model may make it difficult to adopt for tourism practitioners |
| **Annals of Tourism Research**  ***Time and feature varying tourism demand forecasting***  ***Huicai Gao, Hengyun Li, Chen Jason Zhang*** | | | |
| **Theoretical Significance** | - The paper introduces a time- and feature-varying ensemble learning-based meta-learner, a significant advancement over traditional combination forecasting which often used constant weights  - It offers dynamic and feature sensitive weight adjustments during uncertain periods (e.g., pandemics), a gap left largely unexplored in previous tourism forecasting research​  - Meta-learning ("learning to learn") is employed innovatively in tourism forecasting, an area where it had very limited prior application​ | | - Only two destinations (Hong Kong and Sanya) were studied, which raises questions about the broader generalizability of findings  - the study acknowledges that using richer datasets like social media reviews could further strengthen the framework |
| **Methodology** | - Combines statistical, machine learning, and deep learning models along with economic and search engine data  - Extracts multifaceted features, like trend, seasonality, spectral entropy, spikiness, from internal (visitor arrivals) and external (economic, search engine) sources, rather than relying only on simple keyword data  - Weights are automatically and dynamically generated for each forecasting period based on learned features, highly adaptive to new conditions​  - Validation includes comparisons against individual models and traditional combination methods across both stable and uncertain periods  - Conducts time series cross-validation and feature importance analysis to prove the model’s reliability and transparency​ | | - The proposed model requires significant computational resources initially, which could limit its practical use for organizations with fewer technical capacities  - Ensemble and meta-learning models naturally remain more ambiguous compared to traditional econometric models, particularly for non-technical users |
| **Practical Implications** | - Enables more accurate and resilient demand forecasting for policymakers and tourism businesses, especially during crises like COVID-19  - The model's structure is flexible enough to apply beyond Hong Kong and Sanya, extending its value for other destinations or business domains , like finance or transportation  - Helps in better resource allocation, marketing, and policy response based on early detection of demand shifts | | - High setup costs (data collection, feature extraction, model training) could discourage immediate adoption, especially by smaller tourism agencies or emerging destinations  - The model heavily relies on the availability and quality of search engine and economic data, not all destinations may have such data readily accessible |
| **Tourism Management**  **Tourism demand forecasting using compound pattern recognition**  **Mingming Hu, Wenli Liang, Richard T.R. Qiu, Doris Chenguang Wu** | | | |
| **Theoretical Significance** | -The paper proposes the Compound Pattern Recognition (CPR) framework, which integrates calendar and volume patterns into a unified system for tourism forecasting  - Unlike previous models (e.g., HPR), CPR allows for similar but not identical calendar patterns to match, making the system more adaptive  - The study innovatively optimizes the weight between calendar and volume patterns based on minimizing forecasting error, allowing the model to self-adjust over time  - The theoretical advancement lies in moving from rigid, single-dimension pattern recognition to multi-dimensional, weighted pattern matching | | - The model focuses only on calendar and volume patterns, without incorporating additional variables such as weather, economic indicators, or social media sentiment, which could enrich pattern recognition |
| **Methodology** | - The CPR model combines calendar effects (e.g., holidays, weekends) and tourism volume fluctuations into a joint similarity evaluation using k-NN algorithms  - Use of Relative Euclidean Distance (RED) after detrending the volume pattern, and dynamic optimization of the calendar-volume weighting  - Applied to three major Chinese tourist attractions (Siguniang Mountain, Jiuzhaigou Valley, Kulangsu) across normal and COVID-19 periods  - Compared against strong baseline models, including SARIMA, SARIMAX, ETS, TBATS, traditional k-NN, and HPR  - The Diebold-Mariano (DM) test is used to statistically validate forecasting improvements over benchmark models | | - CPR is computationally heavier than simple time-series models, which may limit real-time or low-resource applications​  - If historical data is too sparse or biased (especially after major disruptions like COVID-19), the model may struggle despite its improvements​  - The choice of k=2 for the nearest neighbors, although justified by previous literature, may not always be optimal; adaptive k-selection could enhance performance |
| **Practical Implications** | - Demonstrates strong performance even during highly volatile periods like COVID-19, a major benefit for policymakers and businesses.  - Can help optimize pricing, staffing, resource allocation, and strategic planning at tourist attractions  - The method could potentially be adapted beyond tourism, to other industries needing high-frequency demand forecasting | | - Tourism companies without data science capabilities may find the model difficult to implement without technical assistance  - Requires relatively complete and high-frequency historical data, if data collection is interrupted or inconsistent, performance may degrade​ |
| **Annals of Tourism Research**  **The impact of public health emergencies on hotel demand - Estimation from a new foresight perspective on the COVID-19**  **Ling-Yang He, Hui Li, Jian-Wu Bi, Jing-Jing Yang, Qing Zhou** | | | |
| **Theoretical Significance** | - It acknowledges the limitations of traditional methods like intervention analysis and event studies in the context of such emergencies and offers a more suitable approach. It blends decomposition techniques (CEEMD) with hybrid modeling, advancing the theoretical framework for demand forecasting in the context of extreme events like pandemics  - Moves beyond micro-level qualitative research and helps bridge the gap in macroeconomic modeling under public health emergencies | | - The concept of forecasting demand in a pandemic-free virtual world relies on a strong assumption that past trends would continue, which might not hold true |
| **Methodology** | - It utilizes the Complete Ensemble Empirical Mode Decomposition (CEEMD) technique to decompose hotel demand data effectively  - The method incorporates a hybrid forecasting approach, combining statistical and machine learning models (SARIMAX, LSTM, ANN, SVR) to improve forecasting accuracy  - Compares the proposed Adaptive Hybrid Forecaster (AHF) against six benchmark models (ETS, SARIMA, SARIMAX, ANN, SVR, LSTM) using MAE, RMSE, and MAPE, confirming its superior accuracy across all hotel categories  - Uses real-world hotel demand data from Macao across four hotel star levels and incorporates economic indicators (like CPI growth) as exogenous variables | | - Omission of real-time external data: online search trends, weather data, or mobility data  - The model involves decomposition, multi-model training, parameter tuning, and ensemble integration, which may limit usability for less technically equipped practitioners  - The model outputs point forecasts, without uncertainty intervals, which can be problematic during high-volatility periods like pandemics |
| **Practical Implications** | - The research provides valuable insights for hotel managers and policymakers to understand and respond to the impact of public health emergencies  - The proposed method can help in real-time monitoring and evaluation of the impact of emergencies, enabling timely interventions  - The findings offer guidance to hotel managers on strategies to enhance resilience in the face of crises, such as diversifying services | | - The study's focus on Macao's hotel industry might limit the generalizability of the findings to other regions with different tourism characteristics  - The paper acknowledges that the forecasting errors would inevitably accumulate and eventually lead to a greater evaluation error |