ISSN 2616-5902 Vol. 7, Issue 11: 54-60, DOI: 10.25236/AJBM.2025.071108

Mixed-Frequency Model Forecasting of Coastal Tourism Demand Based on Network Index

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Abstract: *Forecasting coastal tourism demand is crucial for promoting high-quality development of the marine economy. With the deepening of internet technology and the widespread adoption of its applications, online search indices can profoundly reflect the actual needs of tourists during their decision-making process. Therefore, utilizing network index to forecast coastal tourism demand is feasible. Taking Gulangyu Island in Xiamen as a case study, this paper employs a MIDAS model. It constructs a baseline ADL model, univariate and multivariate MIDAS model using high-frequency Baidu Index data and low-frequency Gulangyu tourist growth rates. These models forecast tourism demand for Gulangyu. Subsequently, the fitted data from these models undergo further prediction via the XGBoost machine learning algorithm. Finally, the Root Mean Square Error (RMSE) of each model's prediction results is compared. The results indicate that sudden health events significantly impact the accuracy of predictive models.Both the univariate and multivariate MIDAS models outperform the baseline ADL model in predictive capability.*

Keywords: *Mixed-Frequency Data, MIDAS Model, Coastal Tourism, Demand Forecasting*

1. Introduction

With the steady advancement of high-quality development and the gradual increase in per capita income, residents' demand for travel has become increasingly robust. Coastal tourism, leveraging its unique resources and consumption-driven nature, has progressively emerged as a key growth engine for promoting the high-quality development of the marine economy. However, the COVID-19 pandemic that erupted in late 2019 dealt a severe blow to the coastal tourism industry, significantly increasing its volatility. Following the pandemic's conclusion, China's economy has maintained positive momentum, and the coastal tourism industry has steadily recovered. By December 2023, key tourism indicators—including those for coastal tourism—had returned to pre-pandemic levels, demonstrating robust development. Nevertheless, the lingering effects of the pandemic continue to produce nonlinear lagged impacts through channels such as expectation adjustments, preference shifts, and supply chain restructuring, indicating that the stability of the coastal tourism system remains insufficient. Therefore, conducting relatively accurate forecasts of coastal tourism demand to provide decision-making and operational references for policymakers and practitioners holds significant theoretical and practical significance for promoting the high-quality development of China's coastal tourism industry.

2. Literature Review

Commonly used models for economic forecasting, such as the ADL model and the ARMA model, require the independent variable and the dependent variable to have the same frequency, and due to the reality of inconsistent statistical frequency of data, researchers often treat data of different frequencies as same-frequency data. If the high-frequency data are transformed into low-frequency data by means of summation and averaging, the key information may be neglected due to the reduction of data accuracy, and if the low-frequency data are transformed into high-frequency data by means of interpolation, it is suspected that the data are artificially constructed. Ghysels et al. (2004) proposed the MIDAS mixing model based on the ADL model[1], and the MIDAS mixing model can MIDAS mixed-frequency model can directly use different frequency data to construct mixed-frequency data model. MIDAS mixed-frequency model was first used in the prediction of financial field, and then gradually extended to the field of macroeconomic research. Clements et al. (2008) added

ISSN 2616-5902 Vol. 7, Issue 11: 54-60, DOI: 10.25236/AJBM.2025.071108

autoregressive terms on the basis of MIDAS mixed-frequency model to construct the MIDAS-AR mixed-frequency model, and the autoregressive terms further improved the prediction accuracy of MIDAS mixed-frequency model[2]. Domestic scholars have conducted a number of studies on China's macroeconomy using the MIDAS mixed-frequency model. Liu Jinquan et al. (2010) used the conditional variance of the GDP growth rate from the first quarter of 1992 to the fourth quarter of 2008 and the conditional variance of the monthly inflation rate from January 1992 to December 2008 to construct the MIDAS mixed-frequency model, which proved the applicability of the MIDAS mixed-frequency model to the study of China's macroeconomy[3]. Liu Han et al. (2011) constructed a univariate and multivariate MIDAS mixed-frequency model to forecast China's macroeconomy in the short term, using the data of the "three carriages" that drive China's economic growth, i.e., export, consumption, and investment, from the third quarter of 1992 to the third quarter of 2010[4]. Zheng Tingguo et al. (2013) constructed a mixed-frequency data area system transfer dynamic factor model to empirically model and estimate China's quarterly GDP year-on-year growth rate and five monthly consistent indicators, and examined the reliability and timeliness of the model in China's economic cycle measurement from the perspective of real-time analysis, thus verifying the applicability of the model in China[5].

Research on applying hybrid models to visitor volume forecasting has emerged relatively late both domestically and internationally. Liu Han et al. (2016) used the MIDAS-AR mixed-frequency model to forecast the number of Chinese inbound tourists in the United States using Google index, and found that the MIDAS-AR mixed-frequency model with Almon weight function had the best predictive effect[6].Hirashima (2017) et al. Based on the mixed-frequency model and the homoskedastic model to predict the number of quarterly tourist arrivals in Hawaii and the quarterly labor force in food and accommodation services revenue, and found that the inclusion of high-frequency predictors helped to improve the prediction accuracy[7]. Qin Meng et al. (2019) developed a MIDAS mixed-frequency model of Baidu index and Sanya tourism demand, and found that the predictive ability of the MIDAS mixed-frequency model was better than that of the ARMA model[8].

This paper examines the application of the MIDAS hybrid forecasting model in predicting coastal tourism demand, using Gulangyu Island in Xiamen as a case study. The root mean square error (RMSE) serves as the accuracy metric for forecasting. First, Baidu Index data is utilized as high-frequency decadal data, while monthly visitor counts to the island are employed as low-frequency monthly data, with both datasets undergoing preliminary preprocessing. The MIDAS-AR univariate autoregressive mixed-frequency model and the M-MIDAS-AR multivariate autoregressive mixed-frequency model, both constructed using the Almon weighting function, are employed to forecast coastal tourism demand. The predictions are compared with those from the benchmark ADL model, demonstrating the effectiveness of the MIDAS mixed-frequency model in forecasting coastal tourism demand.

3. Theory and Methods

Given the inconsistencies in the frequency of economic data collection. For instance, China's GDP data is compiled quarterly with a certain time lag, while a series of other leading, coincident, or lagging indicators related to GDP—such as the urban surveyed unemployment rate, consumer price index, and import/export data—are compiled monthly. This issue of inconsistent data collection frequencies is particularly pronounced in the coastal tourism sector. China's coastal tourism output value and related metrics are released as annual data, while some provinces publish monthly figures such as overnight visitor counts. Generally, utilizing higher-frequency data enhances the accuracy of economic forecasting. Consequently, the academic community widely seeks to construct predictive models for economic development based on higher-frequency observations.

Ghysels et al (2004) proposed the MIDAS frequency mixing model based on the ADL model, the MIDAS frequency mixing model overcomes the limitation of the traditional ADL model, which requires the same frequency of data for the independent variable and the dependent variable, by introducing a lag operator polynomial to the high-frequency data[1]. The univariate MIDAS mixed model is as follows:

$$y_t=\beta_0+\beta_1 B\left(L^{1/m};\theta\right)x_t^{(m)}+\varepsilon_t^{(m)} \tag{1}$$

Where y_t denotes the low frequency data, $x_t^{(m)}$ denotes the high frequency data, m denotes the frequency multiplicative difference between the high frequency data and the low frequency data,

ISSN 2616-5902 Vol. 7, Issue 11: 54-60, DOI: 10.25236/AJBM.2025.071108

$B\left(L^{1/m};\theta\right)=\sum_{k=0}^{k} B(k;\theta)L^{k/m}$ denotes the lagging operator polynomial, $L^{k/m}$ is the high frequency lagging operator, $L^{k/m}x_t^{(m)}=x_{t-k/m}^{(m)}$ denotes the lagged k-th period of high frequency data, and $B(k;\theta)$ denotes the lag weighting function.

Based on the univariate MIDAS mixing model, a multivariate MIDAS mixing model can be constructed by introducing multiple high-frequency data. The multivariate MIDAS mixture model is as follows:

$$y_t=\beta_0+\sum_{i=1}^{n}\beta_i B\left(L^{1/m};\theta_i\right)x_{i,t}^{(m)}+\varepsilon_{i,t}^{(m)} \tag{2}$$

Where n is the number of high-frequency data and i is the first high-frequency data. It should be noted that we need to estimate β_i for each high-frequency data separately.

The introduction of autoregressive terms can effectively improve the accuracy of model prediction, and the introduction of autoregressive terms into the MIDAS mixed-frequency model can lead to the MIDAS-AR mixed-frequency model[2]. The univariate mixed-frequency first-order autoregressive model MIDAS-AR is as follows:

$$y_t=\beta_0+\lambda y_{t-1}+\beta_1 B\left(L^{1/m};\theta\right)(1-\lambda L)x_t^{(m)}+\varepsilon_t^{(m)} \tag{3}$$

The multivariate mixed frequency first order autoregressive model M-MIDAS-AR is formulated as follows:

$$y_t=\beta_0+\lambda y_{t-1}+\sum_{i=1}^{n}\beta_i B\left(L^{1/m};\theta_i\right)(1-\lambda L)x_{i,t}^{(m)}+\varepsilon_{i,t}^{(m)} \tag{4}$$

The λ is the parameter of the autoregressive term, and the residuals $\hat{\varepsilon}_t^{(m)}$ can be obtained by computing the univariate MIDAS, and the value of $\hat{\lambda}$ is estimated by constructing $\hat{\lambda}=(\sum\hat{\varepsilon}_{t-1}^2)\sum\hat{\varepsilon}_t\hat{\varepsilon}_{t-1}$ using the resulting residuals.

Through the above introduction to the MIDAS formula, it is evident that the key steps in establishing a MIDAS mixing model involve determining the form of the lag weighting function $B(k;\theta)$, as well as selecting the lag order k and parameter θ. Ghysels et al. (2007) presented common lag weighting functions [9]: the Almon weighting function, exponential Almon weighting function, Beta weighting function, Step weighting function, and U-MIDAS weighting function. Among these, the Almon weighting function is the most widely applied. The Almon weighting function is given by Equation (5):

$$B(k;\theta)=\frac{\theta_0+\theta_1 k+\theta_2 k^2+\ldots+\theta_n k^n}{\sum_{k=1}^{K}(\theta_0+\theta_1 k+\theta_2 k^2+\ldots+\theta_n k^n)} \tag{5}$$

The Almon weighting function and the Almon weight function have no fixed requirement for the selection of the lag order k and the parameter θ. For macroeconomic research, the lag order k is generally chosen as a multiple of 3 is more appropriate, such as 3,6,9,12,18 and so on. According to Clements et al. (2006)[2], the number of parameters θ is generally 2 or 3, and it is necessary to limit $\theta_1\leq 300$， $\theta_2\leq 0$.

4. Data Selection and Preprocessing

4.1 Data Selection

The MIDAS model requires high-frequency data as independent variables and low-frequency data as dependent variables. With the widespread adoption of the internet and mobile devices today, most tourists use search tools to research destinations and plan trips in advance. Major search engine companies publish daily search indices for keywords, such as Baidu Index, Sogou Index, 360 Index, and Google Trends. As China's largest search engine company with the most users, Baidu Index provides a relatively accurate reflection of tourists' actual demands.

Travel planning fundamentally involves considerations of ‘clothing, food, lodging, and

ISSN 2616-5902 Vol. 7, Issue 11: 54-60, DOI: 10.25236/AJBM.2025.071108

transportation.' After thoroughly evaluating travel needs, the specific realities of Gulangyu attractions, and data availability, we selected Baidu Index terms for 'Gulangyu Map', 'Gulangyu Accommodation', 'Gulangyu Attractions', and 'Gulangyu Travel Guide' across both PC and mobile platforms as our high-frequency data. The COVID-19 pandemic that erupted in late 2019 caused significant turbulence and shifts in the domestic tourism market, with January 2020 serving as a turning point. To further demonstrate the feasibility of applying the MIDAS hybrid model in the post-pandemic era, the high-frequency data selected for this study spans January 2020 to December 2024. Data from January 2020 to June 2024 constitutes the in-sample period, while July to December 2024 serves as the out-of-sample period to evaluate the model's short-term forecasting capability. Monthly visitor count data released by the Gulangyu Island Management Committee in Xiamen serves as the low-frequency data, with visitor numbers representing Gulangyu's actual tourism demand.

4.2 Data Preprocessing

Since Baidu Index provides daily data, using raw daily data for high-frequency indices would result in excessive and inconsistent multiples between high- and low-frequency data. This not only reduces model accuracy but also increases prediction difficulty. Therefore, this paper converts high-frequency daily data into ten-day intervals: the 1st to 10th of each month is defined as the first ten days, the 11th to 20th as the middle ten days, and the 21st to the end of the month as the last ten days. After aggregating daily data into ten-day intervals, the average value corresponding to each ten-day period is calculated. The year-over-year growth rate for each average value is then determined, and the year-over-year growth rate for low-frequency monthly data is calculated. Processing data through these steps ensures the ratio between high- and low-frequency data remains within a reasonable range and is fixed at 3, while also eliminating seasonal influences on the data.

5. Empirical Section

5.1 Selection of Benchmark Model and Predictive Indicators

ADL, the Autoregressive Distributed Lag model, is widely applied in studying the autoregressive properties and random fluctuations of time series. Based on the AIC criterion, this paper selects ADL(1,1) as the benchmark model for comparison with the univariate MIDAS hybrid model, the multivariate MIDAS hybrid model, and the prediction results from machine learning algorithms optimized using the MIDAS hybrid model. Root Mean Square Error (RMSE) is employed to evaluate model prediction performance. To compare the benchmark model with MIDAS hybrid models, the ratio of RMSE between MIDAS hybrid models and the benchmark model is used. When R_{ADL} is less than 1, the MIDAS hybrid model outperforms the benchmark model. Conversely, when R_{ADL} is greater than 1, the benchmark model outperforms the MIDAS hybrid model. The RMSE formula is given by Equation (8):

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i\text{-}y_i^{\ *}\right)^2} \tag{6}$$

Where n is the number of forecast periods for the year-on-year growth rate of tourists, $y_i$is the actual year-on-year growth rate of tourist arrivals, and $y_i^{\ *}$ is the year-on-year growth rate of tourist arrivals predicted by the model.

5.2 Univariate MIDAS Mixed Model

Common lag weight functions include almon, exponential almon, beta, step, and U-MIDAS, etc. Referring to Qin Meng et al. (2019)[8], this paper takes the classic Almon lag weight function as an example and establishes a univariate MIDAS mixing model to predict the year-on-year growth rate of tourist arrivals in Gulangyu Island, and the established univariate MIDAS function is as follows:

$$y_t=\beta_0+\beta_1 B\left(L^{1/3};\theta\right)x_t^{(3)}+\varepsilon_t^{(3)} \tag{7}$$

Where y_t denotes the annual growth rate of the number of low-frequency visitors, $B\left(L^{1/3};\theta\right)=\sum_{k=0}^{k}B(k;\theta)L^{k/3}$ denotes the Almon's lag operator polynomial, $B(k;\theta)=\frac{\theta_0+\theta_1k+\theta_2k^2+\theta_3k^3}{\sum_{k=1}^{k}(\theta_0+\theta_1k+\theta_2k^2+\theta_3k^3)}$

ISSN 2616-5902 Vol. 7, Issue 11: 54-60, DOI: 10.25236/AJBM.2025.071108

denotes the Almon lag weight function, and $x_t^{(3)}$ denotes a high-frequency Baidu index.

The baseline model in this paper adopts a first-order PDL model. To facilitate comparison of prediction performance, the univariate MIDAS mixing model also employs a first-order autoregressive structure, specifically the MIDAS-AR (1) model for forecasting. The prediction results are presented in Table 1. The numbers in parentheses within the MIDAS prediction results indicate the optimal lag order.

Table 1: Univariate Model Forecast Results

Real growth rate of tourists	Gulangyu Travel Guide		Gulangyu Map		Gulangyu Attractions		Gulangyu Accommodations	
	MIDAS Results	ADL Results	MIDAS Results	ADL Results	MIDAS Results	ADL Results	MIDAS Results	ADL Results
0.123	2.816	4.400	-0.530	-0.429	0.592	2.810	0.425	0.584
0.183	4.329	4.881	-0.133	-0.251	2.289	2.689	0.330	0.588
-0.091	1.134	3.011	-0.194	0.202	-0.869	1.102	0.292	0.392
0.045	8.646	10.060	-0.160	0.773	2.249	2.831	0.458	1.215
-0.154	7.276	9.527	0.391	1.222	1.204	2.986	0.144	0.488
-0.081	6.931	10.718	0.658	1.110	2.585	4.005	0.521	1.591

Analysis of the single-variable model's predictions reveals that the COVID-19 pandemic has severely impacted the coastal tourism market. Using Baidu Index data on the pandemic to forecast tourist growth rates resulted in significant prediction errors, causing a substantial decline in the predictive capabilities of both the traditional ADL model and the MIDAS mixed-frequency data model.

The ratio of RMSE between the univariate MIDAS hybrid model and the baseline model ($R_{ADL(1)}$) is shown in Table 2. The numbers in parentheses for MIDAS-RMSE indicate the optimal lag order. Simultaneously, we observe that comparing the root mean square error ratios between the ADL and MIDAS models demonstrates that even when confronting sudden shocks from black swan events like the COVID-19 pandemic, the MIDAS model maintains superior predictive capability over the ADL model.

Table 2: Univariate Model RMSE

	MIDAS-RMSE	ADL-RMSE	$R_{ADL(1)}$
Gulangyu Map	0.531801 (12)	1.039067	0.511806
Gulangyu Attractions	2.205334 (3)	4.041596	0.545659
Gulangyu Accommodations	0.682723 (12)	0.898703	0.759676
Gulangyu Travel Guide	7.357943 (6)	8.017591	0.917725

Based on the table above, we can draw the following conclusions. First, a lower RMSE indicates better predictive capability of the model. Judging by the RMSE values, the Baidu Indexes for ‘Gulangyu Map’ and ‘Gulangyu Accommodation’ demonstrate superior predictive power for year-on-year tourist growth rates, while those for ‘Gulangyu Attractions’ and ‘Gulangyu Travel Guides’ show weaker predictive capability. This phenomenon relates to the characteristics of the Gulangyu scenic area. Gulangyu is an offshore island accessible only by ferry. With its dense urban layout, visitors must explore on foot. To enhance their experience, tourists place greater emphasis on using maps for navigation and pay closer attention to accommodation options. Additionally, attractions on Gulangyu are concentrated, and sightseeing routes are relatively fixed, leading visitors to show less interest in attraction-specific guides.

Second, regarding the optimal lag order in the sample, the Baidu Index for ‘Gulangyu Map’ and ‘Gulangyu Accommodation’ exhibits a significant lag order of 12 periods. In contrast, the lag orders for ‘Gulangyu Attractions’ and ‘Gulangyu Travel Guides’ are relatively low at 3 and 6 periods, respectively. This indicates that coastal tourism demand on Gulangyu is more sensitive to shifts in visitor interest toward attractions and travel guides, aligning with practical observations. Generally, such information better reflects a region's unique characteristics and thus exerts greater influence on tourist destination decisions than maps or accommodation details. These two conclusions also indicate that when applying the MIDAS hybrid model to forecast coastal tourism demand, variable selection should be tailored to regional characteristics to achieve more accurate predictions.

Third, overall, under the impact of sudden events, the MIDAS model still demonstrates superior predictive capability compared to traditional co-frequency data models.

ISSN 2616-5902 Vol. 7, Issue 11: 54-60, DOI: 10.25236/AJBM.2025.071108

5.3 Multivariate MIDAS Mixing Model

Based on the above univariate MIDAS mixing model, we put several high-frequency data into the multivariate MIDAS mixing model to construct the following M-MIDAS mixing model:

$$y_t=\beta_0+\sum_{i=1}^{n}\beta_i B\left(L^{1/3};\theta_i\right)x_{i,t}^{(3)}+\varepsilon_{i,t}^{(3)} \tag{8}$$

Where y_t denotes the annual growth rate of the number of low-frequency visitors, $\sum_{i=1}^{n}\beta_i B\left(L^{1/3};\theta_i\right)=\sum_{i=1}^{n}\sum_{k=0}^{k}\beta_i B(k;\theta_i)L^{k/3}$ denotes the polynomial summation of the i Almon's lagged operator,$B(k;\theta_i)=\frac{\theta_{i,0}+\theta_{i,1}k+\theta_{i,2}k^2+\theta_{i,3}k^3}{\Sigma_{k=1}^{k}(\theta_{i,0}+\theta_{i,1}k+\theta_{i,2}k^2+\theta_{i,3}k^3)}$ denotes the ith Almon lag weight function, and $x_{i,t}^{(3)}$ denotes a HF Baidu index.

Like the univariate midas mixing model, to enable comparison with the benchmark first-order autoregressive model, the multivariate MIDAS mixing model also employs a first-order autoregressive model, specifically M-MIDAS-AR(1), for forecasting. The forecast results are presented in Table 3.

Table 3: Multivariate Model Prediction Results

Real growth rate of tourists	M-MIDAS Prediction Results	M-ADL Prediction Results
0.123	1.800	2.662
0.183	2.605	3.004
-0.091	2.532	1.830
0.045	2.341	6.892
-0.154	3.866	5.883
-0.081	5.310	7.431

The ratio of RMSE between the multivariate MIDAS mixing model and the benchmark model ($R_{ADL(2)}$) is shown in Table 4. The number in parentheses for M-MIDAS-RMSE indicates the optimal lag order.

Table 4: Multivariate Model's RMSE

	M-MIDAS-RMSE	M-ADL-RMSE	Rarma (2)
Multivariate	2.017592 (12)	4.465733	0.451794

Observing Table 4, it can be seen that under the severe impact of the COVID-19 pandemic emergency, the predictive accuracy of the multivariate MIDAS hybrid model remains higher than that of the multivariate ADL model.

6. Conclusions and Recommendations

This paper uses Xiamen's Gulangyu Island as a case study to forecast coastal tourism demand using the MIDAS hybrid model. We construct both univariate and multivariate MIDAS hybrid models, employing Baidu Index as high-frequency data to predict low-frequency year-on-year growth rates in visitor numbers. The study reveals that after incorporating the MIDAS hybrid model, both the univariate and multivariate models demonstrate superior predictive accuracy compared to the baseline ADL model. Specifically, the following conclusions can be drawn:

First, Baidu Index can be utilized to study and forecast coastal tourism demand indicators. Driven by sustained economic growth, widespread internet device adoption, and rising public aspirations for quality living, the number of residents choosing coastal tourism continues to increase. As the search data metric from China's largest search engine in terms of scale and audience reach, Baidu Index reflects visitor interest and actual demand trends closely linked to coastal tourism development. Future research may consider leveraging Baidu Index and similar search metrics for coastal tourism studies. Simultaneously, when selecting indicators, it is essential to account for the diversity of coastal tourism destinations and fully consider the unique characteristics of the research subjects. Choosing appropriate indicators can significantly enhance the accuracy of predictions.

Second, under the impact of public health emergencies, predictive models generally failed, with both univariate and multivariate models exhibiting deviations several times greater than normal. The root cause lies in the sharp decline in tourist travel intentions following the outbreak, compounded by tightened control measures, which caused an instant contraction in passenger flow. After temporary

ISSN 2616-5902 Vol. 7, Issue 11: 54-60, DOI: 10.25236/AJBM.2025.071108

lockdowns were lifted, demand rebounded rapidly. Within a short period, the growth rate of tourist numbers fluctuated dramatically between positive and negative values, far exceeding historical fluctuation ranges. Models trained on pandemic-era data and relying on linear assumptions struggled to capture such nonlinear discontinuities, leading to systemic biases in coastal tourism demand forecasts. This highlights the profound challenges public health crises pose to coastal tourism forecasting frameworks.

Third, whether examining predictions from the univariate MIDAS hybrid model or the multivariate MIDAS hybrid model, the MIDAS hybrid model demonstrated significantly superior forecasting performance compared to traditional ADL models. This demonstrates the MIDAS hybrid model's advantage in ensuring data remains unaffected by artificial manipulation while fully leveraging information from different frequency data streams for direct modeling using hybrid data. Currently, research applying MIDAS to coastal tourism remains limited. Future studies could consider incorporating more data sources to expand research on input-output forecasting, operational monitoring, and efficiency evaluation in coastal tourism.

Acknowledgements

This research was supported by the Humanities and Social Sciences Research Planning Fund of the Ministry of Education, Project No. 21YJA630097)

This research was supported by the Hong Kong and Macao Joint Research and Development Fund of Wuyi University, Project No. 2021WGALH20)

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