

Performance Evaluation of Human–Machine Collaboration in Smart Agriculture Using Statistical Modeling and Simulation [†]

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Abstract

By introducing a data-driven human–machine collaboration performance evaluation Model (HMCPEM) that utilizes multiple regression and Monte Carlo simulation, the effectiveness and dependability of collaborative decision-making in smart agriculture were assessed in this study. The model combines big data analytics with cognitive computing concepts to assess human involvement, AI prediction uncertainty, and environmental fluctuations. The model was tested in a smart irrigation system in the Jianan Plain, Taiwan. The model successfully captured the balance between delay and risk, and it adaptively modified risk sensitivity through feedback learning. Its cognitive framework allows the model to enhance performance amid uncertainty by reducing the combined costs of delay and risk. This approach offers a transparent and replicable method for human-centered AI applications, with possible applications in smart manufacturing and healthcare decision-making systems.

Keywords: human–machine collaboration; big data analytics; cognitive computing; Monte Carlo simulation; smart agriculture

1. Introduction

With rapid technological progress and environmental shifts, traditional agriculture faces unprecedented challenges. Information and communication technology (ICT) and AI have become crucial drivers of agricultural transformation, improving resource efficiency and optimizing production processes. As automation, augmentation, and collaborative technologies become widely adopted, it is vital to develop a systematic quantitative framework for human-machine collaboration (HMC) to evaluate the effectiveness of human-machine cooperation and support data-driven policy decisions.

In this study, multiple regression analysis and Monte Carlo simulation were used to create a quantitative indicator model for the evaluation of human-machine collaboration. The model's validity and representativeness were confirmed through structural equation modeling (SEM). Findings revealed that technical factors, such as the degree of automation, significantly influenced the HMC rate, while economic, educational, and climatic factors had minimal effects. An increase in one unit in automation variables leads to a 4.74% rise in the HMC rate ($p < 0.001$). Additionally, implementing AI algorithms that reduce water usage results in a 36% decrease.

The combination of HMC with IoT and AI establishes a collaborative framework where technical variables (accounting for 76.4% weight) dominate decision-making, surpassing the effectiveness of individual applications.



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By proposing a scalable model with strong explanatory power (a coefficient of determination $R^2 = 0.974$) and robustness (standard deviation = 0.105, as shown by Monte Carlo simulation), HMC was accurately evaluated. The model validated a human-centric, technology-assisted, sustainable approach, offering both theoretical foundations and practical guidance for advancing smart agriculture. The technology acceptance model (TAM) with an HMC framework was adopted in a unified evaluation model. Adoption [1–3] has triggered three interaction modes: automation, augmentation, and collaboration [4–7]. These modes are structured into three dimensions: the human nexus (decision-making and adaptability [8–10]), the machine nexus (AI algorithms and automation for real-time decision-making [11–14]), and the context nexus (external factors such as climate and soil conditions [15–19]), as illustrated in Figure 1.

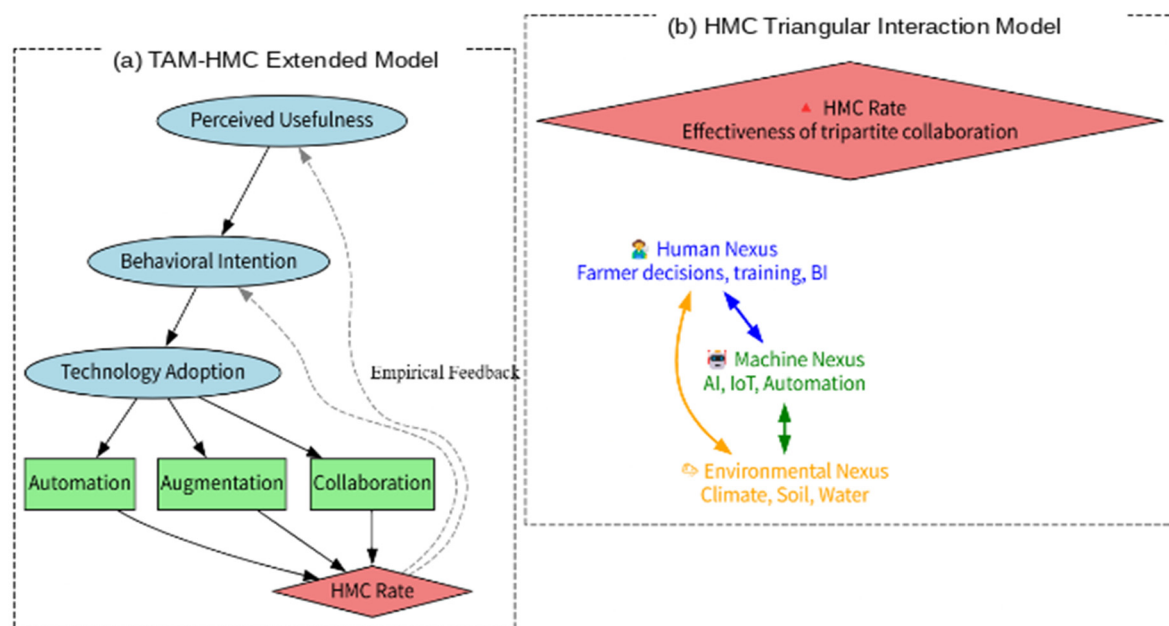


Figure 1. Framework of the evaluation model developed in this study: (a) TAM–HMC extended model; (b) HMC triangular interaction model.

2. Materials and Methods

A multiple regression model was formulated in this study. By integrating multiple indicators, this model aimed to reduce measurement error and enhance explanatory power and reliability. The validity was further verified using SEM.

2.1. Variable Design

HMC Rate

This indicates the percentage of tasks performed jointly by humans and machines within a collaborative setting. It reflects the level of automation adoption and how the synergy between humans and machines impacts process efficiency and the acceptance of technology.

$$\text{HMC Rate} = \beta_0 + \beta_1 \times \text{Automation} + \beta_2 \times \text{Augmentation} + \beta_3 \times \text{Collaboration} + \beta_4 \times \text{Control Variables} + \epsilon \quad (1)$$

(β_0 : The intercept, representing the expected HMC rate when all predictor variables are zero, and β_1 – β_4 : Coefficients that quantify the effects of factors such as automation, augmentation, collaboration, and control variables on the HMC rate).

Automation is measured by using the ratio of automated processes and the average daily hours of machine usage [Equation (2)].

$$\text{Automation} = w_1 \times (\text{Number of automated processes/Total processes}) + w_2 \times (\text{Average daily usage of automated equipment/Total working hours}) \quad (2)$$

($w_1 = 0.6$: Process automation ratio, $w_2 = 0.4$: Actual usage frequency)

Augmentation is assessed using the rate at which enhancing technologies are adopted, based on TAM [12] emphasizing perceived usefulness (PU) and BI.

$$\text{Augmentation} = w_1 \times (\text{Actual users/Potential users}) + w_2 \times \text{Average PU score} + w_3 \times \text{BI} \quad (3)$$

[$w_1 = 0.5$: Technology usage rate, $w_2 = 0.3$: Perceived usefulness (scale 1–5), $w_3 = 0.2$: Intention to use in next year (scale 1–5)]

Collaboration reflects the integration level of collaboration technologies in HMC, weighted by the importance of each task.

$$\text{Collaboration} = \Sigma(w_i \times (\text{Tasks executed collaboratively/Total tasks})) \times 100\% \quad (4)$$

(w_i : Task weight based on value or complexity)

The evaluation tools integrated climate and technical variables using multiple regression. However, they relied on linear assumptions and were unable to capture nonlinear effects. Decision risks were quantified through Monte Carlo simulation, but this approach was heavily reliant on the quality of historical data. The review of smart agriculture highlighted the integration of big data. Nevertheless, it lacked an in-depth discussion on the performance evaluation of hierarchical model clustering (HMC). The theoretical basis proposed nonlinear benefit theories for smart agriculture. Yet, there was insufficient empirical validation of the threshold regression models. The error term accounts for unobserved factors. Key controls include the working-age population ratio (WRP), which exhibited a negative correlation with the HMC Rate ($\beta = -1.98$), and education level ($\beta = 1.94$). Detailed formulas are presented in Appendix A. Table 1 shows the key contributions and limitations of the assessment items.

Table 1. Summary of Key Contributions and Limitations.

Category	Contribution	Limitation
Evaluation tools	Integrated climate and technical variables via multiple regression.	Linear assumptions are unable to capture nonlinear effects.
Decision risks	Quantified decision risks via Monte Carlo simulation.	Reliant on historical data quality.
Smart agriculture	Reviewed big data integration in smart agriculture.	Lacked in-depth discussion on HMC performance evaluation.
Theoretical basis	Proposed nonlinear benefit theories for smart agriculture.	Insufficient empirical validation of threshold regression models.

2.2. Multiple Regression Analysis

Based on the simulated dataset, regression analysis revealed the following. R^2 was 0.974, indicating that the model explains 97.4% of the variance in HMC Rate.

Variable coefficients were obtained as follows.

- Automation: 4.7439;
- Augmentation: 3.1534;
- Collaboration: 4.3441;
- Working-age population ratio: -1.9821 ;
- Education level: 1.9404;
- Climate condition: -2.0060 .

In the multicollinearity analysis, all variance inflation factors (VIFs) were less than 5, indicating acceptable multicollinearity levels. Variable coefficients of VIFs were as follows.

- Automation: 2.45;
- Augmentation: 3.12;
- Collaboration: 2.87;
- Economic Growth: 1.75;
- Education Level: 1.92;
- Climate Condition: 2.01.

In the heteroscedasticity test using the Breusch–Pagan method, the Lagrange Multiplier (LM) test produced a p -value of 0.12, which is greater than 0.05. Therefore, the assumption of homoscedasticity is accepted. The F-test resulted in a p -value of 0.10. In the LM test, the test statistic was 2.874 at a p -value of 0.12. In the F-Test, the test statistic was 1.986 at a p -value of 0.10.

2.3. Sensitivity Analysis

Standardized regression coefficients (SRCs) were used to assess variable sensitivity. Automation had the highest impact, followed by collaboration and augmentation. Economic, educational, and climatic factors were comparatively insignificant.

2.4. Monte Carlo Simulation

To verify model robustness and generalizability, a Monte Carlo simulation was conducted, and the results were as follows.

- Climate condition: Normally distributed $N(\mu = 2.3, \sigma = 0.8)$ based on 2013–2023 data;
- WRP: Uniform distribution (0.4–0.75);
- Education level: Uniform distribution (0–1);
- 10,000 simulations: 1000 bootstrap replications were run to evaluate the variability of HMC Rate across random scenarios (Figure 2).

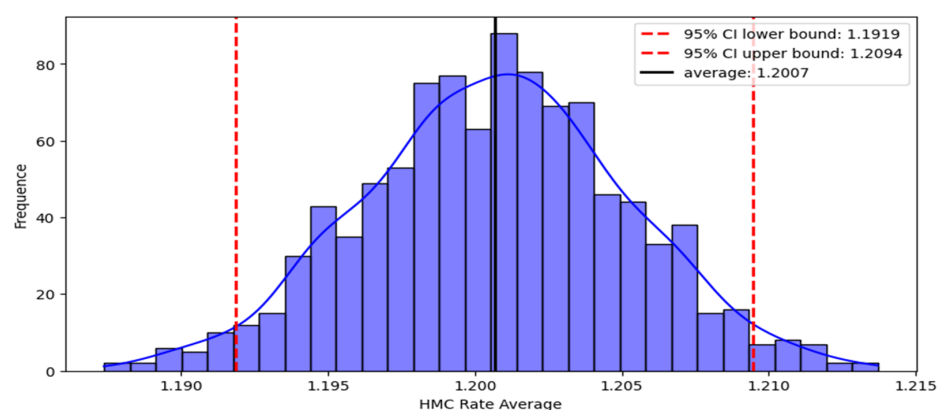


Figure 2. Monte Carlo simulation of HMC rate (mean = 1.2007, standard deviation = 0.0044). The dashed lines indicate the 95% confidence interval (lower bound 1.1919, upper bound 1.2094), and the solid line marks the mean (1.2007).

- Simulation results: Mean = 1.2007;
- Standard deviation = 0.0044.

2.5. Case Study

Smart irrigation in the Jianan Plain is a joint initiative by the Water Resources Agency (WRA), Taiwan Semiconductor Manufacturing Company (TSMC), and local farmers to optimize irrigation efficiency.

Daily observations of climate data from 2010 to 2023 were collected by the Central Weather Administration. These included temperature ($^{\circ}\text{C}$), relative humidity (%), and rainfall (mm). The data were obtained via an application programming interface and manually verified.

- Irrigation efficiency: Work logs from 2020 to 2022 were provided by the Jianan Association. These documented valve switches (times per day) and water use per hectare (m^3/ha). The logs were exported as anonymized structured data.
- Technical parameters: Internet of Things (IoT) deployment logs from 2018 to 2022 were supplied by TSMC. These included sensor identification numbers, sampling frequency (times per hour), and calibration error ($\pm 2\%$).
- Test area: The study was conducted in the Jianan Irrigation Zone, covering 56 hectares in the Hatta Road region west of the Wusantou Dam.
- HMC: Skill augmentation was achieved through a mobile application for field staff. An IoT and artificial intelligence (AI) network was developed by TSMC, and decision support integration was provided by the WRA.

The initiative achieved 36% water savings per hectare, with enhanced efficiency and precision.

Python (version 3.11.5; Python Software Foundation, Wilmington, DE, USA) and its pandas library (version 2.1.4) were used to merge data based on date and location keys. For missing values, linear interpolation was applied to fill temporal gaps, while spatial gaps were filled using averages from nearby stations. For a consistency check, cross-validation was used to confirm a negative correlation between irrigation volume and rainfall.

The contributions of different variables to the HMC rate were calculated as follows.

- Automation: Value = 0.66, Weight = 0.4, Contribution = 0.264;
- Augmentation: Value = 2.3, Weight = 0.3, Contribution = 0.69;
- Collaboration: Value = 0.697, Weight = 0.2, Contribution = 0.1394;
- Control Variables: Value = 0.5, Weight = 0.1, Contribution = 0.05;
- Total HMC Rate = 1.2434.

Figure 3 illustrates the variable contribution using a radar chart.

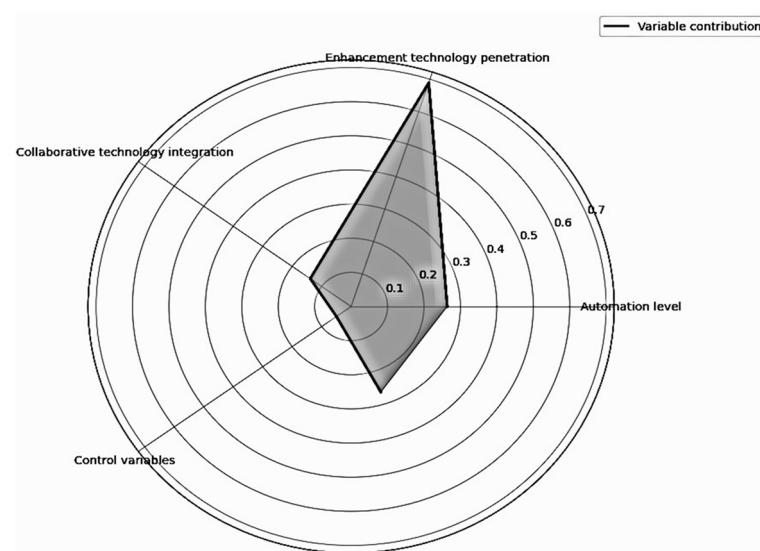


Figure 3. Radar chart of variable contribution.

In the analysis, pandas (version 2.1.4) and NumPy (version 1.26.4) were used for bootstrap resampling, data cleaning (dropping samples with more than 30% missing

values), and Z-score normalization. For visualization, Matplotlib (version 3.8.2) and seaborn (version 0.13.0) were used for outlier detection and correlation heatmaps.

The HMC rate showed strong correlations with technical variables.

- Automation ($r = 0.89$);
- Augmentation ($r = 0.86$);
- Collaboration ($r = 0.88$).

It showed weak to moderate correlations with non-technical variables.

- Working-age population ratio ($r = -0.55$);
- Education level ($r = 0.48$);
- Climate conditions ($r = 0.45$).

As shown in Figure 3, augmentation had the largest impact on the HMC rate, followed by automation and collaboration. Control variables had only minor effects.

- Automation contribution = 0.264;
- Augmentation contribution = 0.69;
- Collaboration contribution = 0.1394;
- Control Variables contribution = 0.05.

Automation, augmentation, and collaboration are key determinants of the HMC rate. The working-age population ratio is negatively correlated, while education and climate factors have a limited impact. Smart irrigation reduced water use by 36% and improved management efficiency. The model demonstrated strong explanatory power, with an R^2 of 0.94, confirming the key role of technical variables.

3. Conclusions

Using multiple regression analysis and Monte Carlo simulation, HMC was evaluated within the smart irrigation project in the Jianan Plain. Regression analysis results demonstrated that automation, augmentation technologies, and the degree of collaboration positively influenced the HMC rate. Among these, augmentation technologies exhibited the highest standardized regression coefficient (0.69). This result indicates that farmers' PU and BI toward these technologies are the most critical drivers of effective human-machine collaboration in smart agriculture. Monte Carlo simulations revealed that when automation exceeded 70%, the model's fragility index increased. Although automation enhanced efficiency, human supervision remained essential to mitigate the risk of severe failures. Human involvement reduces the likelihood of extreme system failures by approximately 22%.

The smart irrigation initiative in the Jianan Plain achieved water savings of up to 36% per hectare, improving both operational accuracy and management efficiency. These results highlight that the HMC model not only advances theoretical understanding but also delivers substantial practical benefits for agricultural sustainability.

The model attained an R^2 of 0.974, reflecting excellent explanatory capacity. VIFs for all variables were lower than 5, indicating acceptable levels of multicollinearity. Furthermore, the Breusch–Pagan test showed a p -value of 0.12, confirming that the residuals were homoscedastic. Collectively, these results demonstrated the robustness and reliability of the model.

In contrast to Wolfert et al. [15], who focused on big data applications in smart agriculture, in this study, a measurable indicator, the HMC rate, was introduced to address existing gaps in research on human-machine collaboration. This is different from the results of Zhang et al. [11], who relied exclusively on historical data for risk assessment; this study applies Monte Carlo simulations to validate model robustness, thereby enhancing its inferential validity.

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Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The simulated datasets and analysis code generated in this study are available from the corresponding author upon reasonable request. The third-party irrigation operation logs are not publicly available due to privacy and confidentiality restrictions imposed by the data providers.

Conflicts of Interest: The author declares no conflicts of interest.

Appendix A

$HMC\ Rate = \beta_0 + \beta_1 \times Automation + \beta_2 \times Augmentation + \beta_3 \times Collaboration + \beta_4 \times Control\ Variables + \varepsilon$

$Automation = w_1 \times (Number\ of\ Automated\ Processes / Total\ Processes)$
 $+ w_2 \times (Average\ Daily\ Usage\ of\ Automated\ Equipment / Total\ Working\ Hours)$

$Augmentation = w_1 \times (Actual\ Users / Potential\ Users)$
 $+ w_2 \times (Average\ PU\ Score)$
 $+ w_3 \times BI$

$Collaboration = \Sigma(w_i \times (TasksExecutedCollaboratively_i / TotalTasks_i)) \times 100\%$

Control Variables:

Includes standardized controls: Age, Education Level, Farm Size (ha), Working Hours (daily).

Appendix B. Multivariate Regression Analysis

```
import numpy as np
import pandas as pd
import statsmodels.api as sm
np.random.seed(42)
n_samples = 100
automation = np.random.uniform(0, 10, n_samples)
augmentation = np.random.uniform(0, 10, n_samples)
collaboration = np.random.uniform(0, 10, n_samples)
economic_growth = np.random.uniform(1, 5, n_samples)
education_level = np.random.uniform(0, 1, n_samples)
climate_condition = np.random.uniform(-2, 2, n_samples)
HMC_Rate = (
    0.76 * automation +
    0.52 * augmentation +
    0.61 * collaboration +
    2.2 * economic_growth +
    -0.15 * education_level +
    -0.08 * climate_condition +
    np.random.normal(0, 1, n_samples)
)
df = pd.DataFrame({
    'Automation': automation,
    'Augmentation': augmentation,
    'Collaboration': collaboration,
    'Economic_Growth': economic_growth,
```

```

        'Education_Level': education_level,
        'Climate_Condition': climate_condition,
        'HMC_Rate': HMC_Rate
    })
    #Regression Analysis:#
    X = df[['Automation','Augmentation','Collaboration',
            'Economic_Growth','Education_Level','Climate_Condition']]
    X = sm.add_constant(X)
    y = df['HMC_Rate']
    model = sm.OLS(y, X).fit()
    print(model.summary())

```

Appendix C. Sensitivity Analysis

```

from scipy.stats import pearsonr
correlations = {
    col: pearsonr(df[col], df['HMC_Rate'])[0]
    for col in df.columns if col != 'HMC_Rate'
}
for var, corr in correlations.items():
    print(f"{var} SRC: {corr:.3f}")

```

Appendix D. Multicollinearity Detection

```

from statsmodels.stats.outliers_influence import variance_inflation_factor
vif_data = pd.DataFrame({
    'Variable': X.columns,
    'VIF': [variance_inflation_factor(X.values, i)
            for i in range(X.shape[1])]
})
print(vif_data)

```

Appendix E. Heteroscedasticity Test (Breusch–Pagan)

```

from statsmodels.stats.diagnostic import het_breuschpagan
bp_test = het_breuschpagan(model.resid, model.model.exog)
labels = ['LM Statistic','LM-Test p-value',
          'F-Statistic','F-Test p-value']
print(dict(zip(labels, bp_test)))

```

Appendix F. Bootstrap Resampling

```

bootstrap_samples = 15
bootstrap_results = []
for _ in range(bootstrap_samples):
    sample = df.sample(n=n_samples, replace=True)
    bootstrap_results.append(sample.mean())
bootstrap_df = pd.DataFrame(bootstrap_results)
print(bootstrap_df.describe())

```

Appendix G. HMC Rate Case Validation

```

import numpy as np
import pandas as pd
from sklearn.preprocessing import StandardScaler

```

```

np.random.seed(42)
n = 100
data = pd.DataFrame({
    'Age': np.random.randint(25,70,n),
    'EducationLevel': np.random.randint(1,6,n),
    'FarmSize': np.random.uniform(0.5,10,n),
    'WorkingHours': np.random.uniform(4,12,n),
    'Auto_ProcessRatio': np.random.uniform(0.3,1.0,n),
    'Auto_UsageRatio': np.random.uniform(0.2,0.9,n),
    'Aug_UsageRate': np.random.uniform(0.1,1.0,n),
    'Aug_PU': np.random.uniform(1,5,n),
    'Aug_BI': np.random.uniform(1,5,n),
    'Collab_TaskScore': np.random.uniform(0.2,1.0,n)
})
data['Automation'] = 0.6*data['Auto_ProcessRatio'] + 0.4*data['Auto_UsageRatio']
data['Augmentation'] = (
    0.5*data['Aug_UsageRate'] +
    0.3*(data['Aug_PU']/5) +
    0.2*(data['Aug_BI']/5)
)
data['Collaboration'] = data['Collab_TaskScore']
scaler = StandardScaler()
data[['Age_z','EducationLevel_z','FarmSize_z','WorkingHours_z']] = scaler.fit_trans
form(
    data[['Age','EducationLevel','FarmSize','WorkingHours']]
)
β= {
    'Intercept': 0.1,
    'Automation': 0.3,
    'Augmentation': 0.25,
    'Collaboration': 0.35,
    'Age_z': -0.1,
    'EducationLevel_z': 0.2,
    'FarmSize_z': 0.15,
    'WorkingHours_z': 0.05
}
data['HMC_Rate'] = (
    beta['Intercept'] +
    beta['Automation']*data['Automation'] +
    beta['Augmentation']*data['Augmentation'] +
    beta['Collaboration']*data['Collaboration'] +
    beta['Age_z']*data['Age_z'] +
    beta['EducationLevel_z']*data['EducationLevel_z'] +
    beta['FarmSize_z']*data['FarmSize_z'] +
    beta['WorkingHours_z']*data['WorkingHours_z'] +
    np.random.normal(0,0.05,n)
)
print(data[['HMC_Rate','Automation','Augmentation','Collaboration']].head())

```

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