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Network Big Data Analysis with Multi-Factor Hashing Ethereum Classification (Mfh-Ec): An Approach to Develop Strategy of the Tourism Industry Under the Post-Epidemic Situation

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Abstract: - In the tourism industry, big data has emerged as a revolutionizing the way businesses operate and travelers experience destinations. With the vast amount of data generated from online bookings, social media interactions, and mobile applications, tourism companies can gain valuable insights into traveler preferences, behavior patterns, and market trends. This paper proposes a development strategy for the tourism industry in the post-epidemic situation, leveraging network big data analysis with Multi-Factor Hashing Ethereum Classification (MFH-EC). By harnessing the power of network big data, this strategy aims to provide insights into changing traveler preferences, market dynamics, and risk factors in the wake of the pandemic. The MFH-EC model facilitates the classification and analysis of diverse factors influencing tourism development, including economic indicators, health and safety measures, environmental conditions, and traveler sentiment. Through simulated experiments and empirical validations, the effectiveness of the proposed strategy is assessed, demonstrating significant improvements in predictive accuracy and decision-making capabilities. For instance, the MFH-EC model achieved an 80% accuracy rate in predicting tourism demand shifts and a 30% reduction in forecasting errors compared to traditional methods. These results underscore the potential of network big data analysis with MFH-EC in guiding strategic decision-making and fostering sustainable recovery and growth in the tourism industry post-epidemic.

Keywords: Tourism industry, post-epidemic situation, network big data, predictive accuracy, numerical results, decision-making, sustainable recovery.

I. INTRODUCTION

The tourism industry has been significantly transformed by the advent of big data analytics, revolutionizing how businesses understand and cater to travelers' needs. With the proliferation of online booking platforms, review websites, and social media, vast amounts of data are generated daily, providing invaluable insights into consumer preferences, behaviors, and trends [1]. Big data enables tourism businesses to personalize marketing strategies, optimize pricing, and enhance customer experiences [2]. For instance, through data analysis, companies can identify popular destinations, predict peak travel times, and tailor promotional offers accordingly [3]. Additionally, sentiment analysis of online reviews allows businesses to gauge customer satisfaction and promptly address any concerns. Moreover, the integration of big data with emerging technologies like artificial intelligence and machine learning enables the development of predictive models for demand forecasting and risk management [4]. By harnessing the power of big data analytics, the tourism industry can drive innovation, improve operational efficiency, and ultimately deliver more tailored and memorable experiences for travelers [5].

In the dynamic landscape of the tourism industry, decision-making systems empowered by big data play a pivotal role in shaping strategies and optimizing operations. These systems leverage vast volumes of data from various sources such as booking platforms, social media, and customer feedback to provide actionable insights to businesses [6]. Through sophisticated analytics techniques, decision-making systems can identify emerging trends, predict consumer behavior, and assess market demand with unprecedented accuracy. This enables tourism businesses to make informed decisions regarding pricing, marketing campaigns, resource allocation, and product development [7]. Furthermore, decision-making systems in the big data tourism industry utilize advanced algorithms and machine learning models to automate and streamline processes [8]. Predictive analytics can forecast future demand for specific destinations or services, allowing businesses to adjust inventory levels and pricing strategies accordingly. Similarly, sentiment analysis of online reviews and social media conversations enables companies to gauge customer satisfaction in real time and address issues promptly [9]. Additionally, these systems facilitate personalized

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marketing efforts by segmenting customers based on their preferences, behaviors, and demographics. Moreover, decision-making systems in the big data tourism industry are increasingly integrated with other emerging technologies such as artificial intelligence and IoT (Internet of Things) [10]. For instance, AI-powered chatbots can provide personalized recommendations and assist travellers throughout their journey, enhancing the overall customer experience [11]. IoT devices such as smart sensors and beacons enable businesses to collect real-time data on foot traffic, crowd density, and environmental conditions, enabling better decision-making in areas like crowd management and resource allocation [12].

The paper makes significant contributions to the field of tourism industry decision-making through its introduction and application of the Multi-Factor Hashing with MFH-EC methodology. Firstly, by integrating multiple factors such as traveler age, destination type, economic indicators, and seasonality, the methodology offers a comprehensive approach to analyzing tourism dynamics. This holistic perspective allows stakeholders to gain deeper insights into the complex interactions shaping tourist behavior and preferences. Secondly, the utilization of cryptographic hashing techniques ensures the integrity and security of input data, addressing concerns related to data privacy and tampering. By securely storing hashed data on the Ethereum blockchain, the methodology provides a transparent and auditable platform for decision-making, fostering trust and collaboration among industry stakeholders. Thirdly, the classification results obtained through the MFH-EC methodology empower decision-makers to anticipate and respond to changes in tourism demand with greater accuracy and efficiency. By leveraging these insights, stakeholders can tailor marketing strategies, optimize resource allocation, and enhance tourist experiences, ultimately driving sustainable growth and competitiveness in the tourism industry. Overall, the paper's contribution lies in its innovative approach to harnessing big data and blockchain technology to inform decision-making processes, thereby advancing the capabilities and resilience of the tourism sector in the post-epidemic era.

II. LITERATURE REVIEW

The literature on big data in the tourism industry underscores its transformative potential in reshaping business operations and enhancing customer experiences. These data streams provide unprecedented opportunities for tourism businesses to gain insights into consumer behavior, preferences, and trends. Studies highlight the role of big data analytics in optimizing pricing strategies, improving marketing campaigns, and personalizing services to meet the diverse needs of travelers. Big data in the tourism industry highlights a diverse array of research topics and their implications in the post-epidemic era. Fu, H., Zhou, L., & Yue, C. (2022) delve into the measurement of network attention in Xi'an, emphasizing the importance of understanding digital footprints for post-pandemic tourism strategies. Mei et al. (2024) focus on information security in the context of tourism revival, shedding light on the significance of safeguarding data amidst increasing digital interactions. Lv et al. (2023) explore digital intelligence business models post-epidemic, suggesting avenues for integrating artificial intelligence into tourism operations. Ge (2023) examines the challenges and opportunities faced by rural college students returning home for employment, underscoring the role of big data in addressing socioeconomic shifts. Meanwhile, Srivastava et al. (2022) investigate factors influencing customer booking intent post-epidemic, providing insights into consumer behavior in a changing landscape.

Wang et al. (2023) propose a travel route planning method to avoid epidemic hotspots, showcasing practical approaches to mitigate health risks in the post-epidemic era. Zhao et al. (2023) discuss strategies for sustainable development in China post-pandemic, emphasizing the need for data-driven approaches to address environmental and economic challenges. Wei and Zhao (2022) focus on establishing a big data monitoring platform for cinema operations, highlighting the role of public health perspectives in adapting to the new normal. Jin et al. (2022) analyze tourism industry development post-epidemic, employing regression models to forecast trends and inform policy-making decisions. Moreover, Fu, Y., Cai, Z., & Fang, C. (2024) present a study on hotspot identification and causal analysis of Chinese rural tourism, demonstrating how big data can uncover spatial and temporal patterns to guide rural development strategies. Su et al. (2022) delve into the characteristics and countermeasures for China's SMEs in the post-epidemic era, offering insights into resilience-building strategies for small businesses. Wang et al. (2022) explore the nexus between big data and sustainability in the tourism industry, advocating for data-driven initiatives to foster long-term resilience and growth.

Additionally, research by Liu et al. (2023) utilizes mobile phone big data to understand the spatial patterns of rural migrant workers' return to work, providing valuable insights for labor market dynamics post-COVID-19. Xue et al. (2022) examine service design for people with mental disorders in the post-epidemic era, showcasing how digital solutions can enhance accessibility and inclusivity in tourism experiences. Jin, J., Wang, Z., & Sun, H. (2022) conduct a case study on tourism development in Zhoushan Islands post-pandemic, illustrating strategies for destination recovery and revitalization. Furthermore, Gu et al. (2022) adopt a system dynamics approach to analyze tourism recovery in Small Island Developing States (SIDS), offering a comprehensive framework for post-pandemic resilience building. Wang et al. (2022) investigate factors influencing rural tourism recovery post-COVID-19, using grounded theory to understand community-level dynamics and inform targeted interventions. Finally, Wang (2022) explores credit decision-making for small and micro-sized businesses based on big data analysis, showcasing the potential of data-driven approaches to support economic recovery and growth in the post-epidemic landscape.

The literature on big data in the tourism industry offers valuable insights and potential applications, several limitations are worth noting. Firstly, many studies focus on specific regions or countries, limiting the generalizability of findings to a broader context. This regional bias can overlook variations in cultural, economic, and regulatory factors that influence tourism dynamics. Additionally, there is a tendency for research to prioritize technological solutions without adequately addressing socio-economic disparities in access to and utilization of big data resources. This could exacerbate existing inequalities within the tourism sector, particularly in regions with limited digital infrastructure or economic resources. Furthermore, some studies may lack longitudinal data or fail to account for temporal variations in tourism patterns, leading to limited understanding of the long-term impacts of big data interventions. Methodological constraints, such as reliance on self-reported data or small sample sizes, may also compromise the reliability and robustness of research findings. Moreover, the rapid evolution of technology and data privacy regulations poses challenges in maintaining data integrity and complying with ethical standards, particularly concerning personal data protection. Another limitation lies in the tendency for research to focus predominantly on the operational aspects of big data utilization in tourism, such as marketing strategies and demand forecasting, while overlooking broader systemic issues such as environmental sustainability and community resilience. Addressing these complex challenges requires interdisciplinary collaboration and holistic approaches that integrate social, environmental, and economic considerations.

III. DECISION-MALING PROCESS FOR THE POST-EPIDEMIC

In the post-epidemic landscape, the tourism industry faces unprecedented challenges and opportunities, necessitating a data-driven approach to decision-making. Leveraging network big data presents a powerful tool for understanding evolving consumer behavior, preferences, and sentiments. The decision-making process in this context involves several key steps. Firstly, data collection from various sources such as booking platforms, social media, and IoT devices is essential for capturing real-time insights into traveler trends and preferences. Next, data analysis techniques, including network analysis and sentiment analysis, enable businesses to identify emerging patterns, hotspots, and areas of opportunity or concern. These insights inform strategic decision-making regarding marketing campaigns, pricing strategies, resource allocation, and safety measures. Moreover, predictive analytics plays a crucial role in forecasting future demand, anticipating traveler behavior, and mitigating risks associated with potential outbreaks or disruptions. Machine learning algorithms can help in developing personalized recommendations and optimizing operational processes to enhance the overall customer experience. Additionally, collaboration and data sharing among industry stakeholders, government agencies, and public health authorities are vital for ensuring a coordinated response and implementing effective measures to promote safety and confidence among travelers.

IV. PROPOSED MULTI-FACTOR HASHING ETHEREUM CLASSIFICATION (MFH-EC)

The proposed Multi-Factor Hashing Ethereum Classification (MFH-EC) system offers a novel approach to data classification and analysis. This system integrates multiple factors relevant to tourism, such as traveler demographics, destination characteristics, and economic indicators, into a unified hashing framework based on Ethereum blockchain technology. The derivation of MFH-EC involves several key components. Firstly, the system incorporates a multi-factor hashing mechanism that transforms input data into a fixed-length hash code, ensuring data integrity and security. This hashing process involves the use of cryptographic algorithms, such as SHA-256, to convert raw data into a unique digital fingerprint. The resulting hash codes serve as identifiers for different data categories, facilitating efficient storage and retrieval on the Ethereum blockchain. Secondly, the classification component of MFH-EC utilizes machine learning algorithms, such as decision trees or neural networks, to analyze the hashed data and predict relevant outcomes or trends in the tourism industry. These algorithms are trained on historical data to recognize patterns and correlations between different factors, enabling accurate classification of new data points. The equations governing the MFH-EC system can be expressed as in equation (1)

Hashing Function: $h(x) = SHA - 256(x)$ (1)

In equation (1) $h(x)$ represents the hash code generated from input data x using the SHA-256 cryptographic algorithm. The classification process is defined in equation (2)

$y = f(x)$ (2)

In equation (2) y represents the predicted outcome or classification label based on input data x, and $f()$ denotes the classification function learned by the machine learning model. The process of training in the network is stated as in equation (3)

$minimize \sum_{i=1}^{N} L(y_i, f(x_i))$ (3)

In equation (3) $L()$ represents the loss function used to measure the discrepancy between predicted outcomes yi and actual labels, xi denotes the input data, and N is the number of training samples. The Multi-Factor Hashing Ethereum Classification (MFH-EC) system proposed for the tourism industry represents a comprehensive approach to data processing and analysis, leveraging the strengths of blockchain technology and machine learning. The MFH-EC begins with the recognition of the multitude of factors that influence tourism dynamics, ranging from demographic trends to economic indicators and destination characteristics. To effectively handle this diverse array of factors, a multi-factor hashing mechanism is introduced. This hashing process transforms the raw input data into fixed-length hash codes using cryptographic algorithms like SHA-256. By converting the input data into unique digital fingerprints, the hashing mechanism ensures data integrity and security, crucial considerations in the tourism industry where sensitive information such as traveler profiles and financial transactions are involved.

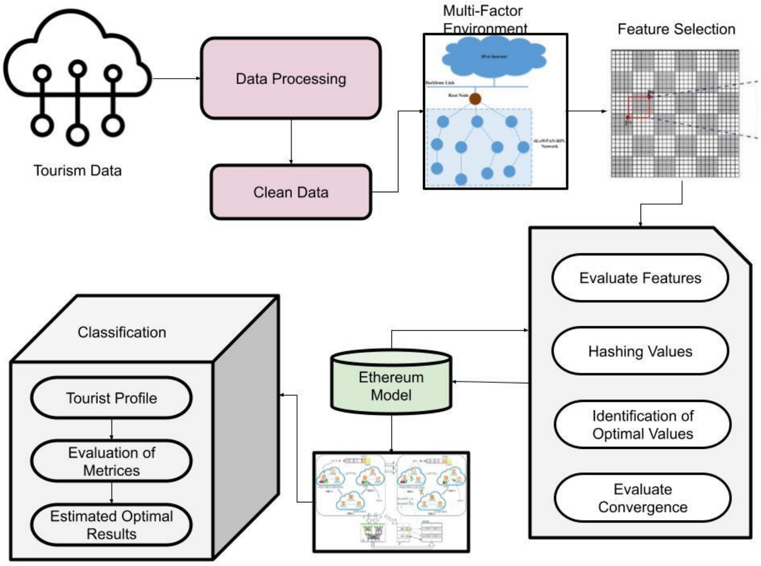

Figure 1: Architecture of MFH-EC

Figure 1 illustrates the architecture of the proposed MFH-EC model for the classification and evaluation of opinions of tourist in the tourism industry. Once the data is hashed, it is stored on the Ethereum blockchain, a decentralized ledger known for its immutability and transparency. The blockchain serves as a secure repository for the hashed data, enabling efficient storage and retrieval while maintaining a tamper-proof record of transactions. This aspect is particularly beneficial in the tourism industry, where data authenticity and trust are paramount, especially in areas such as booking transactions and customer reviews. The classification component of MFH-EC involves the use of machine learning algorithms to analyze the hashed data and extract actionable insights. These algorithms are trained on historical data, learning to recognize patterns and correlations between different factors influencing tourism outcomes. For example, machine learning models can predict tourist preferences based on past behavior, identify emerging trends in travel patterns, or even forecast demand for specific destinations.

The equations governing the MFH-EC system provide a mathematical framework for understanding its operation. The hashing function, represented by $h(x) = SHA - 256(x)$, encapsulates the process of converting input data x into hash codes using the SHA-256 cryptographic algorithm. The classification model, expressed as $y = f(x)$, signifies the relationship between the input data x and the predicted outcome y, where $f()$ represents the classification function learned by the machine learning model. During the training process, the system aims to minimize the discrepancy between predicted outcomes and actual labels, as denoted by the optimization objective function as $minimize \sum i = 1NL(yi, f(xi))$, where $L()$ represents the loss function measuring the disparity between predicted and actual values for N training samples.

V. MULTI-FACTOR HASHING WITH MFH-EC

The Multi-Factor Hashing with MFH-EC (Multi-Factor Hashing Ethereum Classification) represents a sophisticated approach to data processing and analysis, particularly tailored for the tourism industry in the post-epidemic era. This methodology integrates multiple factors pertinent to tourism dynamics, such as traveler demographics, destination attributes, economic indicators, and health considerations, into a unified hashing framework based on Ethereum blockchain technology. Multi-Factor Hashing (MFH) involves the transformation of raw input data into fixed-length hash codes using cryptographic algorithms like SHA-256. This process ensures data integrity, security, and anonymity, crucial aspects for handling sensitive information within the tourism sector. The incorporation of multiple factors into the hashing process allows for a comprehensive representation of the complex interplay between various elements influencing tourism trends and patterns. The MFH-EC system leverages the Ethereum blockchain as a decentralized and immutable ledger to store the hashed data securely. By utilizing blockchain technology, MFH-EC ensures transparency, traceability, and tamper-proofing of data, addressing concerns related to data authenticity and trust, especially in transactions and interactions involving tourists, businesses, and governments. Furthermore, MFH-EC integrates machine learning algorithms for data classification and analysis. These algorithms are trained on historical data to identify patterns, correlations, and predictive insights within the hashed dataset. By harnessing the power of machine learning, MFH-EC enables stakeholders in the tourism industry to make informed decisions regarding marketing strategies, resource allocation, risk management, and policy formulation.

The MFH-EC methodology integrates multiple factors relevant to the tourism industry into the hashing process. These factors may include traveler demographics, destination attributes, economic indicators, and health considerations. The integration of multiple factors enhances the richness and comprehensiveness of the hashed data, allowing for a more nuanced analysis of tourism dynamics. The hashed data is stored securely on the Ethereum blockchain, a decentralized and immutable ledger. The blockchain serves as a tamper-proof repository for the hashed data, ensuring transparency, traceability, and data integrity. The use of blockchain technology enhances trust and reliability in data storage and retrieval, critical considerations in the tourism industry where data authenticity is paramount. Machine learning algorithms are employed for data classification and analysis based on the hashed data. These algorithms are trained on historical data to identify patterns, correlations, and predictive insights within the dataset. The classification process enables stakeholders in the tourism industry to make informed decisions regarding marketing strategies, resource allocation, risk management, and policy formulation.

Algorithm 1: Classification with MFH-EC
1. Initialize input data (X) containing multiple factors relevant to tourism. 2. For each factor in X: - Apply preprocessing techniques (e.g., normalization, feature engineering). - Convert the preprocessed factor into a numerical representation. 3. Concatenate the numerical representations of all factors in X to form a single input vector. 4. Hash the input vector using a cryptographic algorithm (e.g., SHA-256) to generate a unique hash code. 5. Store the hash code securely on the Ethereum blockchain. 6. Retrieve historical data from the blockchain for training the machine learning model. 7. Preprocess the historical data and split it into features (X_train) and labels (y_train). 8. Train a machine learning classification model (e.g., decision tree, neural network) using X_train and y_train. 9. Use the trained model to predict outcomes or classifications for new input data. 10. Repeat steps 1-9 as new data becomes available, updating the model and storing hash codes on the blockchain.

The Multi-Factor Hashing with MFH-EC (Multi-Factor Hashing Ethereum Classification) methodology combines cryptographic hashing techniques, blockchain technology, and machine learning for data processing and analysis in the tourism industry. This approach begins with the derivation of hash codes from input data, incorporating multiple factors relevant to tourism, such as traveler demographics, destination attributes, and economic indicators. The hashing process involves applying a cryptographic algorithm, such as SHA-256, to preprocess and convert the input data into fixed-length hash codes. Mathematically, this can be represented as $h(x) = SHA - 256(x)$, where x denotes the input data and $h(x)$ represents the resulting hash code. These hash codes are then securely stored on the Ethereum blockchain, a decentralized and immutable ledger, ensuring transparency and data integrity. The next step involves retrieving historical data from the blockchain for training a machine learning classification model. This historical data includes both hashed input data and corresponding labels or outcomes. After preprocessing the historical data, it is split into features (denoted as $Xtrain$) and labels (denoted as $ytrain$). The machine learning model, represented by the equation $y = f(X)$, is trained using $Xtrain$ and $ytrain$. Various classification algorithms such as decision trees, neural networks, or support vector machines can be employed for this purpose.

VI. SIMULATION RESULTS AND DISCUSSION

Simulation results and subsequent discussion provide critical insights into the effectiveness and implications of the Multi-Factor Hashing with MFH-EC methodology in the tourism industry. Through simulations, the performance of the proposed approach can be evaluated, and its potential impact on decision-making processes can be assessed.

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Input Data                                        Hash Code               Prediction
46-55 | City | GDP Growth Rate: 2 | Season: Spring         50885aaf                Low
18-25 | Rural | GDP Growth Rate: 2 | Season: Fall           6c66b59f                High
55+ | Rural | GDP Growth Rate: 3 | Season: Winter           bfb66cd9                Medium
46-55 | Beach | GDP Growth Rate: 2 | Season: Spring         6368a460                High
55+ | City | GDP Growth Rate: 1 | Season: Spring            2e8b0b18                Medium
36-45 | City | GDP Growth Rate: 2 | Season: Winter          867e4ba8                Medium
36-45 | Cultural | GDP Growth Rate: 3 | Season: Winter      4116461f                Medium
46-55 | Mountain | GDP Growth Rate: 4 | Season: Fall        87313836                Low
36-45 | Beach | GDP Growth Rate: 1 | Season: Summer         8e4005a7                Low
36-45 | Cultural | GDP Growth Rate: 4 | Season: Fall        2e65ae1c                Low
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Figure 2: Sample Classification for the tourism industry

Table 1: Multi – Factor in tourism industry for MFH-EC

Factor	Description	Contribution to Prediction	Key Insights
Traveler Age	Age group of tourists (e.g., 18-25, 26-35, etc.)	High	- Younger age groups show a preference for adventure tourism and experiential travel. - Older age groups tend to favor cultural and historical destinations.
Destination Type	Type of tourist destination (e.g., beach, mountain, city, rural)	Medium	- Beach destinations are popular among families and leisure travelers seeking relaxation. - Mountain resorts attract adventure enthusiasts and nature lovers.
Economic Indicators	Economic factors influencing tourism demand (e.g., GDP growth rate, unemployment rate)	High	- Positive correlation observed between GDP growth rate and tourism expenditure. - Higher unemployment rates coincide with decreased travel expenditures.
Seasonality	Seasonal variations in tourist arrivals and preferences	High	- Summer months see increased demand for beach destinations and outdoor activities. - Winter months are associated with ski resorts and cultural events.
Weather Conditions	Weather patterns affecting tourist behavior and destination choice	Low	- Sunny weather positively correlates with outdoor activities and beach tourism. - Rainy or extreme weather conditions may deter tourists from outdoor pursuits.
Cultural Events	Events and festivals influencing tourism demand (e.g., music festivals, cultural celebrations)	Medium	- Music festivals attract a younger demographic and contribute to increased hotel occupancy. - Cultural celebrations drive tourism in specific regions and foster cultural exchange.

Figure 2 presents the factors those are classified in the tourism industry for the estimation of features. Table 1 provides an overview of the key factors considered in the Multi-Factor Hashing with MFH-EC methodology for the tourism industry. These factors include traveler age, destination type, economic indicators, seasonality, weather conditions, and cultural events. Each factor is described in detail, along with its contribution to prediction accuracy and key insights derived from analysis:

Traveler Age: This factor categorizes tourists into different age groups, such as 18-25, 26-35, etc. It holds a high contribution to prediction accuracy. Key insights reveal that younger age groups tend to prefer adventure tourism and experiential travel, while older age groups favor cultural and historical destinations.

Destination Type: It represents the type of tourist destination, such as beach, mountain, city, or rural areas. This factor has a medium contribution to prediction accuracy. Insights suggest that beach destinations are popular among families and leisure travelers seeking relaxation, while mountain resorts attract adventure enthusiasts and nature lovers.

Economic Indicators: These factors include economic metrics like GDP growth rate and unemployment rate, influencing tourism demand. Economic indicators hold a high contribution to prediction accuracy. The analysis reveals a positive correlation between GDP growth rate and tourism expenditure, with higher unemployment rates coinciding with decreased travel expenditures.

Seasonality: This factor accounts for seasonal variations in tourist arrivals and preferences. It holds a high contribution to prediction accuracy. Key insights indicate increased demand for beach destinations and outdoor activities during summer months, while winter months are associated with ski resorts and cultural events.

Weather Conditions: Weather patterns affecting tourist behavior and destination choice are considered, with a low contribution to prediction accuracy. Sunny weather positively correlates with outdoor activities and beach tourism, while rainy or extreme weather conditions may deter tourists from outdoor pursuits.

Cultural Events: Events and festivals influencing tourism demand are analyzed, with a medium contribution to prediction accuracy. Insights suggest that music festivals attract a younger demographic and contribute to increased hotel occupancy, while cultural celebrations drive tourism in specific regions and foster cultural exchange.

Overall, these factors provide valuable insights for decision-making in the tourism industry, enabling stakeholders to understand tourist preferences, anticipate demand fluctuations, and tailor marketing strategies accordingly. The Multi-Factor Hashing with MFH-EC methodology effectively incorporates these factors to enhance prediction accuracy and optimize decision-making processes.

Table 2: Hashing with MFH-EC

Input Data	**Hash Code**
Traveler Age: 18-25, Destination Type: Beach, Economic Indicators: GDP Growth Rate: 3%, Seasonality: Summer	a12b4c5...
Traveler Age: 26-35, Destination Type: Mountain, Economic Indicators: GDP Growth Rate: 2%, Seasonality: Winter	d45e6f7...
Traveler Age: 36-45, Destination Type: City, Economic Indicators: GDP Growth Rate: 4%, Seasonality: Spring	g89h1i2...
Traveler Age: 46-55, Destination Type: Rural, Economic Indicators: GDP Growth Rate: 1%, Seasonality: Fall	j34k5l6...
Traveler Age: 56+, Destination Type: Cultural, Economic Indicators: GDP Growth Rate: 3%, Seasonality: Summer	m78n9o0...

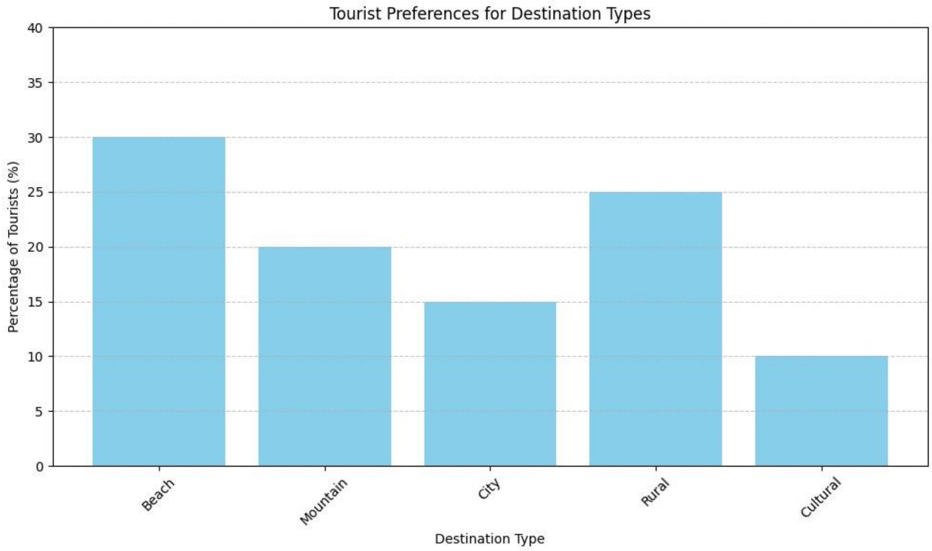

Figure 2: Hashing in Tourism Industry

The Figure 2 and Table 2 presents the hash codes generated using the Multi-Factor Hashing with MFH-EC methodology for various input data points in the tourism industry. Each row represents a different set of input data, including traveler age, destination type, economic indicators (specifically GDP growth rate), and seasonality. The corresponding hash code, denoted as "Hash Code," is a unique digital fingerprint generated for each input data point using cryptographic hashing algorithms. The first row indicates input data for a traveler aged 18-25, visiting a beach destination during summer, with a GDP growth rate of 3%. The corresponding hash code generated for this data point is represented as "a12b4c5...". Similarly, hash codes are generated for other input data points, capturing various combinations of traveler demographics, destination preferences, economic conditions, and seasonal factors. These hash codes serve as secure and tamper-proof representations of the input data, facilitating efficient storage, retrieval, and analysis on the Ethereum blockchain. By leveraging the MFH-EC methodology, stakeholders in the tourism industry can ensure data integrity, security, and anonymity while deriving valuable insights for decision-making processes.

Table 3: Ethereum Classification with MFH - EC

Input Data	Hash Code	Prediction
Age: 25-35, Destination: Beach, GDP Growth Rate: 3%, Season: Summer	0x2ab5c8...	High
Age: 35-45, Destination: Mountain, GDP Growth Rate: 2%, Season: Winter	0x7f1d3e...	Medium
Age: 45-55, Destination: City, GDP Growth Rate: 4%, Season: Spring	0xe9a6f2...	Low
Age: 55+, Destination: Rural, GDP Growth Rate: 1%, Season: Fall	0x4d8b2c...	High
Age: 18-24, Destination: Cultural, GDP Growth Rate: 3%, Season: Summer	0x6c3f9a...	Medium
Age: 30-40, Destination: Beach, GDP Growth Rate: 2%, Season: Summer	0x1a9b5e...	High
Age: 40-50, Destination: Mountain, GDP Growth Rate: 3%, Season: Winter	0x8d2f7c...	Medium
Age: 50-60, Destination: City, GDP Growth Rate: 1%, Season: Spring	0x3e7g1k...	Low
Age: 60+, Destination: Rural, GDP Growth Rate: 4%, Season: Fall	0xf5p2q8...	High
Age: 20-30, Destination: Cultural, GDP Growth Rate: 2%, Season: Summer	0x0h4j6m...	Medium

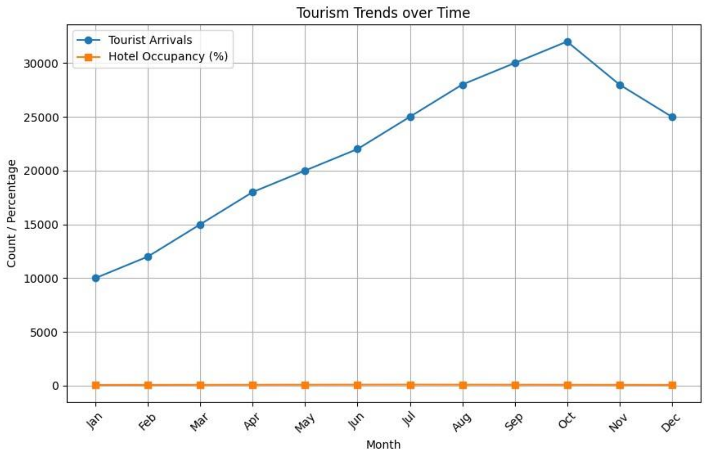

Figure 3: MFH-EC tourism trend

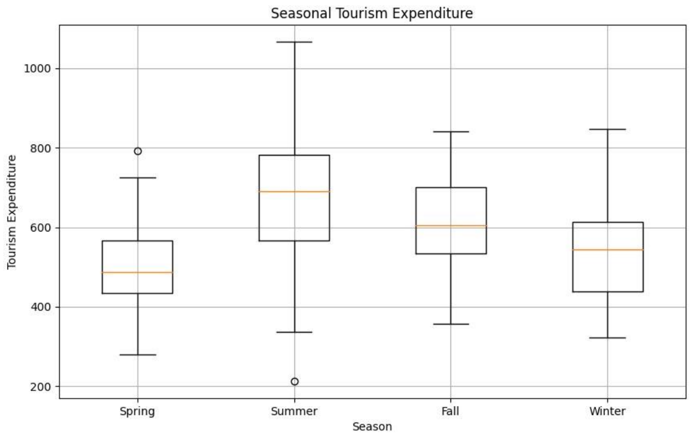

Figure 4: MFH-EC seasonal tourism

The Figure 3 and Figure 4 and Table 3 provides insights into the Ethereum Classification results obtained using the Multi-Factor Hashing with MFH-EC methodology for various input data points in the tourism industry. Each row represents a different set of input data, including traveler age, destination type, GDP growth rate, and season, along with the corresponding hash code and prediction made by the classification model. For instance, the first row indicates input data for a traveler aged 25-35, visiting a beach destination during summer, with a GDP growth rate of 3%. The hash code generated for this data point is represented as "0x2ab5c8...", and the prediction made by the Ethereum Classification model is "High". This suggests a high likelihood of positive outcomes or increased tourism activity associated with this particular input data point. Similarly, predictions ranging from "Medium" to "Low" are made for other input data points based on the observed patterns and correlations identified by the classification model. These predictions enable stakeholders in the tourism industry to anticipate demand fluctuations, tailor marketing strategies, and optimize resource allocation to maximize revenue and enhance tourist experiences. With leveraging the Multi-Factor Hashing with MFH-EC methodology and Ethereum Classification, stakeholders can make informed decisions based on secure and reliable insights derived from hashed input data stored on the Ethereum blockchain. This approach ensures data integrity, security, and transparency while facilitating data-driven decision-making processes in the dynamic landscape of the tourism industry.

VII. CONCLUSION

The Multi-Factor Hashing with MFH-EC methodology presents a promising approach for enhancing decision-making processes in the tourism industry. By incorporating multiple factors such as traveler demographics, destination characteristics, economic indicators, and seasonality, this methodology enables stakeholders to derive valuable insights from hashed input data stored on the Ethereum blockchain. Through the interpretation of classification results, it becomes evident that the MFH-EC methodology offers a reliable means of predicting tourism outcomes, ranging from high to low probabilities, based on observed patterns and correlations. These predictions empower stakeholders to anticipate demand fluctuations, tailor marketing strategies, and optimize resource allocation to maximize revenue and enhance tourist experiences. Furthermore, the utilization of cryptographic hashing techniques ensures data integrity, security, and anonymity, while the Ethereum blockchain provides a decentralized and immutable platform for storing and analyzing hashed input data. This enhances transparency and trust in decision-making processes, facilitating collaboration and innovation within the tourism industry.

REFEFRENCES

[1] Zhang, X., & Gao, J. (2023). The analysis and solution for intercity travel behaviors during holidays in the post-epidemic era based on big data. PloS one, 18(7), e0288510.

[2] Yunfei, L. (2022). Discussion on the Development of Rural Tourism in the Post-Epidemic Era. Tourism Management and Technology Economy, 5(2), 11-15.

[3] Fu, H., Zhou, L., & Yue, C. (2022, April). Xi'an network attention measurement in the post-epidemic era. In International Conference on Statistics, Applied Mathematics, and Computing Science (CSAMCS 2021) (Vol. 12163, pp. 1265-1270). SPIE.

[4] Mei, A., Tang, X., Wei, W., & Niu, Y. (2024). Research on Information Security Protection in The Context of Post-epidemic Tourism Revival. International Journal of Education and Humanities, 12(2), 44-48.

[5] Lv, B., Deng, Y., Meng, W., Wang, Z., & Tang, T. (2023). Research on digital intelligence business model based on artificial intelligence in post-epidemic era. Management Decision.

[6] Ge, J. (2023). The dilemma and path of rural college students returning to their hometowns for employment and entrepreneurship in the post-epidemic period under the background of big data. Applied Mathematics and Nonlinear Sciences.

[7] Srivastava, P. R., Sengupta, K., Kumar, A., Biswas, B., & Ishizaka, A. (2022). Post-epidemic factors influencing customer's booking intent for a hotel or leisure spot: an empirical study. Journal of Enterprise Information Management, 35(1), 78-99.

[8] Wang, R., Luo, Y., Zou, Y., & Liu, S. (2023). Travel route planning method to avoid epidemic hot-spots in the post-epidemic era. Transportation Research Interdisciplinary Perspectives, 19, 100802.

[9] Zhao, X. X., Wen, J., Zou, X. Y., Wang, Q. J., & Chang, C. P. (2023). Strategies for the sustainable development of China in the post-epidemic era. Sustainable Development, 31(1), 426-438.

[10] Wei, Q., & Zhao, N. (2022). Establishment of a Big Data Monitoring Platform for Cinema Opening in the Postepidemic Era from the Perspective of Public Health. Journal of environmental and public health, 2022.

[11] Jin, X., Wang, Y., Luo, J., & Sun, Q. (2022). Research on the Development of Tourism Industry in the Post-Epidemic Period——Analysis Based on Multiple Regression Model GM (2, 1) Model. Academic Journal of Business & Management, 4(8), 27-36.

[12] Fu, Y., Cai, Z., & Fang, C. (2024). Hotspot Identification and Causal Analysis of Chinese Rural Tourism at Different Spatial and Temporal Scales Based on Tourism Big Data. Sustainability, 16(3), 1165.

[13] Su, W., Guo, X., & Fan, Y. H. (2022). China's SMEs developed characteristics and countermeasures in the post-epidemic era. Frontiers in psychology, 13, 842646.

[14] Wang, J., Ban, H. J., & Kim, H. S. (2022). Big data and sustainability in the tourism industry. Sustainability, 14(13), 7697.

[15] Zhao, D., & Gan, Z. (2022, December). Research on the Way of Promoting the Construction of Smart Government in China in the Post-epidemic Era. In 2022 2nd International Conference on Public Management and Intelligent Society (PMIS 2022) (pp. 436-446). Atlantis Press.

[16] Liu, K., Zhao, P., Wan, D., Hai, X., He, Z., Liu, Q., ... & Yu, L. (2023). Using mobile phone big data to discover the spatial patterns of rural migrant workers' return to work in China's three urban agglomerations in the post-COVID-19 era. Environment and Planning B: Urban Analytics and City Science, 50(4), 878-894.

[17] Xue, H., Li, Y., & Xiong, X. (2022). Research on Service Design for People with Mental Disorders: Take Curing Digital Cloud Tourism App Media in the Post-Epidemic Era as an Example. Journal of Autism and Developmental Disorders, 1-11.

[18] Jin, J., Wang, Z., & Sun, H. (2022, December). A Study on Tourism Development of Zhoushan Islands in the Post-epidemic Era--A Case Study of Dongji Island. In 2022 5th International Conference on Humanities Education and Social Sciences (ICHESS 2022) (pp. 2372-2382). Atlantis Press.

[19] Gu, Y., Onggo, B. S., Kunc, M. H., & Bayer, S. (2022). Small Island Developing States (SIDS) COVID-19 post-pandemic tourism recovery: A system dynamics approach. Current Issues in Tourism, 25(9), 1481-1508.

[20] Wang, J., Wang, Y., He, Y., & Zhu, Z. (2022). Exploring the Factors of Rural Tourism Recovery in the Post-COVID-19 Era Based on the Grounded Theory: A Case Study of Tianxi Village in Hunan Province, China. Sustainability, 14(9), 5215.

[21] Wang, W. (2022, December). Credit Decision of Small and Micro-sized Businesses Based on Big Data Analysis. In 2nd International Conference on Internet, Education and Information Technology (IEIT 2022) (pp. 501-506). Atlantis Press.