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Enhancing the Post-COVID Tourism Competitiveness Strategy: Fuzzy Logic-Enhanced Deep Learning for Sentiment Analysis

Zhenghai Ai, Hong Su, Yong Qin, Yuyan Luo, Marinko Škare

Abstract

Amid the digital transformation of the global tourism sector, understanding tourist behavior and preferences is critical for enhancing tourism competitiveness, particularly in the post-COVID-19 context. This study integrates machine learning–based sentiment analysis with configurational methods to examine how tourism destinations achieve high competitiveness. Focusing on 34 5A-level tourism destinations in China, we analyze a large corpus of tourist-generated content to identify key destination attributes and assess their performance. Using topic modeling and sentiment analysis, we extract core attributes reflecting tourists' concerns and experiences. We then apply fuzzy-set qualitative comparative analysis (fsQCA) and necessary condition analysis (NCA) to uncover configurational pathways leading to high tourism competitiveness. The results reveal that no single attribute is sufficient on its own; instead, multiple configurations of destination attributes jointly drive competitiveness. Specifically, five distinct configurational models are identified, representing alternative "recipes" for achieving high-performing and competitive destinations. This study contributes a novel analytical framework that bridges data-driven sentiment analysis and causal configurational logic. The findings provide actionable insights for destination managers to design targeted strategies that enhance both tourist satisfaction and competitiveness. Beyond the Chinese context, the proposed framework is transferable to other tourism settings, offering a scalable approach for analyzing destination competitiveness in the digital era.

Keywords: *Post-COVID tourism, sentiment analysis, fuzzy logic, deep learning, tourist behavior, qualitative comparative analysis*

JEL Classification: C80, D70, Z32

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1 INTRODUCTION

The tourism sector experienced substantial repercussions due to the COVID-19 pandemic, marked by widespread travel constraints and the implementation of global border closures (Zhang et al., 2021). Tourism destinations (TDs) faced challenges, implementing health measures for the well-being of tourists and staff (Pappas, 2021). Standardized safety protocols, such as social distancing and mask mandates, altered the travel experience. Despite difficulties, the industry adapted by accelerating digital transformation and offering virtual travel experiences to meet evolving consumer demands (Lu et al., 2022). Against this backdrop, enhancing tourism competitiveness has become a central concern for both scholars and practitioners, as destinations must not only recover but also re-establish their competitive positioning in an increasingly uncertain and dynamic global tourism market.

Tourism competitiveness refers to a destination's ability to attract and satisfy tourists while maintaining sustainable development and long-term market advantages. Social scientists agree

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that enhancing TD performance involves a complex overlay of multiple destination attributes (Moon & Han, 2018). The governance challenge in TD performance, shifting from traditional single-factor methods, is seen in successful chaotic system research where linear analysis only partially captures complex relationships (Kim et al., 2021). In this regard, tourism competitiveness should be understood as a configurational outcome, emerging from the interaction and alignment of multiple conditions rather than isolated effects of individual attributes. High TD performance depends on the configuration of multiple conditions, without a unified symmetric relationship. Reopening and reshaping the tourism industry post-COVID-19 present imminent challenges, with a significantly altered global tourism landscape. Recent evidence indicates substantial shifts in tourists' preferences and behaviors during crisis (Li et al., 2021), leading to a reconfiguration of demand structures and competitive dynamics in the tourism industry. Consequently, understanding how destination attributes jointly shape tourism competitiveness has become an urgent research priority. The tourism industry must not only recover but also enhance its resilience and competitiveness through strategic adaptation and sustainable development.

Leveraging tourist-generated content (TGC) on the Internet offers valuable insights into the transformation of TD performance logic. TGC, including online reviews, ratings, likes, and photos, is authentic, credible, and interactive, directly reflecting tourists' experiences (Hung et al., 2023). It plays a pivotal role in online word-of-mouth communication, allowing tourists to express preferences and assess TD quality. More importantly, TGC provides a data-driven lens through which destination competitiveness can be empirically captured and evaluated from the tourists' perspective. Additionally, TGC acts as a vital marketing tool for TDs and service providers, aiding in product positioning, improving offerings, and attracting more tourists and consumers.

TGC effectively assesses destination attribute development (Luo et al., 2021), expediting TD strength and weakness discovery. Rapid TD attractiveness restoration requires coordinated implementation of multiple measures. The configurational perspective and qualitative comparative analysis (QCA) show promise in analyzing complex causal relationships in tourism studies (Cheng & Liu, 2022). QCA, uniquely combining qualitative inquiry and comparative analysis, identifies necessary and sufficient conditions for specific outcomes using Boolean algebra and set theory. Unlike mainstream statistical methods, QCA explores multiple concurrent causal relationships (Zhang et al., 2022), comparing cases or destinations to reveal combinations of features (destination attribute performances) contributing to high-performing TDs rather than a single predominant influence.

Despite the growing application of machine learning and big data analytics in tourism research, most existing studies either focus on predictive modeling (e.g., sentiment analysis) without uncovering causal mechanisms, or rely on traditional linear approaches that fail to capture configurational complexity. This creates a critical research gap in understanding how data-driven insights can be translated into causal explanations of tourism competitiveness. To address this gap, this study integrates machine learning-based text mining with configurational analysis to bridge descriptive analytics and causal inference.

This study aims to guide destination managers in enhancing post-COVID-19 performance using collective intelligence (TGC) and big data analysis. Focusing on 34 5A level TDs in China, we identify key destination attributes and operationalize tourism competitiveness using an objective performance-based index. Utilizing fsQCA and necessary condition analysis (NCA), we explore combined effects and conditions of destination attribute performances, identifying configurational pathways through which TDs achieve high competitiveness in the post-pandemic era. By doing so, this study shifts the analytical focus from isolated performance indicators to holistic competitiveness configurations.

This study has a dual contribution. Firstly, it integrates the emerging research paradigm of QCA with tourism big data analysis techniques, enhancing research accuracy and credibility. By incorporating data mining and machine learning, this integration leverages the increased availability of TGC in the tourism big data era, discovering more causal relationships and conditional factors. Secondly, and more importantly, this study contributes to the tourism competitiveness literature by conceptualizing competitiveness as a configurational outcome and identifying multiple causal "recipes" through which destinations can achieve high competitiveness in the post-COVID-19 context. This configurational perspective advances existing research that predominantly relies on net-effect logic.

The remainder of this study is organized as follows: Section 2 is the research design and methodology. Section 3 gives empirical findings. Section 4 presents the discussion and implications. Final conclusions are presented in Section 5.

2 RESEARCH DESIGN AND METHODOLOGY

Integrating tourism big data analysis techniques with the emerging QCA research approach, quantitative data and qualitative data from TGC are combined, thus revealing the complex driving mechanisms of TD revitalization amidst the repercussions of the COVID-19 pandemic. Thus, **Fig. 1** depicts the overall research framework and procedures.

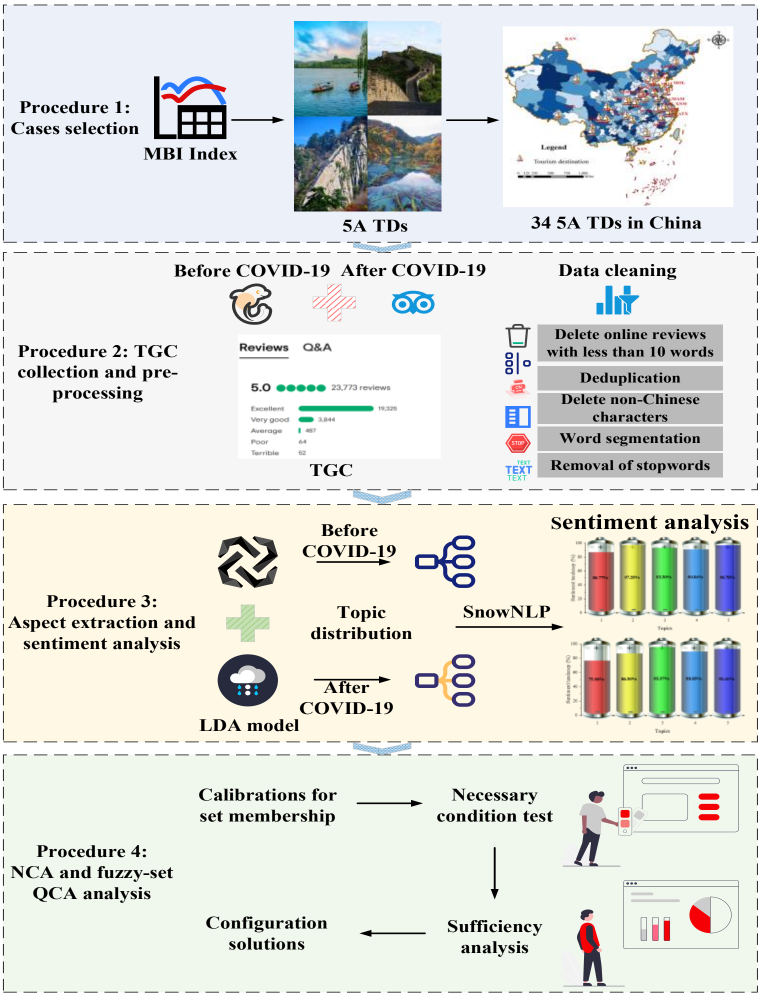

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Fig. 1 – Research architecture. Source: own research

Note: TPM represents the Palace Museum, OTL represents Old Town of Lijiang, CGS represents the Classical Gardens of Suzhou, TAT represents Taierzhuang Ancient Town, TGW represents the Great Wall, MOT represents Mount Tai, CMR represents Chengde Mountain Resort, PGM represents Prince Gong's Mansion, ATX represents the Ancient Town of Xitang, RPM represents Royal Prime Minister's Palace, MOH represents Mount Hua, KAN represents Kanas, SAT represents Sanhe Ancient Town, LGB represents Leshan Giant Buddha, JOT represents Jokhang Temple, HUV represents Huanglong Valley, TEC represents Tenglong Cave, MOL represents Mount Lao, CTT represents the Chongsheng Temple and the Three-Pagoda Culture Tourist Area, CCE represents Caishiji Cultural and Ecological Tourism Area of the Yangtze River, NAN represents Nansan, EQM represents Emperor Qinshihuang's Mausoleum Site Museum, MCP represents Millennium City Park, PMM represents Palace Museum of the Manchurian Regime, RCT represents Red-Flag Canal & Taihang Grand Tourist Attraction, MMC represents Mingsha Mountain Crescent Spring, XNW represents Xixi National Wetland Park, WTM represents Wulingyuan & Tianmen Mountain, TAC represents Tianjin Ancient Cultural Street, MSS represents the Mount Sanqingshan Scenic Area, LJC represents Laojunshan-Jiguan Cave Tourist Attraction, HAV represents Hailuogou Valley, MOD represents Mount Danxia and MAM represents Maoshan Mountain.

2.1 Study cases

National AAAAA level tourist attraction, namely 5A level tourist attraction, is the highest-level TD in China. 5A level TD represents China's world-class tourist attraction level (Luo et al., 2021). More pertinently, 5A TDs have a high popularity and a stable number of tourists, which provide rich TGC data for the implementation of this study. The onset of the COVID-19 pandemic delivered a severe impact on the functioning and progression of China's tourism sector. In response to this scenario, 5A TDs adjust their strategic planning and operation ideas to achieve transformation and breakthrough in the new downturn pattern. However, the performance of TDs has been uneven, and is in dire need of remediation.

For this reason, it is of great value to clarify the complex causal and driving mechanisms behind them. This helps 5A TDs find their self-help direction within the aftermath of the pandemic and accelerate the formation and stabilization of a new tourism market pattern. Considering the large number of 5A TDs, the decision to study cases must be selective. Fortunately, the authoritative big data business analytics agency Mcadion Academy provides solutions and measures that can be addressed. Its list of the top 100 5A TDs in China regarding brand influence allows us to lock in an alternative collection of cases. On this basis, we finally selected 34 typical cases (See the note below **Fig. 1**).

On the one hand, this initiative follows the principle of roughly balanced truth coverage of the results in the subsequent QCA analysis. On the other hand, the results are made more generalizable by including as many types of TDs as possible.

2.2 TGC collection and pre-processing

Following the research setting, we only focused on online reviews and ratings. Online reviews, which travelers freely share and easily access on review sites, are an honest mashup of information, viewpoints, perceptions, and feelings. As an overall rating, rating scores are often used in conjunction with online reviews as an extensive aid to observe tourists' online behavior and characteristics (Ren et al., 2024). The data sources for this study are Ctrip and TripAdvisor, two widely recognized on-line travel communities. On these two online travel information exchange platforms, many tourists give and receive reviews on specific topics related to travel and tourism. TripAdvisor, for example, contains over one billion reviews from real travelers. The abundance and comprehensiveness of reviews can help potential tourists make thorough and timely travel decisions. Specifically, the Ctrip website was used to collect post-pandemic TGC, while the TripAdvisor website was employed to gather pre-pandemic TGC. Using January 1, 2020, as the epidemic cut-off point, TGC data were collected separately on the website for the first two years and the next two years. The Octopus data collector (December

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2022) collects online reviews and rating data for each TD. Due to limitations in data availability, the pre-pandemic data are not available in full. Thus, we only adopted the pre-pandemic TGC for thematic analysis and did not conduct follow-up QCA analysis.

Upon obtaining the raw TGC dataset from the travel community, data cleaning is imperative due to duplicate and blank reviews, as well as irregular characters. Firstly, reviews outside the designated time interval are excluded. Secondly, reviews with fewer than ten words, generally deemed insufficient for comprehensive evaluation (Zhang et al., 2021), are removed. Thirdly, duplicate and blank reviews are eliminated. To enhance subsequent modeling, non-Chinese characters are deleted due to their potential to introduce complications. Additionally, the Jieba Chinese word segmentation library is utilized for word segmentation. Lastly, function words lacking substantive meaning are removed based on a stop words list. Notably, this pre-processing is executed using Python programming software, resulting in a total of 56,124 retained online reviews.

2.3 Aspect extraction and sentiment analysis

In this part, efforts are made to uncover critical destination attributes of tourists' concerns from unstructured and large-scale text reviews. The obtained attributes would be grafted as antecedent variables to participate in the ensuing configuration analysis.

As an unsupervised machine learning method, latent dirichlet allocation (LDA) has the capability to discern latent thematic information within extensive document collections or corpora (Bi et al., 2019; Blei et al., 2003). This technique structures the data into three classes, i.e., words, topics, and documents. Its core view is that documents are generated by a random mixture of hidden topics, considered probability distributions of words (Vayansky & Kumar, 2020). In recent years, LDA has been widely connected to online reviews to extract potential qualitative criteria and important attributes (Ghosh et al., 2023). The easy-to-understand LDA generative process is ulteriorly elaborated upon in **Fig. 2**.

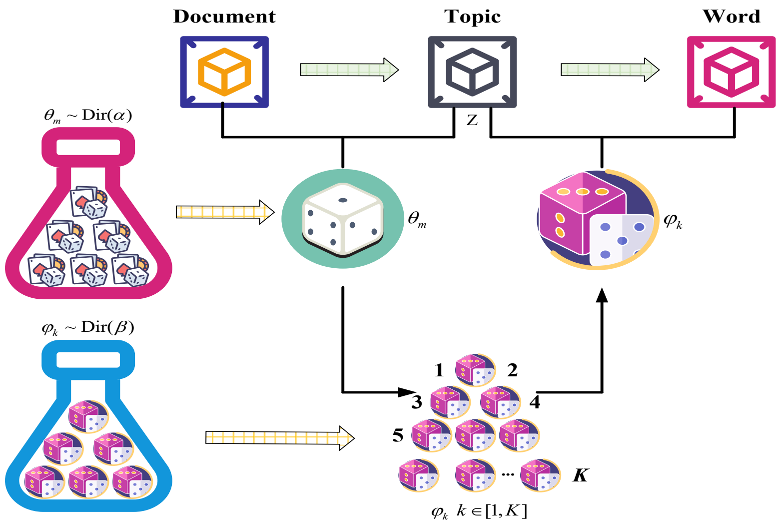

Fig. 2 – Graphical representation of the LDA generative process. Source: own research

Once the critical attributes underlying the large number of online reviews are identified, the next step is to analyze the opinions of the detailed reviews based on the attributes. As aforementioned, the pre-pandemic corpus data and data on online reviews for several TDs need to be completed. Therefore, the mission of opinion analysis is not entrusted to the pre-pandemic online reviews. In parallel, the LDA model assumes that each document contains multiple

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topics and calculates the contribution of each topic to the document. The most likely topic of each online review can be determined based on the contribution size.

Sentiment analysis, or opinion mining, is primarily designed to identify, extract, and quantify the subjective expressions intended to describe emotions, opinions, and feelings in online reviews. Among them, the Snow natural language processing toolkit is highly accessible and popular in processing Chinese textual content (Wu et al., 2023). Moreover, SnowNLP results in values in the range of 0 to 1. The magnitude of the value is directly proportional to the intensity of positive emotions. Given this, this study employs the SnowNLP technique to score the sentiment values of the reviews under each topic. After that, the sentiment scores of online reviews under each topic are aggregated by the arithmetic mean to obtain the average sentiment score of each topic under each TD. By doing so, the performance of each TD in each attribute is portrayed. The calculation formula can be refined as follows:

$$P_{ij}^{average\ sentiment} = \frac{S_{ij}^{total\ sentiment}}{NR_{ij}} \tag{1}$$

where $P_{ij}^{average\ sentiment}$ denotes the average sentiment score of the jth topic of the ith TD, $S_{ij}^{total\ sentiment}$ is the total number of sentiment scores of online reviews under the jth topic of the ith TD, and NR_{ij} denotes the number of online reviews under the jth topic of the ith TD.

2.4 NCA and fsQCA procedures

This study's main point of interest is how the differences in the performance of TDs in various attributes after the COVID-19 pandemic affect their competitive advantage. This, in turn, involves testing and exploring necessary and sufficient causal relationships. To this end, we use NCA and fsQCA methods to reach our goal. NCA is a method that specializes in analyzing necessary relationships and enables the analysis of how antecedent conditions constitute necessary conditions for outcomes (Dul, 2016). Whereas fsQCA can likewise identify necessary relationships on a qualitative statement basis, NCA allows us to assess the degree to which a precursor condition is indispensable for an outcome. Combining NCA and fsQCA yields more discerning insights (Dul et al., 2020).

As an approach suitable for exploring asymmetric and conformational parameters, fsQCA underscores the assessment of the effectiveness of combining precursor conditions to yield outcomes (Kim et al., 2021). Serving as a set-based methodology, fsQCA offers a fitting mechanism to account for intricate complementarities and nonlinear associations among various variables (e.g., precursor variables, causal conditions, and stimuli) comprising the focal outcome (Li et al., 2018). More specifically, this methodology contemplates several aspects grounded in complexity theory. First and foremost, causal complexity, denoting combinations of precursor conditions, can lead to the desired outcome. Secondly, equifinality, indicating multiple combinations of precursor conditions, can result in the same outcome. Thirdly, asymmetry, signifying combinations of high and low performance leading to the desired outcome, does not exhibit mirror opposites (Bigne et al., 2020). **Fig. 3** sheds light on the general steps of fsQCA analysis.

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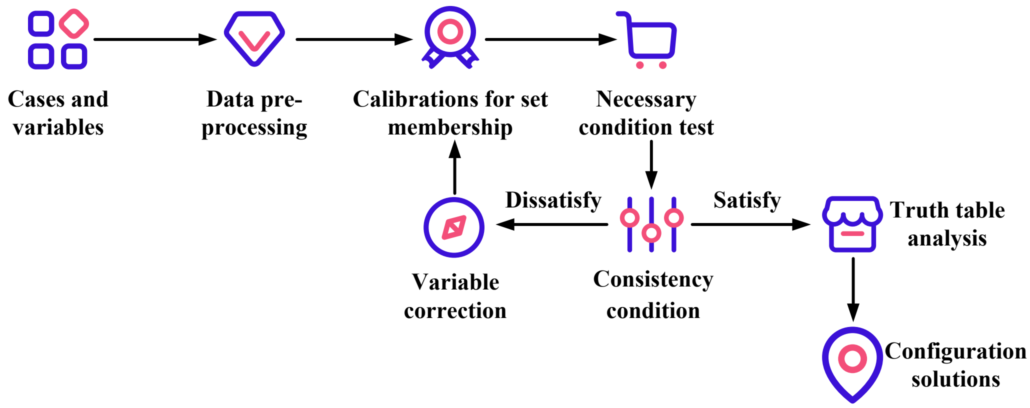

Fig. 3 – Flow chart of fuzzy-set QCA. Source: own research

This study utilizes the NCA method to scrutinize the essential correlation between the competitive advantage of TDs and their performance across diverse attributes. Subsequently, the robustness of the necessity analysis results is examined employing the fuzzy set QCA method. Simultaneously, the fuzzy set QCA method is applied to assess the sufficiency relationship between the competitive advantage of TDs and their performance in various attributes. This approach elucidates the specific performance ecology of TDs across diverse attributes that can engender a heightened competitive advantage.

Antecedent variables

TDs belong to experiential products, and their competitive advantages mainly depend on service quality. When travelers express satisfaction with destination attributes of their concern, the perceived image of TD will naturally improve. As a result, the competitive advantage of TD is bound to be enhanced accordingly. This way of identifying and spying on the effective path configuration of TDs with a highly competitive advantage through free feedback from tourists is cost-effective and more flexible. Consequently, online ratings and the sentiment scoring performance of clustered attributes in online reviews will be treated as configuration dimensions. To calculate sentiment scores for online reviews, sentiment values are obtained using SnowNLP and take values ranging from 0 to 1.

Outcome variable

The outcome of this study concerns the performance and competitive advantage of TDs. Authoritatively, Mcadion Research Academy's 2021 list of the top 100 5A TDs in China in terms of brand influence and its affiliated MBI accomplishes this work precisely. The Mcadion Brand Index (MBI) analyzes the influence of TD brands on the Internet and mobile Internet from four dimensions: search index, review index, operation index, and media index. Hence, the MBI can fully reflect each TD's performance and competitive advantage. Ultimately, the MBI was selected as the measurement indicator of the outcome variable in this study.

Calibrations for set membership

FsQCA is a set-theoretic method that assesses cases in a study through their membership in sets. Hence, the necessary calibration work must be performed before formal analysis (Harms et al., 2021). In the calibration step, the data for the antecedent and outcome variables are converted to fuzzy scores, i.e., values spanning from 0 to 1. Therefore, the establishment of anchor points is pivotal.

Given that the research variables in this investigation are of continuously varying numerical type, the direct calibration method is the most appropriate choice, thus characterizing the advantages and disadvantages of different TDs through numerical intervals (Andrews et al., 2015). Specifically, the direct calibration relies on the log odds of full membership (i.e., the fuzzy score is 0.95), the threshold for full non-membership (i.e., the fuzzy score is 0.05), and the crossover point (i.e., the fuzzy score is 0.5). The calibration task is executed using fsQCA 3.0 software. Importantly, to mitigate the issue of configuration attribution precisely at 0.5 in the case affiliation of antecedent variables, we calibrate the cross-over point using a fuzzy score of 0.501 instead of 0.5.

Necessary condition test

Necessity analysis constitutes a fundamental aspect of QCA. A condition is considered necessary when the outcome is encompassed within that specific condition. Initially, we ascertain the existence or absence of necessary conditions through the NCA method. NCA establishes the presence or absence of necessary conditions by examining the effect sizes of antecedent variables for necessity and their statistical significance. Additional bottleneck level analysis allows us to quantitatively measure the value of the necessary level of the antecedent variable. The effect size is distributed as a closed interval from 0 to 1, and the magnitude of the value is proportional to the strength of the effect. Besides, the significance of the effect size is judged by the Monte Carlo simulation permutation test (Dul et al., 2020). Ceiling regression (CR) is used for continuous variables, while the ceiling envelopment (CE) estimation method is used for discrete variables. A condition is deemed necessary for the results only when both criteria are met: the condition's effect size exceeds 0.1, and it passes the p-value test.

Sufficiency analysis

Constructing a truth table stands as a pivotal element in QCA analysis, serving as a cornerstone that facilitates the identification of configurations of causal conditions leading to the outcome of interest. This truth table delineates the combinations of antecedent variables through fuzzy membership scores, where a score of 0 denotes the absence of a condition, and 1 signifies its presence. The initialization of the truth table involves determining the number of rows, which is the Nth power of 2, with N representing the number of conditions and the Nth power of 2 indicating the total number of logically conceivable combinations. Standard parameter configurations, including frequency benchmark, raw consistency, and proportional reduction in inconsistency (PRI), are applied to streamline the truth table in accordance with the study's requirements (Greckhamer et al., 2018). Given the study's limited sample size (S=34), the case frequency benchmark is established at 1. The specific thresholds for raw consistency and PRI are contingent upon the study's unique circumstances.

Configuration solutions

Ultimately, we employed the Quine-McCluskey algorithm integrated into the fsQCA 3.0 package to convert the truth table into a fundamental configuration solution. Typically, counterfactual analysis yields three solutions: complex, parsimonious, and intermediate. The complex solution is derived under the assumption that the logical remainder is zero, representing the residual configuration not encompassed by the cases (Fiss, 2011). In contrast, both parsimonious and intermediate solutions acknowledge the factual existence of the logical remainder. Conditions present in both intermediate and parsimonious solutions are recognized as core conditions based on the classification of conditions. Conversely, conditions exclusively present in intermediate solutions are designated as peripheral conditions. Consequently, an exploration into the impact of TDs's performance in each attribute on the formation of high-performing TDs involves conducting analyses of configurations after the COVID-19 pandemic.

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3 EMPIRICAL FINDINGS

3.1 Focus discrepancies before and after the COVID-19 pandemic

Firstly, the perplexity metric is employed to examine topics. Based on the calculations, determining the optimal number of topics generated by the LDA model is evident—four topics before the pandemic and five topics after the pandemic. This is because the perplexity score at that point is the lowest, allowing for better data interpretation and capturing of latent topic structures.

The top 5 words of each topic are shown in **Table 1** and **Table 2**. These words are the most relevant to the topic, reflecting the attributes tourists perceive during sightseeing. More importantly, these words appear most frequently in that topic but least frequently in others. Through these frequent and unique words, the labels of each topic are summarized. Specifically, based on the results before the COVID-19 pandemic in **Table 1**, words such as “feelings”, “experience” and “good” construct the topic of EX in the first topic. In the second topic, the words such as “bars”, “sunshine” and “alleyway”, make up the topic of LI. From the third topic in **Table 1**, we see words such as “Heshen”, “Kangxi” and “Qianlong”, representing the SF. In the fourth topic, words such as “ancient”, “wisdom” and “history”, constitute the topic of HC. Focusing on the outcomes after the COVID-19 pandemic in **Table 2**, similarly, we drew up five labels for the topics, namely OM, EX, SF, IR and HC.

Tab. 1 – Topic distribution before the COVID-19 pandemic. Source: own research

Topics	Top words				
EX	Feeling	Grand	Good	Experience	Worthwhile
LI	Bars	Night	Slates	Sunshine	Alleyway
SF	Heshen	Kangxi	Qianlong	Gallery	General
HC	Awe	History	Prosperity	Wisdom	Ancient

Note: EX represents emotional experience for TD, LI represents landscape & infrastructure for TD, SF represents symbolic features for TD, and HC represents history & culture for TD.

Tab. 2 – Topic distribution after the COVID-19 pandemic. Source: own research

Topics	Top words				
OM	Ticket	Route	Queue	Management	COVID-19
EX	Experience	Service	Attitude	Docent	Enthusiasm
SF	Prestige	Feature	Beauty	Celebrity	Charming
IR	Environment	Trestle	Scenery	Fun	Cruise
HC	History	Culture	Wisdom	Taoism	Story

Note: OM represents operations management for TD, EX represents emotional experience for TD, SF represents symbolic features for TD, IR represents infrastructure & recreation for TD, and HC represents history & culture for TD.

In comparison, two key findings emerged. Firstly, topics EX, SF, and HC consistently interested tourists both before and after the COVID-19 pandemic. EX involves emotions and feelings during travel, seeking enjoyable experiences and lasting memories. SF includes distinctive signs and symbols like architectural structures, monuments, or landmarks, forming iconic memories. HC attracts tourists interested in historical monuments, traditional culture, and local arts. Secondly, during the pandemic, safety and health became primary concerns for tourists, shifting attention to destination hygiene measures and travel policies. Consequently,

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post-pandemic tourists prioritize the topic of OM. The pandemic exerted a profound influence on the tourism sector, imposing various restrictions and constraints on tourists.

Based on Eq. (1), **Fig. 4** depicts the performance of four illustrative TDs across five attributes. For presentation purposes, we processed the final results as a percentage. Notably, a higher score for each attribute means that it performs better and tourists are more satisfied with it. In summary, TPM outperforms other TDs in all attributes. Conversely, OTL performs poorly in all attributes. Besides, MOL does great work in SF.

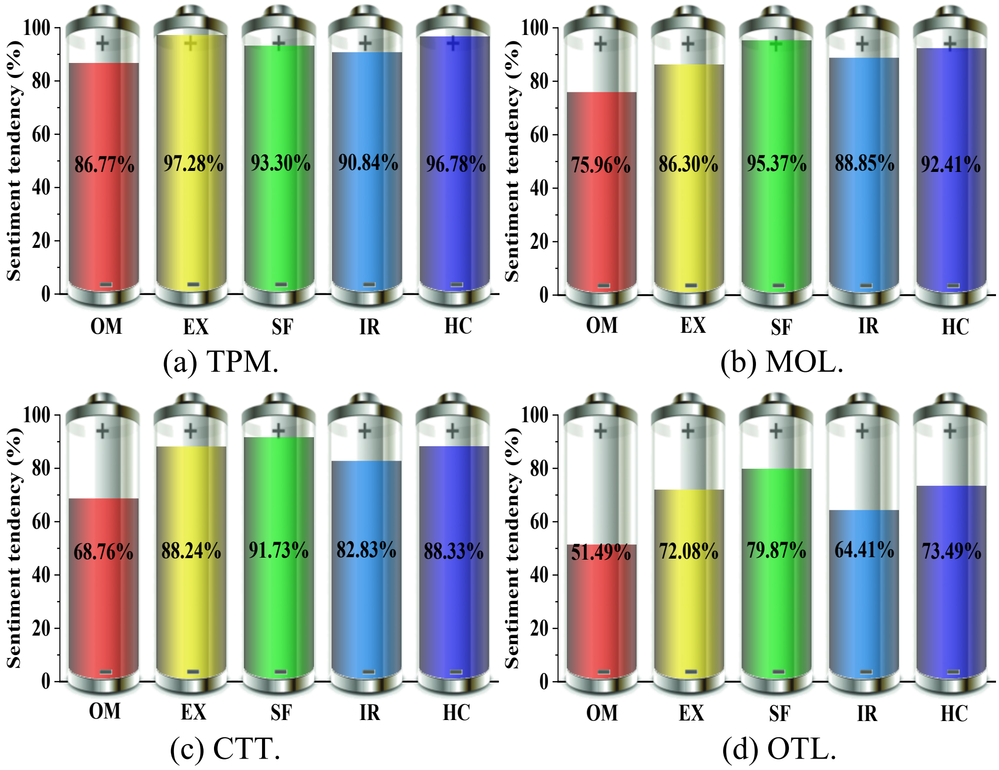

Fig. 4 – Sentiment tendency of five topics in four illustrative TDs. Source: own research

3.2 Configurations identification after the COVID-19 pandemic

Following established fsQCA practices, we calibrated the antecedent and outcome variables to fuzzy sets using the direct calibration method. Then, we tested the necessity of individual antecedent variables in each case. For this purpose, necessity tests were performed on all antecedent conditions to identify the elements necessary to form high performance in TDs. NCA identifies the necessity conditions by observing the effect size concerning the necessity for the antecedent conditions and their significance. Hence, the outcomes of the NCA analysis are presented in **Table 3**, encompassing the effect sizes computed through two distinct estimation approaches, CR and CE. Given that the variables under consideration in this study are continuous, the test outcomes from the CR method offer enhanced precision. The dual reporting aims to facilitate a robust comparison of the results. As articulated earlier, a prerequisite for the existence of a necessary condition is an effect size exceeding 0.1, coupled with simultaneous statistical significance in the Monte Carlo permutation test. Preliminary findings from the NCA analysis suggest that, among the destination attributes, RA and HC potentially serve as necessary conditions for the high performance of TDs. A visual representation of NCA plots is depicted in **Fig. 5**.

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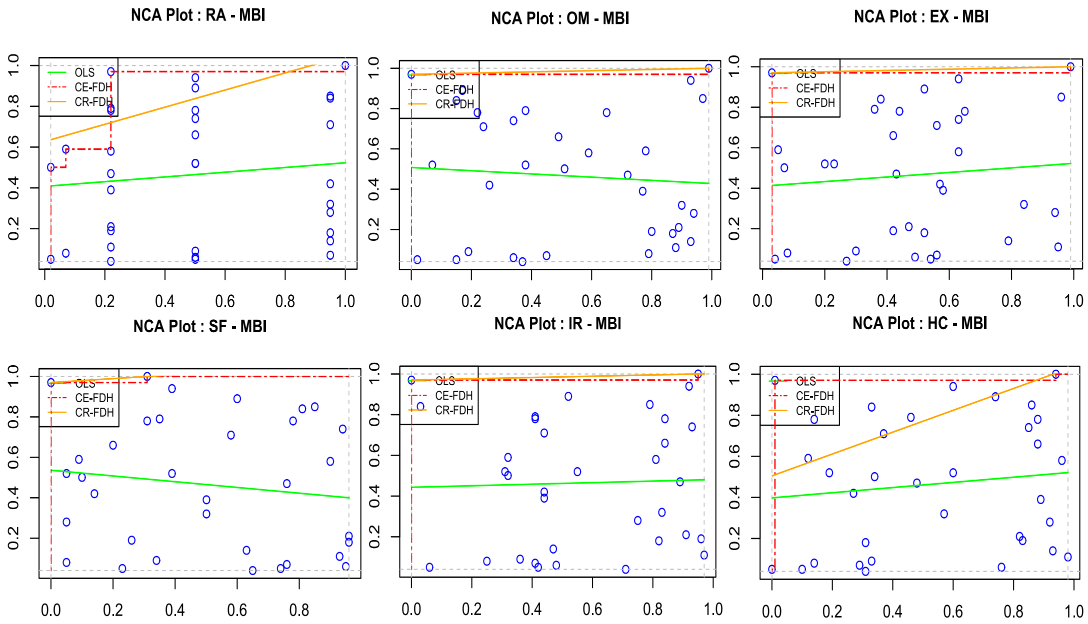

Fig. 5 – NCA plots. Source: own research

Tab. 3 – Necessary conditions for TD performance using NCA. Source: own research

Fuzzy-set condition	Method	Accuracy	Ceiling zone	Scope	Effect size (d)	P value
RA	CR	85.3%	0.158	0.94	**0.168**	**0.051***
	CE	100%	0.110	0.94	0.117	0.154
OM	CR	100%	0.015	0.95	0.016	0.872
	CE	100%	0.030	0.95	0.031	0.835
EX	CR	100%	0.014	0.92	0.016	0.819
	CE	100%	0.029	0.92	0.031	0.728
SF	CR	100%	0.005	0.92	0.005	0.948
	CE	100%	0.009	0.92	0.010	0.947
IR	CR	100%	0.014	0.93	0.015	0.893
	CE	100%	0.029	0.93	0.031	0.874
HC	CR	79.4%	0.230	0.94	**0.245**	**0.027****
	CE	100%	0.037	0.94	0.040	0.771

Note: *, ** and *** represent the 10%, 5% and 1% significance levels, respectively. $0.0 \le d < 0.1$ represents "small size", $0.1 \le d < 0.3$ represents "medium size", and $0.3 \le d < 0.5$ represents "high size". NCA analysis with the permutation test (resampling=10,000).

Also, the QCA method provides the capability to investigate the necessary conditions. As shown in **Table 4**, the consistency benchmark of 0.9 indicates that a single strategy for destination attributes does not enable TDs to obtain high performance. This finding contradicts the results of NCA. For this reason, we created scatter plots of antecedent and outcome variables. The evidence suggests that close to half of the case points are distributed above the diagonal. The consistencies of antecedent variables pass the examination. Nevertheless, they

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do not meet the criteria to be deemed necessary conditions for high performance in TDs (Schneider & Wagemann, 2012).

Tab. 4 – Necessary conditions for high performing TDs using fsQCA. Source: own research

Fuzzy-set condition	Consistency	Coverage
RA	0.6683	0.6238
~ RA	0.6131	0.5682
OM	0.6635	0.5787
~ OM	0.6755	0.6730
EX	0.6761	0.6463
~ EX	0.6730	0.6095
SF	0.6160	0.5709
~ SF	0.6642	0.6200
IR	0.7495	0.6058
~ IR	0.5864	0.6420
HC	0.7160	0.6220
~ HC	0.5914	0.5918

In summary, there are no necessary destination attributes that generate high performing TDs. Thus, the governance complexity of constructing high performing TDs should be accepted. In other words, the destination attributes must be matched in a linkage to jointly influence TD performance. In what follows, we will focus on the configuration effect among destination attributes.

Rather than identifying necessary conditions, configuration analysis unveils the sufficiency of various configurations, comprising multiple conditions, that contribute to the emergence of outcomes. These distinct configurations represent different ecologies of destination attributes that achieve the same result. All possible configurations are identified with the help of the truth table. Specifically, we set some parameters. Because of this study's small and medium-sized sample, the case frequency threshold is set to one. Following a general approach, the raw consistency threshold is set to 0.75, and the PRI threshold is set to 0.7 to ascertain concise configurations of the combination conditions sufficient to produce the results (Greckhamer et al., 2018). In this study, preference is given to the intermediate solution, which achieves a balance between parsimony and complexity (Cheng & Liu, 2022). The intermediate solution is deemed superior to other alternatives as it confines remainders to the most plausible scenarios (Fiss, 2011). Accordingly, **Table 5** presents the intermediate solutions concerning the emergence of high performance in TDs.

Tab. 5 – Configurations for high-performing TDs. Source: own research

Antecedent variables	Configuration solutions				
	S1	S2	S3	S4	S5
RA	●	●	⊗	●	⊗
OM	•		●	⊗	•
EX	•	•	⊗	⊗	⊗
SF		•	●	⊗	⊗
IR	●	●	●	●	●
HC	●	●	⊗	●	●
Consistency	0.7729	0.7797	0.8322	0.8753	0.8256

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Raw coverage	0.4650	0.4189	0.2384	0.2885	0.2694
Unique coverage	0.0608	0.0166	0.0145	0.0077	0.0108
Overall consistency			0.7515		
Overall coverage			0.7251		

Following the recommendations of Pappas et al. (2019), we present the results as visual graphs to intuitively highlight the survival status of the variables in each combination. The analysis results determine the core and peripheral conditions, in which black circles (●) stand for the presence condition, and transparent circles containing x (⊗) indicate the absence condition. Significantly, core conditions are emphasized with large circles, while peripheral conditions are represented by small circles. Furthermore, an empty cell indicates an inconclusive condition, which may or may not be present.

Table 5 presents consistency and coverage values for both the comprehensive solution and individual configurations. The consistency index assesses the degree to which a specific configuration serves as a sufficient condition for the outcomes and can be construed as a measure of reliability. Coverage assesses the empirical pertinence of the consistent subset, and it can be understood as R^2 in traditional quantitative analysis (e.g., regression analysis). Attending to the specific results, the level of consistency is higher than the minimum acceptable criterion of 0.75 for both individual and overall solutions, indicating that no further manipulation of configurations is required. Furthermore, the coverage values fluctuate from 0.2384 to 0.7251, suggesting that the constructed model is informative (Woodside, 2013). The overall consistency is 0.7515, implying that 75.15% of all TD construction cases satisfying these five categories of conditional configurations show a high level of performance. The comprehensive coverage stands at 0.7251, signifying that the five classifications of conditional configurations can account for 72.51% of instances related to the establishment of high-performing TDs. The values for overall consistency and coverage affirm the robustness of the empirical findings.

The results yielded by fsQCA show five driving paths to achieve high performance. These configurations identify the differentiated adaptation relationships of destination attributes in promoting TDs establishment. Overall, IR and HC largely determine whether a destination can achieve high performance and high competitiveness. In particular, IR is the most critical factor in identifying destinations that maintain high performance. Again, of the five high performing destination configurations, S1 has the largest raw coverage, indicating that it has the most robust empirical correlation with high performing destinations.

3.3 Robustness checks

This study conducts robustness tests on the configurational attributes of TDs that contribute to high-performance formation (Qin et al., 2026). On the one hand, since the QCA method is sensitive to the calibration of membership scores, robustness tests are performed by examining whether similar results are obtained with different calibration decisions. Precisely, modifying the calibration anchors to the 90th and 10th percentiles for complete membership and full non-membership, while maintaining the cross-over point unchanged, yields configurations that are predominantly congruent with the initial setups. On the other hand, increasing PRI from 0.7 to a more stringent 0.75 yields configurations that are largely consistent with the original results. Overall, the robustness checks demonstrate that the findings of this study are robust.

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4 DISCUSSION AND IMPLICATIONS

4.1 Discussion of key findings

Against the backdrop of intense competition in the tourism sector, a deep understanding of the factors and interrelationships influencing destination performance is essential for destinations' success and sustainable development. More importantly, from a competitiveness perspective, such a performance should be interpreted as the outcome of complex interactions among multiple destination attributes rather than isolated effects. In the literature, fsQCA is considered the most widely used complexity examination method and a derivative of chaos systems in tourism and hospitality. With natural language processing techniques, the core destination attributes are extracted and captured in TGC data. By integrating these approaches, this study provides a data-driven yet theory-informed explanation of how tourism competitiveness is configurationally formed. Based on this, a comparison is made regarding the differences in tourists' attention to various attributes of a TD before and after the COVID-19 pandemic. Besides, this study employs fsQCA to ascertain the complexity of the effects of destination attribute configurations on TD performance in the post-COVID-19 era. Additionally, NCA is used to analyze the size effect of the examined conditions complementarily.

Our research findings indicate that before the COVID-19 pandemic, tourists emphasized destination attributes related to "emotional experience", "landscape & infrastructure", "symbolic features," and "history & culture". However, after the COVID-19 pandemic, there was an additional focus on "recreation" and "operations management". This shift reflects a structural change in the drivers of tourism competitiveness under crisis conditions. This study's discovery aligns with the viewpoints of many existing scholars. During COVID-19, people faced various restrictions in accessing entertainment and engaging in leisure activities (Alves et al., 2023), particularly in industries such as leisure, entertainment, and tourism that heavily rely on population mobility. Consequently, there has been a widespread increase in the demand for entertainment purposes in TDs. This includes meeting the demand of tourists who, due to the pandemic, required recreational and leisure activities that involved contact with nature (Niezgoda & Markiewicz, 2022). This finding not only confirms existing studies but also extends them by demonstrating that such preferences do not operate independently, but rather interact with other attributes to form competitiveness-enhancing configurations (Zhang, 2025).

Moreover, during the COVID-19 period, tourists demonstrated a heightened level of interest in the "operations management" of TDs. This arose from the substantial influence of the pandemic on the tourism sector, which necessitated destination managers to implement a series of response measures to ensure the safety and health of tourists while maintaining the sustainability and effective operation of tourism activities. Therefore, destinations must take all necessary precautions to ensure the safety of tourists and provide them with a sense of security (Pappas, 2021). In practical terms, those overseeing tourism needed to meticulously evaluate the pandemic's repercussions on their operations and formulate novel risk management strategies to navigate the crisis (Škare et al., 2021). Psychologically, discussions and establishing international cooperation and harmonized safety measures are essential to minimize potential chaos and the resulting levels of fear and anxiety among vacationers (Pappas, 2021).

The fsQCA results have validated the complex configurational nature of destination attributes underlying high performance in TDs. Building upon numerical rating (RA) and destination attributes constituting the relevant antecedent variables, this study proposes five configurational models for predicting high performance in TDs. These models equally contribute to achieving

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high performing TDs, thereby representing distinct activation processes in enhancing destination performance. These causal strategies offered numerous intervention pathways to enhance the operational status of TDs and helped them cope with the impacts of COVID-19.

In accordance with Fiss (2011), the differentiation of core conditions from peripheral conditions can offer supplementary evidence for comprehending causal pathways. Therefore, we focus solely on the core conditions within each driving path. As a result, the original five configurations are simplified into three, i.e., S (1, 2, 4), S (3) and S (5).

Configuration S (1, 2, 4) suggests that high performing TDs combine online ratings, infrastructure, and cultural benefits. On the one hand, online ratings, as a conventional manifestation of word-of-mouth propagation, largely influence potential tourists' attitudes toward tourism products, thereby driving their behavioral decisions. On the other hand, many tourism providers banked on offering virtual tourism to attract tourists amid the COVID-19 pandemic. Relevant studies have also demonstrated the crucial role of virtual reality technology in aiding TD recovery and establishing tourism resilience (Kim et al., 2021). In short, travel restrictions imposed by the COVID-19 pandemic amplified the utility of online evaluations. Developing TD infrastructure and culture ensures the fulfillment of tourists' safety needs and cultural beliefs. S (3) emphasizes the synergistic effects of destination management, symbolic features, and infrastructure. Symbolic features are given importance in this pathway, possibly due to the increased demand for finding new and unique tourism experiences as people's travel choices were limited by the pandemic (Qin et al., 2026). TDs can satisfy tourists' desires for novelty and exploration by offering distinctive activities, attractions, and cultural experiences. S (5) only requires high performance in infrastructure and culture to cultivate a popular TD. This configuration resonates with global evidence that foundational resources and cultural authenticity remain core pillars of long-term tourism competitiveness (Zhang, 2025). However, operations management of the destination also requires some effort, as it is a peripheral condition in this configuration.

4.2 Contributions to theory

This study contributes to tourism literature by identifying diverse destination attribute configurations linked to high performance, offering valuable insights into factors attracting tourists. In contrast to macro-level interventions, often diverging from tourists' interests, these micro-level patterns, rooted in post-pandemic authentic perceptions (TGC), hold significant theoretical value for understanding and enhancing destination performance from tourists' perspectives.

Secondly, the study challenges linear analysis in understanding tourism systems, advocating for an asymmetric configuration approach from configurational theory. This approach unveils the complex generative paths of high-performing TDs post-pandemic, showcasing the independent functions of destination attributes with distinct antecedents and activation processes (Qin et al., 2025b). This supports the complexity of tourism recovery and underscores the value of complexity theory in tourism research. Shifting the focus to a more intricate level enhances understanding of how high-performing TDs, influenced by destination attributes, are formed.

Finally, integrating tourism big data analytics into fsQCA and NCA broadens the research scope and enhances understanding. The study incorporates TGC into QCA, using natural language processing and sentiment analysis for core condition identification, boosting data support and scientific rigor. This novel paradigm, combining tourism big data analytics with fsQCA and

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NCA, marks a unique methodological contribution, likely the first in tourism research, adding novelty to the field.

4.3 Implications to practice

This study provides actionable insights for tourism industry managers. It deepens our understanding of post-COVID-19 shifts in tourist behavior, emphasizing heightened concerns about safety and health. Post-pandemic tourists prioritize destination management and operations. To address this, we recommend collaborative efforts from destination marketers and managers to create a secure experiential environment. Timely dissemination of safety information through diverse channels is crucial.

Secondly, NCA findings highlight the pivotal role of online reputation and cultural heritage in reshaping post-pandemic TDs. During the pandemic, online reputation became crucial as people increasingly sought travel information and reviews online. A positive online reputation enhances visibility and attractiveness, drawing more tourists. Simultaneously, travel restrictions amplify the desire for unique cultural experiences. Destinations with distinctive cultural elements allow tourists to engage with and immerse themselves in the local culture, creating a lasting appeal that encourages repeat visits and positive word-of-mouth. We recommend destination managers prioritize online reputation and preserve local cultural heritage for sustainable tourism development.

Lastly, employing a configurational perspective, we assess the strategic effectiveness of TDs post-pandemic based on causal complexity logic. The identified configurations for popular TDs serve as policy guidelines for the tourism industry's post-COVID-19 recovery. These research results provide normative causal recipes, guiding destination managers in the realistic strategic reshaping of TDs. Managers can tailor their approach to these configurations based on specific needs and available resources.

4.4 Limitations and future research

While substantial effort has been invested in this study, certain limitations exist, offering directions for future research. Firstly, the absence of pre-pandemic data for some TDs impedes subsequent configurational studies despite collecting comparative data before and after the pandemic. To address this, future research should conduct detailed comparisons to elucidate configuration patterns before and after the pandemic. Secondly, this study exclusively focuses on the recovery and reshaping of TDs in the post-pandemic Chinese context. Cultural variations, pandemic differences, and containment strategies may limit the generalizability of insights proposed. Hence, future research should consider specific contexts globally for a comprehensive understanding of the post-pandemic tourism industry. Lastly, the dynamic nature of TD recovery and reshaping post-pandemic suggests potential changes over time and evolving circumstances (Qin et al., 2025a). The study lacks integration of temporal effects, and identified configurations may be more promising within specific periods. Future research should employ advanced dynamic QCA techniques, incorporating time effects to explore causal pathways and ensure continual examination of configurations and causal relationships. Collecting longitudinal information and applying dynamic QCA can bolster the conclusions' robustness and persuasiveness.

5 CONCLUSION

This inquiry marks a groundbreaking stride in intertwining machine learning and big data analytics with fsQCA to decipher the configurational patterns impacting TDs, particularly following the aftermath of the COVID-19 pandemic. By meticulously analyzing a substantial corpus of TGC from 34 5A-level TDs in China, we uncovered pivotal tourist concerns and the performance dichotomy of destinations pre and post-pandemic. More specifically, several key findings emerge from this study. Firstly, tourists' focus significantly shifted in the post-COVID-19 era, with heightened attention to safety, operations management, and recreational experiences, reflecting a reconfiguration of demand-side drivers of tourism competitiveness. Secondly, the results confirm that no single destination attribute constitutes a necessary condition for high competitiveness, highlighting the inherent complexity and nonlinearity of tourism systems. Finally, five distinct configurational pathways are identified, demonstrating that tourism competitiveness can be achieved through multiple equifinal combinations of destination attributes, rather than a one-size-fits-all strategy.

The novel analytical framework employed herein revealed five distinct configuration models predicting high performing TDs, each elucidating unique activation processes to attain high performance. Importantly, these configurations should be interpreted as alternative "recipes" for achieving high tourism competitiveness, thereby offering a more nuanced understanding of how different combinations of attributes jointly shape destination success. From a theoretical perspective, this study contributes to the tourism competitiveness literature by advancing a configurational view of competitiveness, moving beyond traditional net-effect approaches. By integrating machine learning-based text mining with fsQCA and NCA, this research also proposes a novel methodological paradigm that bridges data-driven analytics and causal complexity theory.

The ramifications of our findings are manifold, spanning policy formulation and practical strategy in the global tourism sector. The actionable insights from this research furnish tourism stakeholders with a robust blueprint to tailor policies and strategies, ensuring enhanced tourist satisfaction and destination performance in a digitalized, post-pandemic milieu. From a practical perspective, the identified configurational pathways provide destination managers with flexible strategic options. Rather than relying on isolated improvements, managers can prioritize synergistic combinations of attributes, such as infrastructure, cultural resources, and operational management, to enhance overall competitiveness in line with their specific resource endowments.

Moreover, the generalizable nature of our findings extends beyond the Chinese context, providing a valuable lens through which global TDs can recalibrate their strategies to resonate with evolving tourist preferences and digital trends. This underscores our contribution to the burgeoning discourse of digital transformation in tourism, aligning with the sustainable development goals of promoting innovation within the industry and establishing robust infrastructure to support sustainable cities and communities. More importantly, the generalizability of this study lies not only in the empirical findings but also in the transferability of the proposed analytical framework. Specifically, the integrated pipeline of TGC mining, sentiment-based attribute extraction, and configurational analysis (fsQCA) can be readily replicated in different national and cultural contexts where online review data are available. Given that platforms such as TripAdvisor and other region-specific travel communities provide abundant and comparable user-generated data, future studies can adopt the same methodological procedures to identify context-specific configurations of tourism competitiveness. This enables cross-country comparisons and enhances the external validity of configurational insights.

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