ISSN: 2029-4913 / eISSN: 2029-4921

Article in press

TECHNOLOGICAL and ECONOMIC DEVELOPMENT of ECONOMY

https://doi.org/10.3846/tede.2025.23251

DECODING TOURIST SATISFACTION FOR SUSTAINABLE ECONOMIC DEVELOPMENT: A MULTI-METHOD CONFIGURATION FRAMEWORK USING ONLINE REVIEWS

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Article History:
- received 23 April 2024
- accepted 02 December 2024
- first published online 14 July 2025

Abstract. Online reviews are crucial to understanding tourist satisfaction (TSA) in the digital tourism era. This study deconstructs the factors leading to high TSA performance in reviews, offering guidance for long-term economic benefits for destinations and businesses. Building on the three-factor theory, we create a framework utilizing text mining, affective distribution computing, and fuzzy-set qualitative comparative analysis (fsQCA) to identify patterns driving high TSA. We employ topic modeling to extract destination attributes from reviews, quantifying their performance through affective distribution computing. An enhanced Kano model classifies tourist needs based on emotional expressions in reviews. We investigate how basic, performance and excitement attributes interact and influence TSA. Additionally, we apply the coupling coordination degree model (CCDM) to analyze attribute interconnections within configurations. Our results show that no single attribute leads to specific outcomes; relatively, high TSA results from a combination of attributes. This study identifies three normative causal recipes and is the first to clarify the complex interactions in satisfaction management within the three-factor theory framework, addressing a significant knowledge gap. Ultimately, our operational guidelines aim to sustain the economic vitality of the tourism industry.

Keywords: tourism economy, tourist satisfaction, three-factor theory, FsQCA, online reviews.

JEL Classification: L83, C53, C88, M31, Z32.

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1. Introduction

Tourism, as a vital economic sector, plays a pivotal role in global economies, fostering growth, employment, and cultural exchange (Zhang et al., 2023). With the advancement and widespread adoption of digital technology, digital tourism has emerged as a crucial aspect of the tourism industry, offering new possibilities for enhancing the tourist experience (Luo et al., 2024). In particular, the advent of the Web 3.0 era has fostered a high degree of social interaction among tourists on the Internet and the exchange of travel-related content (Pereira-Moliner et al., 2024). Travel-related content created and uploaded by tourists on the Internet is user-generated, which has garnered increasing attention within the tourism discourse (Mak, 2017; Sun et al., 2015). Within this context, online reviews have been recognized as a crucial data source for measuring and capturing TSA (Bi et al., 2019a).

Compared to traditional survey data, online reviews are considered to be open, more objective, cost-effective, and unbiased evaluations. More importantly, the abundance of viewpoints and opinions from online travel communities provides rich empirical insights (Chang et al., 2014). These reviews offer assessments from tourists and encompass various attribute information regarding the travel experience. Attributes mentioned by tourists in their reviews can encompass multiple aspects of the destination, including attractions, services, transportation, dining, and more. If individual online reviews represent fragmented perceptions of a destination, then the collective wisdom of massive online reviews constitutes a comprehensive understanding of the tourist destination. Thus, the existing literature has explored TSA by placing tourist expectations and perceived performance on a multi-attribute scale (Peng et al., 2019). TSA is an overall performance evaluation of the various attributes that constitute tourism products or services. In this context, emerging social research endeavors to extract destination attributes from online reviews to reevaluate the relationship between attribute performance and TSA. However, comprehending the contributions and significance of these attributes to satisfaction is intricate and necessitates using complex analytical methods to unveil their interrelationships (Yang et al., 2023a).

TSA, its antecedents, and its consequences have long captivated scholarly attention, exploring the multifaceted nature of tourist opinions and evaluations (Peng et al., 2019). Following the assumption of linear combinations in attribute satisfaction for TSA, prior research has primarily focused on identifying influential attributes (Bi et al., 2019a). However, recent studies emphasize the asymmetric and nonlinear relationship between attribute performance and TSA (Anderson & Mittal, 2000). In the realm of social sciences, particularly in tourism and hospitality, leveraging multi-attribute models has proven instrumental in understanding TSA, showcasing that different attributes may wield heterogeneous impacts on TSA (Slevitch & Oh, 2010). The Kano model, a classic tool for gauging customer needs and satisfaction, delineates attributes as basic, performance-driven, excitement-inducing, indifferent, or reversed (Kano, 1984), offering insights into attributes critical for enhancing satisfaction. Although the model identifies five types of attributes, it is commonly known as the three-factor theory. This is because, in practical applications, emphasis is typically placed on the first three categories of attributes.

While the existing literature has established a consistent TSA research framework, critical research challenges and gaps persist. On the one hand, the current research excessively focuses on identifying and prioritizing the impact of individual attributes on TSA. However, this narrow approach only presents fragments of TSA, failing to illustrate this complex phenomenon comprehensively. In the tourism industry, tourists' perceptions and behaviors are influenced by numerous elements, contributing to the complexity inherent in their decision-making processes (Pappas, 2021). Thus, the formation of TSA is inherently intricate, demanding the concurrent presence of multiple antecedent destination attributes to yield specific outcomes, rather than their sequential occurrence (Wang et al., 2023). Yet, scant evidence exists in tourism literature concerning such configurational studies. A thorough exploration of various attribute combinations will offer a fresh perspective and approach toward optimizing destination operations and enhancing TSA. On the other hand, lacking a practical analytical framework to investigate the interactions among various destination attributes has constrained the holistic understanding of TSA. Introducing such an analytical framework as the three-factor theory facilitates a more precise identification of pivotal attribute combinations, comprehending their collective influence, thereby meeting tourists' diversified needs and expectations. In this regard, it can propel the sustainable growth of the tourism economy, thereby creating favorable conditions for the continuous prosperity of the tourism industry (Wang & Jia, 2024).

Recognizing the existing gaps in research, complexity theory has emerged as a valuable perspective for understanding the intricate combinations of causal attributes influencing outcomes in tourism, which inspires our study (Lee, 2022). The study aims to uncover the complexity of TSA by configuring multiple attributes. Employing configurational thinking, we seek a holistic view of the tourism phenomenon, considering attribute interdependencies and interactions forming concurrent antecedents and pathways toward satisfaction outcomes. Specifically, we collect and analyze online reviews from travel communities to extract destination attributes using topic modeling and quantify their performances through affective distribution computing. By integrating the three-factor theory framework, we classify destination attributes into essential, performance, and excitement categories, establishing them as antecedents for configurational analysis. We explore attribute combinations leading to high TSA using fsQCA and necessary condition analysis (NCA). Additionally, we introduce the coupling coordination degree model (CCDM) to quantify coordination among attributes, enhancing our understanding of their connection patterns within configuration theory.

This study makes four distinct contributions. Firstly, it pioneers an innovative approach by integrating advanced methodologies such as topic modeling, affective distribution computing, the three-factor theory, and fsQCA to identify attribute configurations influencing high TSA levels. By providing decision-making support for destination managers, this framework not only enhances tourist experiences but also contributes to the economic sustainability of tourist destinations. Secondly, the introduction of an improved Kano model for categorizing tourists' needs takes into account the intricate and diverse affective expressions in online reviews. This refined model enables a more nuanced understanding of tourists' preferences and expectations, facilitating targeted marketing strategies and investment decisions that optimize economic outcomes in the tourism sector. Thirdly, by elucidating the complex interactions among multiple attributes within the framework of the three-factor theory, this study fills a crucial knowledge gap in tourism management. A deeper understanding of these interactions equips policymakers and industry stakeholders with insights to tailor offerings and infrastructure developments that maximize economic returns while meeting diverse tourist demands. Finally, the application of coupling theory allows for the quantification of interrelationships among attributes within configurations, providing valuable insights into the coordination of tourism offerings. This holistic perspective enables policymakers to prioritize investments and initiatives that foster synergy among various tourism components, ultimately bolstering the economic resilience and competitiveness of tourist destinations.

We first introduce the conceptual background in Section 2. Then, the methodology and the proposed framework are presented in Section 3. Section 4 provides the main results, including the category and prioritization of attributes, multi-attribute configurational patterns for TSA enhancement, and insights into coupling coordination degree. Section 5 gives some discussions and implications. Finally, concluding remarks are illustrated in Section 6.

2. Conceptual background

Table 1 summarizes the literature on multi-attribute exploration and customer satisfaction per our research objectives. Based on the classification in this Table 1, we review the existing literature across three aspects: attribute extraction and affective computing, attribute performance and customer satisfaction, and configurations of product or service attributes.

2.1. Attribute extraction and affective computing of online reviews

The surge in social media and online reviews has attracted considerable scientific interest (Chen et al., 2022). As a vital form of user-generated content, these reviews offer valuable, spontaneous feedback on social platforms, blending facts, opinions, impressions, and emotions (Singh et al., 2017). They provide unfiltered customer sentiments, reflecting genuine experiences and viewpoints (Shin & Nicolau, 2022). Analyzing this textual data can uncover unique insights into product or service attributes (Yang et al., 2023b). Traditional methods like surveys are labor-intensive and limit diverse opinions (Park & Lee, 2021), while the vast text corpora in open environments offer automation opportunities with reduced human involvement (Roelen-Blasberg et al., 2023). Prior research on automated analysis has largely concentrated on attribute extraction and affective computing (Wu et al., 2024a; Zhang et al., 2021a).

Customer evaluations in online reviews encompass various product or service attributes (Qin et al., 2022). Extracting these attributes efficiently from online reviews is crucial for tailored improvements, competitive analysis, and enhancing satisfaction (Wu et al., 2024b). Manual attribute extraction struggles with the vastness and diversity of online review data,

Table 1. Literature on multi-attribute exploration and customer satisfaction (source: authors' own research)

Studies	Attribute extraction	Affective distribution computing	Kano model	Multi-attribute configuration	NCA	CCDM
Bi et al. (2019a)	✓		✓			
Bi et al. (2019b)	✓	✓				
Pan et al. (2022)	✓		✓			
Zhang et al. (2021c)				✓		
Xu (2022)	✓					
Wang et al. (2023)				✓		
Zhao et al. (2023)	✓		✓			
Zhang et al. (2021a)	✓	✓	✓			
Lee (2022)	✓			✓		
Fu et al. (2023)	✓			✓		
Rassal et al. (2023)	✓			✓		
Perdomo-Verdecia et al. (2024)				✓		
Lee et al. (2024)	✓			✓		
Gupta et al. (2024)				✓		
Our study	✓	✓	✓	✓	✓	✓

necessitating more adaptive approaches (Bi et al., 2019b). Automation, mainly through artificial intelligence algorithms like machine learning and deep learning, has gained traction as it replaces manual processes, revolutionizing attribute and topic extraction (Xu & Li, 2016; Zhang et al., 2024).

Topic modeling techniques use mathematical frameworks to capture clusters of related words representing various topics automatically (Vu et al., 2019). These methods aid in uncovering hidden patterns from online text, enhancing information processing efficiency and accuracy (Vayansky & Kumar, 2020). Latent Dirichlet Allocation (LDA) is a popular machine learning-based method widely applied for topic discovery in text (Blei et al., 2003; Lv et al., 2024). However, the LDA model often overlooks word order issues and requires a predetermined optimal number of topics (Kirilenko & Stepchenkova, 2025). Moreover, they may yield poor results when handling short texts like microblogs or online reviews due to data sparsity (Yan et al., 2013). Consequently, recent research has developed advanced topic models like Top2Vec and BertTopic, catering to short texts (Angelov, 2020; Grootendorst, 2022). In particular, Top2Vec, an algorithm for topic modeling and semantic search, automatically identifies topics in text and generates embedded topics, documents, and word vectors (Das et al., 2024).

Online reviews typically contain a substantial amount of subjective information and emotional expressions (Pocchiari et al., 2024). Affective computing helps managers determine customers' perspectives on service or product attributes and comprehend customer emotional experiences and satisfaction levels (Pan et al., 2022). With this in mind, sentiment analysis and emotion identification are frequently applied in various online review-driven practical problems to tailor decision support based on customer emotional states (Kratzwald et al., 2018). Although they do not fall under the same benchmark discipline, they are collectively encompassed within the umbrella of affective computing (Balazs & Velásquez, 2016). Affective computing is a collection of techniques to recognize affects from data with different modalities and granularity scales. For instance, sentiment analysis carries out coarse-grained affect recognition, commonly regarded as a classification task (e.g., binary classification of positive and negative). In contrast, emotion recognition conducts fine-grained affect recognition, as it seeks to classify data based on many sentiment labels (Poria et al., 2017).

Affective computing systems can be broadly categorized into knowledge-based and statistical-based systems (Poria et al., 2017). With the rapid advancements in deep learning algorithms, affective computing research has increasingly focused on deep learning architectures. According to Collobert et al. (2011), a simple deep-learning framework outperforms most state-of-the-art methods. However, the informality and variability of online reviews, stemming from their everyday nature, render single-affect category assignments inadequate. This fact encourages the exploration of multiple affect labels within the text, i.e., addressing affect ambiguity through affective distribution computing (Zhou et al., 2015).

In contrast to the existing single affect assumption, affective distribution computing allows the consideration of the distribution of multiple affect categories in affective computing and models the relative importance of each affective label (Qin et al., 2021). In this regard, the recursive neural tensor network (RNTN) is introduced within the deep learning framework, and it uses a single tensor composite function to define multiple bilinear dependency relationships between words (Socher et al., 2013). Thus, the five affective categories inherent in the text are captured, ranging from very negative to very positive. Affective distribution computing principles are applied to compute the probability distribution of each affect. For the structured representation of affective complexity in online reviews, probabilistic linguistic term sets (PLTS) are widely recognized (Pang et al., 2016; Wu & Liao, 2021). PLTS, in the form of linguistic terms, can simultaneously express affective categories and their corresponding probability information, serving as a powerful statistical tool for describing online reviews (Cui et al., 2022; He et al., 2024).

2.2. Attribute performance and customer satisfaction

Understanding customer satisfaction is critical to business success (Zhao et al., 2021). Therefore, satisfaction has always been a central interest in sociological research (Chen et al., 2022). Customer satisfaction can be defined as "the subjective evaluation of the customer's experience based on some relationship between customer perceptions and the objective attributes of the product" (Klaus, 1985). In other words, customer satisfaction is an overall assessment of the performances of various attributes that constitute a product or service. Initially, a linear and symmetric relationship between the performances of product or service attributes and customer satisfaction was established. This perspective assumes that positive and negative performances of attributes have symmetric effects on overall satisfaction with the product or service. However, Oliver et al. (1997) pointed out that different attributes may have varying degrees of impact on customer satisfaction, suggesting that there may be asymmetric effects of attributes on customer satisfaction. In response, the asymmetric relationship between product or service attributes and customer satisfaction was empirically confirmed by Mittal et al. (1998) through rigorous empirical investigations. Additionally, Slevitch and Oh (2010) provided complementary explanations for this phenomenon. On this basis, some scholars elaborated on this theory by identifying various types of attributes, leading to the development of the Kano model (Kano, 1984; Shin & Nicolau, 2022). The Kano model classifies product or service attributes into different types based on specific relationship patterns. These include basic, performance, excitement, indifferent, and reverse attributes. Researchers unanimously agree that the first three quality attributes should be given priority, which is why the Kano model is also referred to as the three-factor theory model (Velikova et al., 2017).

With the rise of social media, the Internet has become a treasure trove of genuine customer feedback on product and service experiences (Bi et al., 2019a). This vast data source has become pivotal for customer satisfaction research. Scholars now harness user-generated content, like online reviews, to explore how product or service attributes impact customer satisfaction (Zhang et al., 2021a). Typically, researchers employ topic modeling to identify influential attributes and then use affective computing to gauge each attribute's performance. This adaptation of conventional tools, once reliant on surveys and interviews, to extensive web-based data aims to amplify their effectiveness and adaptability in understanding attribute performance and customer satisfaction (Chen et al., 2024).

2.3. Configurations of product or service attributes

As research advances, scholars have begun to recognize the interactions between attributes and the complex impact of attribute configurations on customer satisfaction (Lee, 2022). The previous research paradigm based on symmetrical thinking is discarded, shifting the focus from the marginal net effects of singular attributes to the collaborative interaction and configuration among attributes (Lee et al., 2024). This phenomenon is particularly pronounced in the field of tourism and hospitality (Pappas, 2021). Thus, the reliance on simplistic model settings inherent in traditional symmetric methods has constrained our current comprehension of TSA. Research suggests that TSA arises from complex interactions among multiple factors, forming a holistic configuration of experiences (Wang et al., 2023). Commencing from the complexity theory perspective, configurational thinking is more suitable than scrutinizing the impact of individual attributes (Wattanacharoensil et al., 2024).

Complexity theory argues that complex phenomena result from different combinations of antecedent conditions leading to the same outcome (Feng et al., 2024; Wang et al., 2023). Configuration perspective and fsQCA, an emerging research paradigm, have been widely used to analyze customer experience issues involving multiple factors (Liu et al., 2024; Park et al., 2020). In this regard, to comprehend the complexity of customer experiences, Lee (2022) integrated text analysis with fsQCA, shifting the focus from individual attributes to attribute dimension configurations. Specifically, based on complexity theory, this study examined the configurations of attribute dimensions that lead to positive and negative emotions. To the best of our knowledge, this is the first study to integrate topic modeling, affective computing, and fsQCA, providing a framework for decision support for service providers in responding to customer demands. Fu et al. (2023) employed a similar research approach using the LDA technique to extract factors influencing learners' satisfaction from online reviews. They further applied fsQCA analysis to investigate the high and low-level configurations of learning satisfaction in MOOC courses. Perdomo-Verdecia et al. (2024) pointed out that fsQCA plays an important role in analyzing the causal complexity of hotel processes and activities. It can help practitioners identify key attributes to optimize customer satisfaction. Based on the evolutionary stimulus-organism-response model, Lee et al. (2024) combined social media analysis and fsQCA to explain the attitudinal and behavioral components of customer loyalty. Besides, fsQCA was employed to examine how the causal patterns of consumers' engagement and experts' external engagement are associated with moviegoer satisfaction. The findings highlighted the synergistic benefits of customer engagement behaviors and external participation in driving movie evaluations (Gupta et al., 2024).

These few recent studies present innovative ideas with research implications, but they still have some limitations and shortcomings, which inspire our work. Firstly, the Kano model indicates that not all product or service attributes extracted from online reviews necessarily enhance customer satisfaction, such as indifferent or reverse attributes. However, existing studies often overlook this, treating all extracted attributes as antecedents, which undermines the credibility of their findings. Secondly, while these studies utilize advanced affective computing techniques to assess the performance of product or service attributes, they fail to account for the inherent ambiguity of emotions embedded in online reviews. Finally, although these studies identify equivalent configurations leading to the outcome of interest, they do not explore the interconnections and coordination levels among attributes within these configurations.

In summary, based on Kano's three-factor theory, this study employs affective distribution computing and fsQCA methods to reveal the distinct configurations of destination attributes leading to high TSA. Simultaneously, the operational coordination among the attributes within the configurations is examined using CCDM. Complexity theory asserts the following tenets. (1) Causal complexity. Outcomes are typically the result of interactions among multiple conditions rather than being driven by a single factor. These conditions are interdependent, and their dynamic interplay forms complex causal relationships. (2) Equifinality. Different combinations of conditions can lead to the same outcome, meaning that multiple paths can achieve the same objective through varying configurations of factors. (3) Asymmetry. Causal relationships are not mirror opposites. While certain conditions may be necessary to produce a particular outcome, their absence does not necessarily result in the opposite effect (Kumar et al., 2023). Based on these tenets, we propose the following Hypotheses:

H1: *No single basic, performance, or excitement attribute can independently lead to high TSA.*

H2: *Multiple equivalent causal configurations exist that can lead to the same outcome, i.e., high TSA.*

H3: *High TSA may or may not involve the same causal attributes across different configurations, depending on how these attributes interact with other causal attributes.*

Through a holistic and multi-attribute configurational exploration, we delve into how multiple attributes driving high TSA are matched to create value, unpacking the black box of TSA. The findings of this study offer valuable insights for practical application in the tourism economy, providing effective guidance for destination managers and decision-makers to optimize the tourist experience and maximize economic benefits at destinations.

3. Methodology and proposed framework

Figure 1 presents the research framework proposed in this study, comprising five components corresponding to Subsections 3.1 to 3.5. Firstly, a destination case set alligned with the research objectives is selected based on authoritative tourism destination rankings, and tourist-generated data, including online reviews, ratings, and review dates, are collected from the Ctrip platform. Secondly, the Top2Vec topic modeling technique is applied to identify destination attributes of interest to tourists, while affective distribution computing quantifies tourists' emotional attitudes toward these attributes. Thirdly, an improved Kano model is used to classify destination attributes into distinct categories. Fourthly, leveraging the identified basic, performance, and excitement attributes, fsQCA and NCA are conducted to capture configurational patterns of attributes driving high TSA. Finally, CCDM is employed to assess the coordination levels of the identified attribute configurations.

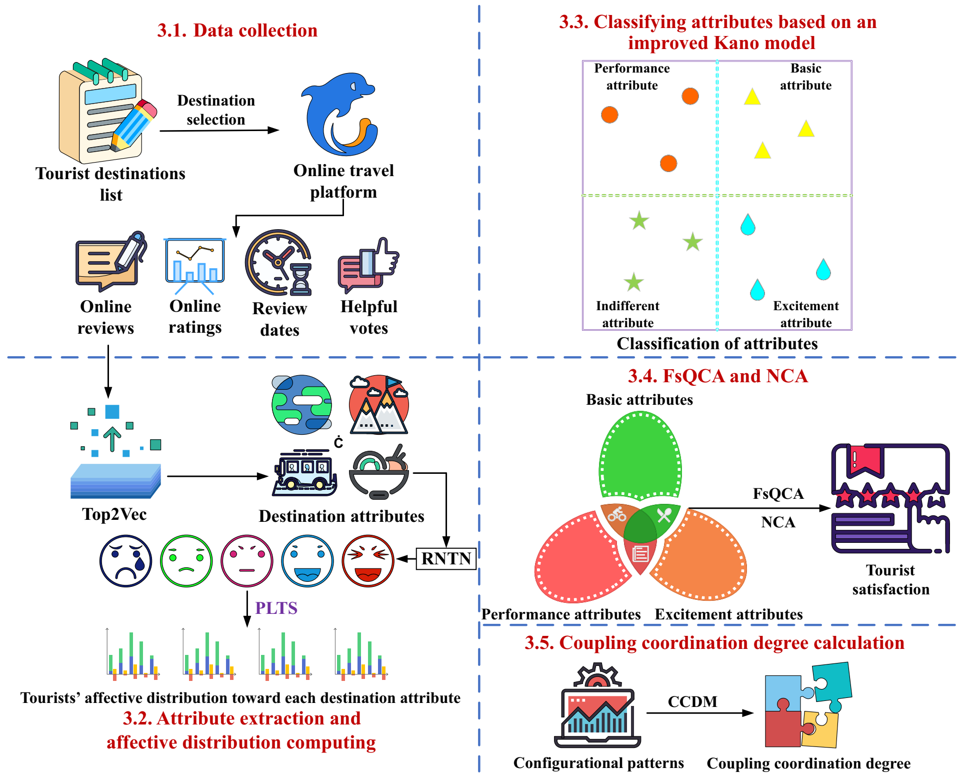


Figure 1. Research framework (source: authors' own research)

3.1. Data collection

The recently released 2022 list of the Top 100 Influential Brands for China's 5A-level tourist destinations by the reputable institution Meadin Academy is utilized. The 5A-level tourist destinations in China refer to the highest-rated scenic areas designated by the National Tourism Administration, ensuring the credibility and representativeness of the research cases. Importantly, these destinations attract many tourists for sightseeing, leisure, and tourism, thus providing a significant corpus of online data for analysis. In adherence to the principle of comparability, 45 humanistic landscape-oriented destinations are eventually finalized. Regarding data collection, Ctrip serves as China's leading online travel service platform, continuously collecting and exhibiting numerous genuine traveler reviews. Hence, Ctrip is the source of online reviews from tourists. Notably, Ctrip predominantly showcases the most recent 3000 reviews, ensuring the timeliness and readability of the reviews. In addition to the primary textual information, supplementary numerical data, such as online ratings, review dates, and helpful votes, are also documented.

Specifically, we employ Web Scraper for the large-scale collection of data. Reviews for the selected destinations were gathered on October 8, 2023, resulting in an initial corpus of 118,900 textual reviews. The following preprocessing steps are undertaken post-data collection to mitigate potential biases in the research findings. Firstly, essential data cleansing procedures are conducted. This involves the removal of blank and duplicate entries.

Furthermore, this study exclusively considers Chinese-language reviews, thereby excluding non-Chinese characters. Subsequently, short texts, often lacking substantive content, are eliminated, with online reviews containing fewer than 10 Chinese characters removed. Lastly, recognizing that each review typically comprises several clauses, spaCy, a dependency parsing tool, identifies and filters out fine-grained clauses. Following these aforementioned preprocessing steps, the final dataset for this study comprises 160,834 reviews.

3.2. Attribute extraction and affective distribution computing

Destination attributes, perceived as an underlying structure, are distributed across textual reviews used by tourists to articulate their experiences, referred to as "topics" in the literature (Lee, 2022). Hence, an efficient automated technique is essential to capture latent attributes, especially in the big data environment. In recent years, extensive application of topic modeling techniques has been witnessed in such scenarios. The emerging unsupervised topic modeling technique, Top2Vec, has been adopted in this study. Unlike traditional methods like LDA, Top2Vec excels in handling large-scale textual data and concurrently discovering both primary and subtle yet crucial topics (Angelov, 2020). Its distinctiveness lies in amalgamating word embeddings with efficient clustering techniques to identify topics and generate document embeddings.

Moreover, this technique autonomously determines the number of topics without necessitating custom stop-word lists, stemming, or lemmatization. We utilize the pkuseg Chinese segmentation toolkit to segment reviews before attribute extraction. This process aims to segment continuous Chinese text into individual words or phrases with independent meanings, facilitating computer processing. By employing the tourism domain model, pkuseg enhances its ability to comprehend and handle Chinese text related to the tourism domain, identifying domain-specific vocabulary and terms and consequently elevating segmentation accuracy.

Once destination attributes of interest to tourists are identified, affective distribution computing technique is employed to ascertain the affective states and reactions within online reviews associated with specific attributes. Sentiments conveyed through online reviews amalgamate various emotions, each displaying different intensities on the same baseline (Zhou et al., 2015). Given these complexities, this study introduces the idea of affective distribution computing to address the ambiguity prevalent in affective computing tasks (Zhou et al., 2015). It represents an effective contemporary model for analyzing multiple emotions within textual data, aiming to model and learn the distribution of different affective categories in the text. Specifically, this study utilizes the RNTN technique to analyze the affective intensity and distribution within online reviews (Socher et al., 2013). RNTN, a deep learning model, employs tensors to model interactions between different words in a sentence, continually learning the semantic information of sentences through a recursive structure. This method enables the model better to comprehend the affective and semantic content within sentence structures. The RNTN technique accurately categorizes textual expressions of sentiment into five distinct levels and provides corresponding probabilities: very negative, negative, neutral, positive, and very positive. This refined classification captures the affective content within the

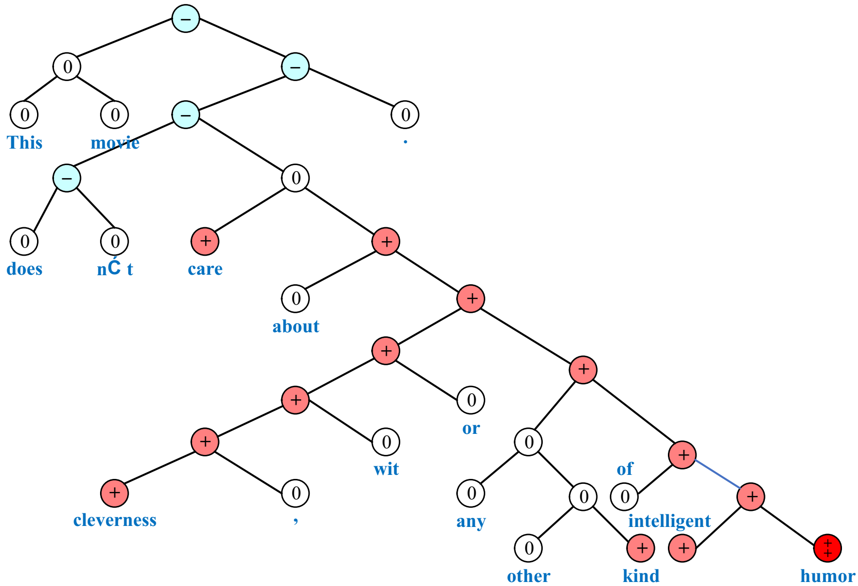


Figure 2. Example of the RNTN accurately predicting five affective classes, very negative to very positive (– –, –, 0, +, + +), at every node of a parse tree and capturing the negation and its scope in this sentence (Socher et al., 2013)

text, facilitating the understanding and prediction of various types and degrees of affective expressions (Poria et al., 2017). Figure 2 illustrates an example of the RNTN model predicting affective classes.

Following Wu and Liao (2021), PLTS is employed to structurally characterize the affective distribution and intensity within online reviews (Pang et al., 2016). It enables the simultaneous representation of multiple linguistic terms and their respective probability information, accurately matching and characterizing diverse affective types and intensities (Zhao et al., 2023). Let $S=\{s_{-\tau},\cdots,s_{-1},s_0,s_1\cdots,s_\tau\}$ (τ is a positive integer), a subscript-symmetric additive linguistic assessment scale, a PLTS can be defined as:

$$L(p)=\left\{L^{(k)}(p^{(k)})\,|\,L^{(k)}\in S, p^{(k)}\geq 0, k=1,2,\cdots,\#L(p), \sum_{k=1}^{\#L(p)} p^{(k)}\leq 1\right\}, \quad (1)$$

where $L^{(k)}(p^{(k)})$ denotes the linguistic term $L^{(k)}$ connected with the probability $p^{(k)}$, and $\#L(p)$ depicts the number of linguistic terms in $L(p)$.

As the RNTN model outputs affective distribution classified into five categories, PLTS employs five linguistic terms $(s_{-2},s_{-1},s_0,s_1,s_2)$ for representation. After completing the affective distribution computing task for all online reviews, 160,834 PLTSs with five linguistic terms are generated.

The subsequent step involves aggregating multiple reviews for each attribute under each destination into an overall PLTS. Within this process, the weight assigned to each review indicates heterogeneity based on considerations of usefulness and acceptability (Pu et al., 2023). Generally, recent online reviews tend to receive greater acceptance from travelers.

Over time, customers' perceptions of products or services may change, and thus, their inclination toward referencing the most recent reviews for the latest information and experiences regarding products or services. Building on this principle, the time weight of the α*th* online review is computed as follows:

$$w_{T^{\alpha}} = \frac{T^{\alpha} - T^{old}}{T^{new} - T^{old}}, \tag{2}$$

where T^{α}, T^{old} and T^{new} represent the release date of the α*th* review, the first review, and the last review under each attribute, respectively.

Additionally, the quantity of helpful votes typically reflects the practicality or popularity of online reviews. These votes serve as an indicator, showcasing the acknowledgment level of other travelers toward the reviews, aiding us in assessing the reliability and value of the feedback. Based on this principle, the helpfulness weight of the α*th* online review is defined as follows:

$$w_{hf^{\alpha}} = \ln(hf^{\alpha} + 1) + 1, \quad hf^{\alpha} \geq 0, \tag{3}$$

where hf^{α} depicts the number of helpful votes of the α*th* online review under each attribute.

Given the existence of two sets of weights, it is necessary to consolidate these weights into a unified set for the final computation. Thus, the combined weight of the α*th* online review is specified as:

$$w^{\alpha} = \zeta w_{T^{\alpha}} + (1-\zeta) w_{hf^{\alpha}}, \quad 0 < \zeta < 1. \tag{4}$$

After the regularization operation, the normalized weight of the α*th* online review is represented as follows:

$$\bar{w}^{\alpha} = \frac{w^{\alpha}}{\sum_{\alpha=1}^{\Upsilon} w^{\alpha}} = \frac{\zeta w_{T^{\alpha}} + (1-\zeta) w_{hf^{\alpha}}}{\sum_{\alpha=1}^{\Upsilon} \left[\zeta w_{T^{\alpha}} + (1-\zeta) w_{hf^{\alpha}} \right]}, \quad 0 < \zeta < 1, \tag{5}$$

where Υ indicates the number of reviews on each attribute under each destination, and ζ is set at 0.5 in the study.

Once the weights of online reviews are determined, the probabilistic linguistic weighted averaging (PLWA) operator is employed to aggregate them into the overall PLTS. The PLWA operator is defined as follows:

$$PLWA(L_1(p), L_2(p), \cdots, L_m(p)) = w_1 L_1(p) \oplus w_2 L_2(p) \oplus \cdots \oplus w_m L_m(p) = \left\{ L^{(k)} \left(\sum_{j=1}^{m} = w_j p_j^{(k)} \right) \right\}, \tag{6}$$

where $L_m(p)$ denotes the *mth* PLTS, and w_j is obtained using Eq. (5), $w_j \geq 0$ and $\sum_{j=1}^{m} = 1$.

Although the overall PLTS adequately portrays the affective distribution and status of various attributes under each destination, the distributed data structure could be more conducive to subsequent computational processes. Hence, the expectation value function of PLTS is introduced to transform it into an affective scoring value within the range of [0,1], enabling the assessment of attribute performance across destinations (Wu et al., 2018). Of note, the magnitude of the expectation value is directly proportional to the attribute performance, indicating that a higher expectation value corresponds to better attribute performance. In contrast, a lower expectation value signifies poorer attribute performance. Let $S = \{s_\theta \mid \theta = -\tau, \cdots, -1, 0, 1, \cdots, \tau\}$ be a linguistic term set, for a PLTS with $\theta^{(k)}$ being the subscript of the linguistic term $L^{(k)}$, then the expectation value function of $L(p)$ is:

$$E(L(p)) = \sum_{k=1}^{\#L(p)} \left(\frac{\theta^{(k)} + \tau}{2\tau} p^{(k)} \right) / \sum_{k=1}^{\#L(p)} p^{(k)}. \quad (7)$$

3.3. Classifying attributes based on an improved Kano model

Kano model, a powerful tool in product development and customer satisfaction analysis, was proposed by Kano in the 1980s (Kano, 1984). This model serves as a framework for understanding and categorizing customer needs and preferences in relation to product or service attributes. It classifies these needs into several categories: basic, performance, excitement, indifferent, and reverse attributes. Basic attributes are fundamental functionalities expected by customers. Their absence leads to dissatisfaction, yet their presence doesn't significantly boost satisfaction. Performance attributes correlate directly with customer satisfaction – more of these attributes means increased satisfaction, and vice versa. Excitement attributes, when present, delight customers, although their absence doesn't necessarily cause dissatisfaction. Indifferent attributes have little impact on satisfaction, while reverse attributes, if present, can lead to dissatisfaction, and their absence results in no particular satisfaction. The Kano model's innovative approach helps practitioners prioritize attributes during product or service development, enabling them to focus on aspects that most strongly impact customer satisfaction, thereby enhancing overall product or service quality and competitiveness in the market. The plot definitions for these five attribute types are shown in Figure 3.

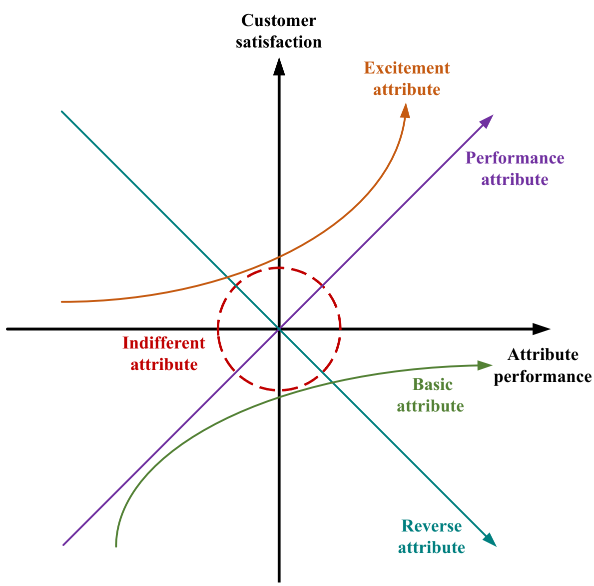


Figure 3. Classification of attributes in the Kano model (source: authors' own research)

Online reviews are more adept at capturing genuine tourist feelings than traditional surveys. Therefore, this subsection aims to conduct feature mining on online reviews, projecting destination attributes into Kano attribute categories. This study endeavors to achieve destination attribute classification by improving the attribute categorization method based on the Kano model developed by (Wang et al., 2022). To facilitate the presentation, we let M = {1, 2, ..., m} be a set of tourist destinations, N = {1, 2, ..., n} be a collection of destination attributes, and R = {1, 2, ..., r} be a series of online reviews. Besides, different reviews under different attributes at different destinations are characterized as $E_i^k = (A_i^k, P_i^k, Q_i^k)$, A_i^k denotes the *ith* attribute of the *kth* destination, P_i^k depicts the performance of the *ith* attribute for the *kth* destination, and Q_i^k indicates the number of reviews on the *ith* attribute of the *kth* destination, in which, $k \in M, i \in N$.

Distinguished from (Wang et al., 2022), the performance of each attribute for respective destinations in this study is derived from the expectation value function in Subsection 3.2. This value is determined by both affective distribution and intensity, mitigating the drawbacks of unilaterally quantifying affective computing in previous online reviews (Zhang et al., 2021a). After obtaining the performance of each attribute under each destination, the average performance of each attribute across destinations (APA_i) can be given.

$$APA_i = \frac{1}{m}\sum_{k=1}^{m} P_i^k. \tag{8}$$

Tourists' demands for destination attributes can be perceived as their levels of attention toward these attributes. The quantity of reviews or the frequency of attribute mentions reflects tourists' attention to these attributes, forming an indicator, denoted as MVA_i, to measure tourist attention. However, before computing MVA_i, it is imperative to establish the proportional values DAS_i of destination attributes. The destination attribute share DAS_i signifies the average degree of the attention attribute i that receives across various destinations, essentially depicting the demand for the attribute i among tourists. This can be defined as:

$$DAS_i = \frac{1}{m}\sum_{k=1}^{m} = \frac{Q_i^k}{Q^k}, \tag{9}$$

where Q^k represents the total number of reviews on all attributes for the *kth* destination.

Using the DAS_i as a benchmark, the comparison among destinations reveals the level of attention received by attributes. Subsequently, this aids in calculating the overall tourist attention to attributes, specifically the mean level of the attention attribute i receives across reviews from various destinations MVA_i:

$$MVA_i = \sum_{k=1}^{m} = \frac{\psi_i^k}{m}, \tag{10}$$

where ψ_i^k is called the decision factor. If the attribute i predominantly features in reviews of the *kth* destination, the ψ_i^k value is 1, otherwise, it is 0.

$$\psi_i^k = \begin{cases} 1, \; Q_i^k / Q^k \geq DAS_i \\ 0, \; Q_i^k / Q^k < DAS_i \end{cases}. \tag{11}$$

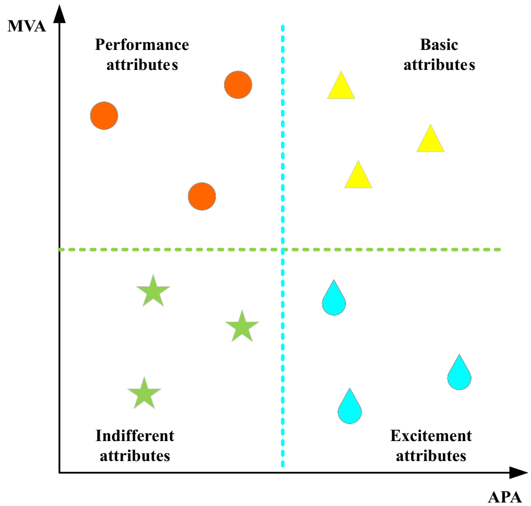


Figure 4. The improved Kano model for destination attributes classification (source: authors' own research)

Evidently, when MVA_i approaches 1, it indicates a high overall level of attention received by the *ith* destination attribute. Conversely, when MVA_i approaches 0, it signifies a low overall level of attention received by the *ith* destination attribute. Finally, according to distinct category demands defined by the Kano model, APA_i and MVA_i categorize destination attributes into basic, performance, excitement, and indifferent attributes. As such, a quartile diagram is constructed, as depicted in Figure 4. This diagram categorizes destination attributes into four quadrants, assigning distinct functional roles based on their distribution along the axes. When destination attributes fall into the first quadrant, they are identified as basic attributes, signifying that these attributes represent the fundamental needs of tourists. Their absence or poor performance significantly reduces TSA, but their excellent performance does not substantially enhance satisfaction. Attributes in the second quadrant are recognized as performance attributes, indicating a linear impact on TSA, where better performance leads to higher satisfaction and vice versa. Attributes in the third quadrant are classified as indifferent attributes, meaning they exert minimal influence on TSA, regardless of their level of performance. Finally, attributes falling into the fourth quadrant are referred to as excitement attributes, signifying that their outstanding performance can greatly enhance satisfaction, while their mediocre performance does not substantially diminish it.

3.4. FsQCA and NCA

Using the three-factor theory as previously outlined, critical destination attributes impacting TSA, i.e., basic, performance, and excitement attributes, are identified. Attributes categorized as indifferent are discarded as they neither attract specific attention from tourists nor influence their decisions. We argue that TSA is a composite outcome of multiple destination attributes, forming a complex combination. Therefore, leveraging complexity theory, this subsection employs the fsQCA technique to comprehensively grasp a holistic picture of antecedents and intricate solutions of TSA. As reported in the research design, the antecedents in fsQCA consist of extracted critical destination attributes, while TSA is set as the outcome in fsQCA. The former's performance is gauged by the derived expectation values. The latter is measured through the aggregated online ratings provided by each tourist. Each rating, representing an overall evaluation of their tour experience, can be seen as an overall satisfaction level (Zhang et al., 2021a).

Similarly, in aggregating online ratings, we consider time-weighted information to enhance the reliability of the outcome. By doing so, the application of fsQCA identifies configurations and combinations of destination attributes leading to high TSA. The theoretical model is exhibited in Figure 5.

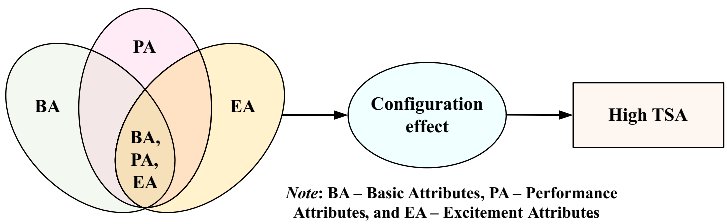


Figure 5. The configurational model of the study (source: authors' own research)

FsQCA is a methodological approach utilized in social sciences, policy studies, and management research to understand complex causal relationships within small-n and medium-n data sets (Ragin, 2014). It blends concepts from fuzzy logic and Boolean algebra, offering a middle ground between qualitative and quantitative methods (Schneider & Wagemann, 2012). FsQCA examines the combinations of conditions that lead to specific outcomes, emphasizing causal complexity rather than linear causality (Park et al., 2020). The technique operates on the principle that different combinations of conditions can lead to the same outcome, or conversely, the same outcome can result from different combinations of conditions. It's particularly valuable in identifying multiple causal pathways contributing to an outcome within a limited sample size, offering a nuanced understanding of causality (Fiss, 2011). FsQCA is advantageous in its ability to handle complex, non-linear relationships and provide a systematic approach to exploring causal configurations (Subramanian et al., 2022). The process involves several steps: identifying the conditions (variables) relevant to the research question, defining and calibrating membership scores for each condition, assessing their configurations against the outcome of interest, and conducting logical minimization to determine necessary and sufficient conditions for the outcome.

NCA is a quantitative method used to identify essential conditions that must be present for a specific outcome to occur (Dul, 2016b). It focuses on establishing the necessity of factors rather than sufficiency in explaining an outcome. NCA employs statistical techniques, such as logistic regression or comparison analysis, to ascertain which conditions are indispensable for a given phenomenon, elucidating the crucial factors without which the outcome is unlikely (Dul, 2016a). While both NCA and fsQCA explore causal relationships, NCA emphasizes the necessary conditions for an outcome, whereas fsQCA delves into configurations of conditions that can jointly produce an outcome, which makes the combination of NCA and fsQCA even more valuable. In this study, NCA is employed to examine whether specific destination attributes are essential for generating high TSA. Additionally, the outcomes of fsQCA are utilized to assess the robustness of the findings from the necessary condition analysis.

3.5. Coupling coordination degree calculation

The CCDM is a theoretical framework utilized in the study of complex systems, aiming to quantify and assess the relationships and interdependencies among various components within a system (Xiao et al., 2021). The CCDM encompasses an analytical approach that measures the extent and quality of interrelations between system elements, determining the degree of coupling and the level of coordination among these elements. It serves as a valuable tool for understanding the intricacies of complex systems across diverse domains such as economics, ecology, social sciences, and tourism (Han et al., 2023).

The CCDM and configurational analysis can be integrated when studying the complex issue of TSA. Configurational analysis offers insights into the states or configurations of various destination attributes within the system. At the same time, the CCDM aids in understanding the interactions and level of coordination among these attributes. After determining the configurations and recipes of destination attributes conducive to high TSA, introducing the CCDM facilitates the measurement of the coordination index for these attributes. The CCDM is computed in the Equations (12)–(14) as follows:

$$C = n \times \left[\frac{U_1 U_2 \cdots U_n}{\left(U_1 + U_2 + \cdots + U_n\right)^n} \right]^{\frac{1}{n}}; \tag{12}$$

$$T = \beta_1 U_1 + \beta_2 U_2 + \cdots + \beta_n U_n; \tag{13}$$

$$D = \sqrt{CT}, \tag{14}$$

where U_i, $i = 1, 2, \cdots, n$, denotes the performance of the *ith* destination attribute, *C* denotes the coupling degree, *T* indicates the coupling coordination development level index, *D* is the coupling coordination degree, β_i, $i = 1, 2, \cdots, n$, is the coefficient to be determined. Considering that each destination attribute possesses equal importance, we have $\beta_1 = \beta_2 = \cdots = \beta_n = 1/n$.

Furthermore, according to the value of the coupling coordination degree *D*, the types of coupling coordinated development are usually classified into 10 categories (Dong et al., 2023), as listed in Table 2.

Table 2. Classification of the coupling coordination degree level (source: authors' own research)

Disorder class			Coordination class		
D	Type	Level	D	Type	Level
$0 \le D < 0.1$	Extremely dysfunctional recession	I	$0.5 \le D < 0.6$	Barely coupled coordination	VI
$0.1 \le D < 0.2$	Severe dysfunctional recession	II	$0.6 \le D < 0.7$	Primary coupling coordination	VII
$0.2 \le D < 0.3$	Moderate dysregulation recession	III	$0.7 \le D < 0.8$	Intermediate coupling coordination	VIII
$0.3 \le D < 0.4$	Mild dysregulation recession	IV	$0.8 \le D < 0.9$	Good coupling coordination	IX
$0.4 \le D < 0.5$	On the verge of a dysfunctional recession	V	$0.9 \le D \le 1$	Quality coupling coordination	X

4. Results

4.1. Attribute detection and attribute performance

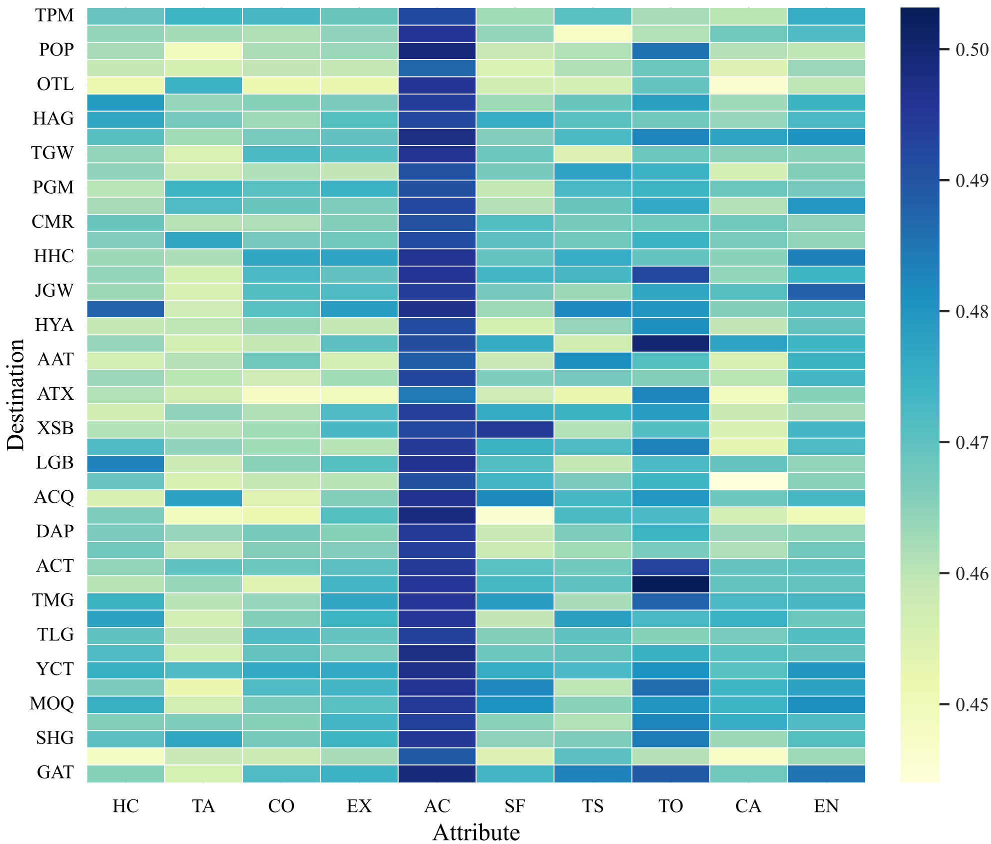
Top2Vec algorithm automatically detects 296 latent topics. However, a challenge arises from the semantic similarity among the feature words within many of these topics. To address this, we adopt a hybrid approach combining human judgment with computational methods to consolidate similar categories. Following optimization, the number of topics is ultimately refined to 10. These thematic labels are derived from the logical connections among key terms. Table 3 illustrates these destination attributes alongside their corresponding feature words.

Table 3. Attributes, acronyms, and partial feature words (source: authors' own research)

Attributes	Acronyms	Feature words
History & culture	HC	Periods, Dynasty, Ancient, Civilization, History
Transport & access	TA	Ticket, Departure, Bus, Subway, Transport costs
Commercialization	CO	Impression, Commercialization, Business, Workforce, Hostel
Emotional experience	EX	Feeling, Peaceful, Silent, Relaxed, Morning
Accommodation	AC	Hotel, Family, Residence, Price, Five-star
Symbolic feature	SF	Statues, Carvings, Artistry, Religion, Tibetan King
Tour style	TS	Ropeway, Plank path, Sightseeing car, Walk, Strop
Tour service	TO	Detail, Specialized, Patience, Explanation, Courier
Catering	CA	Night, Restaurant, Snacks, Coffee, Store
Entertainment	EN	Performance, Show, Program, Ambiance, Awesome

HC emphasizes destinations' historical and cultural significance, highlighting their cultural heritage and historical legacies. TA focuses on transportation accessibility at destinations, reflecting the ease and diversity of travel both within and outside the destination. CO describes the commercialization experience and perceptions of tourists during their travel processes. EX underscores the emotional connections and experiences tourists develop during cultural engagements. AC encompasses tourists' experiences with accommodation within and outside the destination, including perceptions of facilities, services, or environments. SF involves symbolic features such as religious culture, sculpture art, and other significant symbols. TS represents the ways in which tourists choose to explore a destination, potentially involving itinerary planning, visiting patterns, and experiencing local cultures. TO delineates aspects related to tour guide services and professional explanations. CA focuses on the quality, distinctiveness, and diversity of catering services at destinations. EN refers to entertainment activities or performances related to culture, history, and traditions.

Each destination's performance across various attributes is calculated using the method outlined in Subsection 3.2 and depicted in Figure 6. Overall, the attributes of TO and AC demonstrate superior performance compared to other attributes.



Note: TPM represents the Palace Museum, TSP represents the Summer Palace, POP represents Potala Palace, CPY represents the Ancient City of Ping Yao, OTL represents Old Town of Lijiang, YGG represents Yungang Grottoes, HAG represents Humble Administrator's Garden, TOH represents Temple of Heaven, TGW represents the Great Wall, TAT represents Taierzhuang Ancient Town, PGM represents Prince Gong Mansion, QAT represents Qingyan Ancient Town, CMR represents Chengde Mountain Resort, CLZ represents the Ancient City of Lang Zhong, HHC represents House of the Huangcheng Chancellor, HAT represents Huishan Ancient Town Scenic Area, JGW represents Jinshanling the Great Wall, JOT represents Jokhang Temple, HYA represents Huang Yao Ancient Town, DEH represents Deut Hangd, AAT represents Anren Ancient Town, NAT represents Nanxun Town, ATX represents the Ancient Town of Xitang, TAP represents Tang Paradise, XSB represents XiShuangBanNa Tropical Botanical Garden, ZHT represents Zhouzhuang Town, LGB represents Leshan Giant Buddha, TLA represents Tong Li Ancient Town, ACQ represents the Ancient City of Qingzhou, SAT represents Sanhe Ancient Town, DAP represents Daming Palace, EBH represents Earth Buildings of Hakka, ACT represents the Ancient City of Taizhou, KDV represents Kaiping Diaolou and Villages, TMG represents Taihang Mountains Grand Canyon, DRC represents Dazu Rock Carvings, TLG represents the Longmen Grottoes, NAS represents Nansan, YCT represents Yellow Crane Tower, JPB represents Jianmen Pass Beauty Spot, MOQ represents Mount Qingcheng, CTT represents the Chongsheng Temple and the Three-Pagoda Culture Tourist Area, SHG represents Shen's Garden, MCP represents Millennium City Park and GAT represents Guangfu Ancient Town.

Figure 6. Attribute performance comparison of the 45 destinations (source: authors' own research)

4.2. Identifying the category and prioritization of attributes

The improved Kano model further categorizes the identified 10 destination attributes. Figure 7 illustrates the distribution and classification results of these diverse destination attributes.

The first category encompasses basic attributes, with AC classified as essential requirements. This suggests that meeting accommodation needs is pivotal to TSA. The fundamental nature of lodging facilities and services is indispensable for a destination's allure. The second category comprises performance attributes, including HC, CO, EX, and CA. These attributes are not absolute necessities, yet their performances directly impact the tourists' experiences. HC accentuates the allure of historical and cultural significance, while CO elucidates the influence of commercialization experiences on tourists. EX emphasizes emotional connections, and CA delves into the quality and diversity of dining services. These attributes significantly influence tourists' perceptions of a destination. The third category, indifferent attributes, encompasses TA, SF, and TS. These attributes are relatively neutral in tourists' selection, neither significantly enhancing satisfaction nor causing dissatisfaction. These may involve factors like transportation convenience, symbolic features, and various choices of tour styles, which are not decisive for most tourists. Finally, the excitement attributes, EN and TO, are attributes that captivate tourists and offer additional pleasure. EN involves entertainment activities related to culture, history, and traditions, while TO underscores the quality of tour guide services and professional commentary. These aspects play a pivotal role in providing additional enjoyment during travel experiences.

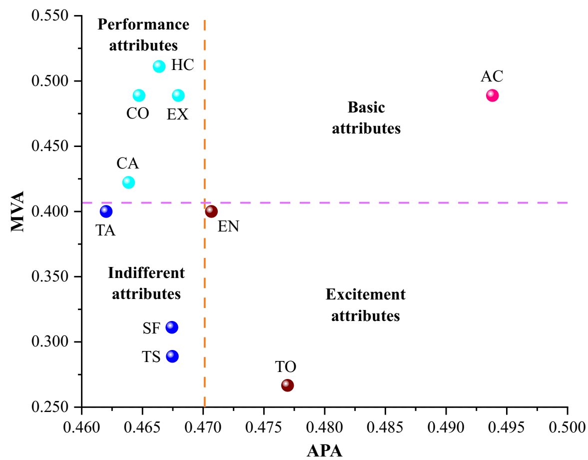


Figure 7. The classification and distribution of the 10 destination attributes (source: authors' own research)

4.3. Multi-attribute configurational patterns for TSA enhancement

Based on the key seven attributes derived from the three-factor theory, fsQCA identifies multi-attribute configurational patterns that explain the presence of high TSA. The literature suggests that an optimal range of four to seven conditions is favorable for configurations within a medium-sized sample (10–50) (Rihoux & Ragin, 2009). Hence, this indicates that the number of destination attributes utilized for the fsQCA analysis is appropriate. Following established fsQCA practices, the core steps encompass data calibration, necessity analysis, and sufficiency analysis. Calibration involves establishing a threshold or score to convert raw case data into membership scores within specific sets of conditions. In this study, the direct calibration method is employed due to the continuous variables. This approach necessitates researchers to define three pivotal values corresponding to full membership, cross-over point, and full non-membership. Specifically, we adhere to standards of 95% (full membership), 50% (cross-over point), and 5% (full non-membership) for calibration purposes (Rihoux & Ragin, 2009). Table 4 presents the calibration results and descriptive statistics of the antecedent and outcome variables.

Using R software, the NCA technique is subsequently utilized for a necessary condition analysis of high TSA. Figure 8 visually illustrates the NCA outcomes. Furthermore, Table 5

Table 4. Fuzzy-set membership calibrations and descriptive analysis (source: authors' own research)

Variable	Calibration values			Descriptive analysis			
	Full membership	Cross-over point	Full non-membership	Mean	SD	Max	Min
TSA	4.8433	4.6484	4.3268	4.6093	0.1744	4.9714	4.1573
AC	0.4980	0.4943	0.4887	0.4938	0.0031	0.4990	0.4842
HC	0.4788	0.4654	0.4554	0.4664	0.0077	0.4879	0.4489
CO	0.4727	0.4655	0.4522	0.4647	0.0066	0.4764	0.4484
EX	0.4768	0.4698	0.4569	0.4680	0.0066	0.4785	0.4496
CA	0.4752	0.4651	0.4480	0.4639	0.0082	0.4774	0.4440
TO	0.4927	0.4751	0.4628	0.4770	0.0096	0.5031	0.4609
EN	0.4829	0.4711	0.4602	0.4707	0.0072	0.4880	0.4507

Table 5. NCA results (source: authors' own research)

Antecedent	Method	Accuracy	Ceiling zone	Scope	Effect size (d)	P-value
AC	CR	93.3%	0.046	0.96	0.047	0.571
	CE	100%	0.060	0.96	0.063	0.356
HC	CR	86.7%	0.079	0.96	0.082	0.333
	CE	100%	0.050	0.96	0.052	0.407
CO	CR	91.1%	0.096	0.95	0.101	0.262
	CE	100%	0.057	0.95	0.060	0.337
EX	CR	93.3%	0.045	0.95	0.047	0.535
	CE	100%	0.036	0.95	0.038	0.542
CA	CR	95.6%	0.041	0.94	0.044	0.588
	CE	100%	0.032	0.94	0.034	0.615
TO	CR	100%	0.000	0.94	0.000	0.955
	CE	100%	0.000	0.94	0.000	0.955
EN	CR	88.9%	0.095	0.97	0.098	0.235
	CE	100%	0.050	0.97	0.051	0.490

Note: $0.0 \le d < 0.1$ 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).

reports specific effect size results, encompassing both ceiling regression (CR) and ceiling envelopment (CE) estimation techniques. Within the NCA method, necessary conditions necessitate meeting two criteria concurrently: an effect size (d) not less than 0.1, and significance confirmed through Monte Carlo simulations of permutation tests (Dul et al., 2020). Overall, only the attribute CO demonstrates an effect size greater than 0.1, while the rest fall below this threshold. Nevertheless, despite CO meeting the effect size criterion, it fails to be deemed a necessary condition due to its non-significant test outcome (p = 0.262).

Consequently, there are no identified preconditions essential for achieving high TSA. Additionally, Table 6 presents the results of bottleneck analysis. The bottleneck table delineates the minimal required levels of various conditions to achieve distinct levels of specific outcomes (TSA). As depicted in Table 6, to achieve a 70% level of TSA, a 6.5% level of AC, a 1.0% level of HC and a 3.1% level of CA are necessary, while other conditions do not pose bottleneck constraints.

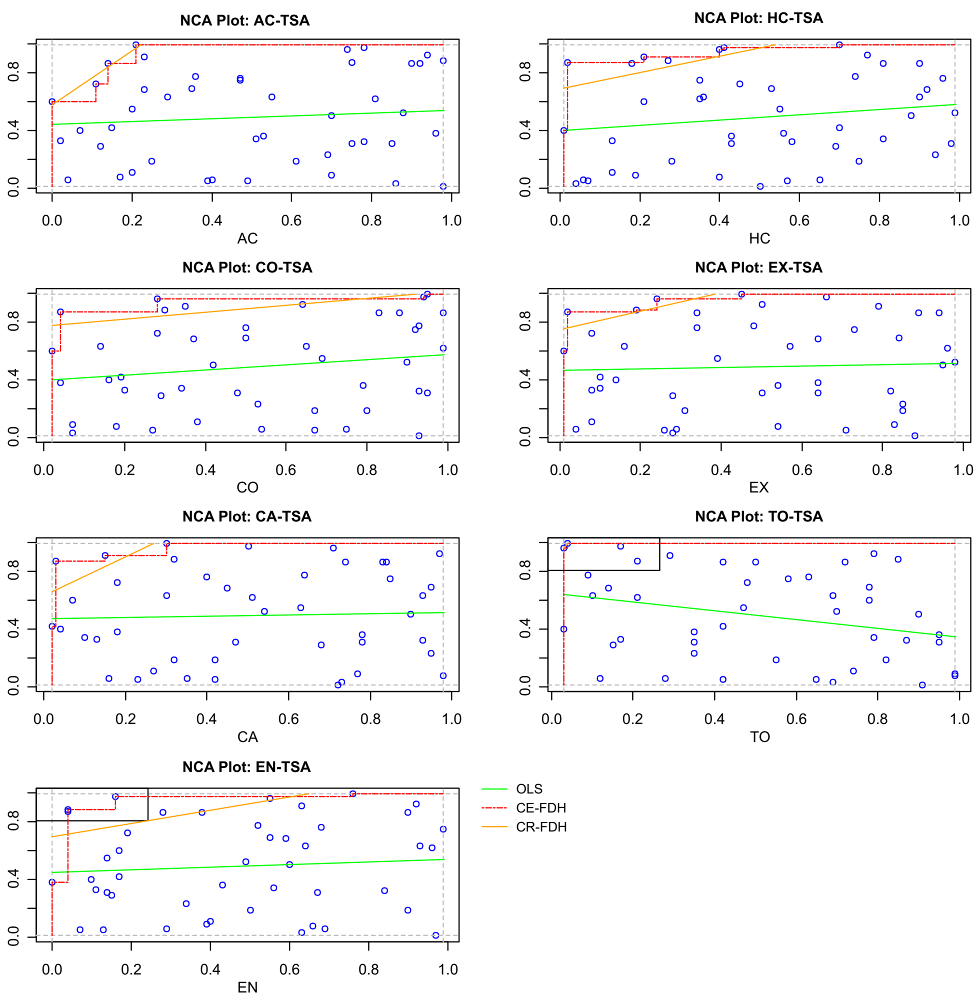


Figure 8. NCA plots (source: authors' own research)

Also, the necessity test in fsQCA is employed to validate the findings derived from NCA. Table 7 summarizes the consistency and coverage of each antecedent condition. Typically, antecedents with consistency exceeding 0.9 can be regarded as necessary conditions for the occurrence of the outcome (Geremew et al., 2024). However, the consistency of each condition falls below 0.9. This aligns with the results of the NCA analysis, indicating the absence of necessary conditions conducive to achieving high TSA.

Table 6. Bottleneck analysis (source: authors' own research)

TSA	AC	HC	CO	EX	CA	TO	EN
0	NN	NN	NN	NN	NN	NN	NN
10	NN	NN	NN	NN	NN	NN	NN
20	NN	NN	NN	NN	NN	NN	NN
30	NN	NN	NN	NN	NN	NN	NN
40	NN	NN	NN	NN	NN	NN	NN
50	NN	NN	NN	NN	NN	NN	NN
60	1.2	NN	NN	NN	NN	NN	NN
70	6.5	1.0	NN	NN	3.1	NN	NN
80	11.8	18.7	8.0	7.1	10.7	NN	21.8
90	17.1	36.3	49.9	22.9	18.2	NN	43.6
100	22.5	53.9	91.9	38.7	25.8	1.0	65.4

Note: CR method is adopted, and NN indicates unnecessary.

Table 7. Analysis of necessary conditions using fsQCA (source: authors' own research)

Antecedent	High TSA	
	Consistency	Coverage
AC	0.658089	0.645850
~AC	0.630908	0.620828
HC	0.691104	0.671368
~HC	0.618697	0.615136
CO	0.713310	0.664308
~CO	0.572520	0.595494
EX	0.638687	0.644487
~EX	0.642621	0.615428
CA	0.666727	0.636226
~CA	0.612772	0.620688
TO	0.613812	0.587253
~TO	0.688300	0.695281
EN	0.643616	0.669663
~EN	0.653521	0.608447

Note: ~ represents the absence of the antecedent.

The evidence from the necessity test highlights the complexity of developing and governing highly satisfying destinations. It signifies the interdependent matching required among the basic, performance, and excitement attributes to collectively impact the performance of TSA. Put differently, the success of creating highly satisfying destinations depends on the concurrent synergistic effects of multiple attributes within the basic, performance, and excitement categories. As such, it is necessary to conduct a sufficiency analysis in configuring conditions comprehensively.

Table 8. Configurations for TSA enhancement (source: authors' own research)

Antecedents	Configuration solutions			
	S1	S2a	S2b	S3
AC	⨂	⨂	⨂	•
HC	●	●	●	⊗
CO	●	•	⊗	●
EX	⊗	⊗	•	•
CA		⨂	⨂	●
TO	⊗		⊗	⨂
EN	•	●	●	●
Consistency	0.9290	0.9277	0.9195	0.9054
Raw coverage	0.2723	0.2669	0.1859	0.2207
Unique coverage	0.0208	0.0317	0.0131	0.0475
Overall consistency	0.9357			
Overall coverage	0.3686			

Using fsQCA 3.0 software, the truth table reveals each potential configuration. The construction of the truth Table 8 involves setting three values: the case frequency threshold, raw consistency, and proportional reduction in inconsistency (PRI) consistency benchmark. The characteristic of a medium-sized sample in this study dictates the selection of a case frequency threshold of 1. According to Rihoux and Ragin (2009), the frequency threshold ensures that at least 80% of the cases in the sample are part of the outcome analysis. Hence, the raw consistency benchmark is specified as 0.8. The PRI consistency benchmark is set at 0.65 in this study to generate informative configuration pathways (Greckhamer, 2016).

FsQCA offers three types of solutions: complex, parsimonious, and intermediate (Pappas & Woodside, 2021). The complex solution incorporates more conditions and configurations using raw case data but disregards logical remainders. The parsimonious solution is minimalistic, involving the fewest conditions and configurations, allowing logical remainders, yet excluding empirical likelihood. The intermediate solution strikes a balance between the two extremes, considering logical remainders while maintaining a certain level of simplification. Typically, researchers tend to favor the intermediate solution as it combines the merits of both complex and parsimonious solutions (Fiss, 2011). However, for a comprehensive understanding of condition importance, this study references the parsimonious solution to identify core and peripheral conditions. Additionally, adhering to the presentation format advocated by many scholars in fsQCA analysis is depicted in Table 8. The ● denotes condition presence, ⊗ denotes condition absence, large circles represent core conditions, and small circles indicate peripheral conditions. Furthermore, empty cells denote conditions that are irrelevant to the outcome, having no impact whether they are present or absent. The results indicate the presence of four different driving pathways explaining high TSA. Each column in the table represents a potential attribute configuration. The derived consistency values surpass the acceptable threshold of 0.75, affirming the validity and utility of the analytical outcomes (Schneider & Wagemann, 2012). It is worth noting that S2a and S2b form a second-order equivalence configuration due to their identical core conditions.

Based on Table 8, the formation of high TSA entails considering the following characteristics. Primarily, the EN attribute significantly contributes to shaping a destination's high satisfaction levels. Despite being identified as a peripheral condition within configuration S1, it supplements the core conditions of HC and CO to achieve the desired outcome. Secondly, S1 exhibits the highest raw coverage among the four driving pathways, indicating its strong empirical correlation with high TSA levels. Consequently, empirically, S1 stands as the most fitting configuration presently. If CA is absent and the performance and development of AC, EX, and TO attributes are poor, adjusting from S1 might be considered. Comparing S2a and S2b reveals their matching core conditions but alternate peripheral conditions, i.e., CO's peripheral presence in S2a contrasts with EX's peripheral presence in S2b. This finding suggests that highly satisfying tourist destinations can be driven through diverse pathways. Unexpectedly, destination attribute TO demonstrates no strong association with any configurations. This finding might stem from tourists' inclination toward autonomously exploring and understanding destinations' historical and cultural essence. Ultimately, the amalgamation of basic, performance, and excitement attribute types concludes that a single type of attribute provision cannot solely lead to the complex phenomenon of high TSA.

In summary, our empirical findings support all three hypotheses. Firstly, none of the individual basic, performance, or excitement attributes can fully explain the success or failure of TSA in any of the four identified configurations, emphasizing the need for synergy and cooperation among multiple attributes in these three categories (**Hypothesis 1**). Secondly, multiple configurations or causal recipes predict high TSA, demonstrating equifinality (**Hypothesis 2**). Finally, the configuration pathways reveal causal asymmetry, as the presence or absence of the same antecedent attributes (e.g., AC and CA) can lead to high TSA, depending on their interaction with other causal attributes in different configurations (**Hypothesis 3**).

Due to the sensitivity of parameter settings in the practice of fsQCA, conducting robustness tests is imperative. FsQCA, as a set-theoretic method, demonstrates robustness if alternative threshold or parameter decisions lead to findings that are subsets of the original outcomes (Scarpi et al., 2022). By elevating PRI consistency from 0.65 to 0.7, the resultant configurations emerge as subsets of the existing ones. Additionally, imposing a stricter raw consistency threshold of 0.9 instead of 0.8 yields results broadly consistent with the original study. The evidence thus underscores the robustness of our findings, indicating sufficient solution stability.

4.4. Insights of coupling coordination degree

Focusing on the core conditions, namely S1 (HC and CO), S2 (HC and EN), and S3 (CO, CA, and EN), Figure 9 demonstrates the coupling coordination degree among attributes within each configuration for tourist destinations. This exploration allows us to comprehend the intrinsic connections and coordination levels among attributes in each configuration, shedding light on the relationships among attributes across various configurations.

Overall, the coupling coordination values for all configurations fall within the range of 0.6 to 0.7. According to the classification criteria in Table 2, these configurations exhibit a coordination level of VII, situated within the primary coupling coordination phase. At this stage, these configurations manifest a certain degree of internal consistency and coordination but still offer considerable room for improvement and refinement. It necessitates attention to potential enhancements and optimizations to enhance attribute performance and interrelationships, better catering to tourist demands, and ultimately augmenting the level of TSA. More importantly, quantifying the configuration effect aids in identifying the optimal configuration path for a specific destination. In the case of TPM, for example, the coupling coordination degree within S2 is superior relative to S1 and S3. Thus, contemporary destination managers should focus on monitoring and refining the developmental trajectory of the S2 configuration to swiftly elevate the overall performance of the destination.

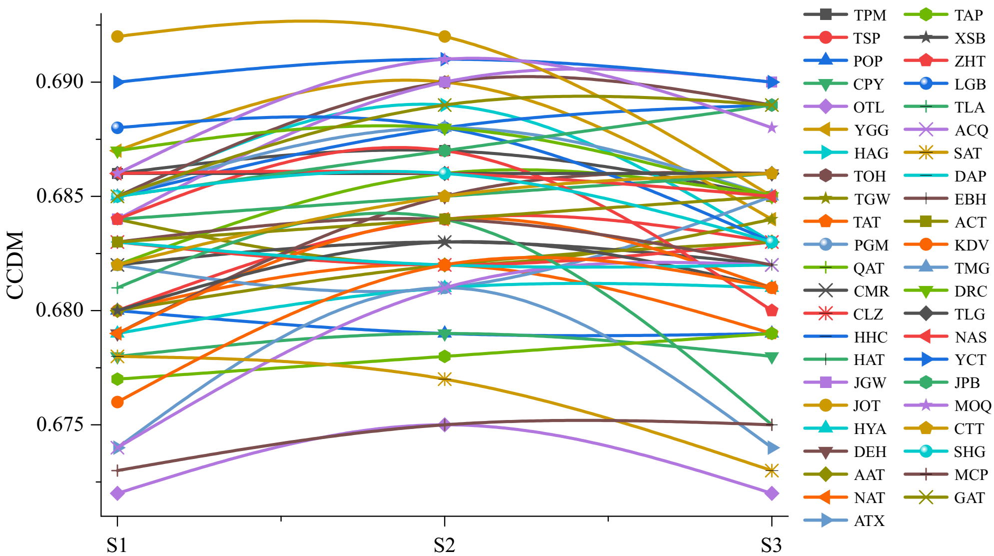


Figure 9. Coupling coordination degree of the three configurations for tourist destinations (source: authors' own research)

5. Discussion and implications

5.1. Discussion of key findings

The study holds a dual purpose. Firstly, it aims to extract pivotal destination attributes influencing TSA, grounded in authentic expressions of tourists' needs from an extensive collection of online reviews. Secondly, it seeks to examine the interactions and coupling coordination levels among various types of destination attributes under the framework of the three-factor theory, contributing to high TSA. To achieve the first objective, an advanced topic modeling technique is employed, automatically generating an initial set of 10 destination attributes. Guided by the improved Kano model, seven crucial destination attributes are identified, i.e., basic attribute AC, performance attributes HC, CO, EX, and CA, and excitement attributes EN and TO. For the second objective, the fsQCA method unveils multiple causal pathways leading to high TSA. Furthermore, various driving configurations are quantitatively assessed for their internal attribute coordination and development levels, drawing upon the theory of coupling coordination. Following the methodological procedures, the study yields the following key findings:

On the one hand, the extracted set of 10 attributes comprehensively encompasses tourists' multifaceted perspectives and experiences concerning humanistic tourist destinations. Specifically, basic attributes like accommodation manifest tourists' perceptions of the lodging environment. Performance attributes, center on historical culture, commercialization, emotional experience, and catering, highlighting tourists' emphasis on culture, commercial aspects, emotional connections, and culinary experiences. Meanwhile, the excitement attributes encompass entertainment and tour service, underscoring tourists' pursuit of entertainment activities related to culture and history, as well as professional tour guidance services. These attributes delineate the diverse expectations and experiences of tourists. Additionally, the presence of three indifferent attributes might stem from the specific type of destination itself or the absence of pronounced emotional inclinations among tourists toward these particular traits.

On the other hand, based on the fsQCA analysis, this study identifies four equifinal configurations leading to high TSA. By focusing on the core conditions, three propositions can be posited to explain and predict high TSA.

In configuration S1, HC and CO emerge as core attributes, indicating their critical role in enhancing TSA. At the same time, AC and EX are peripheral absent attributes, suggesting that their absence does not significantly impact TSA. Additionally, CA is considered a "neutral" attribute, meaning its presence or absence has minimal effect on overall satisfaction. EN, as a peripheral present attribute, implies that while it is not a core driver, it still contributes positively to satisfaction to some extent. Lastly, TO, identified as a peripheral absent attribute, signifies that this attribute is relatively insignificant in this configuration.

This configuration suggests that high TSA primarily depends on the strong appeal of historical culture and commercialization experiences. Even in the absence of high-quality accommodation and emotional immersion, tourists can still achieve high satisfaction due to the richness of cultural heritage and the convenience of commercial facilities. This finding aligns with the research of Zhang et al. (2021b), who emphasized that tourism commercialization can positively influence tourists' perceived authenticity and satisfaction. They argued that balancing authenticity and commercialization enhances the tourist experience and overall satisfaction. Similarly, Sun et al. (2019) highlighted the positive impact of commercialization on the quality of tourist experiences. According to Wang et al. (2019), commercial services have become an integral part of historical and cultural attractions. Furthermore, entertainment, as a peripheral attribute, fits the Kano model's definition of an excitement attribute. Its presence brings additional positive experiences, but even without it, tourists can achieve high satisfaction through other core attributes. This is consistent with previous studies, which suggest that entertainment adds value to the destination, though its significance may not rival that of historical culture and commercialization (Aliedan et al., 2021; Murphy et al., 2011). Thus, we propose:

Proposition 1. The core driving role of performance attributes, i.e., historical culture and commercialization, can significantly enhance TSA, even in the absence of emotional experience, tour services, and accommodation quality, with entertainment providing a marginal positive influence.

Configurations S2a and S2b constitute a second-order equivalence, both driven primarily by HC and EN. The influence of other attributes varies based on their combination. Specifically, in S2a, HC and EN are the core drivers of TSA, while CO is a peripheral attribute, and AC and CA are core absent attributes. EX has no significant impact on satisfaction, and TO is considered optional. This indicates that tourists in this configuration achieve high satisfaction primarily through an in-depth understanding of the destination's historical background and engagement in related entertainment activities. Although commercialization is present, it is not a decisive factor, and accommodation and catering have minimal impact, suggesting that these tourists prioritize cultural and entertainment experiences over material services. In S2b, the difference lies in EX transitioning from peripheral absent to peripheral present, while CO shifts from peripheral present to peripheral absent. HC and EN remain the core drivers, with AC and CA still absent. This configuration shows that while historical culture and entertainment are crucial, emotional experience also contributes to satisfaction, although not as prominently. The diminishing influence of commercialization further indicates that tourists in this configuration are less dependent on commercial activities, focusing more on cultural and entertainment experiences.

Similar to configuration S1, this configuration underscores the combined role of HC, CO, and EN in enhancing TSA. Notably, this configuration highlights the potential significance of EX. Holbrook and Hirschman (1982) in their experiential consumption theory posited that emotional experiences play a crucial role in tourism decisions and satisfaction. This view is widely supported in current literature, which suggests that positive emotional experiences are essential for increasing TSA, encouraging repeat visits, and generating positive word-of-mouth (Brunner-Sperdin et al., 2012; Steriopoulos et al., 2024). Therefore, we propose:

Proposition 2. When historical culture and entertainment serve as core attractors, their synergistic effect can significantly enhance TSA, even when the impacts of commercialization and emotional experience are relatively minor.

In configuration S3, AC emerges for the first time as a basic attribute in the identified configurations, signifying that tourists' fundamental expectations for lodging cannot be overlooked. Especially when combined with performance and excitement attributes, accommodation becomes a potential pillar supporting overall satisfaction. This aligns with Sánchez-Franco and Aramendia-Muneta (2023)'s research, particularly in high-end tourism markets, where comfort and service quality in accommodation can indirectly enhance the tourist experience (Harkison, 2018). CO, CA, and EN, as core attributes, significantly drive TSA, reflecting that tourists not only value cultural depth but also seek rich entertainment experiences and high-quality dining. Notably, CA as a core attribute indicates tourists' high expectations for local cuisine, especially in experience-driven destinations. Previous studies show that catering can heavily influence overall satisfaction and impressions of a destination (López-Guzmán et al., 2017). Tourists often desire a gastronomic experience during travel, making food a key determinant of satisfaction. The core role of catering in this configuration aligns with other research findings, especially in destinations where cultural and historical aspects are not the main attractions (Hernández-Rojas & Huete Alcocer, 2021). Although EX is only a marginal attribute, its moderate presence can enhance the overall tourist experience. The absence of HC in this configuration suggests that, in some contexts, tourists prefer modern entertainment and services over cultural heritage as the primary draw. This configuration emphasizes the diverse synergy between basic, performance, and excitement attributes, which collectively influence TSA.

Proposition 3. When basic attributes like accommodation and performance attributes like emotional experience are developed, and commercialization, catering service, and entertainment act as core attractors, the synergy of these attributes can significantly enhance TSA, even in the absence of historical or cultural attributes.

As a further refinement, we innovatively introduce CCDM to compute the coordinated development levels of attributes within the aforementioned three configurations. The results indicate that all configurations are currently in a nascent phase of coordination development, suggesting a relatively low level of interrelations or coordination among the attributes. This may imply that, at the present stage, the mutual influences among these attributes have not yet reached an optimal state, necessitating further adjustments and optimizations to enhance TSA.

5.2. Contributions to theory

This study yields several theoretical contributions. Firstly, it proposes an improved destination attribute classification model driven by tourist reviews to efficiently uncover the key attributes influencing TSA. This enhancement is evident in the characterization of attribute performance driven by the affective distribution computing technique. Traditional studies often measure attribute performance using single or absolute affective categories, which overlooks the complexity of multiple affective dimensions present in tourist reviews (Zhang et al., 2021a). Compared to solely focusing on positive, negative, or neutral sentiments, affective distribution computing captures a broader spectrum of emotions and attitudes. This method provides a more comprehensive depiction of affective experiences within reviews, offering refined affective computing outcomes.

Secondly, based on the configurational perspective, this study investigates the concurrent synergistic effects and linkage matching patterns of the basic, performance, and excitement attributes within Kano's three-factor theory framework concerning the formation of highly satisfying destinations. This research extends the application of the three-factor theory framework in elucidating complex causal relationships in the tourism domain. Traditionally, the Kano model is extensively employed to assess the relationship between customer needs and satisfaction, categorizing and prioritizing product or service attributes. However, most studies typically discuss the marginal net effects of individual attributes (basic, performance, and excitement) within the realm of statistical regression, neglecting the potential impact of the interplay among multiple attributes on TSA. Our study innovatively reveals this black-box effect within the framework of the three-factor theory, providing fresh insights into how multiple attributes collectively influence and shape TSA.

Thirdly, recent literature suggests that complexity theory, beyond the symmetrical perspective, offers an alternative viewpoint for addressing tourism issues (Kumar et al., 2023). Our research findings substantiate the call for developing and testing the core tenets of this theory (Tuo et al., 2019). TSA does not stem from independently operating destination attributes but arises from a complex interplay of multiple attributes in a nonlinear fashion. These attributes intertwine, playing distinct roles that influence destination managers' choices in governance models. Utilizing configurational methodology, our study identifies three distinct configurations that lead to high TSA, drawn from genuine expressions by tourists. Additionally, our endeavor to combine configurational theory with coupling theory deepens the exploration of relationship patterns within configurations, addressing gaps in prior research. The introduction of a coupling coordination index allows for a more comprehensive assessment of coordination levels among attributes, offering a novel perspective to enhance management decisions and destination operational strategies.

Finally, our work enriches the body of research employing the fsQCA method. Specifically, we effectively integrate a data-driven research paradigm into fsQCA analysis, establishing a comprehensive decision support framework that addresses gaps in the existing literature. Past fsQCA studies primarily relied on manual surveys to determine configurations of customer satisfaction, a method constrained by limited samples and specific datasets, potentially overlooking critical factors. By amalgamating techniques such as topic modeling, affective distribution computing, and the Kano model, fsQCA precisely identifies configurational patterns within tourist reviews, quantifying the contributions of attribute combinations to TSA. This highly automated decision support framework surpasses the limitations of the singular method, capturing the relationship between conditions and outcomes more broadly.

5.3. Implications to practice

Practically, the study provides decision-making advantages for stakeholders, including both tourists and destination managers, with significant implications for the tourism economy. On the one hand, our configurational study offers normative causal formulas for tourists, providing a more realistic comprehension of their choices and enhancing their travel experiences. By understanding how different destination attributes influence their experiences, tourists can enjoy more tailored travel experiences aligned with their interests and preferences. This not only leads to increased TSA but also stimulates economic benefits by attracting more visitors and increasing tourism spending.

On the other hand, this study serves as a warning to destination managers, emphasizing the importance of focusing on the configuration of destination attributes and governance complexities. By re-evaluating the tourism market from an economic perspective, destination managers can identify operational guidelines for achieving high TSA and maximizing economic benefits. Policymakers can use this research to scrutinize the current performance and developmental status of destination attributes and tailor governance approaches accordingly. This enables them to foster distinctive developmental pathways for each location, ultimately contributing to the sustainable growth of the tourism economy. Additionally, by examining the coupling coordination within each destination's configurations, destination managers can identify optimal reorganization strategies, offering personalized management advice for distinct destinations aimed at enhancing their economic performance.

Specifically, the findings of this study shape the following policy and managerial implications for current humanistic landscapes. Based on the results of configuration S1, HC and CO as core drivers suggest that policymakers should prioritize the preservation of cultural heritage, enhance interpretive and interactive experiences, and ensure the sustainable development of historical culture. Simultaneously, careful development of commercial facilities is crucial, providing high-quality shopping and dining services while avoiding over-commercialization to maintain the destination's cultural ambiance. As AC and EX have minimal influence on overall satisfaction, destination managers can allocate resources primarily to enhancing cultural and commercial aspects to optimize core tourist experiences. Although EN is a peripheral attribute, increasing the diversity and cultural relevance of entertainment options can further enhance immersion and satisfaction. Therefore, policies should encourage the provision of more culture-related entertainment, and managers can enrich the tourist experience by introducing performances and interactive programs. Overall, the synergy between cultural and commercial development can effectively boost TSA. However, maintaining a balance between cultural authenticity and commercial vitality is essential in both policy and management efforts.

For configurations S2a and S2b, policymakers should focus on the protection and presentation of cultural heritage, while enhancing tourists' cultural experiences through carefully designed entertainment activities. Since HC and EN are core drivers in both configurations, managers can further integrate cultural displays with entertainment by introducing immersive and interactive experiences related to the destination's historical and cultural background. Although CO plays a peripheral role in S2a, its influence weakens in S2b, indicating that excessive commercialization may detract from tourists' focus on cultural and entertainment aspects. Therefore, policies should limit the over-expansion of commercial development to prevent interference with the cultural experience. Additionally, given the minimal influence of AC and CA in both configurations, managers can reduce investments in these areas and prioritize resources towards enhancing cultural exhibits and entertainment programs.

The findings from configuration S3 have significant implications for destination managers, highlighting the crucial role of AC as a basic attribute in enhancing TSA. Managers should ensure that fundamental accommodation services meet tourists' basic needs, while prioritizing resources on core attributes such as EN and CA to elevate overall satisfaction. For instance, increasing the availability of entertainment options and offering high-quality dining experiences can create an environment where tourists enjoy not only comfort in basic amenities but also a pleasurable, engaging atmosphere. Moderate commercialization can also generate economic benefits for the destination, but it must be carefully balanced with tourists' preferences to avoid the negative impacts of over-commercialization. By offering a diverse mix of services, destinations can effectively enhance the tourist experience and satisfaction, thereby achieving a win-win outcome for both economic and social benefits.

5.4. Limitations and future research

While offering several contributions and implications, this study still has some limitations that pave the way for future research directions. Firstly, the reliance on data solely from the Ctrip platform may introduce bias from a specific demographic, potentially limiting the generalizability of the results. Future research could address this limitation by acquiring data from multiple platforms to compensate for the constraints of a single-source dataset and enhance the study's representativeness. Secondly, the efficient extraction of destination attributes remains an area deserving further attention. Future efforts could explore more intelligent methods for extracting and defining destination attributes. Additionally, exploring attribute extraction methods across diverse languages and cultural backgrounds is pivotal. Lastly, given the constantly evolving nature of the tourism environment, the persistence of discovered configurations and causal relationships requires ongoing examination. Considering the adoption of dynamic QCA represents a proactive outlook. While static QCA offers valuable insights at specific time points, dynamic QCA holds significant potential in analyzing changes and time-series data. Subsequent research could explore the application of dynamic QCA in the tourism domain to comprehend dynamic relationships between destination attributes and TSA, addressing temporal dependencies that static analysis fails to encompass.

6. Conclusions

This study aims to explore the complex dynamics of TSA within the tourism industry by integrating affective distribution computing, fsQCA, and an improved Kano model. Our framework, based on robust computational analyses of tourist reviews, uncovers detailed insights into the interplay of various destination attributes and how they collectively affect TSA. The CCDM model introduced in this study quantifies the symbiotic relationships between these attributes, providing a pioneering perspective on the configuration analysis of tourism complexity.

Our research expands the use of the Kano model and fsQCA in tourism by demonstrating destination attributes' uneven and nonlinear impact on TSA. We have made significant progress in methodology by incorporating topic modeling and affective distribution computing to identify and measure these attributes, thereby overcoming the shortcomings of traditional analytical methods.

This research provides practical insights for destination managers and policymakers. It highlights the significance of optimizing strategic attributes to improve TSA. The configurations identified through fsQCA offer a roadmap for prioritizing interventions that cater to tourists' varied expectations.

This study sets a foundation for further research into tourism's changing complexity. It highlights the need to explore the dynamic relationships among destination features and utilize advanced computational techniques to adapt to the evolving tourism environment. Moreover, the introduction of the CCDM opens the door for innovative studies on the co-ordination and alignment of tourist experiences, prompting a deeper investigation into the mechanisms that influence tourist destinations' attractiveness and competitiveness.

Our research combines computational analytics with tourism management theory to contribute to understanding and improving overall TSA. This highlights the importance of integrated decision support frameworks in managing the complexities of tourist experiences, leading to the sustainable development of the tourism economy. In conclusion, our findings emphasize the crucial role of this combination in enhancing the tourism sector.

Data availability

Data will be made available on request.

Ethical approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Author contributions

Yong Qin: data curation, writing – original draft, writing – review and editing, supervision, visualization, supervision. Chaoguang Luo: formal analysis, methodology, data curation, writing – review and editing, visualization. Zeshui Xu: conceptualization, writing – original draft, writing – review and editing, supervision. Xinxin Wang: formal analysis, software, writing – review and editing, validation, supervision. Marinko Skare: writing – review and editing, visualization, validation, supervision.

Disclosure statement

Yong Qin declares he has no conflict of interest. Chaoguang Luo declares she has no conflict of interest. Zeshui Xu declares he has no conflict of interest. Xinxin Wang declares she has no conflict of interest. Marinko Skare declares she has no conflict of interest.

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