ENHANCING DESTINATION IMAGE CONGRUENCE TO IMPROVE TOURIST SATISFACTION RATINGS: A SENTIMENT ANALYSIS AND TEXT MINING APPROACH ON TOURIST TEXTUAL DATA

ZUO WANG

DOCTOR OF PHILOSOPHY
IN DIGITAL INNOVATION AND FINANCIAL TECHNOLOGY

CHIANG MAI UNIVERSITY
OCTOBER 2024

ENHANCING DESTINATION IMAGE CONGRUENCE TO IMPROVE TOURIST SATISFACTION RATINGS: A SENTIMENT ANALYSIS AND TEXT MINING APPROACH ON TOURIST TEXTUAL DATA

ZUO WANG

A THESIS SUBMITTED TO CHIANG MAI UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY IN DIGITAL INNOVATION AND FINANCIAL TECHNOLOGY

CHIANG MAI UNIVERSITY

OCTOBER 2024

ENHANCING DESTINATION IMAGE CONGRUENCE TO IMPROVE TOURIST SATISFACTION RATINGS: A SENTIMENT ANALYSIS AND TEXT MINING APPROACH ON TOURIST TEXTUAL DATA

ZUO WANG

THIS THESIS HAS BEEN APPROVED TO BE A PARTIAL FULFILMENT OF
THE REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY
IN DIGITAL INNOVATION AND FINANCIAL TECHNOLOGY

Examination Committee:

.....Chairman
(Prof. Dr. Carson Lewis Jenkins)

.....Member
(Asst. Prof. Dr. Nantawan Muangyai)

.....Member
(Lect. Dr. Piyachat Udomwong)

.....Member
(Assoc. Prof. Dr. Fu Jing)

.....Member
(Lect. Dr. Pintusorn Onpium)

Advisory Committee:

.....Advisor
(Lect. Dr. Piyachat Udomwong)

.....Co-Advisor
(Assoc. Prof. Dr. Fu Jing)

.....Co-Advisor
(Lect. Dr. Pintusorn Onpium)

22 October 2024

ACKNOWLEDGEMENT

First and foremost, I extend my heartfelt gratitude to Dr. Piyachat Udomwong for her invaluable guidance throughout my research. Her expertise and insightful perspectives have been crucial in shaping both the direction and quality of my work. Dr. Piyachat's thoughtful consideration have been essential, as she consistently provided constructive feedback and engaged in meaningful discussions to keep me on track.

When I sought approval for my research from the Research Ethics Committee of Chiang Mai University, I initially felt overwhelmed by the requirements. Dr. Piyachat promptly addressed my queries and liaised with relevant staff, which was crucial for securing the necessary approval. During my preparation for the comprehensive exam, Dr. Piyachat's clear explanations, constant encouragement, and detailed guidance were essential in helping me complete the required documents in accordance with the new requirements. Throughout the revision of my doctoral thesis, her meticulous attention to detail and thoughtful suggestions significantly enhanced the rigor of my work.

Each interaction with her has been both enjoyable and profoundly rewarding, significantly enhancing my research experience. Her unwavering support, particularly during challenging times, has been a tremendous source of inspiration. Dr. Piyachat's dedication to her students' success is truly admirable, and I am deeply grateful for her steadfast support and guidance throughout my academic journey.

I am profoundly grateful to Dr. Fu Jing for her invaluable support throughout my study. At the beginning of my doctoral research, when I struggled with writing a literature review paper, Dr. Fu Jing provided exemplary writing samples and generously shared her extensive academic experience. She guided me in efficiently navigating literature and focusing on leading journals and influential authors in the field of tourism research.

Dr. Fu Jing's dedication to my research progress was evident through her meticulous review of each paper, providing detailed and constructive comments that greatly facilitated my ongoing improvement. Despite her demanding schedule, she consistently offered timely guidance, ensuring that my research advanced smoothly.

Additionally, Dr. Fu Jing played a crucial role in teaching me how to effectively address reviewers' comments, which was essential for the successful publication of my papers.

Dr. Fu Jing has been not only an exceptional supervisor but also a sincere friend. Meeting her has been one of the most rewarding experiences of my academic career, and I feel incredibly fortunate to have had the opportunity to learn from and work with such an outstanding mentor and friend.

Once again, I would like to express my sincere thanks to Dr. Pintusorn Onpium for her unwavering support and encouragement. The summer short courses she meticulously organized were instrumental in deepening my understanding of the latest trends in the tourism industry. The field trips she arranged provided a unique opportunity to explore tourism development in Chiang Mai and immerse myself in the local culture.

I would like to express my deep appreciation to Dr. Mu Lei and Prof. Yu Xi from Chengdu University for organizing the weekly seminars that enhanced my understanding of doctoral research. I am also grateful to the faculty and staff of the International College of Digital Innovation at Chiang Mai University, as well as my colleagues and students from the School of Tourism and Cultural Industries at Chengdu University, for their support. Finally, I am deeply indebted to my family for their unwavering dedication and encouragement, which has been vital to my doctoral studies.

As I conclude my thesis, I have come to deeply appreciate that the path of academic research is not merely navigated but enriched by the invaluable guidance and insights shared by supervisors and peers alike. With sincere gratitude, I will continue forward on this journey of learning and discovery. I find inspiration in Chiang Mai University's motto, "The wise cultivate themselves," elegantly engraved in ancient Pali on its logo. Growth is ongoing, and I am committed to cultivating myself and striving for continuous improvement.

Zuo Wang

หัวข้อดุษฎีนิพนธ์	การเสริมสร้างความสอดคล้องของภาพลักษณ์แหล่งท่องเที่ยวเพื่อยกระดับคะแนนความพึงพอใจของนักท่องเที่ยว: การวิเคราะห์ความ รู้สึกและการทำเหมืองข้อความจากข้อมูลเชิงข้อความของนักท่องเที่ยว
ผู้เขียน	นางสาว โจว หวัง
ปริญญา	ปรัชญาดุษฎีบัณฑิต (นวัตกรรมดิจิทัลและเทคโนโลยีการเงิน)
คณะกรรมการที่ปรึกษา	อาจารย์ ดร.ปิยะฉัตร อุดมวงษ์ อาจารย์ที่ปรึกษาหลัก รองศาสตราจารย์ ดร. ฟู่ จิง อาจารย์ที่ปรึกษาร่วม อาจารย์ ดร.พินทุสร อ่อนเปี่ยม อาจารย์ที่ปรึกษาร่วม

บทคัดย่อ

นวัตกรรมดิจิทัลได้เปลี่ยนแปลงอุตสาหกรรมการท่องเที่ยวอย่างมาก ส่งผลกระทบต่อพฤติกรรมนักท่องเที่ยวและวิธีการวิจัย การศึกษาภาพลักษณ์ของแหล่งท่องเที่ยวยังคงมีความสำคัญ เนื่องจากมีผลต่อความสามารถในการแข่งขันของแหล่งท่องเที่ยว ภาพลักษณ์ของแหล่งท่องเที่ยวประกอบด้วยภาพที่ถูกสร้างขึ้นโดยการตลาด และภาพที่ถูกรับรู้จากประสบการณ์ของนักท่องเที่ยว ความไม่สอดคล้องระหว่างภาพเหล่านี้อาจส่งผลเสียต่อความพึงพอใจของนักท่องเที่ยว โดยเฉพาะอย่างยิ่งในยุคที่ความคิดเห็นออนไลน์มีอิทธิพลต่อความดึงดูดใจและความยั่งยืนของแหล่งท่องเที่ยวในระยะยาว แม้ว่างานวิจัยจะเน้นความสำคัญของการปรับภาพลักษณ์ให้สอดคล้องกัน แต่มีการวิจัยน้อยที่สำรวจว่าการปรับนี้ส่งผลต่อความพึงพอใจอย่างไร นอกจากนี้ วิธีการในการประเมินความสอดคล้องของภาพในสื่อดิจิทัลและกลยุทธ์ในการปรับปรุงการตลาดยังไม่พัฒนาเพียงพอ

งานวิจัยนี้มีจุดมุ่งหมายเพื่อศึกษาผลกระทบของความสอดคล้องของภาพลักษณ์ที่มีต่อความพึงพอใจของนักท่องเที่ยว และเสนอแนวทางการตลาดเพื่อเสริมสร้างความสอดคล้องนี้ การศึกษานี้ถูกจัดโครงสร้างตามวัตถุประสงค์หลัก 3 ประการ ได้แก่ (1) การประเมินผลของความสอดคล้องของภาพลักษณ์แหล่งท่องเที่ยวต่อคะแนนความพึงพอใจของนักท่องเที่ยว (2) การพัฒนากรอบแนวคิดวิธีใหม่สำหรับการประเมินความสอดคล้องนี้และ (3) การให้คำแนะนำทางการตลาดเชิงกลยุทธ์ที่ปรับภาพ

ลักษณ์ที่คาดหวังและที่รับรู้ให้สอดคล้องกันเพื่อเสริมสร้างความพึงพอใจของนักท่องเที่ยว

การวิจัยนี้ใช้แนวทางสหวิทยาการรวมทฤษฎีภาพลักษณ์แหล่งท่องเที่ยว พฤติกรรมนักท่องเที่ยว การตลาด และการสื่อสาร เพื่อแก้ปัญหาท้าทายในการวิจัยการท่องเที่ยว มุ่งเน้นไปที่ตลาดการท่องเที่ยวเชิงสัตว์ป่าของจีน โดยใช้ฐานวิจัยการเลี้ยงแพนด้าเฉิงตูเป็นกรณีศึกษา การวิเคราะห์ครอบคลุมข้อความ ส่งเสริมการขายอย่างเป็นทางการ 1,214 ข้อความ และบทวิจารณ์ของนักท่องเที่ยว 12,561 รายการ จากเว็บไซต์ตัวแทนท่องเที่ยวออนไลน์ชั้นนำ การวิเคราะห์หัวข้อโดยใช้แบบจำลอง Latent Dirichlet Allocation (LDA) ระบุความแตกต่างระหว่างภาพลักษณ์ที่คาดหวังและที่รับรู้ การวิเคราะห์ความรู้สึกและการวิเคราะห์ความสำคัญ-ประสิทธิภาพ (IPA) ถูกนำไปใช้ในการประเมินบทวิจารณ์ของนักท่องเที่ยว นอกจากนี้ยังได้ทำการสำรวจความคิดเห็นจาก 307 คน โดยใช้สถิติเชิงพรรณนาและการวิเคราะห์สหสัมพันธ์ Spearman เพื่อตรวจสอบผลของความสอดคล้องของภาพลักษณ์ที่มีต่อความพึงพอใจ นอกจากนี้ การวิเคราะห์ปัจจัยเชิงสำรวจ (Exploratory Factor Analysis - EFA) ได้ถูกนำมาวิเคราะห์ข้อมูลแบบสำรวจ พร้อมกับเปรียบเทียบผลที่ได้กับการวิเคราะห์ LDA งานวิจัยนี้ได้นำเสนอกรอบการวัดความสอดคล้องของภาพลักษณ์แบบใหม่ พร้อมทั้งผสานข้อมูลจากหลายแหล่ง เพื่อให้ได้การวิเคราะห์ที่ครอบคลุมและลึกซึ้งยิ่งขึ้น

ผลการวิจัยแสดงให้เห็นว่า ความสอดคล้องระหว่างภาพลักษณ์ที่คาดหวังและที่รับรู้ของแหล่งท่องเที่ยวมีผลอย่างมากต่อคะแนนความพึงพอใจของนักท่องเที่ยว ที่ฐานวิจัยแพนด้าพบว่ามีความสอดคล้องในหัวข้อสำคัญ 4 หัวข้อ ในขณะที่มีความไม่สอดคล้องในหัวข้ออื่น ๆ อีก 4 หัวข้อ จากผลการวิจัยนี้ การศึกษานี้แนะนำกลยุทธ์ทางการตลาดที่เฉพาะเจาะจง เช่น การจัดการฝูงชนในช่วงฤดูท่องเที่ยว การสร้างเนื้อหามัลติมีเดียที่อัปเดตเป็นประจำเกี่ยวกับแพนด้า การใช้เทคโนโลยี VR/AR สำหรับประสบการณ์เสมือนจริง การให้ข้อมูลที่ชัดเจนเกี่ยวกับสภาพอากาศและเวลา การส่งเสริมการปฏิบัติด้านการท่องเที่ยวอย่างยั่งยืน และการรักษารายละเอียดการเดินทางที่ถูกต้อง นอกจากนี้ยังแนะนำให้ลดการเน้นไปที่แง่มุมที่ไม่สำคัญ เช่น สิ่งอำนวยความสะดวกทั่วไปและสิ่งอำนวยความสะดวกสำหรับเด็ก

งานวิจัยนี้มีส่วนสำคัญทางทฤษฎีโดยให้พื้นฐานเชิงประจักษ์ที่แข็งแกร่งในการทำความเข้าใจความเชื่อมโยงระหว่างความสอดคล้องของภาพลักษณ์กับความพึงพอใจของนักท่องเที่ยว นอกจากนี้ยังขยายการใช้เทคโนโลยีดิจิทัลในการวัดความสอดคล้องของภาพลักษณ์ ด้วยระเบียบวิธีที่สามารถนำไปใช้กับแหล่งท่องเที่ยวอื่น ๆ และเพิ่มคุณค่าให้กับการอภิปรายทางวิชาการเกี่ยวกับการวิจัยภาพลักษณ์ของแหล่งท่องเที่ยว การศึกษานี้ได้แนะนำแนวคิดในการปรับภาพลักษณ์ที่คาดหวังตามการรับ

รู้ของนักท่องเที่ยวจริง สร้างวงจรป้อนกลับแบบโต้ตอบที่ท้าทายสมมติฐานดั้งเดิมและเปิดโอกาสใหม่ ๆ สำหรับการตลาดแหล่งท่องเที่ยว โดยมุ่งเน้นไปที่สถานที่ท่องเที่ยวเฉพาะ เช่น การท่องเที่ยวแพนด้า งานวิจัยนี้เติมเต็มช่องว่างในวรรณกรรม ให้ข้อมูลเชิงลึกที่มีคุณค่าสำหรับการท่องเที่ยวเชิงสัตว์ป่าที่เฉพาะเจาะจงในประเทศจีน และช่วยเพิ่มความเกี่ยวข้องของการวิจัยภาพลักษณ์แหล่งท่องเที่ยว

ในแง่ปฏิบัติการศึกษานี้นำเสนอข้อมูลเชิงลึกที่เป็นประโยชน์สำหรับนักการตลาดและผู้กำหนดนโยบาย โดยให้กลยุทธ์ที่เป็นรูปธรรมในการเพิ่มประสิทธิภาพการตลาดและการจัดการปรับปรุงความสอดคล้องของภาพลักษณ์ และเพิ่มคุณค่าที่รับรู้ของนักท่องเที่ยว กลยุทธ์เหล่านี้มุ่งเน้นไปที่การเพิ่มความพึงพอใจและสนับสนุนการท่องเที่ยวอย่างยั่งยืน ช่วยให้แหล่งท่องเที่ยวเชิงสัตว์ป่าสามารถรักษาสมดุลระหว่างการอนุรักษ์ทรัพยากรธรรมชาติกับความคาดหวังของนักท่องเที่ยว ผลการศึกษานี้สามารถใช้เป็นข้อมูลอ้างอิงที่มีคุณค่าสำหรับรัฐบาลท้องถิ่นและแหล่งท่องเที่ยวเชิงสัตว์ป่าอื่น ๆ ในการทำการตลาดและการจัดการแหล่งท่องเที่ยวอย่างมีประสิทธิภาพในยุคดิจิทัล

คำสำคัญ: ภาพลักษณ์แหล่งท่องเที่ยว, ความพึงพอใจของนักท่องเที่ยว, การสร้างแบบจำลอง LDA, การวิเคราะห์ความรู้สึก, กลยุทธ์การตลาด, การท่องเที่ยวเชิงสัตว์ป่า, ฐานวิจัยแพนด้า, การขุดค้นข้อความ

Dissertation Title	Enhancing Destination Image Congruence to Improve Tourist Satisfaction Ratings: A Sentiment Analysis and Text Mining Approach on Tourist Textual Data	
Author	Ms. Zuo Wang	
Degree	Doctor of Philosophy (Digital Innovation and Financial Technology)	
Advisory Committee	Lect. Dr. Piyachat Udomwong	Advisor
	Assoc. Prof. Dr. Fu Jing	Co-advisor
	Lect. Dr. Pintusorn Onpium	Co-advisor

ABSTRACT

Digital innovation has reshaped the tourism industry, affecting both tourist behaviour and research methods. The study of tourism destination image remains vital, as it influences destination competitiveness. Destination images consist of projected images, shaped by marketing, and perceived images, formed through tourist experiences. A mismatch between these can negatively affect tourist satisfaction, especially as online reviews now impact long-term destination appeal and sustainability. Although research underscores the need to align projected and perceived images, there is limited focus on how this alignment affects satisfaction. Additionally, methods for assessing image congruence in digital media and strategies for improving marketing remain underdeveloped.

This study seeks to investigate the impact of image congruence on tourist satisfaction and proposes marketing strategies to enhance this alignment. The study is structured around three primary objectives: (1) to assess the influence of destination image congruence on tourist satisfaction ratings; (2) to develop a novel methodological framework for evaluating this congruence; and (3) to offer strategic marketing

recommendations that align the projected and perceived images to enhance tourist satisfaction.

This study takes an interdisciplinary approach, combining tourism image theory, consumer behaviour, marketing, and communication to address challenges in tourism research. Focusing on the Chinese wildlife tourism market, with the Chengdu Research Base of Giant Panda Breeding as a case study, it analyses 1,214 promotional messages and 12,561 tourist reviews from online travel agencies. Topic analysis using Latent Dirichlet Allocation (LDA) identifies differences between projected and perceived images. Sentiment analysis and Importance-Performance Analysis (IPA) further examine tourist reviews, while a survey of 307 responses, analysed through descriptive statistics and Spearman rank correlation, assesses the effect of image congruence on satisfaction. Exploratory Factor Analysis (EFA) was also applied to survey data and compared with LDA results. This study's methodological contributions include a new framework for measuring image congruence and integrating diverse data sources for comprehensive analysis.

The findings show that congruence between a destination's projected and perceived images significantly affects tourist satisfaction. At the Panda Base, alignment is found across four key topics, while discrepancies exist in four others. Based on this, the study recommends targeted marketing strategies, including improved crowd management, regularly updated multimedia content on pandas, immersive VR/AR experiences, clearer information on weather and timing, sustainable tourism practices, and accurate transportation details. The study also suggests reducing focus on less critical areas like general facilities and parent-child amenities.

This research makes important theoretical contributions by providing a solid empirical foundation for understanding the link between image congruence and tourist satisfaction. It also advances the use of digital innovations in measuring image congruence, offering a methodology that can be applied to other destinations and enriching the academic discussion on destination image research. The study introduces the concept of adjusting projected images based on real-time tourist perceptions, creating an interactive feedback loop that challenges traditional assumptions and opens new

avenues for destination marketing. By focusing on attractions like giant panda tourism, the study addresses gaps in the literature, offering valuable insights into niche wildlife tourism in China and improving the relevance of destination image research.

In practical terms, this study offers useful insights for marketers and policymakers by providing concrete strategies to optimize marketing and management practices, improving image congruence, and increasing perceived tourist value. These strategies aim to boost satisfaction and support sustainable tourism, helping wildlife destinations balance conservation efforts with tourist expectations. The findings serve as a valuable reference for governments and other wildlife tourism sites for effective marketing and management in the digital age.

Keywords: destination image, tourist satisfaction, sustainable tourism, LDA modeling, sentiment analysis, marketing strategy, wildlife tourism, Panda Base, text mining

CONTENTS

LIST OF TABLES

Page

LIST OF FIGURES

Page

LIST OF ABBREVIATIONS

CTM	Correlated Topic Model
DTM	Dynamic Topic Model
EFA	Exploratory Factor Analysis
IOC	Item-Objective Congruence
IPA	Importance-Performance Analysis
LDA	Latent Dirichlet Allocation
LSA	Latent Semantic Analysis
LSTM	Long Short-Term Memory networks
NLTK	Natural Language Toolkit
NMF	Non-Negative Matrix Factorization
NTUSD	National Taiwan University Sentiment Dictionary
OTAs	Online Travel Agencies
PCA	Principal Components Analysis
PLSA	Probabilistic Latent Semantic Analysis
SVM	Support Vector Machines
UGC	User Generated Content
VADER	Valence Aware Dictionary and sEntiment Reasoner

ข้อความแห่งการริเริ่ม

1) งานวิจัยนี้ได้ริเริ่มการประยุกต์ใช้แบบจำลอง LDA ในภาพลักษณ์ที่คาดหวังและภาพลักษณ์ที่รับรู้ของจุดหมายปลายทาง โดยนำเสนอกรอบการวิเคราะห์ใหม่สำหรับการวัดความสอดคล้องของภาพลักษณ์ดังกล่าว วิธีการนี้ช่วยยกระดับเครื่องมือเชิงวิธีวิจัยที่มีอยู่สำหรับการวิเคราะห์ภาพลักษณ์จุดหมายปลายทางอย่างมีนัยสำคัญ

2) งานวิจัยนี้ได้เสนอวิธีการใหม่ที่เป็นการบูรณาการแบบจำลอง LDA เข้ากับการวิเคราะห์อารมณ์ความรู้สึก (Sentiment Analysis) ซึ่งทำให้การเข้าใจภาพลักษณ์ที่รับรู้ของจุดหมายปลายทางเป็นไปอย่างลุ่มลึกและครอบคลุมมากยิ่งขึ้น แนวทางการวิจัยนี้เปิดโอกาสให้มีการสำรวจมิติทางอารมณ์และหัวข้อหลักของการรับรู้ของนักท่องเที่ยวในเชิงลึกมากยิ่งขึ้น

3) การขยายขอบเขตของแหล่งข้อมูลในงานวิจัยนี้ ทำให้เกิดหลักฐานเชิงประจักษ์ที่มีความน่าเชื่อถือในการศึกษาความสัมพันธ์ระหว่างความสอดคล้องของภาพลักษณ์และความพึงพอใจของนักท่องเที่ยว ซึ่งวิธีการนี้ช่วยเพิ่มความถูกต้องแม่นยำของผลการวิจัย ทั้งยังนำวิธีวิจัยดังกล่าวไปปรับใช้ในบริบทที่หลากหลายเพื่อบรรลุวัตถุประสงค์ที่คล้ายคลึงกัน

4) การศึกษานี้สำรวจความสัมพันธ์เชิงโต้ตอบระหว่างภาพลักษณ์ที่คาดหวังและภาพลักษณ์ที่รับรู้ของจุดหมายปลายทาง โดยเน้นถึงวงจรป้อนกลับที่ทำให้จุดหมายปลายทางสามารถปรับปรุงภาพลักษณ์ที่คาดหวังได้อย่างต่อเนื่องตามการรับรู้ของนักท่องเที่ยว ด้วยการชี้ให้เห็นถึงธรรมชาติของความสัมพันธ์แบบสองทิศทางนี้ การศึกษาได้ท้าทายแนวคิดแบบทิศทางเดียวในงานวิจัยภาพลักษณ์จุดหมายปลายทางแบบดั้งเดิม และเปิดโอกาสให้เกิดกลยุทธ์ที่สร้างสรรค์ในด้านการตลาดจุดหมายปลายทาง

5) การวิจัยนี้เปลี่ยนจุดเน้นจากการศึกษาจุดหมายปลายทางในเชิงภูมิศาสตร์ที่กว้าง ไปสู่แหล่งท่องเที่ยวเฉพาะเจาะจง ซึ่งมอบข้อมูลเชิงลึกที่มีรายละเอียดและกลยุทธ์การตลาดที่สามารถนำไปปฏิบัติได้จริงสำหรับแหล่งท่องเที่ยวแต่ละแห่ง วิธีการเชิงลึกนี้ช่วยเพิ่มความสำคัญในทางปฏิบัติของการวิจัยภาพลักษณ์จุดหมายปลายทางให้สอดคล้องกับสถานการณ์จริงมากขึ้น

6) การวิจัยนี้ถือเป็นจุดริเริ่มที่สำคัญในการวิจัยการท่องเที่ยวเชิงอนุรักษ์สัตว์ป่าในประเทศจีน ซึ่ง

เป็นสาขาที่การสำรวจยังไม่แพร่หลาย โดยเฉพาะตลาดการท่องเที่ยวแพนด้ายักษ์ ผลจากการวิจัยนี้ช่วยเพิ่มความเข้าใจในด้านการตลาดจุดหมายปลายทางในบริบทเฉพาะต่อตลาดการท่องเที่ยวแพนด้ายักษ์ และยังส่งมอบข้อมูลเชิงลึกที่มีคุณค่าต่อการพัฒนาการท่องเที่ยวเชิงอนุรักษ์สัตว์ป่า

STATEMENTS OF ORIGINALITY

1. This study pioneers the application of LDA modeling to both projected and perceived destination images, introducing a novel analytical framework for measuring the congruence between these images. This approach significantly advances the methodological toolkit available for destination image analysis.

2. The research proposes a new method that integrates LDA modeling with sentiment analysis, offering a more nuanced and comprehensive approach to understanding the perceived image of a destination. This innovation allows for a deeper exploration of the thematic and emotional dimensions of tourist perceptions.

3. By expanding the range of data sources, the study establishes a robust empirical foundation for investigating the relationship between image congruence and tourist satisfaction. This underscores the importance of investigating destination image congruence within the context of tourism marketing.

4. This study explores the interactive relationship between projected and perceived destination images, with a focus on a feedback loop that allows destinations to continuously refine their projected images based on tourists' perceptions. By highlighting the bidirectional nature of this relationship, the study challenges the traditional unidirectional approach in destination image research and opens the door to innovative strategies in destination marketing.

5. The research shifts its focus from broad geographical destinations to specific attractions, providing detailed insights and actionable marketing strategies tailored to individual sites. This granular approach increases the practical relevance of destination image research, making it more directly applicable to real-world scenarios.

6. This study makes a pioneering contribution to the underexplored field of wildlife tourism research in China, particularly within the giant panda tourism market. The findings enhance the understanding of destination marketing in this unique context and offer valuable insights for the development of wildlife tourism.

CHAPTER 1

Introduction

1.1 Background of the Study

This section covers the following three aspects: the role of destination image in tourism marketing, the influence of digital innovation on the tourism industry, and the rise of the panda tourism market in China. The first aspect examines how destination image shapes tourist perceptions and influences their travel decisions, highlighting the importance of destination image to the development of tourism. The second aspect explores the transformative impact of digital innovations such as social media and Online Travel Agencies (OTAs) on tourist behaviors and tourism marketing. The third aspect delves into the rapid growth of the panda tourism market in China, introducing the reasons for its rise and its significant value in promoting education, environmental awareness, and regional economic development. In particular, it discusses the development status of the Chengdu Research Base of Giant Panda Breeding as a representative attraction in this market.

1.1.1 The Role of Destination Image in Tourism Marketing

The global tourism market is highly competitive, with destinations actively competing for the attention and patronage of tourists (Cronjé & du Plessis, 2020). Tourism marketing is the strategic process of promoting destinations, products, and services to attract and retain tourists. It involves identifying target markets, understanding their needs and preferences, and crafting tailored campaigns that showcase a destination's unique features and experiences, ultimately driving sustainable growth in the tourism sector (Dolnicar & Ring, 2014). According to Crompton (1979), destination image is defined as the sum of beliefs, ideas, and impressions that a person has of a destination. Destination image is pivotal in tourism marketing as it significantly impacts tourists' decision-making, satisfaction, and loyalty.

Therefore, effectively managing the destination image is crucial for achieving success in tourism marketing (Echtner & Ritchie, 1991; VG et al., 2021).

A successful destination image cultivates the uniqueness and brand identity of a location, enhancing its competitiveness and enriching the tourist experience (Baloglu et al., 2014; Kanwel et al., 2019). A favorable image attracts potential tourists, positively influences their satisfaction and evaluations, and strengthens their willingness to revisit and recommend the destination (Bigne et al., 2001; De Nisco et al., 2015). Destinations with positive images are better equipped to navigate crises or negative publicity and mitigate their adverse impacts (Rittichainuwat et al., 2020). Moreover, disseminating a favorable image that emphasizes environmental preservation, cultural heritage, and social responsibility helps destinations safeguard their resources and environment, fostering sustainable development within the tourism industry (J. C. Zhang et al., 2020).

Due to its significant value to destinations, destination marketing organizations frequently utilize the results of destination image studies to enhance destination management (Echtner & Ritchie, 1991; Tasci et al., 2007). The concept of destination image can be categorized into projected and perceived images from a supply and demand perspective. The projected image represents the intended image conveyed by destination marketing organizations, highlighting the destination's strengths and resources. The perceived image, on the other hand, reflects tourists' mental representation of the destination (Bramwell & Rawding, 1996; Tasci et al., 2007). Understanding both the projected and perceived images of a destination is crucial for effective image management and the development of targeted marketing strategies (Ferrer-Rosell & Marine-Roig, 2020).

Several factors influence the formation of perceived image. Firstly, cultural heritage, natural beauty, and environmental sustainability practices contribute significantly to a destination's overall image (H. Kim & Chen, 2016). Destinations that emphasize these aspects tend to attract tourists who value authentic and responsible travel experiences. Secondly, tourists' actual

experiences during their visit significantly shape their perceptions of a destination. Positive experiences lead to favorable reviews and word-of-mouth recommendations, further enhancing the destination's image (Choirisa et al., 2021). Thirdly, advertising, public relations, and social media campaigns play a crucial role in shaping potential tourists' perceptions of a destination. Effective communication strategies can highlight the unique attributes and experiences a destination offers (Gong & Tung, 2017).

Existing research has extensively explored perceived image; however, the study of projected image remains relatively underdeveloped. There is a notable gap in understanding the factors that influence the projected image. While current literature focuses predominantly on how projected image affects perceived image, there is limited investigation into whether perceived image, in turn, impacts the projected image.

The role of destination image in tourism marketing is multifaceted and critical for the success of destinations in the competitive global market. By understanding and strategically managing their image, destinations can enhance their attractiveness, foster sustainable development, and build lasting relationships with tourists (Stylidis, Belhassen, et al., 2017). Continuous innovation in marketing strategies and the adoption of new technologies are essential for maintaining a positive and dynamic destination image (Fu & Timothy, 2021).

1.1.2 Impact of Digital Innovation on the Tourism Industry

Digital innovation is defined as the co-creation of novel offerings through recombination of digital and/or physical components (Hukal & Henfridsson, 2017). It involves utilizing digital technology platforms such as websites and mobile applications to innovate products, processes, approaches, or models (Ciriello et al., 2018). Over the past decade, digital technologies have revolutionized various aspects of the tourism domain, fundamentally altering how destinations are marketed and experienced. The widespread adoption of digital platforms, social media, online booking systems, and other technological advancements has reshaped the dynamics of the tourism

industry (Marine-Roig & Clavé, 2016).

The digital transformation of the tourism industry has profoundly impacted destination marketing (Nikolskaya et al., 2021; Sorokina et al., 2022). As tourists' methods of information acquisition and behavioral patterns evolve, travel agencies can now gather and analyze data on demographic features, travel preferences, and personal interests to develop targeted marketing strategies (Ardito et al., 2019). With increasing demand for personalized and varied travel experiences, destinations need to implement effective digital marketing strategies tailored to specific market segments. Advanced analytics tools offer essential insights into marketing campaign performance, enabling destinations to optimize strategies and allocate resources more effectively by examining metrics such as click-through rates, conversion rates, and engagement levels (Xiao et al., 2022). Moreover, technologies such as virtual reality (VR), augmented reality (AR), and interactive videos provide immersive experiences, allowing potential tourists to explore destinations virtually and enhancing their understanding and attraction to the destination before making travel decisions (Oliveira & Panyik, 2015).

Additionally, destinations actively utilize digital channels—such as official websites, social media, and Online Travel Agencies (OTAs)—to enhance their image, strengthen marketing efforts, and engage with tourists (Oliveira & Panyik, 2015). Digital media has elevated user-generated content (UGC) on online travel platforms and social media to a pivotal role in destination image marketing (J. Wang et al., 2021). These platforms serve as influential channels where tourists freely share their experiences and opinions, disseminating diverse and unfiltered information about destinations. UGC, known for its authenticity and directness, provides prospective tourists with insights perceived as more genuine and trustworthy compared to traditional promotional materials. UGC encompasses a broad range of content beyond travel experiences, including perspectives on travel-related concerns and detailed satisfaction ratings. Together, these elements construct a comprehensive narrative of tourists' impressions, constituting Electronic Word-of-Mouth (eWOM) (Purbadharmaja et al., 2021).

Satisfaction ratings, a pivotal component of UGC, play a fundamental role as evaluative metrics in tourists' post-visit assessments. These ratings encapsulate tourists' perceptions of the quality of services, amenities, and attractions encountered during their travel experiences. They serve not only as reflections of tourists' personal experiences but also as influential signals for prospective travelers considering a destination (Z. Liu & Park, 2015; Schuckert et al., 2015). Positive satisfaction ratings affirm a destination's ability to meet or exceed expectations in terms of service excellence, infrastructure quality, cultural richness, and overall tourist experience. Such endorsements can significantly enhance a destination's perceived desirability and appeal in the eyes of potential tourists, thereby stimulating interest and increasing visitation rates. Conversely, negative satisfaction ratings can signify areas where a destination falls short in meeting tourist expectations, highlighting deficiencies in service delivery, infrastructure maintenance, or overall tourist satisfaction. These critical evaluations can deter potential tourists from selecting a destination, underscoring the importance of effectively managing and addressing concerns raised through UGC (Celotto et al., 2015). Destination marketers and tourism stakeholders must attentively monitor and respond to satisfaction ratings to address shortcomings promptly and enhance overall tourist satisfaction.

Through active monitoring of UGC, destination marketing organizations gain valuable insights into tourists' real-time experiences and sentiments. This enables them to respond swiftly to concerns and capitalize promptly on positive feedback. Such proactive engagement not only mitigates potential negative impacts but also fosters a dynamic and responsive destination image that resonates effectively with prospective tourists (Naeem & Ozuem, 2021). By effectively utilizing these channels, destination marketers can harness the authentic voices of tourists to establish and uphold a compelling destination image that appeals to diverse audiences. Strategic management of UGC involves leveraging positive feedback, addressing negative perceptions, and nurturing ongoing engagement to ensure that a destination's image remains robust, attractive, and competitive in the global tourism arena (Nguyen &

Tong, 2022).

In addition to its impact on destination marketing, digital innovation has significantly transformed destination image research.

Firstly, digital tools and platforms enable comprehensive data collection on tourists' perceived images. UGC monitoring and big data analytics provide deep insights into how tourists perceive and engage with a destination (Alarcón-Urbistondo et al., 2021). Researchers can track real-time changes in destination image, allowing them to quickly adjust their studies to reflect current trends and emerging issues.

Secondly, digital media platforms are instrumental in efficiently collecting destination marketing content, which is crucial for studying the projected image of a destination. Platforms such as official websites, social media channels, and Online Travel Agencies (OTAs) offer a rich array of information on how destinations are marketed to potential tourists. By aggregating and analyzing this content, researchers can obtain a thorough understanding of the projected image.

Thirdly, digital innovation facilitates the use of various data mining techniques, such as topic modeling, sentiment analysis, and social network analysis, to extract valuable insights from online data (Albalawi et al., 2020). By examining the gap between marketing content and UGC, patterns and trends in the disparity between the projected and perceived images of destinations can be uncovered. This analysis offers actionable insights for refining destination marketing strategies.

1.1.3 Wildlife Tourism and the Giant Panda Tourism Market

1) Wildlife Tourism and Sustainable Development

Wildlife tourism is an emerging sector within the tourism industry, intertwining with the interests of travelers seeking authentic encounters with natural environments and local wildlife (Reynolds & Braithwaite, 2001). Broadly defined as travel involving the observation or encounter of wildlife, wildlife tourism occurs in a variety of natural or managed

environments, where animals are either wild or captive. Tourists may engage closely with animals or observe them from a distance (Higginbottom, 2004). Wildlife tourism experiences provide opportunities to observe and interact with endangered, threatened, or rare animals. The demand for interactions with wildlife, particularly with rare or endangered species, has led to the proliferation of various wildlife tourism activities.

Approximately 12 million wildlife tourism trips occur annually, with a growth rate of about 10% per year (Curtin, 2010). In 2018, the Travel & Tourism sector contributed 10.4% to global GDP, with wildlife tourism accounting for 3.9% of this total, equivalent to $343.6 billion. This amount is comparable to the GDP of South Africa or Hong Kong. Additionally, wildlife tourism supported approximately 21.8 million jobs, representing 6.8% of all jobs sustained by the global Travel & Tourism sector in that year (WTTC, 2019). In 2022, the global wildlife tourism market was valued at USD 154.65 billion and is projected to grow at a compound annual growth rate of 7.9% from 2023 to 2030 (GVR, 2022). This growth is anticipated to be driven by several factors, including government initiatives such as the UNWTO/Chimelong initiative for wildlife site conservation, efforts to promote sustainable tourism in Africa and the Asia Pacific region, and policy support for ecotourism development by China's Ministry of Culture and Tourism (MCTC, 2023; PATA, 2023; UNWTO, 2021). These initiatives are expected to significantly enhance the industry's growth in the coming years.

The development of wildlife tourism has garnered considerable attention from researchers, policymakers, and conservationists due to its strong ties to sustainable tourism (Green & Giese, 2004). Sustainable tourism is defined as tourism that meets the needs of present tourists and host communities while safeguarding and enhancing opportunities for the future. It involves the management of all resources in a way that allows for economic, social, and aesthetic needs to be fulfilled while

preserving cultural integrity, essential ecological processes, biodiversity, and life support systems (WTO, 2005). This definition emphasizes the balance between environmental, cultural, and economic factors to ensure that tourism development remains viable and beneficial over the long term.

Sustainable tourism offers a comprehensive framework for wildlife tourism, serving as a guiding principle for wildlife tourism managers in balancing conservation and development goals.

The impacts of wildlife tourism are complex and multifaceted. Ecologically, wildlife tourism has both positive and negative effects on biodiversity and ecosystems. On one hand, it raises awareness among tourists about conservation, promoting responsible behavior and long-term support for preservation efforts. On the other hand, research indicates potential risks such as habitat disturbance, altered animal behaviors, and increased vulnerability to poaching or predation due to animals becoming habituated to human presence (Newsome & Rodger, 2012). Conservation efforts often struggle to balance visitor access with the protection of fragile ecosystems, necessitating rigorous management practices and monitoring protocols (Mbaiwa, 2003).

From an economic perspective, wildlife tourism supports the conservation of endangered species and the establishment of protected areas. Moreover, it significantly contributes to local economies through revenue generation, job creation, and infrastructure development. Studies show that communities benefit from increased employment opportunities in guiding, hospitality, and related services (Spenceley, 2012). Furthermore, revenue from park fees and wildlife viewing permits funds conservation initiatives, promoting sustainable management practices that benefit both wildlife and local stakeholders (Goodwin, 2011). Therefore, well-planned wildlife tourism creates a positive feedback loop that reinforces both environmental and economic sustainability.

Socio-culturally, wildlife tourism can enhance cultural pride and heritage preservation among indigenous communities. However, it also raises concerns about commodification and the potential erosion of traditional values (Mbaiwa, 2003). Local perceptions of wildlife tourism vary, influenced by factors such as community involvement in decision-making, equitable distribution of economic benefits, and cultural sensitivity in visitor interactions (Lindberg & Veisten, 2012). Achieving positive social outcomes requires robust community engagement strategies and collaborative partnerships among stakeholders.

Integrating sustainable practices into wildlife tourism management ensures a balanced approach that benefits both nature and people, safeguarding ecosystems while enhancing visitor experiences. Effective management and marketing of wildlife tourism destinations can also contribute to the broader development of sustainable tourism (Ballantyne et al., 2009).

A conceptual framework for wildlife tourism was proposed by Reynolds and Braithwaite (2001), highlighting six intrinsic quality factors that enhance the richness and intensity of wildlife tourism experiences Reynolds and Braithwaite (2001). Four factors—authenticity, intensity, uniqueness, and duration—are said to be present in all tourism experiences. The other two factors—species popularity (e.g., physical attractiveness, size, danger) and species status (rarity and endangered status of animals)—are specific to wildlife tourism experiences. Orams (2002) analyzed reasons why people are drawn to wildlife tourism, concluding that reduced opportunities for interacting with nature are a significant factor.

Exploring tourist preferences, behavior, and experiences with specific wildlife species can provide valuable insights for destination management and marketing strategies, thus promoting the sustainable development of the tourism industry (Mazanec & Strasser, 2007).

However, research on wildlife tourism in Asia, particularly in wildlife-rich countries like China, remains limited (Cong et al., 2017; Higginbottom, 2004). Specifically, there is a scarcity of studies on Chinese tourists' experiences with wildlife encounters.

2) Giant Panda Tourism Market in China

The giant panda (Ailuropoda melanoleuca) is one of the rarest members of the bear family and one of the most endangered animals in the world. These pandas inhabit the bamboo forests of six isolated mountain ranges in southwestern China (Reid, 1994). As a conservation-dependent endangered species, significant progress has been made in their preservation. China conducts national giant panda surveys approximately every ten years. In 2015, the Chinese government released the results of the fourth national giant panda survey. The survey reported a wild giant panda population of 1,864 individuals and the establishment of 67 giant panda nature reserves. These reserves host 1,246 pandas, accounting for 66.8% of the wild population (WWF, 2015). The giant panda is the symbol of the World Wildlife Fund (WWF). The WWF's list of "Top 10 Must-See Species" includes the giant panda as one of the world's most sought-after animals to view (Cong et al., 2014).

Pandas, as iconic symbols of Chinese biodiversity and conservation efforts, have garnered immense international interest, driving the development of specialized tourism initiatives centered around these beloved animals (Ong et al., 2023). China's strategic focus on panda conservation, coupled with efforts to promote sustainable tourism practices, has led to the establishment of dedicated panda reserves and breeding centers. These facilities not only serve as crucial habitats for panda preservation but also as key attractions for domestic and international tourists seeking immersive wildlife experiences (Cong et al., 2014).

The allure of giant panda tourism extends beyond conservation efforts

to encompass cultural and educational dimensions. Tourists have the opportunity to observe pandas in their natural habitats, contributing to public awareness of wildlife conservation and biodiversity protection. Moreover, panda tourism plays a vital role in promoting environmental stewardship and fostering appreciation for China's rich natural heritage (D. Xu et al., 2019). Educational programs offered at these sites highlight the importance of wildlife conservation and sustainable tourism practices, influencing tourists' attitudes and behaviors towards environmental conservation both locally and globally (Mazaruddin & Anuar, 2019).

Giant panda tourism is undoubtedly one of China's most distinctive wildlife attractions. As a crucial part of the wildlife tourism sector, China's giant panda tourism market is rapidly emerging, as evidenced by a significant increase in tourist numbers (PD, 2023; Yi, 2023).

The Chengdu Research Base of Giant Panda Breeding, commonly referred to as the "Panda Base," stands out as the premier attraction in this sector (Zou, 2020). Located in Chengdu city’s urban area, the facility houses over 200 giant pandas, accounting for a quarter of the world's captive giant panda population (CRBGPB, 2024a). The Panda Base functions as both a research institute and a tourism destination, integrating scientific research, breeding, and public education with educational tourism. As a non-profit organization, it is dedicated to endangered wildlife research and conservation. Due to the symbolic significance of pandas to China, the Panda Base plays a crucial role in diplomatic exchanges and contributes significantly to scientific research, endangered species protection, and public environmental education.

Chengdu city, a major hub in southwest China, is globally renowned as a prominent tourist destination. The Chengdu Municipal Government's tourism development plan highlights the importance of sustainable tourism growth in the city. It strongly supports the development of the

Chengdu Panda International Tourism Resort, with the Panda Base at its heart (CMBCRTT, 2022; Qianwei Li, 2020). With robust government support, the Panda Base has experienced rapid development. In 2022, it notably expanded its area from 1,035 acres to 3,570 acres (L. Zhang, 2022). As a leading destination for giant panda tourism, the Panda Base is crucial to advancing sustainable tourism in Chengdu city.

Designated as a national 4A-level site, the Panda Base is recognized as one of China's top ten tourist attractions (X. Li et al., 2023). Before the Covid-19 pandemic in 2019, the Panda Base attracted over 9 million tourists, with projections estimating an annual visitation of 21.3 million by 2035 (Qianwei Li, 2020; X. Yan, 2022). Since 2023, the Panda Base has experienced a remarkable surge in visitor numbers, highlighting its significant development potential. In March 2023, ticket sales at the Panda Base surged ninefold year-on-year, placing the site first in ticket sales among attractions in Sichuan Province and fifth nationally (PD, 2023). During the May Day holiday from May 1 to 3, 2023, the Sichuan Provincial Department of Culture and Tourism reported that 264,000 tourists visited the panda base, making it the second most popular attraction in the country (Yi, 2023). The growth continued into 2024, with the Chengdu Municipal Bureau of Culture, Radio, Television, and Tourism reporting a more than 30% increase in tourist numbers at the panda base compared to the same period the previous year (KN, 2024).

The increase in tourist numbers at the Panda Base has significantly stimulated regional development and boosted the local economy. Lin Huanjie, president of the China Theme Park Research Institute, observed that the recent surge in the giant panda tourism market has significantly increased the sales of panda-related products and driven up demand for transportation, hotels, and catering services (Y. Xu, 2024). This influx of tourists has spurred extensive infrastructure development, created employment opportunities in tourism-related industries for local communities, and substantially bolstered local

economic growth. The Qunar Big Data Research Institute estimates that a 50-yuan ticket to the Chengdu Research Base of Giant Panda Breeding can generate an additional 1,450 yuan in local spending on transportation, accommodation, and other related expenses (Yi, 2023). This "panda tourism economy" has attracted considerable media attention, with the South China Morning Post publishing a special report on August 12, 2024 (Y. Xu, 2024).

The rise of the giant panda tourism market can be attributed to several key factors. Firstly, the unique appeal of giant pandas, an endangered species and a national treasure of China, draws significant international attention. The conservation efforts and success stories of panda breeding programs are well-publicized, enhancing the global allure of the Panda Base. Additionally, the Chinese government's strategic promotion of ecotourism aligns with broader environmental and conservation goals, supporting the development of panda tourism (Wei, 2020). Moreover, digital marketing measures, including live-streaming of panda activities and the promotion of panda video clips, broaden the reach of panda tourism to a global audience unable to visit in person, thereby increasing interest and attracting potential tourists (X. Li, 2023).

The Panda Base has played a key role in promoting sustainable tourism development. The revenue generated from the giant panda tourism could contribute to funding conservation efforts and habitat restoration initiatives. This financial support reinforces the symbiotic relationship between tourism development and environmental sustainability within the panda tourism market. By channeling tourism revenues into conservation programs, the initiatives ensure that the natural habitats of the wildlife are preserved and enhanced, securing the long-term viability of both the species and the tourism sector that depends on it (Cong et al., 2017).

Despite its rapid development, the Panda Base faces significant challenges. The sharp increase in tourist numbers has created

substantial management and marketing pressures. Tourists, influenced by promotional messages, often arrive with high expectations of close interactions with pandas (Cong et al., 2014). When these expectations are unmet—whether due to overcrowding, long wait times, limited visibility of pandas, or greater distances—disappointment and dissatisfaction can arise. Additionally, this growing influx of tourists places greater demands on the Panda Base's management, particularly in transportation and service delivery (He et al., 2022).

If the Panda Base fails to effectively bridge the gap between tourists' expectations and their actual experiences, dissatisfaction may spread through digital media, shaping online word-of-mouth and influencing potential visitors' decisions. Such negative feedback could hinder the expected growth in tourist numbers and pose a serious threat to the sustainable development of tourism at the Panda Base.

In this context, leveraging digital innovation technologies to promptly and accurately gauge tourists' perceptions of the Panda Base is crucial. Understanding the alignment between tourists' perceived image of the Panda Base and the image projected by the base can reveal critical gaps, guiding the formulation of effective marketing strategies. By managing the projected image effectively, the Panda Base can help tourists establish realistic expectations, thereby enhancing satisfaction and supporting the sustainable development of tourism.

While China has made significant strides in giant panda conservation and extensive research has been conducted on various aspects of giant panda biology, including breeding, feeding, population monitoring, and habitat construction (R. Li et al., 2015; Wei et al., 2015) , there has been limited focus on the giant panda tourism. Research on giant panda tourism, particularly in the context of the Panda Base, can address this gap.

1.2 Research Scope

This study investigates the influence of destination image congruence on tourist

satisfaction, focusing on how the alignment between projected and perceived images affects satisfaction ratings. By integrating digital innovation with tourism destination image analysis, the research introduces a novel methodological framework for evaluating image congruence, validated through multiple data sources, to provide deeper insights into perceived images. The study also proposes data-driven marketing strategies designed to enhance image congruence, ultimately supporting the sustainable development and competitiveness of tourism destinations.

Using the emerging giant panda tourism market in China as a case study, specifically the Chengdu Research Base of Giant Panda Breeding (Panda Base), the research explores how digital tools can be effectively leveraged to analyze and optimize destination image. A comprehensive mixed-methods approach is adopted, combining online textual data mining with a structured questionnaire survey to capture both quantitative and qualitative perspectives.

Data sources for this study include 1,214 official promotional messages from the Panda Base's digital platforms and 12,561 tourist reviews from leading OTAs such as Ctrip and Meituan, covering the period from January 1, 2023, to March 31, 2024. Additionally, a structured questionnaire survey conducted in July 2024 provides 307 valid tourist responses. A cross-validation approach, integrating both online textual data and survey responses, is employed to ensure the robustness and reliability of the findings.

This study is expected to deepen the understanding of destination image congruence and tourist satisfaction, providing a robust methodology for enhancing image congruence. The methods developed can be applied to various destinations, refining marketing strategies and aligning projected images with tourist expectations. For local governments, this research offers insights to optimize policies, strengthen regional tourism brands, and promote economic growth.

1.3 Problem Statement

In the contemporary digital landscape, tourists increasingly rely on a range of online resources—including official websites, social media platforms, and Online travel agencies (OTAs)—to gather comprehensive information about potential travel destinations. This information is often meticulously curated to construct an idealized projected image of the destination (C.-K. Lee et al., 2012). The purpose of this projected

image is to attract potential tourists, generate interest, and encourage them to select the destination for their travel plans.

However, when tourists arrive at the destination and encounter a reality that significantly deviates from the projected image, they face a considerable challenge. This discrepancy can lead to profound feelings of disappointment and disillusionment (Milman, 2011). The fundamental issue is the misalignment between the tourists' perceived image—i.e., their actual experiences during the visit—and the projected image they were initially presented with. Such inconsistencies can undermine the trust and credibility of the destination, resulting in decreased overall tourist satisfaction and potentially lower satisfaction ratings.

The impact of low satisfaction ratings extends beyond individual tourist experiences. Negative feedback and reviews can swiftly proliferate through social media and online review platforms, severely damaging the destination's online reputation. This deterioration in reputation can diminish the interest of potential tourists, leading to reduced tourist numbers and revenue. Over time, persistent negative feedback and declining satisfaction can threaten the destination's long-term viability, obstructing its future development and competitive positioning in the tourism market (Choirisa et al., 2021; Purbadharmaja et al., 2021).

Therefore, the disparity between the projected and perceived images of a destination can trigger a series of complex issues that significantly affect not only tourist satisfaction but also the destination's long-term sustainability.

To address these challenges, it is essential for tourism destinations to carefully balance the projected image with the actual experiences they offer. Marketing strategies should be precisely crafted to reflect the true nature of the destination's experiences, thereby preventing the dissemination of misleading information to potential tourists. Consequently, when formulating marketing strategies, destinations must prioritize aligning the projected image with the actual experience to ensure that promotional materials provide an accurate representation of the tourism experience (Y. Li et al., 2023).

Given the dynamic nature of destination image, ongoing monitoring of both the projected and perceived images is crucial. This involves systematically collecting and analyzing information disseminated about the destination, along with gathering and evaluating tourist feedback (Marine-Roig & Ferrer-Rosell, 2018). By identifying and addressing

discrepancies between the projected and perceived images, destinations can make informed adjustments to their marketing strategies (Xiao et al., 2022).

Such a proactive approach not only enhances tourist satisfaction by ensuring that expectations are consistent with actual experiences but also plays a critical role in maintaining the destination's long-term reputation and economic sustainability.

1.4 Purpose of the Study

This study adopts an interdisciplinary approach, integrating theories from tourism destination image, consumer behavior, marketing, and communication, with a focus on leveraging digital innovation to address challenges in tourism destination research.

The primary aim of this research is to empirically investigate the impact of destination image congruence on tourist satisfaction, introduce a novel methodological framework for evaluating image congruence, and propose marketing strategies to enhance the alignment between projected and perceived destination images.

The study is structured around three core objectives:

Firstly, to evaluate the impact of destination image congruence on tourist satisfaction: The research will empirically assess how the congruence between the image projected by destination marketing efforts and the image perceived by tourists during their visit influences their satisfaction. Gaining insights into this relationship will be essential for enhancing tourist experiences and improving destination competitiveness.

Secondly, to develop an innovative method for evaluating destination image congruence: The study will introduce a novel methodological approach to measure the congruence between projected and perceived images. This method will be validated through the integration of multiple data sources, ensuring robustness and reliability, and will provide a deeper exploration of perceived images.

Thirdly, to propose marketing strategies to enhance destination image congruence: Based on the empirical findings, the study will offer practical, data-driven marketing strategies aimed at improving the alignment between projected and perceived images. These strategies will support the sustainable development and competitiveness of tourism destinations.

Using the emerging giant panda tourism market in China, particularly the Chengdu

Research Base of Giant Panda Breeding (Panda Base), as a case study, this research will explore how digital tools can be effectively utilized to analyze and optimize destination image. A comprehensive mixed-methods approach will be employed, integrating online textual data mining with a structured questionnaire survey to capture both quantitative and qualitative perspectives.

Based on the findings, this study will offer strategic recommendations to enhance the Panda Base's destination image marketing. Beyond improving image congruence, the Panda Base could better integrate tourist education, increase visitor numbers, and boost satisfaction, while also supporting environmental protection, species conservation, and biodiversity. These measures will foster sustainable tourism development.

This study is anticipated to enhance the understanding of the relationship between destination image congruence and tourist satisfaction and will provide a robust methodology for evaluating and improving image congruence in the digital era. The findings are expected to make significant contributions to both academic research and practical applications in tourism destination image marketing and management.

Furthermore, the methods developed in this study are expected to be applicable to other forms of tourism destinations to refine marketing strategies and better align projected images with tourists' expectations and needs. For local governments, this research will offer valuable insights for developing optimized policies, building strong regional tourism brands, and fostering tourism economic growth.

1.5 Organization of the Thesis

The thesis comprises six chapters, each contributing to a comprehensive exploration of the research topic.

Chapter 1 serves as the introduction, providing a foundational overview of the study. It outlines the research purpose, elucidating the specific objectives to be achieved through the investigation. Furthermore, the chapter discusses the significance of the research, highlighting its potential contributions to the field and its implications for theory, practice, and policy. Lastly, the scope of the research is delineated, outlining the boundaries within which the study will operate.

Chapter 2 delves into the literature review, where the theoretical foundations of the

research are examined in detail. This chapter elucidates the basic concepts relevant to the study and reviews existing literature and research findings related to the topic under investigation. By synthesizing and analyzing prior scholarship, this chapter provides a comprehensive understanding of the current state of knowledge in the field, identifying gaps, inconsistencies, and areas warranting further exploration.

In Chapter 3, the research methodology is elucidated, providing insight into the approach taken to conduct the study. It outlines the research framework and process, providing a detailed explanation of the steps involved in conducting the research. Additionally, this chapter discusses the data sources utilized in the study, the analysis tools employed, and the specific methods of analysis employed to interpret the data. By elucidating the research methodology, this chapter ensures transparency and rigor in the research process.

Chapter 4 presents the research results, offering a detailed analysis and interpretation of the data collected. This chapter illustrates the key findings and insights, providing a clear picture of how the data supports the research objectives. Through meticulous examination of the data, this chapter highlights the most significant trends and patterns identified during the study.

Chapter 5 provides a detailed discussion of the research findings and practical suggestions. It interprets the results in relation to the research questions and objectives, demonstrating how they address these aspects. The chapter also compares the findings with previous studies, noting similarities and differences and analyzing possible reasons for the discrepancies. Furthermore, it explores the theoretical and practical implications of the findings, offers actionable recommendations, and outlines how the research can be applied or extended to other areas.

Chapter 6, the final chapter, summarizes the research conclusions, proposes theoretical and practical contributions, identifies the study's limitations, and outlines potential areas for future research. It begins by summarizing the main findings and drawing overall conclusions, reflecting on the research objectives and evaluating their achievement. The chapter then presents the theoretical and practical contributions of the study. It also addresses the limitations encountered, acknowledging any constraints. Finally, potential areas for future research are suggested, offering directions for further investigation based on the current study's findings.

CHAPTER 2

Literature Review

2.1 Fundamental Concepts

This section introduces three key concepts: destination image, destination image congruence, and satisfaction ratings. By defining and elucidating these terms, the study's specific focus is clarified. Destination image is a complex concept that encompasses multiple dimensions, including projected and perceived images. Destination image congruence refers to the alignment between the image projected by destination marketing efforts and the image perceived by tourists based on their experiences. Satisfaction ratings are numerical assessments provided by tourists that reflect their level of satisfaction with various aspects of their travel experience. These concepts are fundamental to this study, forming the core framework and providing a comprehensive understanding of its basis.

2.1.1 Destination Image

Since the foundational research by Gunn Clare (1972), the concept of destination image has garnered significant attention in tourism marketing literature. Destination image refers to the sum of beliefs, ideas and impressions that a person has of a destination (Crompton, 1979). In the research of Gartner (1994), destination image is conceptualized into three components: cognitive image, affective image, and conative image. The cognitive image encompasses the knowledge and beliefs about a destination's attributes; the affective image pertains to the feelings or emotions towards the destination; and the conative image involves the likelihood of visiting or recommending the destination based on these cognitive and affective evaluations.

Bramwell and Rawding (1996) introduced another perspective to understand the destination image, distinguishing it into two distinct dimensions from the

supply and demand perspective: projected image and perceived image. The projected image represents the intended image of a destination conveyed by destination marketing organizations (DMOs) through their marketing efforts, emphasizing the destination's strengths and resources. This image is traditionally disseminated through channels like travel magazines, promotional videos, and news reports. However, with the advent of digital media, platforms such as social media have gained importance in projecting destination images (S. Khan, 2013).

On the other hand, the perceived image refers to the mental representation of a destination from the perspective of tourists (A. Khan et al., 2021). It reflects the actual experiences and interpretations that tourists form based on various information sources, including various promotional messages, social media interactions and personal visits. Both facets of image—the projected and the perceived—are crucial in comprehensively understanding a destination's image. Considering both perspectives allows for a more holistic analysis, as it integrates the DMOs' intended messages with tourists' actual perceptions and experiences. This dual consideration is essential for effective destination image studies, ensuring that the complexities and dynamics of destination image formation and transformation are adequately captured (Chan & Zhang, 2018).

2.1.2 Destination Image Congruence

Destination image congruence refers to the consistency or alignment between the intended image projected by destination marketing organizations (DMOs) and the image perceived by tourists based on their experiences and interpretations (Y. Li et al., 2023). Various information sources, including official tourism websites, travel brochures, and social media campaigns, often have incentives to present destinations in a positive light, thereby increasing tourists' expectations and motivating them to visit. Additionally, many tourists tend to imagine and fantasize about their future destination experiences, influenced by the idealized portrayals they encounter. This phenomenon underscores the importance of the projected destination image in shaping

tourists' expectations prior to their visit (C.-K. Lee et al., 2012).

The projected destination image sets the stage for tourists' expectations, creating a framework within which they anticipate their travel experiences. In contrast, the perceived image is formed based on tourists' actual interactions and experiences at the destination, as well as through secondary information sources such as reviews and word-of-mouth. Often, there is a misalignment between these two images, with the perceived image frequently being less ideal than the projected one (Grosspietsch, 2006). Such incongruence indicates that the tourists' experiences do not match their expectations, which can lead to negative evaluations and dissatisfaction. This discrepancy highlights the critical role of managing tourists' expectations accurately to avoid disillusionment and negative feedback.

Conversely, when the projected and perceived images are congruent, the likelihood of tourists positively evaluating their destination experiences is significantly enhanced. This congruence suggests that the destination has met the tourists' expectations, leading to satisfaction and positive word-of-mouth (Marine-Roig & Ferrer-Rosell, 2018). Achieving image congruence is essential for DMOs, as it not only fosters positive evaluations and repeat visitation but also strengthens the destination's reputation and competitive advantage in the tourism market. Therefore, continuous monitoring and alignment of projected and perceived images are crucial strategies for ensuring sustainable tourism development and enhancing overall tourist satisfaction.

2.1.3 Satisfaction Ratings

The concept of satisfaction in the field of tourism has been extensively examined in academic literature. C.-F. Chen and Tsai (2007) define satisfaction as the pleasure derived by tourists when the travel experience meets their desires, expectations, and needs. This concept is pivotal because it directly impacts tourists' future travel intentions and the likelihood of recommending a destination to others. Understanding and enhancing tourist satisfaction is critical for destinations seeking to build a loyal customer base

and stimulate positive word-of-mouth promotion. Tourist satisfaction can be impacted by the difference between pre-travel expectations and post-travel experiences (C.-F. Chen & Chen, 2010). This gap analysis approach helps identify areas where the actual experience fell short of, met, or exceeded expectations, providing actionable insights for improving service quality and overall tourist experience. Similarly, Ozdemir et al. (2012) suggest that satisfaction is influenced by subjective comparisons between perceptions and tourists' expectations. When tourists' actual experiences align with their pre-visit expectations, they tend to feel more satisfied, confirming the critical role of managing expectations in tourism (Huete Alcocer & López Ruiz, 2020). Effective expectation management involves clear communication and delivering consistent, high-quality experiences that meet or exceed what is promised.

Satisfaction ratings refer to the numerical assessments provided by tourists who have booked and experienced a particular destination, accommodation, or service through online platforms (Guo et al., 2017). Online Travel Agencies (OTAs) act as intermediaries between tourists and travel service providers, enabling individuals to make reservations, access information, and provide feedback on their travel experiences. These ratings are a form of user-generated content (UGC) and often utilize a scale, such as star ratings or numerical scores from 1 (not good) to 5 (very good). Satisfaction ratings reflect the positive or negative orientation of reviewers' experiences and are crucial for other potential tourists who rely on these evaluations to make informed decisions (Park & Nicolau, 2015). Reviews that assign high ratings are typically shared when tourists are satisfied with their experience, while lower ratings highlight areas needing improvement (Nieto et al., 2014).

Satisfaction ratings directly reflect tourists' post-visit evaluations of a destination and significantly influence potential tourists' destination choices (Z. Liu & Park, 2015; Schuckert et al., 2015). Given that an overwhelming abundance of reviews can lead to confusion and suboptimal decisions, users often rely on the positivity and negativity of satisfaction ratings to guide their choices (O'connor, 2010). Consequently, satisfaction ratings are considered a

powerful tool for efficiently and effectively promoting offerings (Barreda & Bilgihan, 2013). They not only serve as a feedback mechanism for service providers to enhance their offerings but also act as persuasive endorsements that attract new tourists. High satisfaction ratings can create a virtuous cycle, where positive reviews generate more interest and bookings, leading to further positive experiences and reviews. Therefore, maintaining high satisfaction ratings is crucial for destinations and service providers aiming to enhance their market competitiveness and ensure long-term success.

2.2 Theoretical Foundation

2.2.1 Destination Image Theory

The research landscape of destination image studies spans several key areas, including conceptualization, formation factors, measurement, and the influence of destination image on tourist intentions, behavior, and satisfaction (Ferrer-Rosell & Marine-Roig, 2020; Kyungmi Kim et al., 2012; K. Lai & Li, 2015; Maghrifani et al., 2021; Marine-Roig, 2021). This section focuses on the structure and formation process of destination image, which are central to destination image theory.

1) Destination Image Structure

Consumer decisions on destinations are influenced by various factors. Image is the decisive factor that affects consumers' choice among various information (Levy, 1978).The concept of destination image was initially introduced to the field of tourism by Hunt (1971) during the early 1970s, marking its inception as a significant research area (Stepchenkova & Morrison, 2008). After decades of popularity, it now plays an important role in tourism and related research and has been widely studied (Stylidis, 2022).

During the early stages of research on destination image, scholars such as Crompton (1979), Gartner (1989), and Echtner and Ritchie (1991) examined the internal structure and attributes of destination image. Their contributions not only advanced the understanding of destination image but also laid the groundwork for research on measuring

destinations.

Crompton (1979) considered destination image as the sum of beliefs, ideas and impressions that a person has of a destination. This definition was prominently guided early research in this field. Later, scholars gradually realized that destination image is a complex concept. As destination image is a highly abstract concept with the characteristics of comprehensiveness, diversity, relativity and dynamics, this concept lacks a unified definition. Echtner and Ritchie (1991) reviewed definitions used by previous destination image researchers and proposed six components of destination image which can be categorized into three groups (Functional-Psychological, Attributes-Holistic, Common-Unique). This conceptual structure provided ideas for measuring the characteristics of destination image from three dimensions. In the research of Gartner (1994), destination image is composed of three components which include cognitive image, affective image and conative image. Cognitive image refers to tourists' perception of the attributes or characteristics of the destination, including tourist attractions, environment, public service and other infrastructure. Meanwhile, affective image refers to tourists' cognition of a destination based on personal attitudes and values, whereas conative image is the tourists' intention or the possibility of visiting a destination, equivalent to travel tendency. This framework of destination image has been widely applied and further expanded in many subsequent studies (Agapito et al., 2013; Steven Pike & Ryan, 2004; Stepchenkova & Mills, 2010; Woosnam et al., 2020).

Bramwell and Rawding (1996) introduced another perspective to understand the destination image, distinguishing it into two distinct dimensions: projected image and perceived image. The image that tourism marketing organizations try to establish and promote in travel markets through various media channels is called the projection image, whereas the image formed in the mind of tourists or potential tourists, including impression, cognition and feeling, is called the perceived

image (Andreu et al., 2000; Choi et al., 2007; Govers & Go, 2004b). Despite the projected image playing a pivotal role in shaping the perceived image, there is often a significant difference between the two. (Echtner & Ritchie, 2003).

Based on these three important destination image components models, referring to the study of Tasci et al. (2007), the integration of the conceptual structure of destination image is depicted in Figure 2.1. The concept of destination image can be analyzed through two distinct aspects: the projected image and the perceived image (Bramwell & Rawding, 1996). The perceived image mainly represents the holistic impression held by tourists towards a destination, encompassing three fundamental components: cognitive image, affective image, and conative image. Furthermore, destination attributes can be comprehended through two dimensions: common characteristics and unique characteristics, as well as functional characteristics and psychological characteristics. Functional characteristics relate to tangible aspects of the destination, while psychological characteristics pertain to intangible aspects. The cognitive, affective, and conative image of tourists, along with the attributes of the destination, form a dynamic interactive system, wherein each element can act as both a cause and a consequence of changes, emphasizing the interconnected nature of these factors (Tasci et al., 2007). Obviously, the study of the perceived image occupies a central position in destination image research. Previous studies have revealed that academic literature places greater emphasis on analyzing the perceived image compared to the projected image (Picazo & Moreno-Gil, 2019).

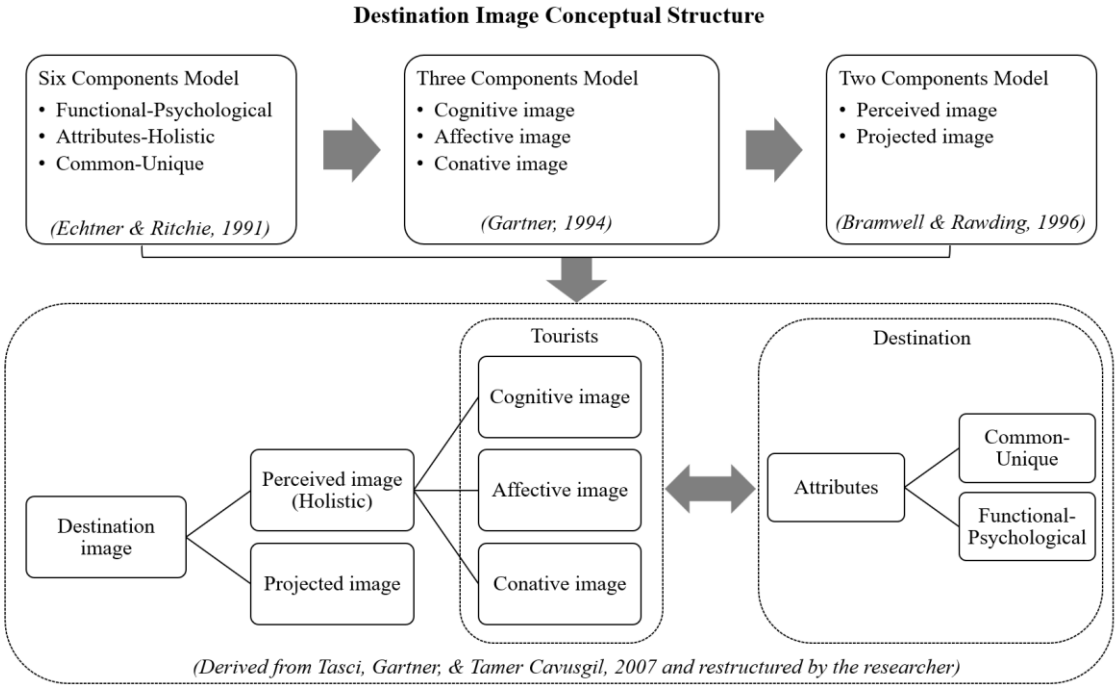

Figure 2.1 Conceptual structure of destination image

(Source: Compiled by the author from the literature)

With the development of digital technology, the concept of electronic word-of-mouth (eWOM) image has emerged (González-Rodríguez et al., 2016). The eWOM image refers to the destination image conveyed through user-generated content (UGC) on electronic platforms like social media and Online Travel Agencies (OTAs). This image is derived from various forms of information shared by tourists, including reviews, photos, videos, and ratings that pertain to a destination (Choirisa et al., 2021). These elements serve as reflections of tourists' experiences and perceptions, encompassing both the period during and after their visit. The eWOM image is particularly significant as it offers a real-time, authentic portrayal of destinations, influenced directly by the tourists' personal encounters and sentiments (Assaker & O'Connor, 2020).

As UGC data becomes increasingly integral to destination image research, numerous scholars directly use the eWOM image as a proxy for the perceived image when studying a destination's perceived image (González-Rodríguez et al., 2016; Marine-Roig & Ferrer-Rosell, 2018;

M. Sun et al., 2014). This approach is grounded in the recognition that UGC provides a rich, diverse, and unfiltered source of information that can capture the nuanced and multifaceted nature of tourist perceptions. It allows for the collection of large volumes of data over extended periods, providing a comprehensive understanding of how destination images evolve. Moreover, eWOM data can reveal trends and patterns that might not be apparent through traditional survey methods, offering a more dynamic and real-time perspective on tourist sentiments (Z. Wang et al., 2023b).

2) Perceived Destination Image Formation

In destination image research, scholars extend their focus beyond definitions and components to include the formation process and influencing factors. Specifically, the emphasis is on perceived image, which remains central to this field of study. Researchers seek to elucidate how perceived image is shaped, highlighting the unique characteristics of each stage in the formation process. This involves exploring the initial creation of perceptions, their evolution through various information sources, and the impact of personal experiences and external influences in modifying these perceptions over time.

Gunn Clare (1972) proposed a framework in which destination images transition from organic images to induced images, and eventually to modified induced images. The organic image is formed through exposure to non-tourism-specific sources of information. This organic image then develops into an induced image, which is influenced by directed information from DMOs. While a destination has limited control over its organic image, it can significantly impact the modification of an induced image through promotional and publicity efforts. This highlights the importance of destination marketing in managing and influencing tourists' perceptions and attitudes towards a particular location. Fakeye and Crompton (1991) build upon this formation process and define the final stage image as a complex image.

This implies that upon visiting a destination, a tourist will develop a more intricate image based on actual experiences and contact with the area. H. Kim and Chen (2016) proposed three essential driving processes that contribute to the formation of destination image: schema-driven, data-driven, and experience-driven. While their model emphasizes the identification of key factors at different stages of the image formation process, it does not introduce any fundamental advancements.

The formation of the destination image is influenced by a multitude of factors. Gartner (1994) categorized these factors as overt information, autonomous information, and organic information. Baloglu and McCleary (1999) proposed two aspects: stimulus factors, which refer to external influences, and personal factors, which pertain to tourists' internal characteristics. Tasci and Gartner (2007) analyzed the formation of destination image from the perspectives of supply and demand, highlighting the influence of destination-oriented information and perceiver characteristics. Building upon this research, R.-Y. Huang et al. (2021) introduced the consideration of environmental factors.

Influencing factors mentioned in the literature encompass a wide range of elements, including tourists' cultural background, beliefs, personality traits, and social networks, as well as the destination's political environment, sports events, popular culture, brands, and commodities (Eid et al., 2019; Elliot et al., 2010; C.-K. Lee et al., 2005; MacKay & Fesenmaier, 2000; Seo & Oh, 2017; Stylos et al., 2016). Particular attention has been paid to the role of media influence, recognizing that potential tourists primarily rely on various media channels for obtaining destination information (Stepchenkova & Eales, 2010).

Figure 2.2 summarizes the key perspectives on the factors and formation process of perceived destination image. The scholars highlighted in this figure consistently emphasize the impact of destination marketing information on the formation of perceived image.

In essence, they assert that the projected image of a destination significantly influences its perceived image.

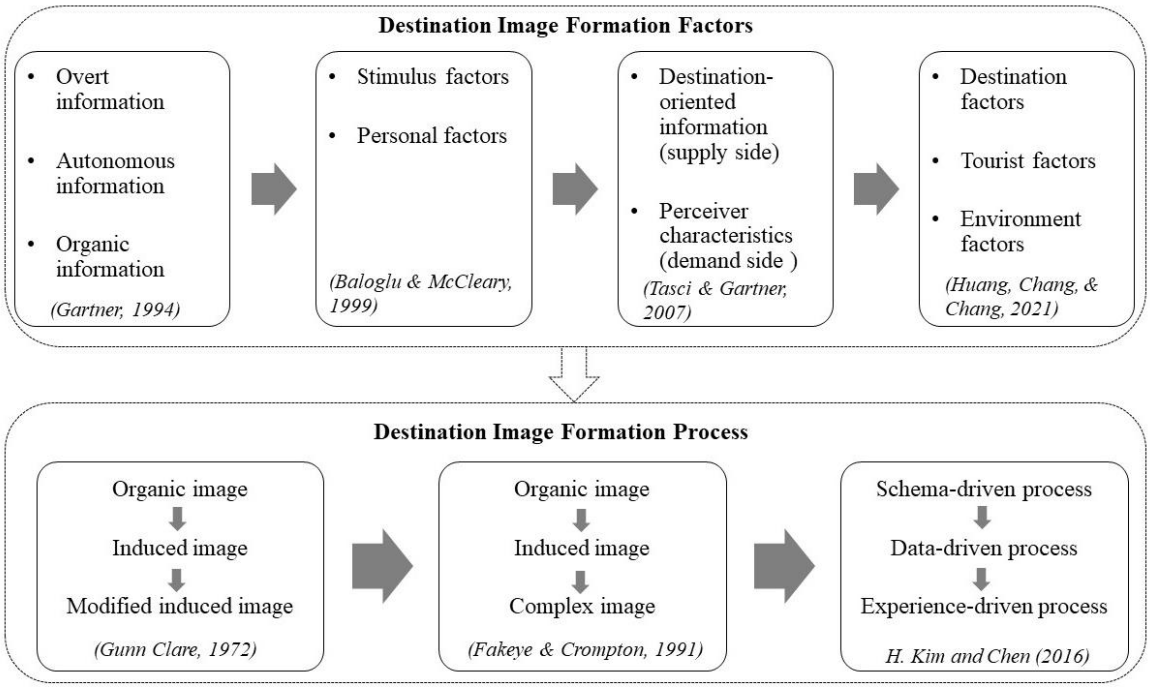

Figure 2.2 Factors and formation process of perceived destination image

(Source: Compiled by the author from the literature)

2.2.2 Expectancy-Disconfirmation Theory

Expectancy-Disconfirmation Theory was proposed by Oliver (1980). This theory posits that consumer satisfaction is fundamentally influenced by the discrepancy between pre-consumption expectations and the actual performance of a product or service. The theory comprises fundamental elements: Expectations (pre-consumption beliefs), Perceived Performance (actual experience), and Disconfirmation (the gap between expectations and perceived performance). Satisfaction occurs when perceived performance surpasses expectations, dissatisfaction arises when perceived performance falls short of expectations, and neutral satisfaction is achieved when perceived performance aligns with expectations (Yüksel & Yüksel, 2008).

Expectancy-Disconfirmation Theory has been widely applied in various fields, particularly in tourism, where it has emerged as a fundamental tool for comprehending and gauging tourist satisfaction (Pizam & Milman, 1993;

Weber, 1997; Zehrer et al., 2011). In the tourism context, tourists craft expectations from diverse sources such as promotional materials, online reviews, word-of-mouth, and past experiences, which they then juxtapose against their actual experiences at destinations (Farmaki, 2012). The degree of disconfirmation, whether positive or negative, directly influences satisfaction levels. Positive disconfirmation, where actual experiences exceed expectations, leads to heightened satisfaction, while negative disconfirmation, where actual experiences fall short of expectations, results in dissatisfaction. Neutral disconfirmation, where actual experiences meet expectations, results in a state of moderate satisfaction.

The implications of tourist satisfaction, driven by Expectancy-Disconfirmation Theory, are profound. Tourist satisfaction significantly impacts repeat visitation, destination loyalty, and positive word-of-mouth, all of which are pivotal for the sustainable growth of tourism destinations (Culic et al., 2021). A satisfied tourist is more likely to revisit the destination, recommend it to others, and share positive experiences, thereby enhancing the destination's reputation and attracting new tourists (Assaker & Hallak, 2013). Conversely, dissatisfaction can lead to negative word-of-mouth and deter potential tourists, posing a risk to the destination's image and economic viability.

Expectancy-Disconfirmation Theory provides insights into the drivers of tourist satisfaction, thereby guiding strategies aimed at enriching tourism experiences and nurturing destination loyalty (Hui et al., 2007). For instance, tourism managers can utilize feedback to identify gaps between tourist expectations and their actual experiences, thereby informing service improvements and marketing strategies (Cai & Chi, 2021). This approach helps in aligning promotional efforts with the actual offerings, reducing the likelihood of negative disconfirmation.

2.2.3 Value Perception Theory

Value Perception Theory, also known as Value-Based Theory, originates from the realm of consumer behavior and marketing literature, with its

conceptualization credited to Holbrook (1994). Holbrook proposed that consumers' perceptions of value are pivotal in their decision-making processes, addressing the limitations of traditional economic models that primarily focused on monetary aspects. This theory emerged as a response to the need for a more comprehensive framework to understand consumer behavior.

According to Value Perception Theory, consumers assess products or services based on the perceived value they offer, rather than solely on price or functional attributes. Value is understood as subjective and multidimensional, encompassing not only monetary considerations but also emotional, social, and experiential aspects. This holistic approach to value assessment is integral to understanding consumer behavior (Sánchez-Fernández & Iniesta-Bonillo, 2007).

In addition to Expectancy-Disconfirmation Theory, Value Perception Theory provides a complementary perspective on understanding consumer satisfaction. Both theories together offer a more comprehensive view. Tourist satisfaction with a destination is shaped by the discrepancy between expectations and actual experiences. When the perceived value of a destination is high, the likelihood of the experience meeting or exceeding expectations increases, resulting in higher levels of tourist satisfaction.

Value Perception Theory is widely employed in destination satisfaction studies, this theory is fundamental for exploring tourists' perceptions of the value provided by destinations and the factors influencing their overall satisfaction (Pandža Bajs, 2015). Value Perception Theory has been employed to investigate various dimensions of value perception in destinations, including facility quality, dining experiences, transportation, and hospitality services (Haji et al., 2021; Ramseook-Munhurrun et al., 2015). Through meticulous exploration of tourists' perceptions of these aspects, key determinants of destination satisfaction and loyalty can be identified.

Furthermore, by elucidating how value perception influences tourists' behaviors, destination marketers can effectively tailor their offerings and

promotional strategies to enhance overall satisfaction and encourage repeat visitation (Chang et al., 2016). This strategic approach is essential for destination management and marketing in an increasingly competitive tourism industry.

Empirical evidence suggests that enhancing tourists' value perception of a destination is essential for boosting satisfaction. For example, Raza et al. (2012) found that perceived value significantly influenced tourists' satisfaction and intention to revisit a destination. Similarly, T.-L. Wang et al. (2017) and Khuong and Phuong (2017) established a positive correlation between perceived value and tourists' overall satisfaction, leading to favorable word-of-mouth recommendations.

2.2.4 Agenda-Setting Theory

Agenda-Setting Theory, proposed by M. E. McCombs and Shaw (1972), asserts that the media wield significant influence over public perception by consistently spotlighting certain topics, thereby elevating their importance in the public consciousness. This theory posits that the media's selection and emphasis on specific issues guide audiences to perceive them as more salient and significant than others. The theory is grounded in two core principles: (1) the media do not dictate what individuals should think, but rather what they should think about, and (2) the frequency and prominence of media coverage influence the perceived importance of issues (M. E. McCombs et al., 2018).

Agenda-Setting Theory provides valuable insights into the mechanisms through which the media shape public perceptions and agendas. By repeatedly covering certain topics, the media can make these issues seem more important to the audience. This process involves both the first-level agenda setting, which concerns the relative salience of issues, and the second-level agenda setting, which deals with the specific attributes or aspects of these issues that are highlighted (M. McCombs & Reynolds, 2002).

In the realm of tourism destination marketing and communication, Agenda-Setting Theory plays a pivotal role. Within the competitive landscape where various destinations vie for attention and tourist interest, a comprehensive

understanding and application of this theory can significantly enhance the efficacy of marketing strategies (Schweinsberg et al., 2017). By strategically crafting narratives and emphasizing specific attractions, experiences, or amenities, destination marketers can influence potential tourists' expectations.

For instance, through well-designed promotional messaging, destination marketers can effectively shape the narrative surrounding their destination, highlighting its unique appeal and attractions. Additionally, marketers can address tourists' concerns through targeted communications. This approach can guide tourists to develop a favorable image of the destination prior to making travel decisions (Qiuju & Juanjuan, 2014). Consequently, Agenda-Setting Theory provides a framework for destination marketers to manage and enhance their communication strategies, ultimately driving increased tourist interest and satisfaction.

Furthermore, the application of Agenda-Setting Theory in tourism marketing is not limited to traditional media. In the digital age, social media platforms and online travel forums also play a crucial role in setting the agenda. Research has shown that user-generated content on platforms like TripAdvisor, Instagram, and YouTube significantly influences tourists' perceptions and decisions (Fotis, 2015). By leveraging these platforms, destination marketers can amplify their message and reach a broader audience.

Moreover, the theory's implications extend to crisis management in tourism. During crises, such as natural disasters or political unrest, the media's portrayal of events can dramatically affect a destination's image. By proactively engaging with media outlets and providing accurate, timely information, tourism authorities can mitigate negative perceptions and help stabilize tourist confidence (Avraham, 2015).

2.2.5 Two-Sided Persuasion Theory

Two-Sided Persuasion Theory originates from the broader domain of communication and persuasion theories. It was initially conceptualized by Carl I. Hovland and his colleagues during the 1950s at Yale University. The fundamental idea behind this theory is that a persuasive communication can

be more effective if it presents both sides of an argument rather than just one. This approach acknowledges counterarguments and refutes them, thereby enhancing the credibility of the message and reducing resistance from the audience (Hovland et al., 1953).

The fundamental premise of Two-Sided Persuasion Theory posits that messages acknowledging opposing viewpoints are more persuasive than one-sided messages. The theory highlights several key components: first, enhanced credibility, achieved by presenting and refuting counterarguments, which renders the communicator more trustworthy and knowledgeable; second, reduced resistance, as acknowledging opposing views diminishes the audience's perception of bias, thereby making them less inclined to counterargue; and third, increased persuasion, whereby two-sided messages can lead to more significant attitude changes, especially among audiences who are initially opposed or neutral (Allen, 1991; Crowley & Hoyer, 1994).

Hovland's seminal research in 1953 revealed the particular effectiveness of two-sided messages in contexts where the audience possesses a high level of information or is exposed to opposing viewpoints from alternative sources (Hovland et al., 1953). The application of Two-Sided Persuasion Theory in tourism destination communication is multifaceted. This approach is particularly advantageous for managing destination image, navigating crises, and fostering a more realistic and trustworthy rapport with prospective tourists (Min et al., 2013). Additionally, it enhances tourists' perceived risk management and serves as a sustainable communication strategy (Ivanov et al., 2018).

Destination marketers can enhance their credibility by acknowledging potential drawbacks or criticisms and addressing these concerns constructively. Providing a balanced portrayal of a destination's attributes helps manage tourist expectations and reduces the likelihood of disappointment. For instance, a beach destination that contends with occasional seaweed problems can candidly acknowledge this issue while emphasizing ongoing efforts to maintain cleanliness and highlighting other

attractions that make the destination appealing (Hampton & Hampton, 2009). Similarly, a destination renowned for its hot climate can acknowledge this aspect while highlighting alternative indoor attractions or evening activities that offer respite from high temperatures (Min et al., 2013). A rural destination might emphasize its picturesque landscapes while also acknowledging the limited availability of luxury amenities, thereby appealing to tourists seeking an authentic experience (Rasoolimanesh et al., 2017). Two-sided messages, which present both strengths and weaknesses, are crucial for shaping realistic expectations and fostering trust. This approach contributes to a robust and appealing destination image, ultimately leading to heightened tourist satisfaction.

During periods of crisis, such as natural disasters, political instability, or health emergencies, the use of two-sided messages becomes imperative. Gurtner (2016) explored the image recovery of the island destination of Bali, demonstrating how acknowledging past issues and illustrating improvements can aid in rehabilitation. This strategic approach was notably evident during the global COVID-19 pandemic, with numerous destinations openly acknowledging associated risks while concurrently communicating the implemented safety measures (Hassan & Soliman, 2021). Their investigation showed that this transparency led to a favorable reassessment of the destinations by potential tourists. Engaging in transparent dialogue and articulating the steps being taken to mitigate adverse circumstances allow destination marketers to address concerns effectively.

As tourism marketing continues to evolve in the digital landscape, the enduring relevance of two-sided persuasion principles in engaging and persuading discerning tourists remains evident. Research by L. R. Tang et al. (2012) revealed that the incorporation of two-sided messages significantly enhanced the credibility and persuasiveness of travel websites. Tourists perceived websites employing two-sided communication as more trustworthy, thereby increasing their likelihood of considering visits to the featured destinations (Tseng & Wang, 2016). Recent studies, such as L. M. Meng et al. (2023) explore how to increase customers' willingness to communicate with

AI chatbots by adopting a two-sided message strategy after AI's nonhuman identity is disclosed. Results indicate that this strategy enhances customers' willingness to interact with AI chatbots through the mediating role of perceived authenticity.

For destinations targeting well-informed and discerning tourists, the adoption of two-sided messages is particularly advantageous. These tourists are inclined to conduct thorough research and value transparent and honest communication (Ivanov et al., 2018). By adeptly addressing potential drawbacks and offsetting them with compelling positives, destinations can effectively resonate with this demographic. Table 2.1 presents the summary of theoretical foundations.

Table 2.1 Summary of theoretical foundations

Theories and Major Contributors	**Origins**	**Main Points**	**Implications for This Study**
Destination Image Theory (Fakeye & Crompton, 1991; Bramwell and Rawding, 1996; Baloglu & McCleary, 1999; Tasci, A. D., Gartner, W. C., & Tamer Cavusgil, S., 2007)	Tourism management studies	Destination image can be categorized into projected image and perceived image, with a significant gap often existing between them. The formation of the destination image is shaped by destination marketing efforts.	The projected image of a destination shapes tourists' expectations, while the perceived image reflects their actual experiences. By refining marketing strategies, a destination can effectively influence both expectations and experiences.

Table 2.1 Summary of theoretical foundations (continued)

Theories and Major Contributors	**Origins**	**Main Points**	**Implications for This Study**
Expectancy-Disconfirmation Theory (Oliver, 1980)	Consumer behavior studies and marketing research	Consumer satisfaction is fundamentally influenced by the discrepancy between pre-consumption expectations and the actual performance of a product or service.	Tourist satisfaction is influenced by the gap between expectations and actual experiences. Thus, destination marketing strategies should focus on aligning projected and perceived images to enhance satisfaction.
Value Perception Theory (Holbrook, 1994)	Consumer behavior studies and marketing research	Consumers assess products or services based on the perceived value they offer, rather than solely on price or functional attributes.	Tourists evaluate a destination based on its perceived value. Consequently, destination marketing strategies should aim to enhance the perceived image to improve tourist satisfaction.
Agenda-Setting Theory (M. E. McCombs and Shaw, 1972)	Communication studies	The media's selection and emphasis on specific issues guide audiences to perceive them as more salient and	Destinations can strategically emphasize certain attributes through media to manage tourists' expectations, leading to a more accurate projected image that aligns better

Table 2.1 Summary of theoretical foundations (continued)

Theories and Major Contributors	Origins	Main Points	Implications for This Study
		significant than others.	with tourists' experiences.
Two-Sided Persuasion Theory (Hovland, C. I., Janis, I. L., & Kelley, H. H., 1953)	Communication Studies	A persuasive communication can be more effective if it presents both sides of an argument rather than just one.	Providing a balanced description of a destination's attributes, including shortcomings, reduces the likelihood of disappointment and enhances the credibility and persuasiveness of promotional messages.

2.3 Methodological Foundation

Digital innovation has profoundly transformed destination marketing and introduced new opportunities for studying destination image. In contrast to traditional methods, big data text mining technologies enhance both the efficiency and reliability of this research. Utilizing digital innovation to examine discrepancies between projected and perceived destination images allows for effective addressing of image congruence issues, ultimately leading to improved destination marketing strategies.

This section begins with a review of literature on destination image measurement. It then delves into three key areas: the application of Latent Dirichlet Allocation (LDA) modeling in destination image analysis, sentiment analysis, and the impact of destination image congruence on tourist satisfaction ratings. These areas form the methodological foundation for this research.

2.3.1 Measurement Approaches in Destination Image Research

1) Traditional Measurement Methods

In terms of data collection, scholars have identified several reliable sources for measuring destination image. Traditional data sources encompass two primary aspects: firstly, gathering relevant information about destinations from traditional media channels such as television, movies, newspapers, magazines, and travel guides; secondly, directly collecting data from respondents (Andreu et al., 2000). The first aspect focuses on studying the projected image of destinations, where information disseminated through these media informs how destinations are portrayed to potential tourists. The second aspect involves studying the perceived image of destinations, where data directly collected from respondents, such as through surveys or interviews, provides insights into tourists' actual experiences and perceptions (Grosspietsch, 2006). These dual approaches to data collection enable a comprehensive analysis of destination image from both promotional and experiential perspectives (CFVG, 2011).

Content analysis is a widely used method in destination image research for analyzing collected media data (Govers & Go, 2004b). This method involves systematically categorizing and interpreting textual or visual content to derive insightful understandings of how destinations are portrayed. In destination image research, the process begins with gathering data from diverse sources such as traditional media articles and promotional materials. Then coding schemes are developed to categorize content based on predefined criteria, which include destination attributes (e.g., scenery, culture) and tourist activities (e.g., sightseeing, dining) (Choi et al., 2007). This approach allows for both quantitative and qualitative analyses, often employing statistical techniques to uncover patterns, frequencies, and correlations within the dataset.

One of the key advantages of content analysis in destination image

research is its systematic approach to analyzing data, offering rigorous insights into how destinations are represented across different media platforms (Govers & Go, 2004b). However, content analysis also presents challenges. It demands significant time and effort to code and analyze large volumes of data comprehensively. Ensuring the reliability and validity of coding schemes and interpretations can be complex, as subjective biases may influence categorization decisions. Moreover, content analysis cannot fully capture subtle nuances or context-specific meanings embedded in media content, potentially limiting the depth of understanding derived from the analysis (Stemler, 2000).

Research focused on the perceived image of destinations constitutes a significant portion of the existing literature. Surveys targeting respondents are commonly employed to assess both the cognitive and emotional dimensions of destination image, providing insights into how tourists perceive various attributes of a destination. Within the literature, researchers have utilized a variety of methods, encompassing both structured and unstructured approaches, to measure destination image (Gallarza et al., 2002; Jenkins, 1999; J. Wang et al., 2021).

Structured methods in destination image research involve systematic data collection through surveys with predefined questions and scales, aiming to assess tourists' perceptions across specific dimensions such as scenic beauty, cultural richness, and hospitality. These methods are designed to provide standardized data that enable comparative analyses and statistical validation (Steve Pike, 2002).

In structured methods, various image attributes or constructs are typically specified to contribute to the overall perception of a destination (Echtner & Ritchie, 1993). These attributes are incorporated into a standardized instrument, such as a survey, where respondents rate their perceptions on each attribute using Likert scales or semantic differential scales. Likert scales allow respondents to indicate their level of agreement or disagreement with statements about different aspects

of the destination, while semantic differential scales use polar adjectives to capture perceptions along multiple dimensions.

After collecting data, statistical techniques such as averaging ratings and conducting factor analysis are employed to compute composite scores of destination image or to condense semantic scores into a smaller set of fundamental perceptual dimensions. These analyses serve to uncover patterns and correlations among various image attributes, offering valuable insights into tourists' perceptions and evaluations of destinations (Al-Azri & Morrison, 2006).

However, structured methods in destination image research are not without limitations. One main criticism is their potential to overlook the holistic aspect of destination image due to biases or incompleteness in selecting attributes for measurement. As highlighted by Jenkins (1999), unless careful consideration is given to compiling the list of attributes, some attributes may be deemed unimportant by individuals, or crucial attributes may be unintentionally omitted from the measurement framework. This limitation underscores the importance of thoughtful instrument design and validation in ensuring that structured methods effectively capture the diverse facets of destination image as perceived by tourists.

To address the limitations associated with structured methods, unstructured approaches in destination image research eschew predefined destination attributes and instead employ qualitative techniques such as open-ended interviews and focus groups. These methods encourage participants to freely articulate their impressions and perceptions of specific destinations, yielding rich and detailed insights. Techniques like focus groups, interviews, free elicitation, and essay writing are utilized to gather nuanced data for destination image assessment, enabling a comprehensive exploration of tourists' subjective interpretations and emotional responses (Echtner & Ritchie, 2003; Gallarza et al., 2002).

Combining structured and unstructured methods for measuring destination image, as recommended by Jenkins (1999), entails a systematic two-phase approach aimed at harnessing the strengths of each method while mitigating their respective limitations.

In the first phase, known as the qualitative or construct elicitation phase, the focus is on identifying and defining the relevant constructs or attributes of destination image. This phase employs qualitative techniques such as open-ended questions, content analysis of media sources, triads (where participants rank three aspects of a destination), and photo elicitation (using images to prompt discussion). These methods allow for capturing a wide range of perspectives and dimensions of destination image without imposing predefined constructs, thereby minimizing the risk of overlooking important aspects that may influence tourists' perceptions.

Once the constructs are identified and defined through the qualitative phase, the second phase involves quantitative measurement. Here, structured methods such as Likert scales and semantic differential scaling are employed to quantify tourists' perceptions across the identified constructs. Likert scales measure the intensity of agreement or disagreement with statements related to destination attributes, while semantic differential scales assess perceptions based on opposing adjectives (e.g., modern vs. traditional, crowded vs. serene). Jenkins (1999) also advocates for using separate rating scales to evaluate overall destination preference and construct-specific preferences, enhancing the holistic understanding of destination image formation.

This integrated approach not only ensures a comprehensive exploration of destination image but also enhances the validity and reliability of the findings by triangulating qualitative insights with quantitative measurements. By combining the qualitative depth of unstructured methods with the quantitative rigor of structured approaches, the complexity and nuances of tourists' perceptions and preferences

towards destinations can be effectively captured (Grosspietsch, 2006).

Table 2.2 summarizes the traditional measurement methods. However, traditional data collection techniques, including elicitation methods and surveys, continue to face challenges. Interviewer bias, respondent interpretation of survey questions, and scalability in larger studies must be addressed to ensure robust data collection (Dolnicar & Grün, 2012).

Table 2.2 Traditional methods for destination image measurement

Measurement Objectives	**Data Sources**	**Methods**
Projected image	Traditional media (e.g., television, movies, newspapers, magazines, and travel guides)	Content analysis
Perceived image	Participants (respondents)	Unstructured methods for data collection (e.g., open-ended interviews, focus groups, free elicitation, and essay writing). Analysis methods (e.g., content analysis)
		Structured methods for data collection (e.g., surveys with Likert scales, semantic differential scales). Analysis methods (e.g., descriptive statistics, factor analysis, multidimensional scaling, cluster analysis, t-test and ANOVA)

2) Big Data Approaches for Measurement

In addition to traditional measurement methods, the rise of digital

technology has significantly expanded the array of data sources accessible for destination image research, leading to the adoption of Big Data analysis methods. Big Data has been defined in various ways within academic literature, with the influential 3V model originally describing it by its volume, velocity, and variety (Laney, 2001). Building on this model, Kaisler et al. (2013) added attributes such as Value and Complexity. Mayer-Schönberger and Cukier (2013) defined Big Data as the capability to process vast volumes of data, analyze it, and uncover unexpected insights. Big Data analytics refers to the process of employing advanced analytical methods to extract insights from large, complex datasets generated from diverse sources. The application of Big Data in tourism has the potential to revolutionize the way destination image is measured and managed (Bui et al., 2021). The integration of Big Data research methods marks a new era in destination image research, providing unparalleled opportunities to explore and understand both the projected image of destinations and tourists' perceptions and behaviors in greater depth and detail.

Big Data measurement methods leverage a wide array of data sources, ranging from destination websites and social media platforms to Online Travel Agencies (OTAs), serving as crucial repositories for investigating both the projected and perceived images of destinations (Zhong et al., 2023).

In examining the projected image, the focus is on data sourced from destination marketing organizations (DMOs), which include promotional content, advertisements, and official announcements aimed at shaping external perceptions (Bui et al., 2021). Official DMO websites are particularly valuable, as they offer curated content showcasing a destination's attractions, cultural offerings, events, and practical tourist information (Mele & Cantoni, 2019).

Social media platforms and OTAs have become integral to destination image research (Briciu et al., 2019; Wacker & Groth, 2020), hosting a

blend of content from both DMOs and tourists themselves.

User-generated content (UGC), including textual reviews, photos, and satisfaction ratings, represents a rich data source for analyzing the perceived image of destinations (Iglesias-Sanchez et al., 2020). Platforms like Facebook, Twitter (later, it is rebranded as X), and Weibo play a significant role in capturing real-time tourist experiences and evolving sentiments towards destinations. These platforms facilitate continuous interaction and feedback, offering a dynamic dataset to assess how tourists perceive and engage with destinations over time. OTAs such as TripAdvisor, Booking.com, and Ctrip contribute reviews and ratings from a diverse user base. Beyond numerical ratings, these platforms offer qualitative insights through detailed reviews that delve into specific aspects of tourist experiences. This extensive dataset can be utilized to gauge satisfaction, discern patterns in tourist preferences, and uncover deeper insights into the factors driving destination choices and perceptions.

The incorporation of user-generated content (UGC) into destination image research aligns with modern practices in leveraging Big Data and computational methodologies within the realm of social sciences (Alarcón-Urbistondo et al., 2021; Hunter, 2016; Serna et al., 2013). This approach enables the use of advanced analytical techniques on large-scale datasets, extracting meaningful insights that enhance understanding of destination image dynamics and tourist behaviors in nuanced and comprehensive ways.

In destination image research from 2013 to 2022, the majority of studies focused on collecting textual data, whereas a smaller proportion gathered image data, and very few included video data (Z. Wang et al., 2023a). Textual data sources spanned online reviews, social media posts, blog entries, and official tourism publications, offering diverse perspectives on how destinations are portrayed and perceived.

The limited collection of image and video data in destination image

studies can be attributed to the inherent complexities in processing and analyzing visual media. Image and video data necessitate advanced computational techniques for tasks such as feature extraction and context recognition, which are more intricate and resource-intensive compared to text mining (Arefieva et al., 2021). Despite these challenges, recent advancements in computer vision and multimedia analytics have started to facilitate more integrated approaches. These approaches aim to combine textual and visual data to achieve a comprehensive understanding of destination image dynamics, leveraging technological innovations to enhance analytical capabilities and extract deeper insights (H. Li et al., 2022).

Computer-based Big Data mining techniques utilize a diverse array of sophisticated analytic methods to extract profound insights from a wide range of data sources (Albalawi et al., 2020). These methods play a crucial role in unraveling the intricate dimensions of how destinations are perceived and depicted in digital landscapes.

Topic Modeling is a prominent technique that uncovers prevalent themes and topics within textual data. By applying algorithms like Latent Dirichlet Allocation (LDA), patterns in social media posts and other textual sources can be identified (Kirilenko et al., 2021). This approach allows for the systematic categorization and summarization of large volumes of content, revealing dominant narratives and key aspects of destination image.

Cluster Analysis groups similar items based on predefined characteristics. This method helps segment data into clusters that share common attributes, facilitating a nuanced understanding of different facets of destination perception (Zhong et al., 2023). For instance, clusters can distinguish between aspects like cultural attractions, natural landscapes, or hospitality experiences based on textual or image data.

Social Network Analysis explores the relationships and interactions within social media networks. By examining network structures and

user interactions, one can identify influential nodes and communities discussing specific destinations (Y. Wang et al., 2017). This analysis elucidates how information spreads and how influential users shape perceptions and discussions about destinations.

Semiotic Analysis delves into the symbolic meanings embedded in textual and visual representations of destinations. It focuses on decoding signs, symbols, and cultural references that contribute to the construction of destination identity and appeal. This method is crucial for understanding how destinations are marketed and perceived through visual media and promotional materials (Hunter, 2016).

Geospatial Analysis utilizes Geographic Information Systems (GIS) to map and analyze spatial data related to destinations. Geographic patterns such as tourist flows, distribution of attractions, or geographic clusters of positive or negative sentiment towards destinations can be visualized. Geospatial analysis provides spatial context to destination image research, revealing geographic variations in perceptions and tourist behaviors (Lyu et al., 2022).

Sentiment Analysis adds another layer of analysis by assessing the sentiment expressed in textual data. Natural language processing techniques classify opinions as positive, negative, or neutral towards destinations (Q. Jiang et al., 2021). This method helps quantify public sentiment and identify sentiment trends over time, informing destination managers and marketers about the effectiveness of their strategies and initiatives.

Recent advancements in natural language processing (NLP) and machine learning have significantly bolstered analytical capabilities in destination image research. The increasing adoption of machine learning highlights its growing relevance and popularity in this field (Dong et al., 2023). Using both supervised and unsupervised techniques, machine learning models automate and improve the accuracy of data analysis. This allows for the discovery of intricate patterns and the

derivation of deep insights from large datasets. Zhou et al. (2017) emphasize that machine learning offers substantial advantages in analyzing Big Data, empowering models to refine and amplify analytical capabilities effectively. This integration not only streamlines data processing but also elevates the precision and reliability of content analysis outcomes. Consequently, these advancements contribute significantly to a more profound comprehension of destination image dynamics, thereby fostering the development of more effective destination marketing strategies and refined management practices. Table 2.3 provides an overview of Big Data approaches for destination image measurement.

Table 2.3 Big data approaches for destination image measurement

Measurement Objectives	**Data Sources**	**Methods**
Projected image	Website (e.g., Official DMO website) Online travel agencies (e.g., TripAdvisor, Booking.com, Ctrip) Social media (e.g., Facebook, Instagram, Twitter, Weibo, Wechat)	Data collection: Utilize web crawlers to systematically gather data from various online sources. Data analysis: Apply big data mining techniques, such as topic modeling, social network analysis, cluster analysis, and sentiment analysis, utilizing advanced natural language processing (NLP) and machine learning methods for enhanced accuracy and depth.
Perceived image	Online travel agencies (e.g., TripAdvisor, Booking.com, Ctrip) Social media (e.g., Facebook, Instagram, Twitter, Weibo, Wechat)	

However, research on the use of Big Data in destination image measurement is still in its early stages. As scholars continue to explore and develop methodologies for harnessing Big Data, the field is poised for significant advancements. Future research efforts will likely focus on refining analytical techniques and integrating various data sources to provide a more holistic and nuanced analysis of destination image, enhancing the accuracy and depth of research findings (Z. Wang et al., 2023a).

In the existing literature, destination perceived image is typically measured using either traditional methods or big data approaches, with few studies integrating both. The reliability of big data methods has not been fully established, leaving a critical gap in understanding whether online data alone can accurately reflect tourists' perceived images.

Therefore, it is essential to explore whether user-generated content (UGC) data effectively captures the full scope of tourists' perceptions. To address this gap, a hybrid approach that combines traditional measurement methods, such as questionnaires, with big data techniques, like online text mining, should be considered. This combined approach can provide a more comprehensive understanding of perceived images, thereby enhancing the reliability and depth of research findings.

2.3.2 Utilizing LDA Modeling for Destination Image Analysis

As big data analysis has gained prominence in the study of destination image, a variety of sophisticated text mining techniques have been adopted. By leveraging these advanced methodologies, profound insights into how destinations are perceived and promoted can be uncovered, enhancing the understanding and management of destination image.

One of the most frequently applied text mining techniques is topic modeling, which aims to identify and extract hidden themes within a body of text. Compared to traditional methods of topic extraction involving high-frequency word counting and manual classification, topic modeling presents advantages in terms of objectivity, efficiency, and comprehensiveness. It

enables a more precise elucidation of topic information within natural language textual data (Kirilenko et al., 2021).

Topic modeling helps in understanding the main subjects or topics discussed in the data, thus providing a comprehensive view of the underlying patterns in tourist perceptions and destination marketing strategies. The integration of advanced text mining techniques such as topic modeling into destination image research has significantly enhanced the ability to analyze and interpret large volumes of textual data, revealing complex and nuanced insights. Prominent techniques in topic modeling include Latent Semantic Analysis (LSA), Probabilistic Latent Semantic Analysis (PLSA), Non-Negative Matrix Factorization (NMF), Correlated Topic Model (CTM), Dynamic Topic Model (DTM), and Latent Dirichlet Allocation (LDA) (Vayansky & Kumar, 2020).

Latent Semantic Analysis (LSA) is a foundational technique that employs singular value decomposition to reduce the dimensionality of textual data, thereby revealing latent relationships between terms and documents. This method helps in identifying co-occurring terms that form meaningful topics, providing a deeper understanding of the textual data. Probabilistic Latent Semantic Analysis (PLSA) builds on LSA by introducing a probabilistic framework, where each word in a document is modeled as a mixture of topics (Vayansky & Kumar, 2020). This enhancement improves the interpretability and robustness of the results, making it a powerful tool for topic identification.

Non-Negative Matrix Factorization (NMF) is another influential technique that factorizes the term-document matrix into non-negative matrices, ensuring that the resultant topics are more interpretable. NMF is particularly useful for highlighting distinct and coherent topics that align closely with human intuition, making the findings more accessible and understandable. The Correlated Topic Model (CTM) extends traditional topic modeling by accounting for correlations between topics, offering a more nuanced understanding of the relationships between different themes. This allows for a richer and more interconnected view of the data. The Dynamic Topic Model (DTM) introduces a temporal dimension to topic modeling, enabling the

study of how topics evolve over time. This capability is particularly valuable in destination image research, where tourist perceptions and marketing strategies can change dynamically (Kherwa & Bansal, 2019).

Latent Dirichlet Allocation (LDA) is a generative probabilistic model used for topic modeling in text mining. This three-level hierarchical Bayesian model assumes that each document in a corpus is a mixture of several topics, and each topic is a distribution over words (Blei et al., 2003). LDA assigns probabilities to each word in a document for each topic, allowing for the identification of latent themes within large collections of text. Each topic generated by LDA can serve as an attribute, and associated words play a pivotal role in characterizing these attributes (Poria et al., 2016).

Although various topic modeling techniques have their own advantages, LDA has become the most commonly used method in text mining for destination image analysis. Other topic modeling techniques have certain limitations: LSA relies on linear algebra techniques such as singular value decomposition (SVD), which can sometimes lead to less interpretable results compared to LDA's probabilistic topics. PLSA, though similar to LDA, lacks the generative model framework, which can limit its flexibility and scalability. NMF, while producing interpretable topics, often requires more fine-tuning and is less scalable for very large datasets. CTM and DTM introduce additional complexity by modeling topic correlations and temporal dynamics, respectively. While these features can provide deeper insights, they also require more sophisticated modeling and computational resources, which can be a barrier to widespread adoption (Jelodar et al., 2019; Kherwa & Bansal, 2019).

LDA modeling offers several key advantages and characteristics that make it particularly suitable for addressing the specific needs of destination image analysis (Q. Chen et al., 2023; X. Chen et al., 2021).

Firstly, LDA's probabilistic framework provides a robust and flexible approach to topic modeling. It assumes that documents are generated by a mixture of topics and that each topic is a distribution over words. This

probabilistic nature allows LDA to handle the inherent uncertainty and variability in large text corpora, making it particularly effective for analyzing diverse and unstructured textual data related to destination image.

Secondly, LDA is highly scalable and can efficiently process large datasets, which is crucial in big data environments. Destination image research often involves analyzing vast amounts of data from various sources such as social media, online reviews, and official tourism websites. LDA's scalability allows handling of these large datasets without significant computational limitations.

Thirdly, the output of LDA is relatively easy to interpret. It provides a clear representation of topics as distributions over words and documents as distributions over topics. This clarity helps researchers and practitioners understand the main themes and patterns within the data, making it easier to derive actionable insights for destination marketing and management.

Fourthly, LDA's flexibility allows it to be applied to a wide range of text types and structures. Whether dealing with short social media posts, detailed blog entries, or comprehensive reviews, LDA can adapt to the varying lengths and styles of textual data commonly found in destination image research. This adaptability makes it a versatile tool for different types of textual analysis.

Fifthly, LDA has gained widespread adoption in the research community, leading to extensive documentation, tutorials, and implementation support. This broad acceptance has led to a wealth of resources available for leveraging, including well-maintained libraries in programming languages like Python (e.g., Gensim, scikit-learn) and R. The availability of these tools simplifies the implementation process and reduces the technical barriers for researchers.

Sixthly, LDA's strong theoretical foundation in Bayesian statistics provides a rigorous basis for its application. Its well-established underlying assumptions and mathematical formulation provide a solid framework for building upon. This theoretical robustness enhances the credibility and reliability of the results obtained through LDA, ensuring that findings are both scientifically sound and trustworthy.

In addition, LDA offers distinct advantages over other text mining methods such as social network analysis (SNA) and cluster analysis (Jelodar et al., 2019). While SNA is adept at mapping and analyzing relationships within text networks, it primarily focuses on structural properties like key nodes and opinion leaders in social interactions rather than the thematic content of texts. This makes SNA less effective in extracting and interpreting topics from unstructured textual data, which is crucial for uncovering nuanced perceptions and descriptions of destinations. Cluster analysis, on the other hand, relies on predefined attributes or similarity measures to group documents into clusters based on structural similarities. In destination image analysis, this approach may overlook subtle or emerging themes that are not explicitly defined beforehand. Unlike LDA, cluster analysis lacks a probabilistic interpretation of themes in text, limiting its ability to reveal latent patterns or themes that underpin tourists' perceptions and descriptions of destinations (Qin Li et al., 2019).

The LDA model has been extensively employed to uncover hidden thematic structures, facilitate document classification, and offer insights into large, unstructured text datasets (Jelodar et al., 2019). Its probabilistic framework and ability to identify latent topics without predefined categories make it particularly suited for exploring the complex attributes of destination image perception. By extracting and interpreting themes from extensive text datasets, LDA enhances our understanding of tourists' subjective experiences and preferences towards destinations. Its widespread adoption in tourism research underscores its effectiveness in identifying topics that resonate with tourists (Q. Chen et al., 2023), thereby contributing to the definition of destination image attributes, improving reliability, and potentially introducing novel theoretical perspectives (X. Chen et al., 2021).

Before employing LDA modeling for text analysis, it is imperative to pre-process the text to ensure that it is in an optimal format for analysis (R. Wang et al., 2019). Text pre-processing involves several crucial steps, including word segmentation, punctuation removal, stop words removal, and other normalization procedures. These steps are essential for reducing noise and

improving the quality of the input data, thereby making the subsequent analysis more accurate and meaningful. Effective pre-processing establishes the foundation for robust topic modeling, enabling uncovering significant patterns and insights from the text. Given that each language possesses unique grammatical structures and usage patterns, it is essential to utilize text processing tools that are specifically designed for the language of the text being analyzed.

For English text, the Natural Language Toolkit (NLTK) in Python is a widely used and powerful suite of libraries for text pre-processing (M. S. Lin et al., 2021). NLTK provides comprehensive tools for tokenization, stemming, lemmatization, and stop word removal, among other functions. It enables breaking down sentences into individual words or tokens, removing irrelevant punctuation, filtering out common but uninformative words, and normalizing the text to its base form. For Chinese text, the preferred text processing tool is typically Jieba (Peng et al., 2022). This tool, which can be implemented through Python, is highly effective for Chinese word segmentation. Chinese text presents unique challenges due to the lack of spaces between words and the complexity of characters. Jieba addresses these challenges by using efficient algorithms to segment sentences into individual words or phrases, making it easier to analyze the text. Additionally, Jieba offers functionality for removing stop words and performing other pre-processing tasks that are tailored to the nuances of the Chinese language (Jinyan Chen et al., 2022). Selecting the right text processing tool is a critical step in the pre-processing phase, as it significantly impacts the quality of the data used in LDA modeling.

Scholars have employed LDA modeling to analyze perceived images from both static and dynamic perspectives. From a static perspective, researchers have examined destination images without considering potential changes over time. For example, they identified the attributes of destination images or compared images from multiple destinations (Peng et al., 2022; Ren & Hong, 2017; Taecharungroj & Mathayomchan, 2019). Conversely, from a dynamic perspective, changes in destination images over time have been investigated in separate studies. These included examining public attitudes towards the

post-earthquake recovery of the Indonesian islands, investigating shifts in international tourists' perceptions of a South Korean island during two distinct periods, and comparing destination images before and after tourists traveled to Jiuzhaigou, China (Kun Kim et al., 2019; J. Wang et al., 2021; Y. Yan et al., 2020). However, there is a lack of literature exploring the use of LDA modeling for analyzing projected images.

2.3.3 Sentiment Analysis in Destination Image Research

Sentiment analysis, a pivotal area in text mining and natural language processing, has garnered substantial attention due to its ability to decode emotional nuances within textual data (Guerreiro & Rita, 2020). This computational process not only identifies but also comprehends the underlying sentiments expressed in various forms of text, ranging from social media posts and online reviews to news articles and customer feedback (González-Rodríguez et al., 2016). It plays a crucial role in understanding public opinion, customer satisfaction, and user engagement across digital platforms.

Beyond a simplistic classification of positive, neutral, or negative sentiments, sentiment analysis aims to capture the contextual polarity embedded in user-generated content (UGC), reflecting the complexities of human emotions and attitudes (Alaei et al., 2019). It involves analyzing not just individual words but also the syntactic structure and semantic context of sentences to infer the intended sentiment accurately. This nuanced approach allows sentiment analysis to discern subtle variations in sentiment expression, such as sarcasm, irony, or ambiguity, which are prevalent in informal online communication.

The proliferation of digital platforms has exponentially increased the volume of online data, underscoring the methodological advantages of sentiment analysis over traditional manual approaches (Mehraliyev et al., 2022). By automating the analysis of large-scale textual data, sentiment analysis offers cost-effectiveness and efficiency, enabling organizations to swiftly gauge public opinion, monitor brand reputation, and detect emerging trends. Moreover, its application extends beyond commercial realms to encompass

diverse fields such as political analysis, healthcare feedback assessment, and social sciences research.

Sentiment analysis methodologies exhibit diverse approaches, which include lexicon-based methods, machine learning techniques, and hybrid models that combine these strategies to enhance accuracy (Q. Jiang et al., 2021)

1) Lexicon-based methods

Lexicon-based methods form a foundational approach, leveraging predefined sentiment dictionaries that assign scores to words based on their semantic orientation. These dictionaries are meticulously curated to include emotion-related words and their corresponding polarity values, facilitating the computation of sentiment scores for individual words and overall texts. This method is advantageous for its transparency and simplicity in assigning sentiment values, making it suitable for quick assessments across different types of textual data (Manosso & Domareski Ruiz, 2021).

In English text sentiment analysis, several prominent dictionary-based tools are widely used. SentiWordNet functions as a lexical resource that assigns sentiment scores to words based on their synsets, facilitating the assessment of sentiment intensity through semantic relationships. VADER (Valence Aware Dictionary and sEntiment Reasoner) is specifically designed for social media text, integrating a sentiment lexicon with grammatical rules to accurately measure sentiment intensity. This tool is particularly effective in deciphering informal expressions. Similarly, AFINN applies sentiment scores to words using a predefined list of sentiment words and their associated valences, providing a straightforward method for analyzing sentiment across diverse English texts (Al-Natour & Turetken, 2020; Mehraliyev et al., 2022).

In Chinese text sentiment analysis, lexicon-based tools like HowNet and NTUSD (National Taiwan University Sentiment Dictionary) distinguish themselves from their English counterparts. HowNet

utilizes semantic relationships within Chinese texts to derive sentiment scores, thereby enhancing the accuracy of sentiment analysis through comprehensive lexical coverage. Yi Liu et al. (2019) detailed the sentiment scoring calculation rules based on the HowNet lexicon and applied them to destination image research. NTUSD, on the other hand, is specifically designed for sentiment analysis in Chinese texts, providing a structured framework to evaluate sentiment polarity and intensity across various domains and contexts. These tools are instrumental in deciphering and interpreting sentiment expressions in Chinese (Ren & Hong, 2017; Zhai & Chen, 2020).

2) Machine learning methods

Machine learning techniques in sentiment analysis delve into the intricacies of language patterns and relationships. By training on annotated datasets containing labeled sentiment categories, these models learn to discern nuanced sentiment expressions and generalize from the learned patterns to classify sentiments effectively (Kirilenko et al., 2018). This approach excels in handling complex linguistic contexts and can adapt to varying domains and languages, provided sufficient annotated data for training.

Machine learning approaches in sentiment analysis include several effective methods. The Naive Bayes Classifier stands out for its application in text classification tasks, leveraging probabilistic models to classify sentiments based on feature extraction from labeled datasets. This classifier assumes strong (naive) independence between features, making it computationally efficient and straightforward to implement. Support Vector Machines (SVM) are also prominent, known for their ability to identify optimal hyperplanes that separate positive and negative sentiment classes in complex data spaces. Deep Learning Models, such as Long Short-Term Memory networks (LSTM), excel in capturing intricate dependencies in textual data, allowing for the nuanced analysis of sentiment patterns over longer sequences. Each of

these methods offers distinct advantages depending on the complexity of the sentiment analysis task and the nature of the textual data being analyzed (Manosso & Domareski Ruiz, 2021; Mehraliyev et al., 2022).

Due to its efficiency, simplicity, and low resource requirements, the Naive Bayes Classifier demonstrates significant advantages over SVM and LSTM in sentiment analysis of tourist online reviews, especially in scenarios involving large datasets and limited computational resources (H. Xu & Lv, 2022).

3) Hybrid methods

Hybrid methods represent a synthesis of lexicon-based and machine learning approaches, aiming to capitalize on their respective strengths. By integrating lexicon-based sentiment scoring with the pattern recognition capabilities of machine learning, hybrid models enhance accuracy and robustness across diverse textual datasets. This integration addresses inherent limitations such as domain-specific biases in lexicon methods and the dependency on extensive labeled data in pure machine learning approaches (Alaei et al., 2019; T. Zhang et al., 2022). Consequently, hybrid models are well-suited for applications requiring precise sentiment analysis across domains ranging from customer feedback in e-commerce to public sentiment analysis in social media.

The selection of sentiment analysis methodology depends on various factors, including the nature of the textual data, the desired level of granularity in sentiment analysis, and computational resources available for model training and deployment.

In the field of tourism research, SnowNLP is widely used for sentiment analysis of Chinese texts and has demonstrated proven effectiveness (Zhiyong Li et al., 2024; H. Xu & Lv, 2022; S.-N. Zhang et al., 2022). SnowNLP is a Python library specifically designed for processing Chinese texts, including sentiment analysis. It employs a hybrid approach that integrates machine learning techniques with lexicon-based sentiment analysis, leveraging the strengths of both methodologies.

SnowNLP utilizes a Naive Bayes Classifier to model the training data. It is trained on labeled Chinese sentiment datasets, comprising sentences with positive and negative sentiments. During the training process, SnowNLP extracts features from the text, using the Naive Bayes Classifier to calculate the probability that a given feature belongs to a particular category. Although the core algorithm is the Naive Bayes Classifier, SnowNLP incorporates sentiment lexicons during the feature extraction stage to enhance the accuracy of sentiment analysis (S.-N. Zhang et al., 2022).

The sentiment analysis module of SnowNLP uses a pre-trained model that can effectively analyze the sentiment tendencies of Chinese text. The model outputs a sentiment score ranging from 0 to 1, indicating the sentiment tendency of the text, with values closer to 1 representing positive sentiment and values closer to 0 representing negative sentiment. SnowNLP's sentiment analysis relies on built-in corpora and models, which have varying levels of effectiveness depending on the specific field or context of the text. The model can be retrained using additional manually labeled data to optimize and adapt it for specific domains, thereby enhancing its effectiveness in text analysis tasks (Zhiyong Li et al., 2024; Y. Lin et al., 2022).

Sentiment analysis has been employed in the examination of tourism-related online texts, offering valuable insights into tourists' attitudes and effectively representing the affective image of a destination (Ali et al., 2021). This analytical technique captures and quantifies the sentiments expressed by tourists in their reviews, social media posts, and other forms of user-generated content. Additionally, sentiment analysis is often integrated with topic extraction methods to analyze destination images more holistically. Topic extraction involves identifying themes or topics within the text, revealing the cognitive image of a destination as perceived by tourists. By combining sentiment analysis with topic extraction, the cognitive and affective dimensions of tourists' perceptions can be merged, providing a more comprehensive understanding of destination images. This integrated approach has been shown to be highly effective in enhancing our knowledge of how destinations are viewed and experienced, ultimately aiding in better

destination management and marketing strategies (Jinyan Chen et al., 2022; Q. Jiang et al., 2021).

However, current methods for topic extraction predominantly rely on counting high-frequency words followed by manual classification (L. Meng et al., 2021). While this approach can be effective, it is labor-intensive and may miss nuanced themes within the data. Research that integrates LDA topic modeling with sentiment analysis remains limited. Combining LDA with sentiment analysis could potentially enhance the granularity and depth of insights by not only identifying the key topics within the text but also associating these themes with the sentiments expressed (Z. Wang et al., 2024). This integrative approach holds promise for more comprehensive and scalable analysis of tourism texts, yet it requires further exploration and development to realize its full potential.

2.3.4 Impact of Destination Image Congruence on Satisfaction Ratings

Bramwell and Rawding (1996) distinguished destination image into projected image and perceived image, research on destination image congruence has gained prominence. Extensive efforts have been dedicated to exploring various methods for assessing this congruence.

A seminal study in this field by Andreu et al. (2000) investigated the relationship between the perceived and projected image of Spain in the British market. The projected image was derived from an analysis of principal sources of secondary information promoting Spain, while the perceived image was obtained from a study conducted among 120 British tourists. Notable differences were observed between the projected and perceived images, leading to the recommendation of a consumer-focused orientation in marketing strategies. Subsequently, Grosspietsch (2006) employed questionnaire surveys to compare the images of Rwanda as perceived by tourists and as projected by international tour operators.

In another study, Farmaki (2012) identified and compared the projected and perceived images of Cyprus. They used secondary sources such as brochures, advertising campaigns, and tourism websites to identify the projected image

and conducted a questionnaire survey with 393 British tourists to measure the perceived image.

With the rapid development of Internet technology and digital media, from 2013 onwards, the data source for studying destination image consistency has increasingly shifted from offline to online platforms. S. Khan (2013) examined the perceived and projected image of India by utilizing online content from the travel blog virtualtourist.com and the official tourism promotion website of India, IncredibleIndia.org. The study found that there was congruence between the perceived and projected images.

Silva and Costa (2017) analyzed the projected image of Brazil based on the official website (visitbrasil.com) and the perceived image through a questionnaire survey. Marine-Roig and Ferrer-Rosell (2018) explored the projected and perceived images of the Mediterranean destination Catalonia, using data from the Catalan Tourist Board dossier, Lonely Planet travel guide, and user-generated content (UGC). The UGC consisted of a random sample of 80,000 online travel reviews written in English by tourists who visited Catalonia during 2015.

Since 2019, most studies on the gap between projected and perceived images have utilized online data, primarily from social media, Online Travel Agencies (OTAs) and official destination websites. For example, Wacker and Groth (2020) compared photos collected from Instagram to identify differences between the projected and perceived destination images in posts by the Tyrol Tourist Board and actual tourists. Q. Chen et al. (2023) analyzed Xiamen city by collecting 110,098 official promotional texts and tourist online reviews, using topic modeling for analysis.

Such analyses have proven invaluable in illuminating the gaps between the promotional material created by destination management organizations and the actual experiences encountered by tourists. By examining the relative representation of different aspects within the projected and perceived images, these studies enable analysis of disparities and identification of specific areas of incongruence. This knowledge is instrumental in devising effective

marketing strategies that align more closely with tourists' perceptions.

However, most research on destination image congruence focuses on macro-level units such as countries or cities, often overlooking the image congruence of smaller, individual attractions (Y. Li et al., 2023; Ramkissoon et al., 2011). This focus on broader destinations leaves a significant research gap, as the perceived image of specific attractions can differ markedly from that of the larger destination. By adopting a more granular perspective to examine image congruence at the attraction level, researchers can gain fine-grained insights that allow for more precise and targeted destination marketing strategies. Additionally, while many studies have identified the gap between projected and perceived images, they often fall short in providing in-depth analysis and actionable recommendations on how to bridge this gap and enhance the congruence between the two. Table 2.4 provides an overview of the studies on destination image congruence utilizing online data.

Table 2.4 Overview of destination image congruence studies using big data

Source	Title	Sample Size	Contributions	Limitations
Michaelidou, Siamagka, Moraes, & Micevski, 2013	Do Marketers Use Visual Representations of Destinations That Tourists Value? Comparing Visitors' Image of a Destination with Marketer-Controlled Images Online	100 photos from visitors, 1,526 pictures from a variety of website sources	Highlighted the disparities between the holistic image of Taiwan construed by visitors and the image created by marketers.	The sample size is limited, and no insight is provided on how to bridge the disparities.
Stepchenkova & Zhan, 2013	Visual destination	1,255 photos	Compared images of Peru	The application of research methods

Table 2.4 Overview of destination image congruence studies using big data (continued)

Source	Title	Sample Size	Contributions	Limitations
	images of Peru: Comparative content analysis of DMO and user-generated photography		collected from a DMO's site and from Flickr and identified and visualized differences.	outside of Peru is challenging. The accuracy of image semantic analysis requires improvement.
Mak, 2017	Online destination image: Comparing national tourism organization's and tourists' perspectives	71,469 words and 2,744 photos	Compared tourist and organization content for destination images. Tourists' content is more effective for conveying affective attributes.	The method of sentiment analysis on photos is difficult to replicate. No suggestions for improving affective attributes of image by organizations.
Marine-Roig & Ferrer-Rosell, 2018	Measuring the gap between projected and perceived destination images of Catalonia using compositional analysis	80,000 online travel reviews	Comparison of three information sources: user-generated content differed significantly from Lonely Planet and Catalan Tourist Board content,	There is a lack of implications on how to bridge the gap to keep the destination image congruence.

Table 2.4 Overview of destination image congruence studies using big data (continued)

Source	Title	Sample Size	Contributions	Limitations
			which were more alike.	
Lojo, Li, & Xu, 2020	Online tourism destination image: components, information sources, and incongruence	208,348 words and 4,990 pictures	Compared four sources: DMOs, agencies, guides, and blogs. Blogs and agencies provide more appraisive images, while guides and blogs present more prescriptive images.	The classification of images into designative, appraisive, or prescriptive types may be influenced by subjectivity. Additionally, there is a lack of suggestions for enhancing image congruence.
He, Deng, Li, & Gu, 2021	How to "Read" a Destination from Images? Machine Learning and Network Methods for DMOs' Image Projection and Photo Evaluation	28,106 photos	Identified gap between content types. Used user-generated content to guide organization-generated content on social media.	The analysis solely relied on data from social media, disregarding the more direct impact of OTAs on tourist decision-making.
Qu, Xiang, & Dong, 2022	Network mechanism contrast: a new perspective of the 'projection-perception'	331 texts from DMOs and 347 blogs	Examined 'projected-perceived' image networks of the destination and discussed	The sample size is limited, and it overlooked semantic analysis in text mining, resulting in a lack

Table 2.4 Overview of destination image congruence studies using big data (continued)

Source	Title	Sample Size	Contributions	Limitations
	contrast of the destination image	from tourists	implications of achieving congruity between them.	of attributes comparison in destination image.
Li, He, Li, Huang, & Liu, 2023	Keep it real: Assessing destination image congruence and its impact on tourist experience evaluations	83,333 online travel reviews	Destination image congruence positively affects tourists' appraisal of their destination experiences.	The data source is limited, as it is derived from a single OTA. The analysis focuses solely on text similarity, without a comparison of destination image attributes.

The congruence between the projected and perceived images of a destination is widely acknowledged as critically important (Duan et al., 2020; Iordanova & Stainton, 2019; W. Sun et al., 2021). While extensive research has explored destination image congruence, few studies have specifically addressed its relationship with satisfaction ratings.

The existing literature includes studies by Joppe et al. (2001) and Govers and Go (2004a), who explored the intricate relationship between destination image and tourist satisfaction. They affirmed that both the projected image (how a destination portrays itself) and the perceived image (how tourists perceive the destination) collectively shape tourists' satisfaction levels through a process of mutual expectation matching. The degree of tourist satisfaction is closely linked to the alignment between the projected image of the destination and tourists' actual perceptions upon arrival (Farmaki, 2012).

Building upon this foundational understanding, recent empirical research by Y. Li et al. (2023) further illuminates the significance of congruence between the projected image and the perceived image in influencing tourists' satisfaction ratings on Online Travel Agencies (OTAs). This analysis enhances our comprehension of the impact of destination image on tourist satisfaction in the digital era, emphasizing the critical role that image congruence plays in shaping overall satisfaction levels. However, the study's data source is limited, relying on a single OTA, and the analysis primarily focuses on text similarity, lacking a comprehensive comparison of destination image attributes.

Tourist satisfaction is crucial for the sustainable development of a destination (Razović, 2013). Given the substantial attention destination image has garnered as a critical determinant of tourist satisfaction (Bigne et al., 2001; C.-F. Chen & Phou, 2013; Chi & Qu, 2008; B. Lee et al., 2014), further research is warranted to deepen our understanding of the relationship between destination image congruence and tourist satisfaction.

2.4 Research Gaps

2.4.1 Destination Image Congruence and Satisfaction

While extensive research has examined destination image congruence, few studies have focused on its correlation with satisfaction ratings. Currently, only one study has explicitly stated that destination image congruence significantly positively affects tourists' satisfaction ratings on Online Travel Agencies (OTAs) (Y. Li et al., 2023). However, the analysis of the destination's projected image in this study is limited by a narrow data source, relying solely on promotional texts from one OTA.

Considering the diverse range of marketing channels utilized by destinations, it is crucial to expand data collection platforms to ensure comprehensive reflection of the destination's projected image. Further research should integrate broader and more diverse data sources to validate the correlation between destination image congruence and satisfaction ratings. Given the pivotal role of destination image in influencing tourist satisfaction, enhancing

our understanding of this relationship is essential for developing effective strategies to improve overall tourist satisfaction.

2.4.2 Integration of LDA Modeling and Sentiment Analysis

Although scholars have employed Latent Dirichlet Allocation (LDA) modeling to analyze perceived images, there is a notable gap in the literature regarding the use of LDA for analyzing projected images.

Additionally, while LDA modeling and sentiment analysis have been separately utilized to analyze user-generated content (UGC) in perceived image research, their integration remains underexplored. LDA modeling identifies various destination image attributes through topic extraction, with each topic's intensity indicating its relative importance. Sentiment analysis, on the other hand, captures the emotional orientation of the text publisher toward these attributes (Jinyan Chen et al., 2022). This research proposes a systematic integration of two established methods into a novel framework for analyzing destination image. This approach not only elucidates the perceived importance of various destination attributes but also captures tourists' attitudes towards them.

2.4.3 Data Sources for Analyzing Perceived Image

In destination image research, the data sources used to understand tourists' perceived images are predominantly derived from either user-generated content (UGC) or questionnaires. Recent studies have increasingly favored UGC data due to its public accessibility and vast volume (Ashfaq et al., 2022; W. Sun et al., 2021). However, a critical research gap persists regarding the extent to which online data alone can effectively capture tourists' perceived images.

It is essential to investigate whether UGC data accurately captures the breadth and depth of tourists' perceptions, as online reviews might be influenced by certain biases. To address this gap, a mixed-methods approach, which combines UGC with traditional questionnaire data, should be considered. This integrated method would provide a more nuanced and comprehensive understanding of perceived destination image, thereby enhancing both the

reliability and depth of research outcomes.

2.4.4 Dynamics Between Projected and Perceived Images

While existing research has extensively explored perceived images, the study of projected images remains relatively underdeveloped, particularly concerning the factors influencing them. Current literature predominantly examines how projected images affect perceived images, with limited investigation into whether perceived images, in turn, influence projected images. The potential for a bidirectional influence between these two dimensions and the feasibility of adjusting projected images based on perceived images represent significant research gaps that require further exploration.

To address this gap, it is crucial to investigate the congruence between projected and perceived images using advanced digital innovation methods and to explore strategies for adjusting the projected image based on the perceived image. Such an approach has the potential to uncover an interactive relationship, challenging the existing unidirectional framework and advancing destination image theory by introducing a bidirectional dynamic. Additionally, this perspective could provide theoretical support for developing methodologies that utilize real-time assessments of tourists' perceptions, enabling continuous refinement and adjustment of projected images.

2.4.5 Focus on a Specific Attraction

Most studies on destination image congruence focus on macro-level units such as countries or cities, often overlooking smaller entities like individual attractions (Y. Li et al., 2023; Ramkissoon et al., 2011). This focus on broader destinations presents a significant research gap, as the perceived image of specific attractions can differ markedly from that of the broader destination. Employing a microscopic perspective to study image congruence at the attraction level can yield fine-grained insights, enhancing the precision of destination marketing strategies. This approach reveals nuances in tourist perceptions that might be obscured in macro-level studies.

Furthermore, although many studies have identified the gap between projected and perceived images, they frequently lack in-depth analysis and actionable recommendations for bridging this gap and improving the alignment between the two.

2.4.6 Giant Panda Tourism Market in China

China's burgeoning giant panda tourism market, particularly those centered around panda bases, demonstrates substantial growth potential (X. Li et al., 2023). Despite the significance of this market segment, research focusing on panda tourism is notably underdeveloped. This research gap poses a significant challenge for destination managers in developing effective marketing strategies tailored to this niche.

Understanding the unique aspects of panda tourism and the gap between projected and perceived images is vital for developing effective marketing strategies. Analyzing the congruence between the image promoted and the image perceived by tourists can identify key areas for enhancement. Accurately conveying and delivering the unique appeal of giant panda tourism will help maximize the potential of this market segment.

CHAPTER 3

Methodology

3.1 Research Questions

3.1.1 Question 1

What is the impact of destination image congruence on tourists' satisfaction ratings?

Question 1 is raised to establish the foundational importance of destination image congruence on tourist satisfaction, highlighting why maintaining congruence is critical and setting the stage for measuring congruence.

This question is addressed through a questionnaire survey. The questionnaire gathers tourists' views on the consistency of the destination image and their travel satisfaction. Additionally, it collects tourists' opinions on whether this consistency affects their satisfaction. Descriptive statistics and correlation analysis are employed to draw conclusions from the collected data.

3.1.2 Question 2

How can the congruence between the projected image and the perceived image of a destination be measured?

Question 2 is crucial for developing a robust scale to measure image congruence, which is essential for identifying any discrepancies between the projected and perceived images. This question emphasizes the methodological aspect of the research, aiming to establish reliable and valid measures to assess the alignment between the projected image (as communicated through official channels) and the perceived image (as experienced and reported by tourists).

To address this question, LDA modeling was first employed to identify the topics within both the projected and perceived images of the destination, assess the importance of each topic, and track their trends across different quarters. Next, sentiment analysis was conducted to evaluate the performance of each topic within the perceived image. The results from the questionnaire survey were then analyzed and compared with the online textual data to validate the reliability of the online text analysis. Finally, the comparison between the topics, their importance, and their quarterly trends in the projected and perceived images was made to identify any gaps between the two, providing insights into areas of misalignment that require attention.

3.1.3 Question 3

How can marketing strategies be employed to enhance destination image congruence and thereby improve tourist satisfaction ratings?

Question 3 seeks to develop targeted marketing strategies that address gaps between the projected and perceived images of a destination, enhance tourists' perceived value, and optimize the allocation of marketing resources. To answer this question, the study utilizes the data analysis results from previous questions and conducts an Importance-Performance Analysis. By applying relevant theories such as value perception theory, agenda-setting theory, and two-sided persuasion theory, the study formulates effective marketing strategies aimed at improving tourist satisfaction.

The three research questions are interrelated and build upon each other to achieve a comprehensive understanding and practical solutions for destination image management. These questions guide a systematic exploration, moving from understanding the impact of image congruence on satisfaction, to developing measurement tools, and finally to proposing actionable strategies. This progression ensures that the study not only identifies problems but also offers practical solutions, ultimately aiming to enhance the destination's appeal and competitiveness.

The research questions are closely aligned with the theories discussed in Chapter 2. Destination Image Theory provides the framework for

understanding the projected and perceived images of a destination and emphasizes the importance of measuring their alignment. Expectancy-Disconfirmation Theory explains how satisfaction is influenced by the gap between expectations and actual experiences, supporting the empirical exploration of the relationship between destination image congruence and tourist satisfaction. Value Perception Theory informs the development of marketing strategies aimed at enhancing the destination's perceived image.

Moreover, Agenda-Setting Theory suggests that strategic marketing can promote congruence between projected and perceived images by emphasizing certain attributes of the destination. Two-Sided Persuasion Theory advocates for providing balanced information to manage tourists' expectations effectively. It supports the creation of marketing messages that address both the strengths and potential shortcomings of a destination, contributing to better image consistency.

These theories collectively offer a robust theoretical foundation for understanding and addressing issues related to destination image congruence, satisfaction, and effective marketing strategies.

3.2 Research Design

This study employs a mixed-methods approach, integrating qualitative and quantitative research methods, to investigate the disparity between the projected and perceived images of the Panda Base within China's emerging giant panda tourism market. By analyzing the collected data, the study aims to propose effective marketing strategies that enhance the alignment between these two images, ultimately improving tourists' satisfaction ratings and fostering the long-term sustainable development of the destination. The research design comprises four key phases:

Phase 1: Online Textual Data Collection and Analysis

In the initial phase, online textual data is gathered and analyzed. Web crawler technology is employed to systematically collect official promotional materials and tourist reviews concerning the Panda Base. Subsequently, text mining techniques are applied to comprehensively analyze the collected data, facilitating an in-depth exploration of the Panda Base's destination image, encompassing both its projected and perceived facets.

Phase 2: Questionnaire Survey

Phase 2 involves the collection and analysis of questionnaire data through a structured survey conducted among tourists who have recently visited the Panda Base. The survey gathers information on tourists' evaluations of the congruence between the projected and perceived image of the Panda Base, their satisfaction ratings, and their perceptions on various aspects of the destination. The primary aim of this survey is to verify the impact of destination image congruence on tourists' satisfaction ratings and to cross-validate these findings with the results of online textual data analysis of tourists' reviews.

Phase 3: Cross-Validation of Questionnaire and Textual Data

In the third phase, data obtained from the questionnaire survey is compared with the results from the online textual data analysis of tourist reviews. This comparison aims to validate the robustness and reliability of the text mining methodology. By integrating these two data sources, insights into the effectiveness of textual data analysis will be gained, enabling a more comprehensive understanding of the destination's perceived image. This cross-validation process enriches the analysis and findings of the study, ultimately leading to a reasonable evaluation of tourists' perceived image of the Panda Base.

Phase 4: Comparative Analysis and Strategy Formulation

The final phase involves the comparative analysis of the projected and perceived images of the Panda Base to identify existing gaps. Building upon this analysis, the study proposes tailored marketing strategies aimed at enhancing the congruence of the destination image. These strategies encompass improvements in the dissemination of official promotional messages and enhancements in related tourism products and services. The overarching goal is to drive the sustainable development of the destination by aligning tourists' expectations with their actual experiences.

It is important to note that all raw data collected for this study are in Chinese. As this paper is written in English, the data analysis results have been translated into English in the following sections for presentation.

3.3 Data Collection Methods

3.3.1 Online Textual Data Collection

The online textual data collected in this study comprise two main types: official promotional messages reflecting the projected image of the destination, and tourist reviews conveying the perceived image of the destination. A customized web crawler tool was employed to systematically gather this data, which includes textual content accompanied by corresponding publication or posting timestamps.

1) Platform for Collecting Promotional Messages Data

The data sources for the official promotional messages, which represent the projected image of the destination, include the Panda Base's official website and official social media channels such as WeChat (a leading Chinese instant messaging, social media, and mobile payment app developed by Tencent), the official Weibo account (a Chinese microblogging website), and the official Douyin account (a short-form video hosting service owned by ByteDance, with its overseas counterpart known as TikTok). The selection of these platforms is based on several considerations: each is directly managed by the Panda Base, ensuring high authority and credibility. Second, WeChat, Weibo, and Douyin are among the most popular social media applications in the current Chinese internet market, with a significant user base (Fitzgerald et al., 2022). Third, apart from the official website, the Panda Base maintains official accounts solely on these three social platforms for disseminating information (CRBGPB, 2024b). By integrating the textual content from these platforms, a comprehensive understanding of the Panda Base's official promotional efforts is achieved, effectively reflecting its projected image. A detailed overview of these four platforms is provided below:

The Panda Base official website (https://www.panda.org.cn/) offers extensive information on giant panda conservation, research, and information services. Key sections include news updates, event

information, tourist services (such as hours, tickets, transport, maps, dining, and shopping), and scientific research. The website also provides other information like educational resources and volunteer opportunities. Language options available on the website include Simplified Chinese, Traditional Chinese, Japanese, and English. Since most of the information on the official website has not been updated for a long time, this study aims to analyze the projected image of the Panda Base over a specific period. Therefore, only the frequently updated news and event information from the official website was collected.

Figure 3.1 The official simplified Chinese website of the panda base

Figure 3.2 The official English website of the panda base

The official Weibo account of the Panda Base can be found at https://weibo.com/u/1798176285, with the account name on the Weibo app listed as "Chengdu Research Base of Giant Panda Breeding." Weibo, a popular Chinese social media platform similar to Twitter, allows users to post short messages, pictures, videos, and other content, and to interact with other users. It is widely used in China by individuals, companies, and organizations for sharing information, brand promotion, and fan engagement (Jia Chen et al., 2020).

Figure 3.3 The official Weibo account of the panda base

The Panda Base's official Weibo account serves as a crucial channel for public interaction and information sharing. It currently has more than 563,000 followers and has garnered 1.74 million reposts, comments, and likes. The content published on this account includes news, activities, announcements, real-time tourist numbers in the scenic area, daily photos and videos of giant pandas showcasing their living conditions and behaviors, updates on the base's progress and achievements in giant panda protection and breeding, educational materials on giant panda conservation, and information on volunteer recruitment and public participation in protection activities. All the aforementioned content was collected.

The WeChat public account of the Panda Base is only accessible via the

WeChat app and does not have a separate website. The account name is "Chengdu Research Base of Giant Panda Breeding."

WeChat, the most popular social media platform in China, offers multifunctional capabilities such as messaging, payments, shopping, gaming, and lifestyle services. WeChat public accounts allow enterprises, institutions, and individuals to publish content and provide services to engage users (B. Yang et al., 2023).

The Panda Base's WeChat public account offers extensive information to the public. It regularly shares updates on news, events, and research related to giant panda conservation. Users can access electronic maps, contact information, panda updates, and volunteer services. The account also provides detailed introductions to indoor venues like the Panda Art Gallery and Panda Museum, as well as the outdoor attraction Panda Valley. Moreover, it facilitates ticket purchases for visiting the base, including entry and sightseeing bus tickets.

Through this platform, the Panda Base enhances communication with the public and offers more convenient services, ensuring that tourists have easy access to all necessary information and resources for their visit. All the articles pushed by WeChat public account to followers during a specified period of time were collected for this study.

Figure 3.4 The WeChat public account of the panda base

The official Douyin account of the Panda Base is accessible at https://www.douyin.com/user/MS4wLjABAAAA8l3R5iQTWJc_W0_7HVDQhoVdvAUEC_IuDmvYeI9x4ug, under the account name "Chengdu Research Base of Giant Panda Breeding." The official Douyin account ID of the Panda Base is 1973805224. This digital portal serves as a vibrant window into the daily rhythms and conservation efforts of giant pandas, seamlessly blending entertainment with education.

Douyin, the Chinese video-sharing social platform synonymous with its international counterpart TikTok, provides an immersive space for users to create, share, and consume short-form videos spanning an array of genres (Ying Liu et al., 2023).

At the heart of the Panda Base's official Douyin account are its meticulously curated videos, meticulously crafted to showcase the endearing antics and natural behaviors of giant pandas. From playful

romps to serene moments of repose, each video captures the essence of these beloved creatures, fostering a deep connection with viewers. Beyond mere entertainment, the Panda Base leverages its Douyin platform to champion the cause of panda conservation. Through engaging narratives and informative content, followers are not only entertained but also enlightened about the pressing issues facing giant pandas and the efforts underway to safeguard their future.

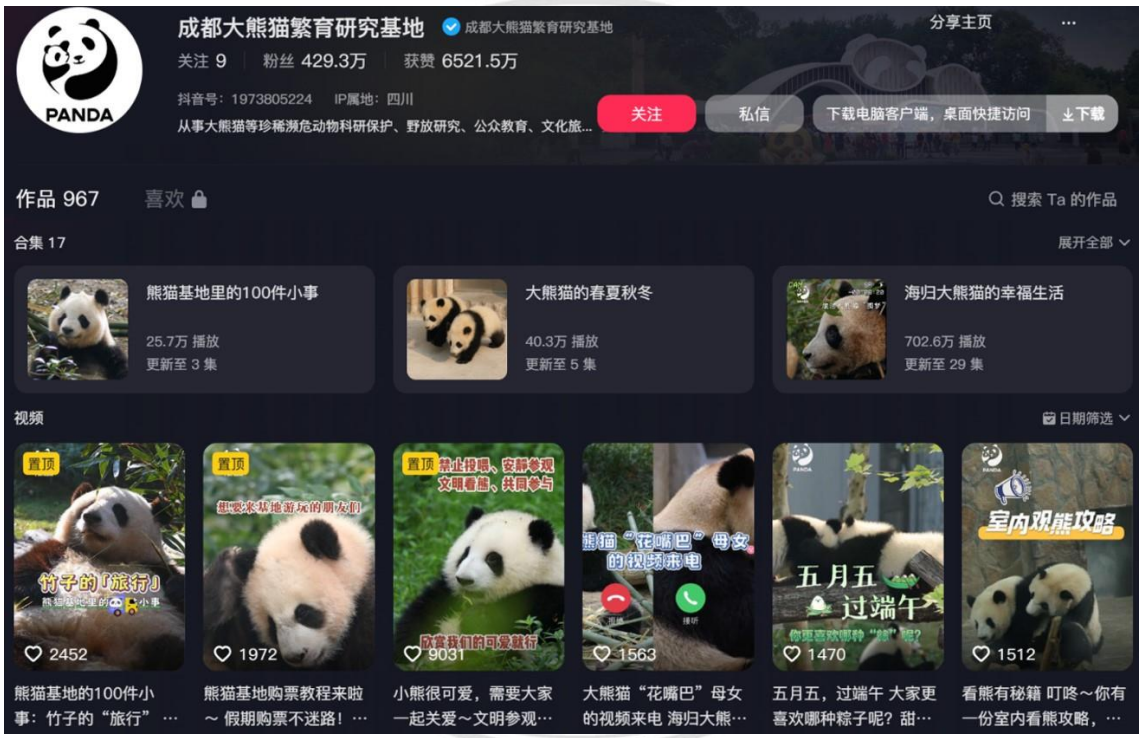

Figure 3.5 The official Douyin account of the panda base

This platform enables the Panda Base to engage with the public more vividly. With 4.293 million followers and 65.215 million likes, the Panda Base's official Douyin account captivates audiences of all ages, particularly drawing the attention of younger demographics who frequent the platform. During a specified period, the text under all videos pushed by this official Douyin account to its followers was collected for this study.

It is crucial to emphasize that this study exclusively gathers textual data disseminated by the Panda Base across the aforementioned four

platforms. The research scope explicitly excludes the collection of pictures, audio files, or videos. For instance, on Douyin, only the textual descriptions accompanying each video were collected, which are typically presented alongside the corresponding video content. Notably, the videos themselves are not collected as part of this study.

Furthermore, when collecting data from WeChat, Weibo, and Douyin, each piece of content posted on these platforms is treated as a document due to their real-time streaming nature. In contrast, data from the official website were collected directly from webpages, where each webpage's entire content is considered as a document. Specifically, only the content from webpages in simplified Chinese was collected. This version is preferred for its comprehensive and enriched content compared to other language versions.

2) Platform for Collecting Tourists Reviews Data

Tourist reviews were collected from leading Online Travel Agencies (OTAs) in China, namely Ctrip and Meituan. According to Fastdata, a third-party industry research institution, Ctrip held a 36.3% share of the tourism market transaction volume in 2021, while Meituan accounted for 20.6% (Fastdata, 2022). Given its significant presence in China's tourism market, Ctrip has often been utilized as a primary data source in prior studies (Ren & Hong, 2017; Wu et al., 2020). Ctrip has emerged as a crucial online data source for numerous studies in the domain of destination research within China, and previous research underscores the reliability of Ctrip as a data source (Y. Li et al., 2023). However, research on Meituan remains limited. This study aims to address this gap by incorporating data from Meituan, thereby diversifying the sample distribution and enabling a more comprehensive and robust exploration of the research questions.

Both platforms, Ctrip and Meituan, serve as comprehensive platforms offering brief introductions to popular attractions like the Panda Base. They facilitate travel reservation services, allowing tourists to

conveniently book tours and related activities. After their visits, tourists have the option to share in-depth reviews detailing their travel experiences, perceptions of the attractions, and overall satisfaction ratings (Y. Jiang, 2022; Zhu, 2022). These reviews contribute to a collective understanding of tourist perspectives and provide valuable feedback for both the attractions and future tourists planning their visits. For this study, only tourist reviews were collected from the Panda Base's homepage on these two platforms. Below is an overview of these two data sources:

The homepage of the Panda Base on the Ctrip website can be accessed at https://you.ctrip.com/sight/chengdu104/4229.html#ctm_ref=www_hp_his_lst. Tourists can reach this page by entering the URL directly into their browser or searching for "Chengdu Research Base of Giant Panda Breeding" within the Ctrip app. As of May 1, 2024, the Panda Base's homepage has accumulated a total of 73,725 tourist reviews, including more than 65,000 post-visit reviews. The satisfaction rating given by tourists for the Panda Base averages at 4.6 out of 5, indicating high overall satisfaction among tourists. Tourists have the option to post text, pictures, or videos in their reviews.

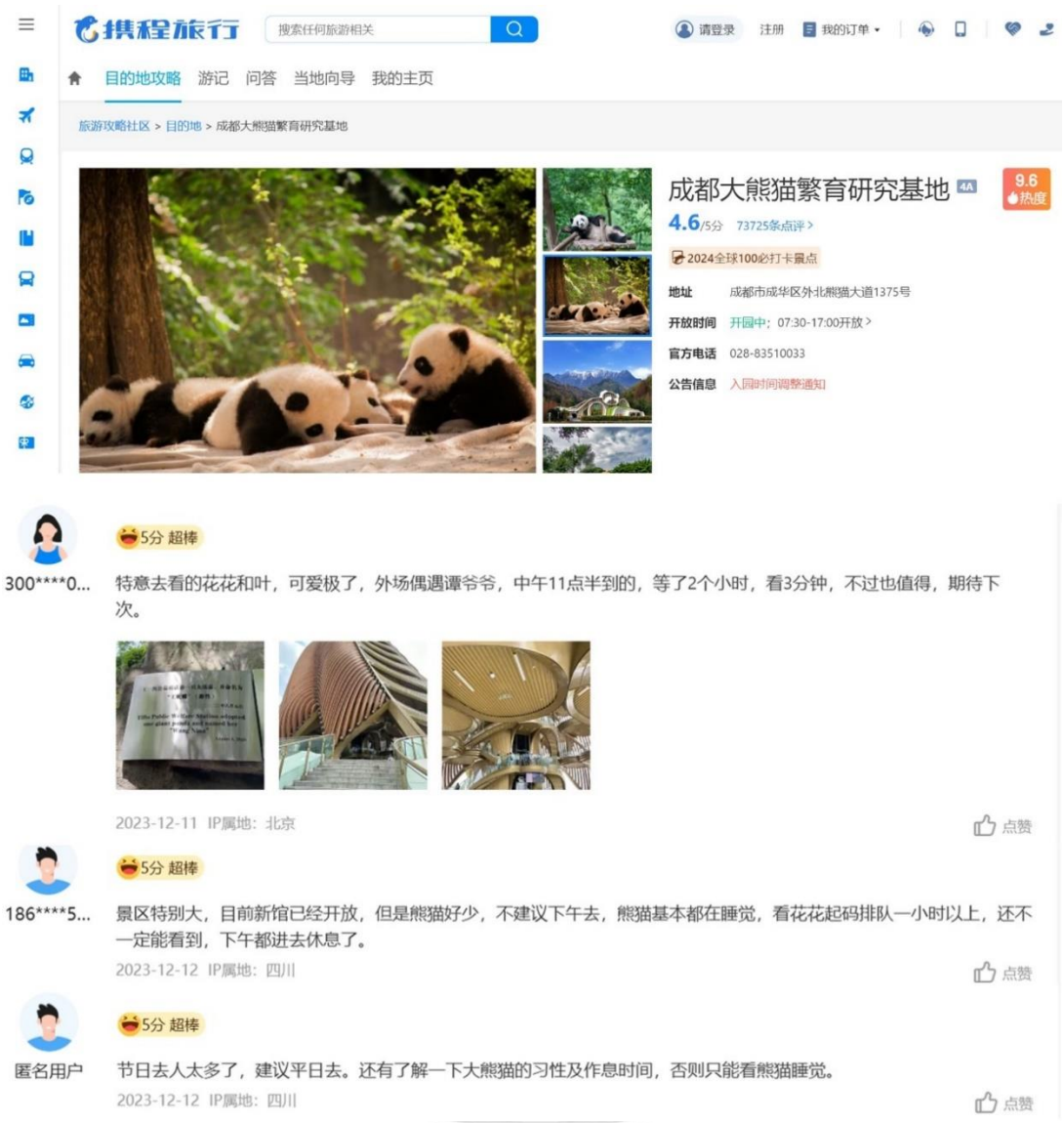

Figure 3.6 The panda base's homepage on Ctrip

Meituan does not provide website access services; tourists can exclusively access the homepage of the Panda Base through the Meituan app by searching for "Chengdu Research Base of Giant Panda Breeding." As of May 1, 2024, the Panda Base's homepage has accumulated over 275,000 reviews from tourists, including more than 27,000 post-visit reviews. The average satisfaction rating among tourists for the Panda Base is 4.4 out of 5 points. Similar to Ctrip, tourists using Meituan can share their experiences through text, pictures, or videos in their reviews.

Figure 3.7 The panda base's homepage on Meituan

It is noted that this study exclusively collected post-visit tourist reviews from the Panda Base homepage on Ctrip and Meituan to accurately reflect tourists' perceptions of the destination after completing their trip. Additionally, this study only gathered textual content from the reviews, explicitly excluding pictures and videos.

3) Data Collection Period

The data collection period spans 15 months, from January 1, 2023, to

March 31, 2024. This timeframe was chosen based on several considerations. Firstly, the destination image is inherently dynamic, and selecting recent data can more accurately reflect the current destination image, thereby providing better insi Following the expert review, a pilot test was conducted with a small sample from ghts for formulating marketing strategies. Secondly, this period excludes the timeframe impacted by the COVID-19 pandemic. This study defines the pandemic period from December 31, 2019 (when a viral pneumonia case was reported on the official website of the Wuhan city government), to December 7, 2022 (when China's State Council issued new COVID-19 prevention and control measures). From January 2023 onward, the Chinese tourism market began to recover gradually. Between January 2023 and March 2024, China's tourism market developed steadily without major political, economic, or social disruptions, allowing the destination image to remain relatively stable (Wen, 2023; J. Yang, 2024). Thirdly, spanning five quarters, from January 2023 to March 2024, facilitates convenient quarterly analysis of destination image trends. Data collection occurred on April 26-30, 2024.

3.3.2 Questionnaire Data Collection

1) Questionnaire Design

The questionnaire survey aims to verify the influence of destination image congruence on tourists' satisfaction ratings and to gain insights into their perceptions of the Panda Base. Subsequently, the questionnaire results are cross validated with findings from online textual data analysis. Analyzing the consistency between questionnaire and online survey results enhances the study's comprehensiveness by providing deeper insights into the perceived image of the destination, thereby enriching its overall analysis and findings.

The questionnaire is structured into three primary sections to achieve its objectives: the first section focuses on gathering participant demographics, the second section explores the congruence of

destination image and participants' travel satisfaction, and the third section measures participants' perceptions of the destination image.

The measurement of perceived destination image in this study includes 17 attributes, meticulously selected to capture both the general perceptions and unique features of the Panda Base as a tourist destination. The attributes are derived from two principal sources:

Firstly, the indicators were grounded in established frameworks and seminal studies on destination image measurement. This involves a thorough review of influential academic works by leading scholars, who provide comprehensive models and discussions on the complexities of destination image. (Beerli & Martin, 2004; Echtner & Ritchie, 1993; Gallarza et al., 2002; Iordanova & Stylidis, 2019; H. Song & Hsu, 2013).

Based on their work, destination image attributes can be primarily categorized into several types: natural resources, natural environment, social environment, infrastructure, and tourist leisure and recreation. Natural resources include elements such as weather and biodiversity. The natural environment encompasses features like landscapes, crowding, and pollution (air and noise). Social environment factors involve aspects such as hospitality, friendliness, and language barriers. Infrastructure cover transportation, facilities, tourist information services, and other related amenities. Tourist leisure and recreation pertains to specific activities available to tourists, such as hiking, skiing, and wildlife viewing. As noted by Beerli and Martin (2004), these measurement attributes are not fixed and should be adapted to reflect the unique characteristics of each destination.

Secondly, to enhance the practical relevance and comprehensiveness of the indicators, expert opinions were sought through consultations with two tourism scholars from the School of Tourism and Cultural Industries at Chengdu University. These scholars were invited due to their extensive research experience in panda tourism, including their

participation in research projects related to the Giant Panda National Park and their supervision of student investigations into panda cultural and creative products at the Panda Base. Additionally, input from a senior tourism practitioner was sought, who is a manager at the Panda Base, offering a practical perspective on the most relevant and significant attributes from an industry standpoint.

By integrating these two sources of information—theoretical frameworks and expert insights—the study constructs a robust and comprehensive measurement of the perceived destination image of the Panda Base. This method ensures that the selected attributes are not only theoretically sound but also practically relevant, providing a reliable basis for analyzing how the Panda Base is perceived as a tourist destination.

In the third part of the questionnaire, respondents are asked to rate each attribute using a Likert five-point scale. This scale measures both the perceived importance of each attribute and its corresponding performance during the tourists' visit. This structured approach established a foundation for comparing questionnaire data with text analysis results.

After drafting the questionnaire, expert reviews and pilot testing were conducted to evaluate its clarity, effectiveness, and accuracy in measuring the target variables. These steps were essential for identifying and addressing potential issues, thereby enhancing the validity of the questionnaire. Initially, the questionnaire was reviewed by three experts who assessed its validity using an Index of Item-Objective Congruence (IOC) check. Based on their evaluations, revisions were made to improve each item.

Following the expert review, a pilot test was conducted with a small sample from the target population. This pilot test served two key purposes: firstly, it provided critical insights for further refining the questionnaire; secondly, it enabled the calculation of the sample

standard deviation, which was used to estimate the population standard deviation and determine the required sample size for the main survey. Based on the feedback from the pilot test, additional revisions were made, and the finalized version of the questionnaire is presented in the Appendix of this study.

2) Sample Size Calculation

The questionnaire survey employed a Likert five-point scale to gather consumers' perception data regarding the destination. Each question in the third part was structured on this scale, typically considered suitable for processing continuous or nearly continuous data, as it represents a continuous rating scale. According to the formula for calculating sample size for continuous data, determining the sample size requires establishing the confidence level, estimating the population standard deviation, and defining the allowable margin of error (precision) beforehand (Israel, 1992; Kotrlik & Higgins, 2001).

The sample size calculation formula is presented as follows (Formula 1), where Z (Z-score) denotes the critical value on the standard normal distribution curve that aligns with the desired confidence level, σ stands for the estimated population standard deviation, and E signifies the allowable error margin (precision).

$$n = \frac{z^2\sigma^2}{E^2} \quad (1)$$

These parameters are essential for determining the appropriate sample size in statistical calculations, ensuring reliable results within specified confidence intervals and margins of error.

The study's confidence level was set at 95%, which corresponds to a Z-score of 1.96 on the standard normal distribution curve. This Z-score represents the critical value required to achieve the desired level of confidence in the study's results. Simultaneously, the allowable error range (precision), denoted as E, was specified at 0.1. This margin defines the maximum acceptable deviation between the sample's results

and the population's true characteristics.

Estimating the population standard deviation, denoted as σ, is crucial but often requires preliminary data. In this study, a pilot survey was conducted with a sample size of 42 individuals from the target population. The survey focused on the third section of the questionnaire, assessing various aspects related to the destination's image. For each question in this section, individual standard deviations were calculated, and then averaged to derive an overall sample standard deviation of 0.86.

Given these parameters—$Z = 1.96$, $\sigma = 0.86$, and $E = 0.1$—the sample size calculation formula was applied to determine the required number of participants for the main questionnaire survey. The formula ensures that the sample size is adequate to achieve a 95% confidence level with a precision level of 0.1. The calculation yielded an approximate sample size of 284 participants, rounded up to the nearest integer to ensure statistical validity and reliability in the study's findings. This approach not only establishes a robust framework for data collection but also ensures that the study's conclusions are based on a sufficiently large and representative sample of respondents.

The total number of questionnaires to be collected depends on the estimated proportion of invalid questionnaires. In this study, the estimated proportion of invalid questionnaires is 20%. Therefore, at least 355 questionnaires need to be collected to ensure 284 valid responses.

3) Data Collection Process

The questionnaire survey was conducted from July 11 to 15, 2024, at the Chengdu Research Base of Giant Panda Breeding. Four trained research assistants, who are students at Chengdu University, assisted in distributing and collecting the questionnaires.

The survey targeted tourists aged 20 and above who had visited the Panda Base in 2023 or 2024. Tourists were randomly invited to

participate in a questionnaire survey, where the purpose and benefits of the survey were explained. Emphasis was placed on the voluntary nature of participation and the right to withdraw at any time. Upon submitting the questionnaire, participants received a small souvenir, such as a pen shaped like a bamboo shoot with a panda headdress or a notebook with a panda cover, as a token of appreciation for their participation. This approach not only facilitates effective data collection but also ensures immediate feedback and clarification, thereby enhancing the efficiency of the recruitment process.

The questionnaires were distributed in both paper and electronic formats. The electronic version was administered through the WJX Professional Questionnaire Platform (https://www.wjx.cn/), accessed by participants through QR code scanning.

A total of 355 questionnaires were collected, including 120 paper questionnaires and 235 electronic questionnaires. After collection, the following steps were taken to exclude invalid questionnaires. For paper questionnaires, any with unanswered questions or missing data were marked as invalid. For electronic questionnaires, a two-step check was performed. First, if the completion time recorded by the survey platform was less than 120 seconds, indicating that the respondent might not have answered seriously, the questionnaire was marked as invalid. Second, it was checked whether multiple questionnaires were submitted from the same IP address. If so, only one questionnaire was retained. After excluding invalid questionnaires, a total of 307 valid responses were obtained, yielding an effective response rate of 86.5%.

Subsequently, data from paper questionnaires were transcribed into Excel for processing, while data collected via WJX was directly downloaded as an Excel file.

3.4 Data Analysis Methods

This study employed a range of analytical methods to achieve its objectives. Descriptive statistics and Spearman's rank correlation coefficient were utilized to examine the impact

of image congruence on tourist satisfaction based on questionnaire data. Latent Dirichlet Allocation (LDA) modeling was applied to both promotional messages and tourist reviews to identify and compare differences in content, importance, and trends between projected and perceived images. Sentiment analysis and Importance-Performance Analysis (IPA) were used to explore perceived images in greater detail. These analyses informed the development of marketing strategies. Additionally, Exploratory Factor Analysis (EFA) was conducted on the questionnaire data, and the findings were compared with topics derived from LDA modeling of online textual data. Cross-validation was employed to ensure the reliability of the analyses.

3.4.1 LDA Modeling

Before conducting LDA modeling, the textual data underwent thorough cleaning. This pre-processing step ensures the data is in a suitable format for analysis. Subsequently, LDA modeling was performed to extract topics from the dataset. The importance of each topic was then evaluated based on its probability within the document-topic matrix generated by the LDA model. This probability indicates the prevalence of each topic, allowing for a comprehensive understanding of the main themes within the textual data.

The entire LDA modeling process was applied to both the promotional messages dataset and the tourist reviews dataset. This section focuses specifically on the analysis of tourist reviews for illustration.

1) Textual Data Pre-processing

In this study, the online textual data includes two datasets: promotional messages and tourist reviews, all in Chinese. Before conducting LDA modeling, the text needs to be thoroughly cleaned and pre-processed. Jieba was chosen as the text pre-processing tool due to its specialized capabilities in effectively handling Chinese text. It is widely recognized and extensively used in tourism research (Dong et al., 2023; Zhiyong Li et al., 2024; T. Zhang et al., 2022). The Jieba library was imported into Python and employed for textual data pre-processing.

Text pre-processing is pivotal in preparing collected data for analysis.

The process ensures data quality through essential steps. Initially, Jieba was used to remove duplicate data and handle any missing values in the dataset. It then segmented continuous Chinese text into meaningful units—separate words or tokens. After segmentation, punctuation marks, special characters, emoticons, numbers, and URLs were systematically removed to streamline the text. Following this, stop words like conjunctions and prepositions were eliminated, allowing the analysis to focus on substantive content. Additionally, synonym replacement and normalization techniques were applied to ensure consistency. The result was segmented textual data output generated by Jieba, which maintained the original structure of the text for further analysis.

Subsequently, Gensim, a Python library, was utilized to create a dictionary that maps each unique word to a unique ID. The tokenized text was then converted into a "bag of words" representation using Gensim's functionality within Python. This representation transformed each document into a vector where each element denotes the frequency of a specific word. The "bag of words" model is commonly referred to as the corpus input for LDA (Latent Dirichlet Allocation). This vectorized format helps the LDA model understand the distribution of words within documents, enabling it to infer latent topic structures.

2) LDA Modeling

Python Gensim Toolkit was employed to implement the LDA model for topic extraction, as depicted in Figure 3.8. Each review, denoted as the m-th review, generates a topic probability distribution denoted as $\theta m \sim \text{Dirichlet}(\alpha)$. Here, θm represents the topic probability distribution for the m-th review, and α is the Dirichlet prior parameter for the multinomial distribution of each topic. Similarly, each topic (indexed as k) generates a probability distribution of words, denoted by $\varphi k \sim \text{Dirichlet}(\beta)$. In this context, φk signifies the probability of words for the k-th topic, and β acts as the Dirichlet prior for the multinomial

distribution associated with words linked to a topic. The parameters for testing, Zm,n ~ Multinomial(θ) and Wm,n ~ Multinomial(φZm,n), signify the generated topics and words, respectively.

In this model, hyperparameter K, signifying the number of topics, plays a crucial role in shaping the ultimate output results. The optimal number of topics needs to be determined prior to initiating the LDA model. When considering the selection of hyperparameter K, perplexity emerges as a valuable metric, serving as a reference for assessing the model's performance (Blei et al., 2003).

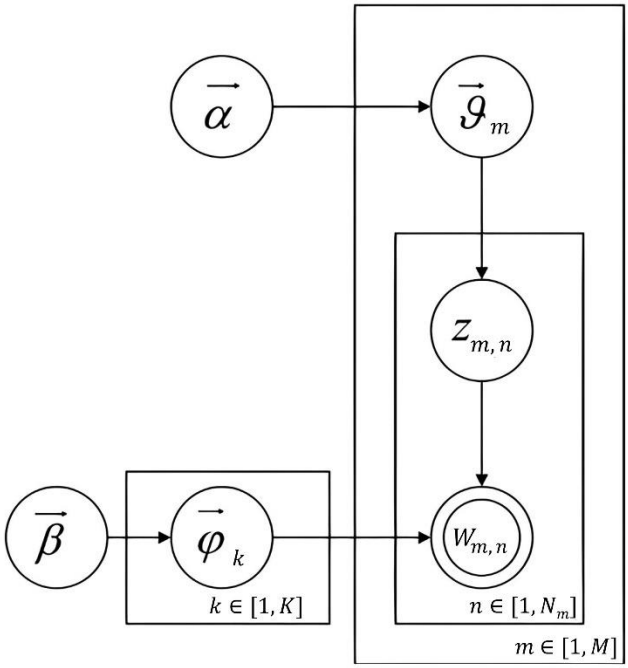

Figure 3.8 LDA model structure

(Source: Blei et al., 2003)

Perplexity reflects the model's predictive capability for unseen textual data, indicating the difficulty the model faces in predicting new textual information given its trained parameters (Vayansky & Kumar, 2020). In LDA, Perplexity is computed based on the probability distribution of each word given the inferred topics. It evaluates the model's performance by comparing the predicted word sequences with the actual observed sequences in the data. If a model effectively captures

the underlying topic structure of the corpus during training, its perplexity on unseen test data should be relatively low. Conversely, if the model fails to generalize well to new data, the Perplexity will be higher (Cao et al., 2009; Hagen, 2018).

Perplexity can be seen as the logarithmic expectation of how confused or uncertain the model is about predicting each word in new documents. Perplexity calculation helps assess the generalization ability and predictive accuracy of LDA models on unseen data, making it a crucial metric for evaluating the quality of topic models (Arun et al., 2010; Jelodar et al., 2019). The formula of how Perplexity is computed in LDA is presented as below:

$$\text{Perplexity} = \exp\left(-\frac{\Sigma_{d=1}^{D}\log p(\mathrm{w}_d)}{\Sigma_{d=1}^{D}N_d}\right) \quad (2)$$

Where, D denotes the number of documents in the dataset. Each document d contains N_d words. w_d denotes the word sequence in the d-th document. $p(\mathrm{w_d})$ represents the probability of generating document w_d according to the trained LDA model, computed as the product of probabilities of each word in the document under the inferred topic and word distributions.

Log-Likelihood ($\log p(\mathrm{w}_d)$) represents the logarithm of the probability that the LDA model assigns to generating document w_d. The sum of the word counts across all documents in the dataset is denoted by $(\Sigma_{d=1}^{D}N_d)$.

Typically, the perplexity score declines with an increase in the number of topics but may rise again at a certain point. This is because more topics lead to increased overfitting, reducing the predictive performance on unseen text (L. Huang et al., 2017).

Drawing from relevant literature (Eid et al., 2019; Steve Pike, 2002), this study defined the range of the number of topics, K, as [1, 12], and calculated the perplexity score for different values of K. Subsequently, the perplexity curve was generated using the Matplotlib data visualization package in Python, facilitating the observation of

perplexity trends. Building upon the insights provided by J. Tang et al. (2014), Kirilenko et al. (2021) and X. Chen et al. (2021), the number of topics corresponding to the elbow-like point on the perplexity curve is suggested to represent the optimal number of topics.

Afterward, the optimal number of topics to be determined was substituted into the LDA model for testing. The PyLDAvis package in gensim was utilized to generate the topic distance map, visually representing the topic distribution. Within the topic distance map, each circle signifies a distinct topic, and the size of the circle represents the percentage of tokens that the topic comprises within the entire corpus. The proximity on the map indicates similarity in topic distributions across the documents. The delineation and relative positioning of the topics offer valuable insights into their prominence and interrelationships. When clear boundaries exhibit good independence and minimal overlap between topics, it suggests that the selection of the K value may be appropriate (Sievert & Shirley, 2014). By integrating insights from the perplexity curve and topic distance map, the optimal number of topics can be determined.

Subsequently, LDA modeling was performed, and the word-topic matrix and document-topic matrix were generated. The word-topic matrix illustrates the relationship between each topic and the words, representing the probability distribution of each word for each topic. Meanwhile, the document-topic matrix unveils the relationship between individual documents and topics, depicting the probability distribution of each topic within every document.

3) Topic Labeling and Importance Calculation

Drawing upon the methodology outlined by Maier et al. (2021), a detailed examination of the list of keywords defining each latent topic was conducted. The semantic characteristics of these keywords were analyzed to determine the most representative name for each topic. This process involved a careful assessment of the words' meanings and their

relevance to the topic's content. Following this analysis, the topics were manually summarized and assigned descriptive names based on their predominant keywords.

To facilitate the interpretation of the topics, a manual extraction process was employed to select the top 10 most representative keywords for each topic. This selection process was guided by the probability of words within each topic and their distinctiveness from words in other topics. The topic keywords were carefully chosen to minimize potential noise and enhance the interpretability of the topics. By focusing on the most probable and distinctive words, this approach facilitated a more precise summary of each topic's content, thereby aiding in the accurate labeling and understanding of the topics.

The importance of each topic extracted from tourists' reviews was evaluated based on its probability within the document-topic matrix generated using the Latent Dirichlet Allocation (LDA) model. This probabilistic assessment provides insights into how prominently each theme features in tourists' perceptions of the destination, as derived from their written feedback.

The method proposed for assessing topic importance is based on the concept that individuals are inclined to allocate greater attention to specific stimuli or information based on their perceived relevance, significance, or prominence in a given context (Bordalo et al., 2013). It underscores the influence of perceived importance on individuals' attention and memory. In the context of this study, the frequency of discussion among tourists regarding a particular topic reflects their level of concern, thereby indicating the perceived importance of that topic. In other words, topics that are more salient in the reviews are considered more important. This aligns with the findings of Steven Pike and Kotsi (2018), who regarded destination image attributes that are more salient carry greater importance.

According to X. Li et al. (2023), the average probability value of a topic

across all documents represents the topic's relative frequency in discussions, thereby reflecting its overall importance. Equation (3) is used to calculate the topic importance. δ_z represents the importance of topic z; $\delta_{d,z}$ signifies the probability of topic z within document d; and D represents the total number of documents in the corpus.

$$\delta_z = \frac{1}{D} \sum_{d=1}^{D} \delta_{d,z} \quad (3)$$

4) Changing Trends in Topics

The data collected in this study spans five quarters. Given the dynamic nature of destination image, understanding the trend of changes over time requires calculating the importance of each topic in each quarter. The equation (4) used for this calculation is as follows:

$$\delta_{z,t} = \frac{1}{D_t} \sum_{d=1}^{D_t} \delta_{d,z} \quad (4)$$

Where, $\delta_{z,t}$ represents the importance of topic z in quarter t; $\delta_{d,z}$ signifies the probability of topic z within document d; D_t represents the total number of documents in the corpus in quarter t.

Calculating the changing trends in topics allows for the analysis of how the importance of specific topics evolves across different quarters, offering insights into the temporal dynamics of destination image. Comparing these calculated intensities between quarters helps identify patterns and characteristics in the evolution of the destination image over time.

3.4.2 Topic-based Sentiment Analysis

Given that promotional messages issued by destination marketing organizations aim to attract tourists, they typically lack negative sentiment. This study exclusively analyzes tourist reviews to explore the perceived destination image among tourists.

The sentiment analysis process primarily involves two essential steps. Firstly, it computes the sentiment score for each individual review, analyzing the textual content to assess its emotional polarity. Secondly, it utilizes the

document-topic matrix generated through LDA modeling to calculate the sentiment score for each topic by aggregating sentiments from all reviews assigned to that topic. This score serves as an indicator of topic performance.

1) Sentiment Analysis

Sentiment analysis was conducted on each dataset to obtain a sentiment score for each document. This study employs the SnowNLP library in Python for sentiment analysis. SnowNLP is a natural language processing tool specifically designed for processing Chinese texts, including a sentiment analysis module, and is widely used for online text analysis (Zhiyong Li et al., 2024; H. Xu & Lv, 2022; S.-N. Zhang et al., 2022). SnowNLP employs a hybrid approach that integrates machine learning techniques with lexicon-based sentiment analysis. The model outputs a sentiment score ranging from 0 to 1, indicating the sentiment tendency of the text, with values closer to 1 representing positive sentiment and values closer to 0 representing negative sentiment.

SnowNLP utilizes a Naive Bayes Classifier to model the training data. Although the sentiment analysis module of SnowNLP has a pre-trained model, it was not developed specifically for research in the tourism industry. To better adapt the model to the tourism industry corpus, a small dataset (10% randomly selected from the total reviews) was used for model training and testing to optimize the accuracy of model evaluation.

The dataset was manually annotated with positive and negative reviews. The reviews were then randomly divided into training and test sets, with 80% of the reviews used for training and 20% used for testing.

Initially, the original SnowNLP was utilized to predict sentiment scores for the testing dataset, categorizing them into positive and negative samples based on a score threshold of 0.5, with scores of 0.5 or higher considered positive reviews. Subsequently, the newly trained SnowNLP model was employed to predict sentiment scores for the same testing

dataset, using identical classification criteria. Ultimately, a comparison was conducted between the outcomes generated by the original SnowNLP and the new SnowNLP models.

Additionally, both the original SnowNLP and the new SnowNLP were compared with the lexicon-based sentiment analysis method using the HowNet lexicon to comprehensively evaluate the performance of the models. The evaluation metrics included accuracy, precision, recall, and F1 score (Agrawal et al., 2018; X. Li et al., 2023).

Accuracy measures the overall correctness of the model in predicting both positive and negative instances. It is calculated as the ratio of correctly predicted instances to the total instances. Equation (5) demonstrates the calculation process.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{5}$$

In equations (5) to (7), TP (True Positives) represents correctly predicted positive instances, TN (True Negatives) represents correctly predicted negative instances, FP (False Positives) represents incorrectly predicted positive instances, and FN (False Negatives) represents incorrectly predicted negative instances.

Precision measures the accuracy of positive predictions. It is the ratio of correctly predicted positive instances to the total predicted positive instances. Equation (6) illustrates the calculation method.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{6}$$

Recall measures the ability of the model to correctly identify positive instances. It is the ratio of correctly predicted positive instances to the actual positive instances. Equation (7) outlines the calculation procedure.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{7}$$

The F1 score is the harmonic mean of precision and recall, providing a single metric that balances both precision and recall. Equation (8)

illustrates the calculation method.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (8)$$

The results indicated that the new SnowNLP demonstrated superior performance across all metrics. Subsequently, SnowNLP was utilized to perform sentiment analysis on the whole dataset, calculating a sentiment score for each tourist review.

2) Topic Performance Calculation

After obtaining the sentiment score for each review, the sentiment score for each topic was calculated by matching the reviews with their respective topics. Because reviews may relate to multiple topics, they are assigned to topics based on a defined threshold value (Ren & Hong, 2017). Establishing μ=1/K (where K is the number of topics) determines the affiliation of a review with a particular topic. Based on the document-topic matrix, if the probability of a topic corresponding to a review is greater than or equal to μ, the review is allocated to that topic, thereby permitting multiple topic assignments. The average sentiment score of all reviews assigned to each topic is then calculated to provide a sentiment score for each topic.

To compute the sentiment score for each topic, the authors employed equation (9) to calculate the average sentiment score of all reviews assigned to that topic.

$$T_j = \frac{1}{n_j} \sum_{i=1}^{n_j} s_{i,j} \quad (9)$$

In the context of this study, variable i signifies each review within the corpus, whereas j represents each topic in the LDA model. Variable n_j denotes the number of reviews assigned to the j-th topic, and $s_{i,j}$ signifies the sentiment polarity score calculated by SnowNLP for the i-th review within the j-th topic. Given that each review is associated with only one sentiment polarity score irrespective of the assigned topic, its value remains constant. Additionally, T_j signifies the average

sentiment score for all reviews allocated to the j-th topic, representing the sentiment score specifically associated with topic j.

It should be noted that the sentiment analysis results of tourists' reviews can be considered as the performance of the topics perceived by tourists. The assessment of topic performance involves computing sentiment scores derived from sentiment analysis. These scores, linked to each topic, offer valuable insights into tourists' attitudes towards different aspects of the destination image. As emphasized by Jinyan Chen et al. (2022), this approach indirectly evaluates topic performance. Such performance data forms the foundation for subsequent Importance-Performance Analysis (IPA). Specifically, higher sentiment scores indicate more positive evaluations by tourists regarding the topic. Consequently, there exists a positive correlation between sentiment scores and topic performance, with higher sentiment scores reflecting better performance of the respective topic.

3) Trends in Sentiment Dynamics

Based on the sentiment scores assigned to each topic and considering the timeline, it is possible to compute the trend of sentiment scores for each topic over time. Given the study's data spanning five quarters, sentiment scores for each topic are calculated quarterly using the following equation (10):

$$T_{j,t} = \frac{1}{n_{j,t}} \sum_{i=1}^{n_{j,t}} s_{i,j} \quad (10)$$

Where, $T_{j,t}$ represents the average sentiment score for all reviews assigned to topic j in quarter t. The sum $\sum_{i=1}^{n_{j,t}} s_{i,j}$ calculates the total sentiment polarity scores of all reviews associated with topic j in quarter t, and $n_{j,t}$ is the count of reviews assigned to topic j in quarter t.

Analyzing sentiment trends reveals evolving tourist perceptions of a destination over time, identifying shifts across different aspects.

Understanding these trends facilitates deciphering the reasons behind tourists' emotions, proactive addressing of negative sentiments, leveraging of positive trends, and ultimately guiding the development of targeted marketing strategies to enhance overall tourist experiences and strengthen the destination's image.

3.4.3 Descriptive Statistics

Upon collecting the questionnaires, it is essential to assess their reliability to gauge the internal consistency of the measurement items. This step ensures that the measurement tool maintains sufficient reliability during subsequent analysis, thereby enhancing the reliability and validity of the results. Cronbach's Alpha (α) is predominantly employed to assess the interrelatedness among questions within the questionnaire. A generally accepted criterion suggests that the questionnaire exhibits good internal consistency when $\alpha \geqslant 0.7$ (Stylidis, Shani, et al., 2017; Stylos et al., 2016). Once the questionnaire reliability meets this standard, further analysis can proceed.

The first step in analyzing the questionnaire survey data is to perform descriptive statistics. Descriptive statistics summarize and describe the main features of a dataset, presenting the basic characteristics of the data in an understandable way (Hahm et al., 2018). These statistics include measures of central tendency, which provide information about the central point of the data, and measures of dispersion, which describe the spread or variability of the data. Additionally, frequency distributions show how often each value occurs in the dataset. For instance, one of the questionnaire items asks, "Does the degree of congruence between the projected image of the Panda Base and your perception affect your travel satisfaction?" The frequency and percentage of responses to this question can offer valuable insights for further analysis.

This preliminary step ensures that the dataset is well-characterized and that subsequent analyses are based on a solid understanding of the underlying data.

3.4.4 Spearman's Rank Correlation Coefficient

The Spearman's Rank Correlation Coefficient was employed to verify the relationship between destination image congruence and tourists' satisfaction ratings in the questionnaire survey data. Although existing literature suggests that destination image congruence positively impacts tourists' satisfaction ratings (Farmaki, 2012; Y. Li et al., 2023), this study aims to empirically verify this relationship through a questionnaire survey. To achieve this, two specific questions have been incorporated into the second section of the questionnaire, with their responses intended for correlation analysis.

In the questionnaire survey, the first specific question posed to participants is, "How closely does the image of the Panda Base projected on the platforms mentioned above align with your perception?" Respondents are instructed to rate their perceptions on a Likert scale from 1 to 5, where 1 signifies the least consistency and 5 signifies the highest consistency between the projected image and their own perception. Responses to this first question represent the degree of congruence between the projected and perceived images of the Panda Base, constituting the first variable.

The second specific question is, "Please rate your overall satisfaction with your visit to the Panda Base." Participants respond on a Likert scale from 1 to 5, where 1 indicates strong dissatisfaction and 5 indicates strong satisfaction with their visit. Responses to this second question reflect the overall satisfaction levels of the tourists, constituting the second variable.

Given that the data for both variables are ordinal, Spearman's Rank Correlation Coefficient is an effective statistical tool to assess their correlation. This coefficient does not require the data to be normally distributed, nor does it require homoscedasticity, and it is robust to outliers.

Spearman's Rank Correlation Coefficient is employed within the SPSS statistical software. Spearman's rho correlation coefficient assesses the strength and direction of the monotonic relationship between two variables, with values ranging from -1 (indicating a perfect negative relationship) to 1 (indicating a perfect positive relationship), and 0 suggesting no discernible

correlation (Ali Abd Al-Hameed, 2022). The accompanying P-value (Sig. (2-tailed)) gauges the statistical significance of the correlation coefficient. In statistical terms, a P-value below the conventional threshold of 0.05 signifies a statistically significant correlation.

3.4.5 Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) is a statistical method employed to unveil the latent structure of a variable set without presupposing the number or composition of underlying factors. In the context of investigating destination image attributes, EFA is extensively utilized for discerning and categorizing these attributes based on their interrelationships (Beerli & Martin, 2004; Nghiêm-Phú, 2014). By aggregating variables into factors, EFA simplifies the complexity of analyzing multiple attributes individually, allowing for a focused exploration on a reduced number of factors that account for the majority of variability in the dataset. This approach aids in uncovering and categorizing the fundamental dimensions (factors) of various attributes, offering a systematic framework for comprehending the intricate concept of destination image (Borlido & Kastenholz, 2021). These factors can encompass diverse facets such as natural beauty, cultural richness, or infrastructure quality.

The variables employed for EFA were the importance values of 17 attributes concerning destination image from the questionnaire. To determine the suitability of the data for EFA, conducting the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test is crucial (Beerli & Martin, 2004; Tse & Tung, 2021). The KMO test evaluates the suitability of data for EFA by measuring the correlations among variables. Typically, KMO values above 0.6 indicate adequate suitability for EFA. Conversely, Bartlett's test assesses whether the observed correlation matrix is statistically significant, indicating if the variables are sufficiently correlated for EFA. A significantly low p-value from Bartlett's test (usually below 0.05) suggests that the data is suitable for factor analysis.

Using the statistical software SPSS, EFA was conducted based on criteria

such as eigenvalues greater than 1 and cumulative explained variance. Principal Components Analysis (PCA) was used to reduce data dimensionality by finding linear combinations (principal components) that maximize the total variance of the explanatory variables. To improve interpretability, Varimax rotation was applied, which simplifies the factor structure by reducing the number of variables loading onto each factor and enhancing the clarity of the underlying structure.

The loading values under each factor were observed. A variable with a high loading value (positive or negative) indicates a strong correlation with that factor. Variables with higher loadings were considered more influential in defining the factor. The factor to which each variable belongs can be determined based on the magnitude and direction of the loading value. After examining factor loadings, variables that clustered closely under each factor were identified.

After determining the factor affiliation of each variable, individual internal consistency tests were conducted for each factor. Cronbach's Alpha (α) was computed using the variables under each factor to assess its reliability. This step ensures the robustness of each factor's measurement integrity and contributes to the overall validity of the factor analysis results.

The resulting factors from EFA represented the perceived dimensions of destination image by respondents. Subsequently, factors were named based on the variables that exhibit the strongest loadings onto them. This process involves examining the content of the variables that load highly on each factor. The names assigned to the factors are meant to reflect the underlying concepts or themes that these variables collectively represent. This naming helps to interpret and understand the meaning of each factor in the context of the data being analyzed.

To determine the importance of each factor, the importance score for each attribute was calculated by averaging respondents' ratings. Subsequently, the average of these importance scores for all attributes within each factor was computed. This average represents the overall importance of the factor.

Finally, the alignment of identified factors with topics extracted using LDA modeling was evaluated. This comparison enabled cross-validation with findings from both the questionnaire survey and online textual data analysis, enhancing the understanding of the perceived destination image dimensions.

3.4.6 Importance-Performance Analysis

Importance-Performance Analysis (IPA) is a widely utilized strategic analysis tool in marketing and consumer research (Padlee et al., 2020; A. Wang et al., 2020; Wohlfart et al., 2022). Initially proposed by Martilla and James in their seminal 1977 work, IPA provides a framework for prioritizing product and service attributes based on their importance and performance from the consumer's perspective (Martilla & James, 1977). Since its inception, IPA has been employed across diverse industries to enhance customer satisfaction and inform organizational strategies.

In the field of tourism research, IPA is extensively applied (Jang et al., 2020; Rašovská et al., 2021; Simpson et al., 2020). Steven Pike and Kotsi (2018) highlight that an appealing destination is characterized by a positive image, shaped by attributes deemed important by tourists. Analyzing the importance and performance of these attributes provides valuable insights for destination marketing strategies. Given that IPA is based on consumer perception, this study employs the framework to deepen the understanding of the perceived image of a destination.

LDA modeling and sentiment analysis of tourist reviews can be integrated into the IPA framework. In this approach, the intensity of a topic signifies its importance, while the sentiment tendency of a topic indicates its performance (Jinyan Chen et al., 2022). Consequently, IPA can be employed to analyze tourists' perspectives on the importance and actual performance of destination image attributes.

IPA employs Grid Analysis, where data on importance and performance are typically plotted on a two-dimensional grid (Martilla & James, 1977). The importance axis ranks attributes from low to high based on their importance scores, while the performance axis ranks attributes from low to high based on

their performance scores. This grid facilitates the categorization of attributes into four quadrants, as illustrated in Figure 3.9.

Given that the Importance-Performance Analysis framework requires the importance scale to range from 0 to 5, with 5 indicating the highest importance (I. K. W. Lai & Hitchcock, 2015), equation (11) is formulated based on equation (3) to calibrate the scale. In this equation, λ_z signifies the transformed importance score of topic z in the Importance-Performance analysis grid, and $\max(\delta_z)$ represents the maximum value of δ_z.

$$\lambda_z = 5 * \frac{\delta_z}{\max(\delta_z)} \quad (11)$$

Similarly, when analyzing the performance of a topic in the Importance-Performance analysis grid, data transformation is necessary. The sentiment polarity score typically ranges from 0 to 1. However, as a 5-point scale is commonly used for performance assessments (I. K. W. Lai & Hitchcock, 2015), the performance scale in this study was adjusted to extend from 0 to 5. This adjustment is executed using equation (12) based on equation (9), where P_j represents the transformed performance score of topic j.

$$P_j = 5 * T_j \quad (12)$$

High Importance, High Performance: Attributes in this quadrant are performing well and are highly valued by tourists. They are considered strengths that should be maintained and highlighted.

High Importance, Low Performance: Attributes here are highly valued but are not meeting tourists' expectations. Improvement efforts should focus on these areas to enhance overall satisfaction.

Low Importance, High Performance: These attributes are performing well but are not considered crucial by tourists. As such, they are not central to the destination's priorities. The focus should be on maintaining their current performance, strategically allocating resources, and leveraging these strengths for marketing and future opportunities.

Low Importance, Low Performance: Attributes in this quadrant are neither

highly valued nor performing well. They may be candidates for potential elimination or minimization of resources allocated to them.

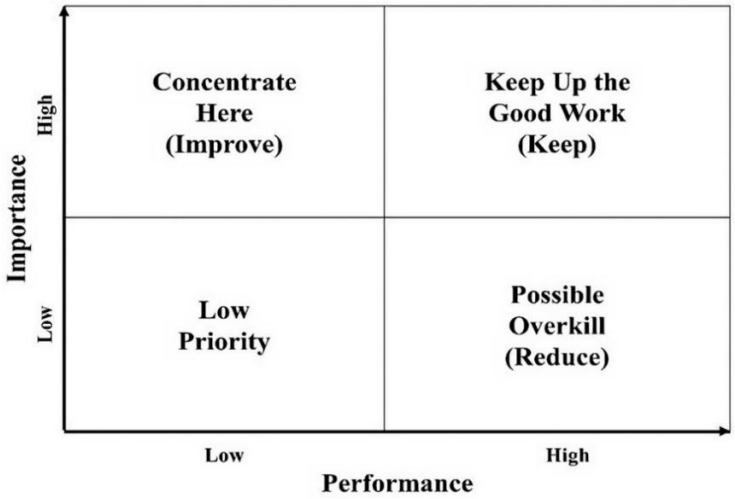

Figure 3.9 Importance-Performance Analysis grid

(Source: Martilla & James, 1977)

IPA is a robust tool for identifying strengths, weaknesses, and improvement opportunities based on the relative importance and performance of attributes within a destination image (Rašovská et al., 2021). It offers a structured approach to understanding tourists' perceptions and preferences, providing a visual representation of the current status of products and services as perceived by tourists (Ma et al., 2022). This enables data-driven decision-making and offers valuable insights for refining marketing strategies.

IPA highlights where resources should be allocated to effectively improve a destination's perceived image by identifying key attributes that require attention. Additionally, it provides insights into how to adjust a destination's projected image to better align with tourists' perceptions. By focusing on attributes that are both important to tourists and performing well, as well as addressing areas where performance falls short, destinations can optimize their marketing efforts, improve overall satisfaction, and attract more tourists (Mustafa et al., 2020).

3.5 Research Framework

Based on the outlined research design, research questions, data collection methods, and data analysis methods, the research framework of this study is depicted in Figure 3.10 as below.

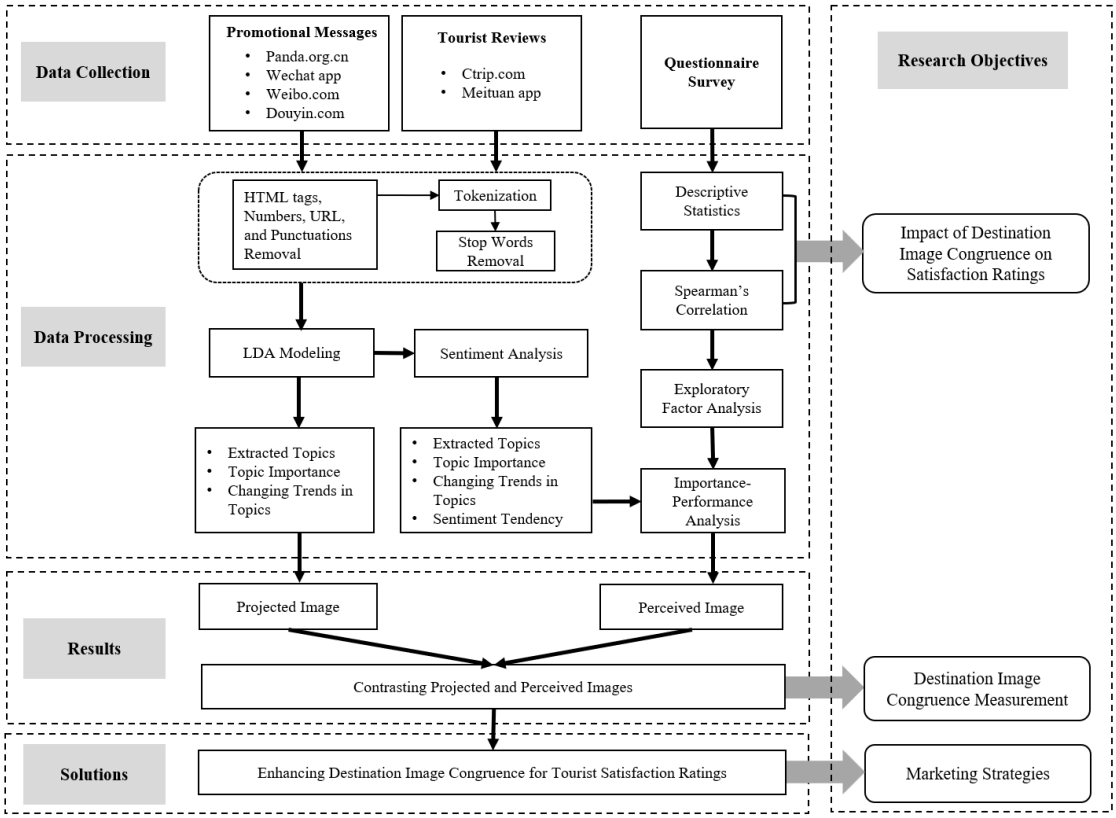

Figure 3.10 Research framework

(Source: Drawn by the author)

The comparison between projected and perceived images is conducted across three key dimensions. First, the content of topics extracted from promotional messages is compared with those derived from tourist reviews, focusing on identifying both overlapping and distinct topics. Second, the relative importance of these shared topics is analyzed, providing insights into how different aspects are prioritized in both projected and perceived images. Third, the evolution of the importance of these common topics is examined over five quarters, offering a longitudinal perspective on the shifting emphasis of certain topics over time. The framework for measuring destination image congruence is illustrated in Figure 3.11 below.

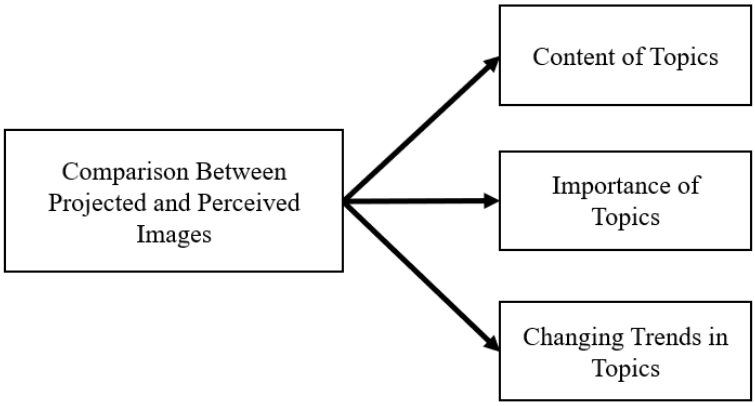

Figure 3.11 Framework for measuring destination image congruence

(Source: Drawn by the author)

Table 3.1 presents a summary of the research objectives, questions, theoretical support, and analysis methods as below.

Table 3.1 Summary of research objectives and methods

Research Objectives	**Research Questions**	**Theoretical Support**	**Analysis Methods**
To evaluate the impact of destination image congruence on tourist satisfaction	What is the impact of destination image congruence on tourists' satisfaction ratings?	Expectancy-Disconfirmation Theory	Descriptive Statistics, Spearman's Correlation
To develop an innovative method for evaluating destination image congruence	How can the congruence between the projected image and the perceived image of a destination be measured?	Destination Image Theory	LDA Modeling, Exploratory Factor Analysis

Table 3.1 Summary of research objectives and methods (continued)

Research Objectives	Research Questions	Theoretical Support	Analysis Methods
To propose marketing strategies to enhance destination image congruence	How can marketing strategies be employed to enhance destination image congruence and thereby improve tourist satisfaction ratings?	Value Perception Theory, Agenda-Setting Theory and Two-Sided Persuasion Theory	Sentiment Analysis, Importance-Performance Analysis

3.6 Ethical Considerations

This study rigorously adheres to ethical guidelines and has been approved by the Research Ethics Committee of Chiang Mai University under reference CMUREC No. 67/191. All online texts collected for this research are publicly accessible and equally available to all individuals. The questionnaire survey process was conducted with meticulous attention to ethical standards as follows:

Stringent measures were implemented to protect the rights and well-being of all participants. Participants were guaranteed anonymity throughout the questionnaire completion process, ensuring no collection of personally identifiable or sensitive information. The study methodology excluded interviews, voice recordings, photographs, or video recordings, reinforcing confidentiality and establishing a trustworthy environment.

A fundamental ethical principle emphasized was voluntary participation. Participants were clearly informed of their autonomy, with a firm assertion that their involvement was entirely optional and free from coercion or obligation. They retained the unequivocal right to decline participation or withdraw from the study at any point without fear of repercussion, underscoring the importance of respecting individual autonomy and agency.

Before their participation, participants received comprehensive information detailing the research's purpose, procedures, potential risks, and benefits, presented in a clear and understandable manner to facilitate informed decision-making. Participants were required to read the participant information sheet and sign the informed consent form before completing the questionnaire, indicating their understanding and agreement to participate in the study.

Throughout interactions with participants, ethical communication was paramount. Language used in written and verbal communication was carefully chosen to ensure appropriateness, respectfulness, and the absence of coercion or manipulation. Any concerns or queries raised by participants were met with empathy and promptly addressed, fostering an environment of trust, transparency, and mutual respect.

The ethical framework prioritized the well-being and comfort of participants. Measures were in place to promptly address any concerns or discomfort experienced by participants, aiming to mitigate potential negative impacts on their psychological or emotional welfare.

To maintain the utmost confidentiality of participants' data, a robust coding system was employed for data recording. Access to this data was strictly controlled, with stringent protocols to ensure security. Furthermore, upon completion of the study, all collected information will be securely disposed of in accordance with designated retention periods, safeguarding participants' privacy and confidentiality.

CHAPTER 4

Results

The research objectives are: (1) to evaluate the impact of destination image congruence on tourist satisfaction; (2) to develop an innovative method for assessing destination image congruence; and (3) to propose marketing strategies to enhance destination image congruence. Correspondingly, the research questions are: (1) What is the impact of destination image congruence on tourists' satisfaction ratings? (2) How can the congruence between the projected and perceived images of a destination be measured? (3) How can marketing strategies be employed to enhance destination image congruence and thereby improve tourist satisfaction ratings? Based on the methodology outlined in Chapter 3, the analysis results are as follows.

4.1 Textual Data Overview

The data collection period spans 15 months, from January 1, 2023, to March 31, 2024. All collected textual data were cleaned, resulting in the retention of 12,561 tourist reviews and 1,214 promotional messages for LDA (Latent Dirichlet Allocation) modeling. Among the tourist reviews, 6,623 were sourced from Ctrip and 5,938 from Meituan. The promotional messages included 127 from the official website of the panda base (Panda.org.cn), 602 from WeChat, 260 from Weibo, and 225 from Douyin. For more details, refer to Tables 4.1 and 4.2 below.

Table 4.1 Number of tourist reviews by different data sources

Period		**Data Source**		
Quarter	Month	Ctrip	Meituan	Total
Q1	2023-01	394	352	746
	2023-02	526	436	962
	2023-03	362	223	585
Q2	2023-04	295	247	542
	2023-05	349	206	555
	2023-06	407	236	643
Q3	2023-07	519	982	1,501
	2023-08	488	814	1,302
	2023-09	372	354	726
Q4	2023-10	687	440	1,127
	2023-11	416	233	649
	2023-12	412	225	637
Q5	2024-01	428	312	740
	2024-02	627	495	1,122
	2024-03	341	383	724
Total		6,623	5,938	12,561

Table 4.2 Number of promotional messages by different data sources

Period		**Data Source**				
Quarter	Month	Panda.org.cn	Wechat	Weibo	Douyin	Total
Q1	2023-01	9	47	19	17	92
	2023-02	8	38	22	18	86
	2023-03	7	38	18	13	76
Q2	2023-04	11	51	17	15	94
	2023-05	7	49	21	18	95
	2023-06	9	39	15	11	74
Q3	2023-07	8	34	23	19	84
	2023-08	8	34	15	12	69
	2023-09	10	40	13	16	79
Q4	2023-10	7	33	14	16	70
	2023-11	9	34	19	12	74
	2023-12	9	39	16	13	77

Table 4.2 Number of promotional messages by different data sources (continued)

Period		Data Source				
Quarter	Month	Panda.org.cn	Wechat	Weibo	Douyin	Total
Q5	2024-01	8	40	20	19	87
	2024-02	8	48	13	11	80
	2024-03	9	38	15	15	77
Total		127	602	260	225	1,214

Regarding tourist reviews, the data collected from Ctrip slightly surpasses that from Meituan, reflecting the current market share distribution between the two platforms. For promotional messages, nearly half of the data originates from WeChat, highlighting its role as the primary promotional platform for the Panda Base.

4.2 LDA Modeling Results

4.2.1 Topic Distribution

LDA modeling was conducted on two distinct corpora: promotional messages and tourism reviews. To evaluate the performance of the model, perplexity was utilized as a measure. The perplexity curves for these corpora were generated using the Matplotlib data visualization package in Python, facilitating a detailed analysis of perplexity trends. The elbow point on the perplexity curve indicates the potential optimal number of topics.

Upon examining the perplexity curves of the two corpora, it was observed that perplexity gradually decreases as the number of topics increases. A notable elbow-like inflection point occurs when the number of topics reaches 8. Beyond this point, as the number of topics continues to increase, perplexity begins to rise and fluctuate. Both corpora exhibited similar perplexity trends, suggesting that 8 topics may be an optimal choice for both datasets. Figures 4.1 and 4.2 illustrate the perplexity curves for promotional messages and tourism reviews, respectively.

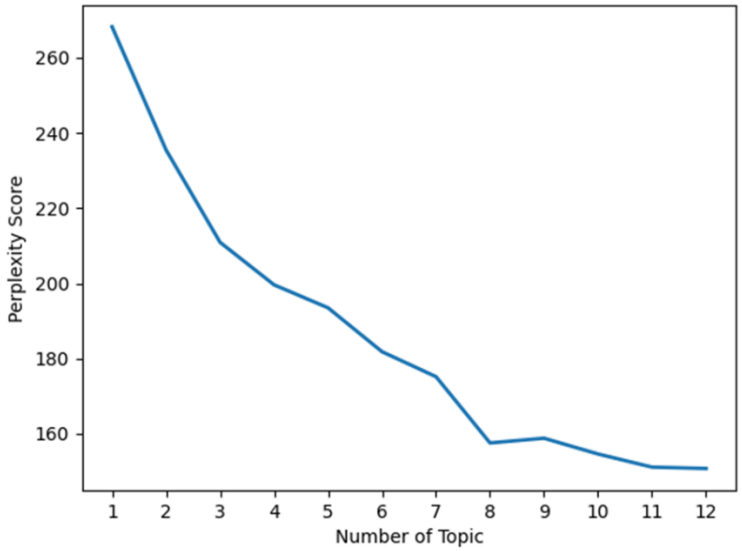

Figure 4.1 Perplexity curve for promotional messages

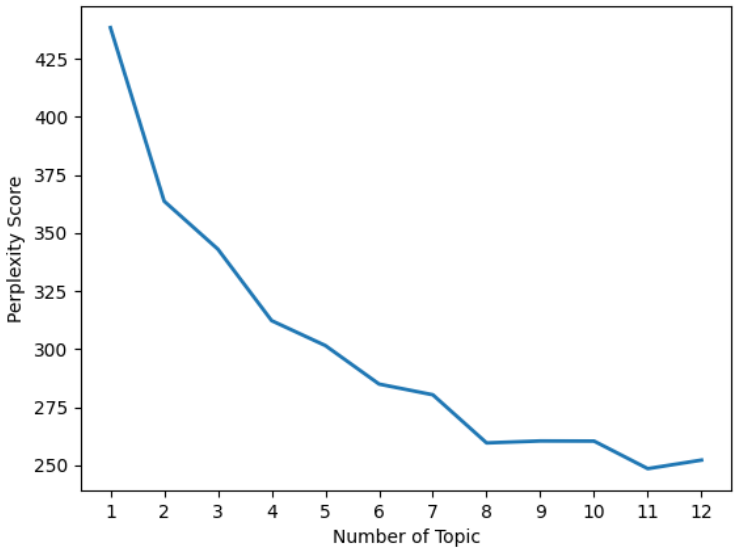

Figure 4.2 Perplexity curve for tourist reviews

The optimal number of topics, identified as 8, was subsequently applied to the LDA model for further validation. The PyLDAvis package in gensim was employed to generate topic distance maps, which visually represent the distribution of topics. The clear boundaries and minimal overlap between topics on these maps indicate that selecting 8 as the optimal number of topics

is appropriate for both corpora. Consequently, the number of topics for LDA modeling of both corpora was determined to be 8. Figures 4.3 and 4.4 depict the topic distance maps for promotional messages and tourism reviews, respectively. In these figures, the top 30 words with the highest probabilities associated with a specific topic are shown, providing insight into the internal structure of that topic.

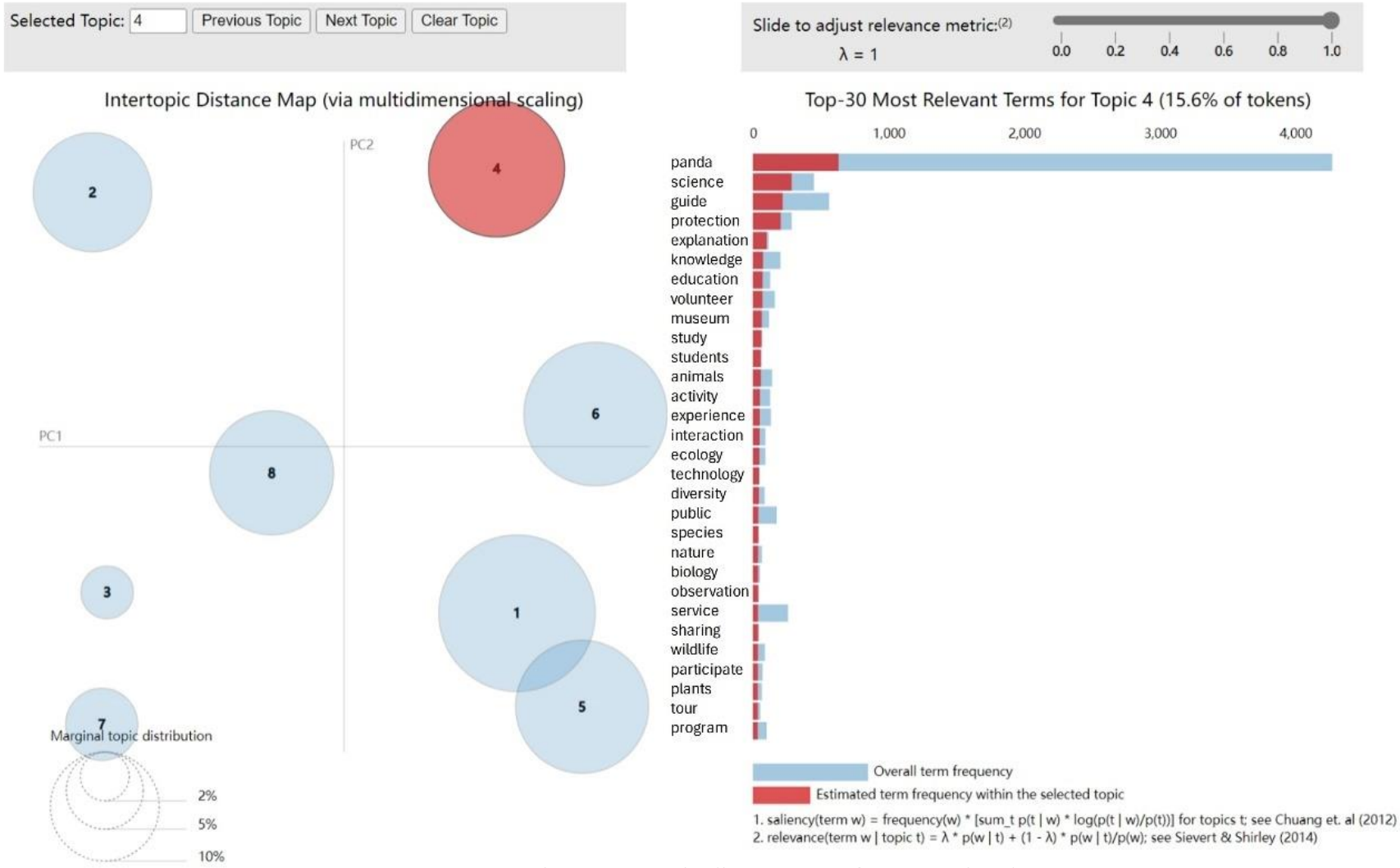

Figure 4.3 Topic distance map for promotional messages

In Figure 4.3, the topic distance map for promotional messages reveals several key insights into the topic structure. Topics 1, 4, 5, and 6 emerge as larger topics, each encompassing a higher proportion of tokens, suggesting their significant presence and importance within the corpus. Conversely, Topics 3 and 7 are identified as smaller topics, containing a lower proportion of tokens, indicating their relatively minor role in the corpus. Notably, Topic 1 and Topic 5 are positioned closely to each other with some degree of overlap. This proximity indicates a high distributional similarity between these two topics within the documents, suggesting that the content associated with these topics is closely related or often discussed together.

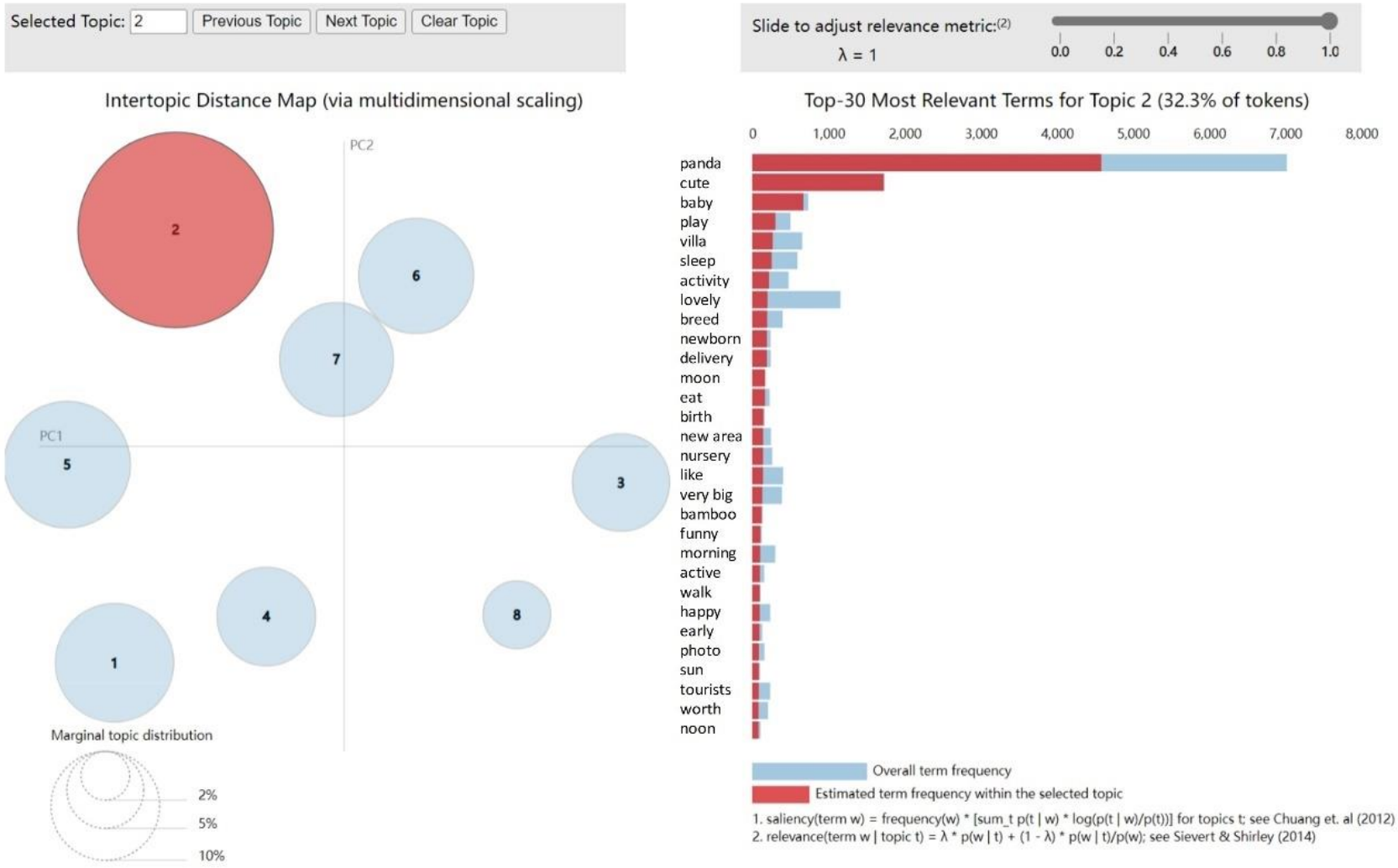

Figure 4.4 Topic distance map for tourist reviews

In Figure 4.4, which illustrates the topic distance map for tourism reviews, Topic 2 stands out with the highest proportion of tokens, making it the most prominent and frequently discussed topic among the reviews. On the other hand, Topic 8 has the lowest proportion of tokens, indicating that it garners the least attention from tourists. Additionally, the proximity of Topic 6 and Topic 7 on the map suggests a higher distributional similarity between these two topics compared to others. This implies that the content related to Topic 6 and Topic 7 is more closely related or often co-occurs in the documents.

4.2.2 Topic Labels and Importance

The LDA modeling of the two corpora was performed to generate the word-topic matrix and the document-topic matrix, respectively. The word-topic matrix elucidates the relationship between topics and words, representing the probability distribution of each word across topics. In contrast, the document-topic matrix reveals the relationship between individual documents and topics, depicting the probability distribution of each topic within every document. Together, these matrices provide a comprehensive understanding of the underlying topic structures within the corpora.

The list of keywords defining each latent topic was meticulously examined. The semantic characteristics of these keywords were analyzed to identify the most appropriate label that accurately represents the topic's content. The topics were then manually summarized and named based on their predominant keywords. To facilitate the interpretation of the topics, the top 10 keywords for each topic were carefully chosen to minimize potential noise and enhance interpretability. This selection process was guided by the probability of words within each topic and their distinctiveness from words in other topics. Upon completing the topic labeling and keyword selection processes, the importance of each topic was assessed according to its probability in the document-topic matrix.

Table 4.3 presents the topic labels, corresponding keywords, and topic importance derived from the LDA modeling results of promotional messages. Similarly, Table 4.4 presents the topic labels, corresponding keywords, and

topic importance derived from the LDA modeling results of tourist reviews.

Table 4.3 Topics extracted from promotional messages using the LDA method, ranked by importance in descending order

Topics		Topic Keywords	Topic Importance
Topic 6	Fascinating Updates on Panda Life	panda, bamboo, villa, rolling, interaction, surprise, cute, wonderful, moments, funny	0.199
Topic 5	Ticket Reservations and Visitor Capacity	window, official account, purchase, tickets, free, in advance, wechat, may day, capacity, reservation	0.164
Topic 1	Notices and Lost Property	open time, contact, claim, keeper, passport, ID card, property, owner, lost, found	0.156
Topic 8	Transportation and Travel Routes	west gate, south gate, subway, tour bus, route, map, signs, shuttle, sightseeing, bus stop	0.129
Topic 4	Guided Tours and Science Education Programs	guide, observation, interaction, explanation, education, science, study, knowledge, volunteer, museum	0.119
Topic 7	Responsible Tourism and Smoking Awareness	cause, disease, responsible, no feeding, isolation, health, smoking, civilization, smokers, tobacco	0.093
Topic 2	Events and Activities	performance, rules, drawing, final, judges, sign-in, competition, players, exhibition, works	0.091
Topic 3	Biodiversity and Wildlife Conservation	conservation, zoologists, diversity, nature, migration, hydrangea, azalea, spring, wildlife, bird	0.050
Total			1.000

Table 4.3 indicates that among the topics extracted from promotional messages, Topic 6, “Fascinating Updates on Panda Life,” holds the highest importance. This is followed by Topic 5, “Ticket Reservations and Visitor Capacity,” and Topic 1, “Notices and Lost Property.” Topics 8, “Transportation and Travel Routes,” and 4, “Guided Tours and Science Education Programs,” are of medium importance and closely ranked. Topic

7, “Responsible Tourism and Smoking Awareness,” and Topic 2, “Events and Activities,” are of lesser importance, each with less than half the importance of Topic 6. The least important topic is Topic 3, “Biodiversity and Wildlife Conservation.”

Table 4.4 Topics extracted from tourist reviews using the LDA method, ranked by importance in descending order

	Topics	Topic Keywords	Topic Importance
Topic 2	Panda Life and Fascinating Moments	villa, activity, cute, delivery room, eat, panda, baby panda, play, moon, bamboo	0.290
Topic 5	Crowd and Waiting Times	crowd, people, queue, wait, time, minutes, hours, too long, flow control, waste	0.159
Topic 1	Panda Superstars and Their Habitat	hua hua, heye, butt, sleeping, early, off work, lucky, regret, scenery, environment	0.121
Topic 3	Guided Tours and Knowledge Enrichment	guide, children, explanation, patient, nutritionist, interesting, professional, profound, knowledge, educate	0.113
Topic 7	Facilities and Service Quality	security, sanitation, facilities, convenient, information, staff, customer service, enthusiasm, attitude, friendly	0.097
Topic 6	Transportation and Travel Routes	bus tickets, subway, very large, expense, route, gate, map, walk, shuttle, signs	0.094
Topic 4	Weather and Panda Attendance	too hot, summer, air conditioner, rainy, winter, morning, afternoon, few pandas, can't see, many people	0.080
Topic 8	Parent-child Experience	family, bring kids, take care, baby, parent-child, interesting, children, stroller, again, fun	0.045
Total			1.000

Table 4.4 indicates that, among the topics extracted from tourist reviews, Topic 2, “Panda Life and Fascinating Moments,” is the most important, accounting for nearly one-third of the overall topic importance. The next most

important topics are Topic 5, “Crowd and Waiting Times,” and Topic 1, “Panda Superstars and Their Habitat.” Topics of medium importance include Topic 3, “Guided Tours and Knowledge Enrichment,” Topic 7, “Facilities and Service Quality,” and Topic 6, “Transportation and Travel Routes.” The least important topics are Topic 4, “Weather and Timing of Visit,” and Topic 8, “Parent-child Experience,” with “Parent-child Experience” being the least important of the two.

4.2.3 Changing Trends in Topics

Figure 4.5 illustrates the trends in the importance of promotional message topics over five quarters. Specifically, Q1 encompasses January 1 to March 31, 2023; Q2 spans April 1 to June 30, 2023; Q3 covers July 1 to September 30, 2023; Q4 includes October 1 to December 31, 2023; and Q5 extends from January 1 to March 31, 2024. The figure reveals a narrowing gap in the importance of each topic over time. Figure 4.6 presents a heatmap depicting changes in topic importance within promotional messages across the same five quarters.

The analysis reveals several trends in the importance of topics over the five quarters. Topic 1, "Notices and Lost Property," showed a continuous increase after a decline in Q2. Topic 3, "Biodiversity and Wildlife Conservation," remained low throughout the first four quarters but saw a significant rise in Q5. Topics 2, "Events and Activities," 4, "Guided Tours and Science Education Programs," and 5, "Ticket Reservations and Visitor Capacity," exhibited fluctuating importance levels. Despite being the most important overall, Topic 6, "Fascinating Updates on Panda Life," demonstrated a downward trend, with its importance peaking in Q2 and diminishing by Q5. Topic 7, "Responsible Tourism and Smoking Awareness," experienced a steady increase from Q1 to Q4, followed by a decline in Q5. Notably, Topic 8, "Transportation and Travel Routes," faced a continuous decline in importance across the quarters.

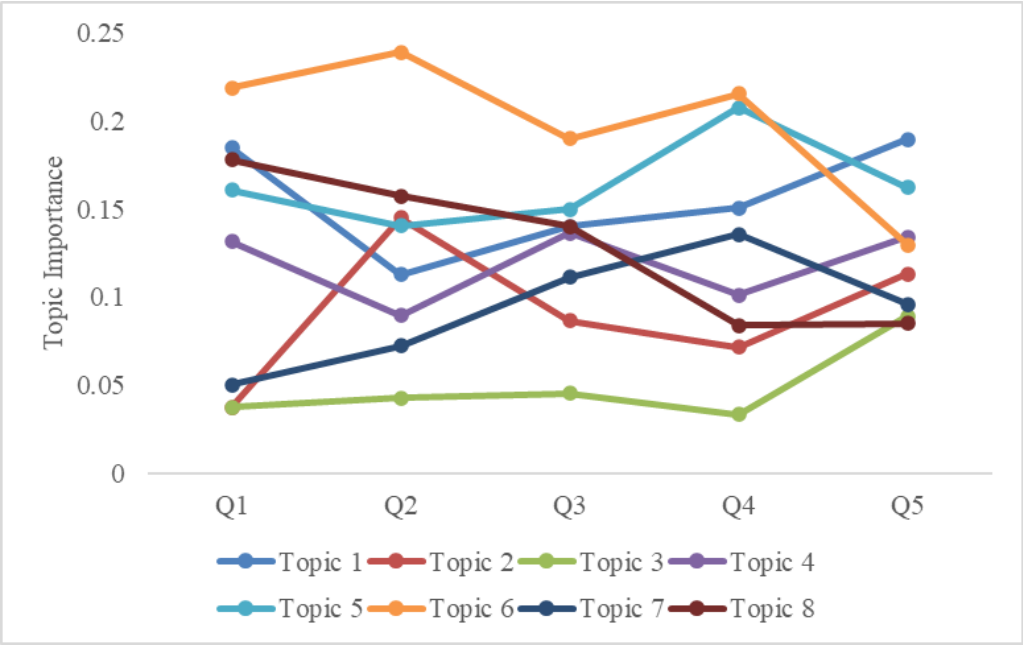

Figure 4.5 Trends in the importance of promotional message topics

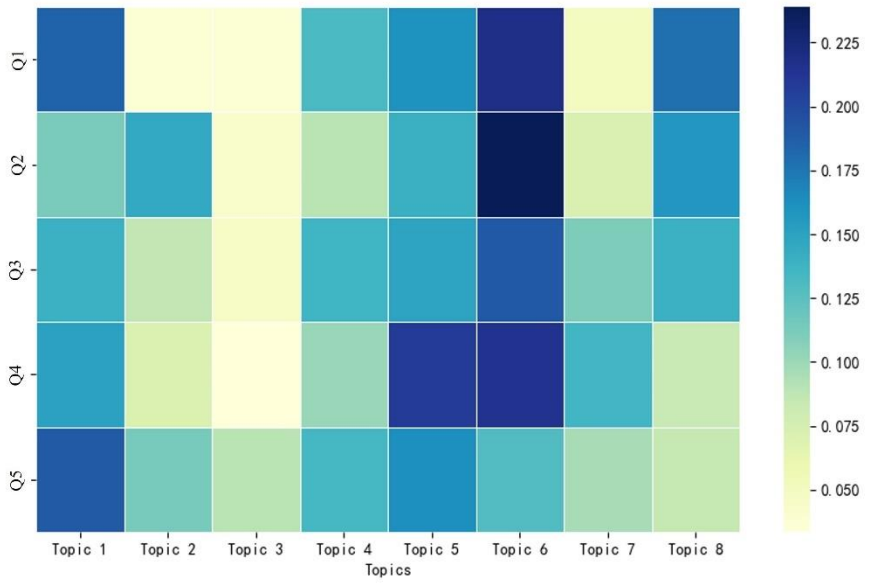

Figure 4.6 Heatmap of topic importance in promotional messages

Figure 4.7 illustrates the trends in the importance of tourist review topics over five quarters, while Figure 4.8 presents a heatmap depicting changes in topic importance within tourist reviews across the same periods.

Topic 2, “Panda Life and Fascinating Moments,” has consistently been the

most important topic, except in the third quarter, but it shows a downward trend overall. The importance of Topic 5, “Crowd and Waiting Times,” fluctuates significantly, surging in the third quarter to exceed Topic 2 and rank first. In the fourth quarter, its importance drops but remains prominent, then continues to decline in the fifth quarter to the level observed in the second quarter. The importance trends of Topic 1, “Panda Superstars and Their Habitat,” Topic 3, “Guided Tours and Knowledge Enrichment,” and Topic 8, “Parent-child Experience,” are similar, with relatively gentle fluctuations. The trends for Topic 4, “Weather and Timing of Visit,” Topic 6, “Transportation and Travel Routes,” and Topic 7, “Facilities and Service Quality,” are closely aligned, with similar importance levels. It is worth noting that Topic 4 experienced a significant decline in the last quarter.

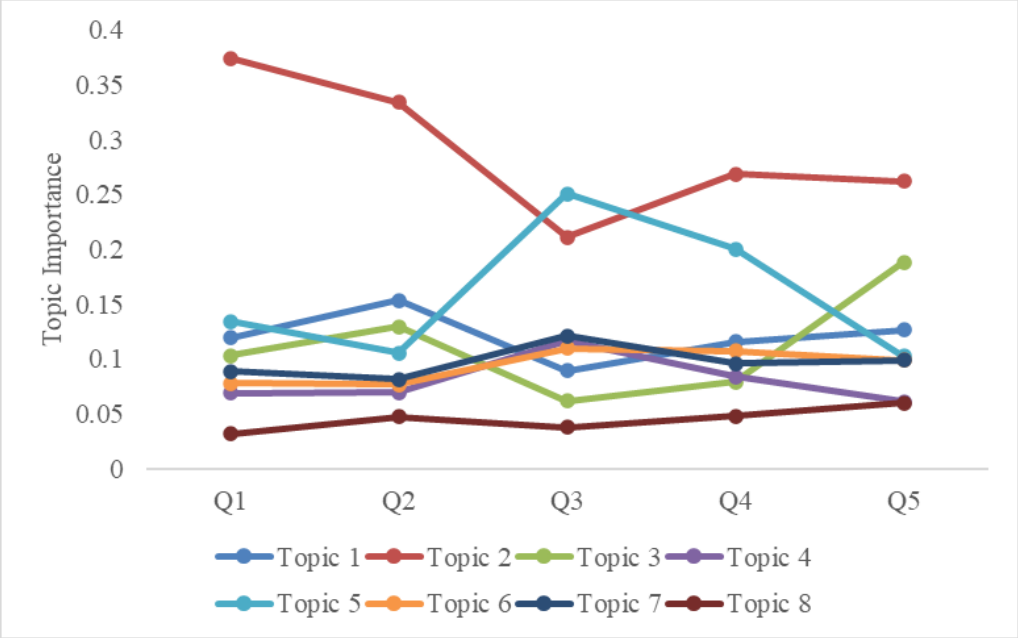

Figure 4.7 Trends in the importance of tourist review topics

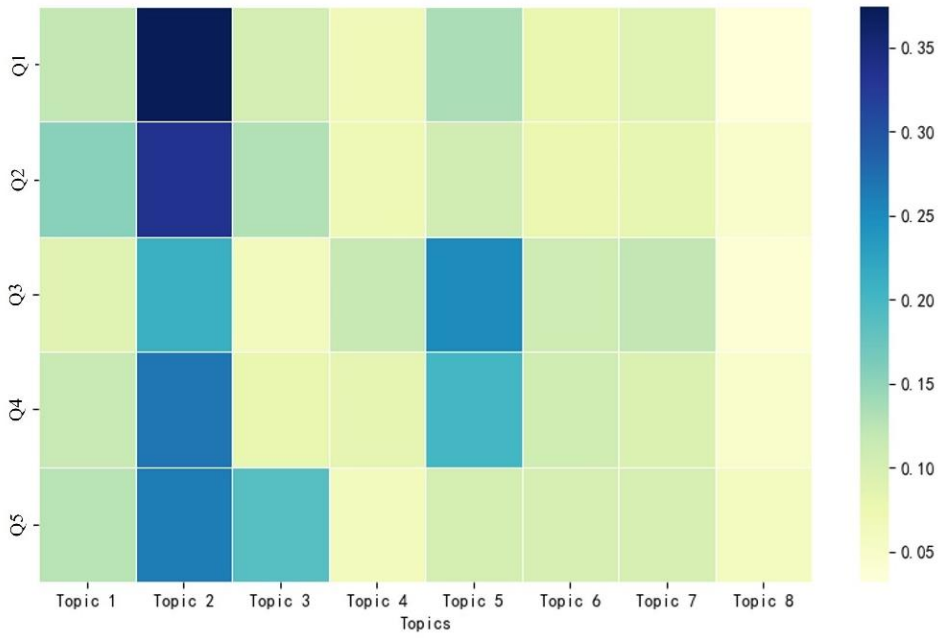

Figure 4.8 Heatmap of topic importance in tourist reviews

4.3 Topic-based Sentiment Analysis Results

This section comprises three parts. First, the sentiment analysis model is tested, and the performance of sentiment analysis models designed for Chinese text is evaluated. Second, the selected sentiment analysis model is employed to calculate the sentiment scores for each topic in tourist reviews. Finally, the changing trends in sentiment scores for each topic over five quarters are analyzed.

4.3.1 Sentiment Analysis Model Test

To enhance the accuracy of sentiment analysis, the SnowNLP model was retrained. Although the sentiment analysis module of SnowNLP includes a pre-trained original model, it was not specifically developed for research in the tourism industry. To better adapt the model to the tourism industry corpus, 10% of the total collected tourist reviews, amounting to 1,256 reviews, were randomly selected for training and testing the new model with the aim of improving its performance.

First, the dataset of 1,256 reviews was manually annotated with positive and negative labels to establish a reliable ground truth. These reviews were then

randomly divided into training and test sets in an 80:20 ratio, resulting in 1005 reviews for training and 251 reviews for testing. The trained model was then saved as the new SnowNLP model.

The prediction results of the original SnowNLP model, the newly trained SnowNLP model, and the HowNet Lexicon-based model on the test dataset were compared against the manual annotations, as presented in Table 4.5.

Table 4.5 Sentiment analysis model outputs categorized by true positive, true negative, false positive, and false negative for the test set

Model	True Positives	True Negatives	False Positives	False Negatives	Total
Original SnowNLP	129	62	16	44	251
New SnowNLP	159	70	8	14	251
HowNet Lexicon	133	51	27	40	251

Subsequently, the original SnowNLP model, the new SnowNLP model, and the HowNet Lexicon-based model were evaluated based on key performance metrics: accuracy, precision, recall, and F1 score. The results, displayed in Table 4.6, demonstrate that the new SnowNLP model outperforms the other models across all metrics, achieving a prediction accuracy of 0.912. Consequently, the new SnowNLP model was applied for conducting the sentiment analysis in this study, due to its superior performance.

Table 4.6 Performance evaluation of sentiment analysis model

Model	Accuracy	Precision	Recall	F1 score
Original SnowNLP	0.761	0.890	0.746	0.811
New SnowNLP	0.912	0.952	0.919	0.935
HowNet Lexicon	0.733	0.831	0.769	0.799

4.3.2 Sentiment Score and Topic Performance

The sentiment score for each topic was calculated using the sentiment scores of individual reviews as output by the new SnowNLP model. Given that there

are 8 topics, the assignment of each review to specific topics was determined by the document-topic matrix generated through LDA modeling. A review was assigned to a topic if the probability of the topic corresponding to the review was greater than or equal to 0.125. This method ensured the affiliation of each review with one or more specific topics. The sentiment score for each topic was then derived as the average sentiment score of all reviews assigned to that topic, as presented in Table 4.7.

Table 4.7 Sentiment scores of topics in tourist reviews using the new SnowNLP, ranked by sentiment score in descending order

	Topics	**Sentiment Score**
Topic 2	Panda Life and Fascinating Moments	0.831
Topic 1	Panda Superstars and Their Habitat	0.784
Topic 8	Parent-child Experience	0.74
Topic 3	Guided Tours and Knowledge Enrichment	0.703
Topic 7	Facilities and Services	0.657
Topic 6	Transportation and Travel Routes	0.571
Topic 4	Weather and Timing of Visit	0.51
Topic 5	Crowd and Waiting Times	0.451
Average		0.656

The sentiment score directly correlates with tourists' evaluations of a topic. Consequently, the topic-based sentiment score is utilized to assess the performance of each topic as perceived by tourists. A higher sentiment score indicates better topic performance.

Topic 2, "Panda Life and Fascinating Moments," received the highest sentiment score with 0.831, indicating the most positive evaluation from tourists. This was followed by Topic 1, "Panda Superstars and Their Habitat," and Topic 8, "Parent-child Experience." Topics 3, "Guided Tours and Knowledge Enrichment," and 7, "Facilities and Services," also performed well, both scoring above 0.6, suggesting that tourist sentiment towards these

topics is generally positive.

In contrast, Topics 6, "Transportation and Travel Routes," and 4, "Weather and Timing of Visit," received relatively lower scores, with values close to 0.5, indicating a neutral evaluation from tourists. Notably, Topic 5, "Crowd and Waiting Times," scored only 0.451, reflecting negative sentiment and the poorest performance among all topics.

4.3.3 Trends in Sentiment Dynamics

The sentiment score for each topic was calculated on a quarterly basis. Figure 4.9 illustrates the sentiment trends of topics in tourist reviews over five quarters.

The sentiment score trends for Topic 1, "Panda Superstars and Their Habitat," and Topic 2, "Panda Life and Fascinating Moments," are similar, with both rising in the second quarter, falling in the third quarter, and then continuously increasing in the fourth and fifth quarters. Topic 8, "Parent-child Experience," exhibits a slightly different pattern, showing a slight decline in the second quarter.

The sentiment score trends for Topics 4, "Weather and Timing of Visit," 5, "Crowd and Waiting Times," and 6, "Transportation and Travel Routes," follow a similar pattern, with initial declines followed by increases. These topics reach their lowest sentiment scores in the third quarter.

The sentiment score for Topic 7, "Facilities and Services," fluctuates significantly but shows an overall upward trend. Notably, the sentiment score for Topic 3, "Guided Tours and Knowledge Enrichment," displays a clear and consistent upward trend, making it the only topic with continuously rising sentiment scores throughout the quarters.

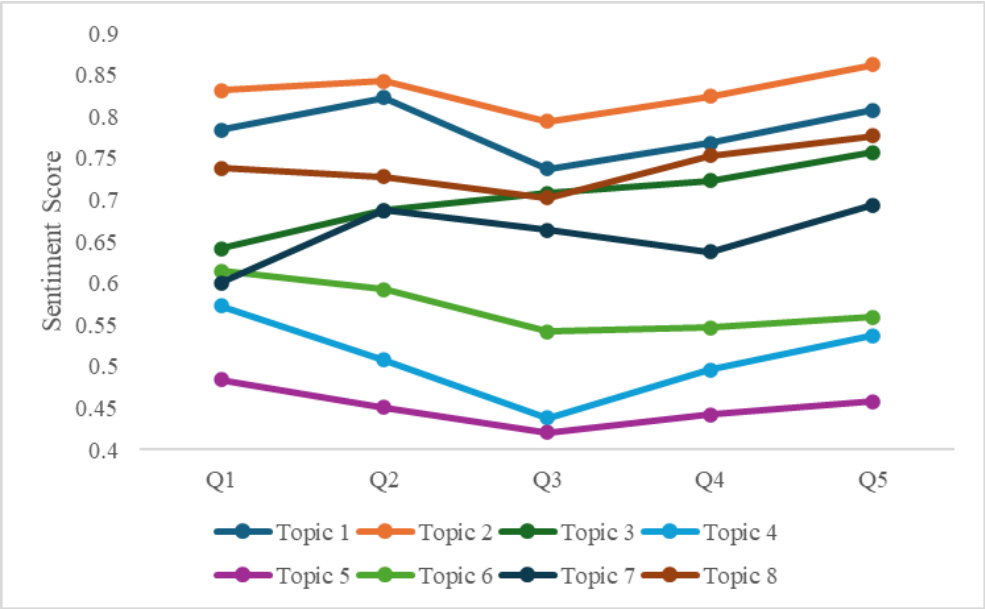

Figure 4.9 Sentiment trends of topics in tourist reviews

4.4 Descriptive Statistics Findings

4.4.1 Reliability Statistics

Before analyzing the questionnaire data, its reliability was assessed. Cronbach's Alpha was used to evaluate the internal consistency among the questions within the questionnaire. The questionnaire measures two types of indicators—importance and actual performance—each consisting of 17 items. Cronbach's Alpha was calculated separately for these two indicators to determine the scale's internal consistency. The results indicate that the Cronbach's Alpha values were 0.917 and 0.884, respectively, demonstrating good reliability of the questionnaire. Table 4.8 presents the reliability statistics for the questionnaire.

Table 4.8 Reliability statistics of the questionnaire

Items	Cronbach's Alpha	N of Items
Indicators of importance	0.917	17
Indicators of performance	0.884	17

4.4.2 Demographic Statistics

Table 4.9 presents the demographic statistics of the respondents. The data reveal that the majority of tourists are young or middle-aged, with individuals aged 39 and below comprising over 60% of the sample. This trend is consistent with Cong et al. (2017), who noted that wildlife tourism in China predominantly attracts younger and middle-aged individuals. In terms of gender distribution, there are slightly more women than men, consistent with the gender ratio reported in "Analysis and Forecast of China's Tourism Development (2023–2024)" (R. Song et al., 2024).

The educational attainment of the tourists is notably high, with approximately 75% holding a junior college degree or higher. This finding corroborates the report on the educational profile of domestic Chinese tourists and aligns with the observation of a high educational level among wildlife tourists (Cong et al., 2017; Zhigang Li, 2022)

Geographically, tourists from Chengdu city represent 23.78% of the sample, while those from other areas within Sichuan province (excluding Chengdu) account for 27.36%. Tourists from other regions of mainland China constitute the largest proportion at 45.28%, and 3.58% of the tourists come from overseas. These statistics suggest that the Panda Base attracts a diverse range of tourists, highlighting its broad appeal to local residents, as well as domestic and international tourists.

Table 4.9 Demographic statistics of the respondents

Categories	Items	Frequency	Percentage	Total
Age	20-29	87	28.34%	307 (100%)
	30-39	98	31.92%	
	40-49	65	21.17%	
	50-59	37	12.05%	
	60 and above	20	6.51%	

Table 4.9 Demographic statistics of the respondents (continued)

Categories	Items	Frequency	Percentage	Total
Gender	Male	139	45.28%	307 (100%)
	Female	161	52.44%	
	Don't want to mention	7	2.28%	
Education Level	Junior high school or below	17	5.54%	307 (100%)
	High school or technical secondary school	58	18.89%	
	Junior college	69	22.48%	
	Undergraduates	122	39.74%	
	Postgraduates	41	13.36%	
Place of Residence	Chengdu city	73	23.78%	307 (100%)
	Other areas in Sichuan province except Chengdu city	84	27.36%	
	Other areas in Chinese mainland except Sichuan province	139	45.28%	
	Overseas	11	3.58%	

4.4.3 Tourist Perceived Channels

Table 4.10 presents an overview of the channels through which tourists perceive the Panda Base, as determined by a multiple-choice question. The most frequently perceived channel is the official Douyin account, cited by 60.91% of respondents. This is followed by the official WeChat account, selected by 55.37% of respondents. The official website and official Weibo account are perceived by 34.53% and 26.71% of tourists, respectively. Additionally, 9.45% of respondents identified other channels not listed in the options. Among these, Xiaohongshu and Bilibili were mentioned. Although these platforms are not official marketing channels of the Panda Base, they

do feature information about the base shared by other organizations or users. The selection of these options by respondents may reflect uncertainty about the official origins of the information encountered.

Table 4.10 Tourist perceived channels for the Panda Base

Multiple-choice Question	Frequency	Percentage
Official website of the Panda Base	106	34.53%
Official WeChat account of the Panda Base	170	55.37%
Official Weibo account of the Panda Base	82	26.71%
Official Douyin account of the Panda Base	187	60.91%
Other (Please specify)	29	9.45%
Total Respondents	307	/

(Note: This question allows for multiple answers.)

4.4.4 Destination Image Congruence and Travel Satisfaction

Table 4.11 illustrates the impact of destination image congruence on travel satisfaction, as per responses to Question B3 in the questionnaire. The data reveal that a significant majority of 294 respondents, or 95.77%, believe that the degree of congruence between the projected image of the Panda Base and their own perception affects their travel satisfaction. Conversely, only 13 respondents, accounting for 4.23%, feel that image congruence does not impact their satisfaction. This indicates a strong consensus among the respondents that alignment between the destination's projected image and their personal expectations plays a crucial role in shaping their overall travel satisfaction.

Table 4.11 Impact of destination image congruence on travel satisfaction

Items	Frequency	Percentage
Image congruence affects satisfaction	294	95.77%
Image congruence does not affect satisfaction	13	4.23%
Total	307	100%

The 294 respondents who believed that destination image congruence affects travel satisfaction were asked to rate the extent of this impact on a scale from 1 to 5, with 1 representing "Strongly Disagree" and 5 representing "Strongly Agree," as indicated in Question B4 of the questionnaire. Table 4.12 summarizes their responses.

The majority of respondents indicated agreement with the statement that a closer alignment between the projected image of the Panda Base and their personal perception enhances their travel satisfaction. Specifically, 50.34% of respondents chose "Agree," and 30.27% selected "Strongly Agree," together accounting for 80.61% of the sample. This suggests a strong positive correlation between image congruence and travel satisfaction. Conversely, 3.06% of respondents "Strongly Disagree," and 3.74% "Disagree," reflecting a minority opinion that image congruence has a minimal impact on their satisfaction. Additionally, 12.59% of respondents were "Neutral," indicating no strong opinion. Overall, these results demonstrate that a significant majority of tourists report higher travel satisfaction when the projected image of the Panda Base aligns with their perceptions.

Table 4.12 Agreement levels on image congruence and travel satisfaction

Items	Frequency	Percentage
Strongly disagree	9	3.06%
Disagree	11	3.74%
Neutral	37	12.59%
Agree	148	50.34%
Strongly agree	89	30.27%
Total	294	100%

4.5 Spearman's Rank Correlation Results

Based on the responses to questions B2 and B5 from the questionnaire, Spearman's Rank Correlation analysis was conducted to examine the relationship between image congruence and satisfaction ratings.

Question B2 asked respondents to rate how closely the image of the Panda Base projected on various platforms aligns with their personal perception, using a scale from 1 to 5, where 1 represents "Not consistent at all" and 5 represents "Completely consistent." Question B5 inquired about overall satisfaction with the visit to the Panda Base, rated from 1 to 5, with 1 indicating "Strongly dissatisfied" and 5 indicating "Strongly satisfied."

Table 4.13 displays the results of the Spearman's Rank Correlation analysis. The correlation coefficient between image congruence and satisfaction ratings is 0.358, with a significance level of less than 0.001. This positive correlation indicates a moderate, statistically significant relationship between the alignment of the projected image and personal perception of the Panda Base and overall travel satisfaction. As the image congruence increases, so does the level of satisfaction, suggesting that better alignment between the projected image and visitors' perceptions enhances their overall satisfaction with the Panda Base.

Table 4.13 Spearman's Rank Correlation: Image congruence vs. Satisfaction ratings

Spearman's rho		**Image Congruence**	**Satisfaction Ratings**
Image Congruence	Correlation Coefficient	1	.358**
	Sig. (2-tailed)	.	<.001
	N	307	307
Satisfaction Ratings	Correlation Coefficient	.358**	1
	Sig. (2-tailed)	<.001	.
	N	307	307

**. Correlation is significant at the 0.01 level (2-tailed).

4.6 Exploratory Factor Analysis Findings

Based on responses to questions C1 to C17 in the questionnaire, which assessed the importance of 17 attributes related to the image of the Panda Base, an exploratory factor analysis (EFA) was performed. This analysis used tourists' evaluations of these attributes to identify underlying dimensions and classify them accordingly. The objective was to determine the key factors influencing perceptions of the Panda Base and to group the

attributes into meaningful categories.

4.6.1 Suitability for Factor Analysis

Table 4.14 provides the results of the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. The KMO measure is 0.806, indicating that the sample size is adequate for factor analysis, as values above 0.6 are generally considered acceptable. Bartlett's Test of Sphericity shows an approximate chi-square value of 725.712 with 136 degrees of freedom and a significance level of less than 0.001. This result confirms that the correlation matrix is significantly different from the identity matrix, thus validating the suitability of the data for factor analysis.

Table 4.14 KMO and Bartlett's test for Exploratory Factor Analysis

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.806
Bartlett's Test of Sphericity	Approx. Chi-Square	725.712
	Df	136
	Sig.	<.001

4.6.2 Factor Analysis Results

Table 4.15 provides a comprehensive overview of the results from the exploratory factor analysis (EFA). This analysis, which included 17 attributes of the Panda Base, used Varimax rotation to clarify the factor structure. The table presents several key metrics: factor loadings, eigenvalues, variance explained, and Cronbach's Alpha for each identified factor.

Factor loadings indicate the correlation between each attribute and the underlying factors, with higher loadings reflecting stronger relationships. Eigenvalues represent the amount of variance accounted for by each factor, with values above 1.0 typically considered significant. The variance explained by each factor reveals the proportion of total variance attributed to that factor. Cronbach's Alpha values assess the internal consistency and

reliability of each factor, with higher values indicating greater reliability.

The EFA effectively classifies the 17 attributes into meaningful groups that reflect different facets of the tourist experience at the Panda Base. The analysis reveals four distinct factors—Resources, Visitor Numbers, Services, and Transportation—that collectively explain 72.639% of the total variance among these attributes.

1) Resources

This factor, with a Cronbach's Alpha of 0.869, demonstrates high internal consistency and reliability. It explains 25.701% of the total variance and has an eigenvalue of 4.369. It encompasses attributes related to the resources and experiences available for observing and interacting with giant pandas. Specifically, it includes opportunities to observe diverse panda behaviors, see renowned pandas such as "Hua Hua," and witness a plentiful number of giant pandas. The prominence of this factor reflects tourists' strong emphasis on the richness and diversity of panda-related experiences, indicating that the quality and variety of interactions with the pandas are crucial to them.

2) Visitor Numbers

This factor, with a Cronbach's Alpha of 0.789, accounts for 17.657% of the variance and has an eigenvalue of 3.002. It focuses on the management of visitor numbers and crowd control. The attributes associated with this factor include efficient crowd flow management, reasonable visitor capacity limits, and advance notice of potential visitor numbers. This factor highlights the importance of logistical aspects related to managing visitor numbers and ensuring a well-organized experience at the attraction.

3) Services

This factor, characterized by a Cronbach's Alpha of 0.745, explains 15.789% of the variance and has an eigenvalue of 2.684. It encompasses the quality and range of services offered at the Panda Base. The

attributes associated with this factor include fully equipped service facilities, science and educational programs, flexible and professional tour guide services, and welcoming staff. These attributes highlight the role of well-equipped facilities, educational opportunities, and effective service delivery in shaping the tourist experience.

4) Transportation

This factor, with a Cronbach's Alpha of 0.751, accounts for 13.491% of the variance and has an eigenvalue of 2.294. It encompasses attributes related to transportation and navigation within the Panda Base. Key attributes associated with this factor include convenient transportation within the attraction, well-planned viewpoints and travel routes, clear signage including maps and directional signs, and reasonable ticket prices. These attributes emphasize the role of logistical and directional support in facilitating ease of access and movement within the site.

Table 4.15 Exploratory Factor Analysis results

Factors	**Cronbach's Alpha**	**Factor Loadings**	**Eigenvalues**	**Variance (%)**
1. Resources	0.869		4.369	25.701
C4. Observe diverse behaviors of giant pandas		0.799		
C5. See superstar giant pandas like "Hua Hua"		0.783		
C3. A plentiful number of giant pandas		0.745		
C14. Advance notice of the pandas available for viewing		0.699		
C2. Good habitat conditions for giant pandas		0.584		
2. Visitor numbers	0.789		3.002	17.657
C16. Efficient crowd flow management		0.808		
C13. Reasonable visitor capacity limits		0.763		
C15. Advance notice of potential visitor numbers		0.639		

Table 4.15 Exploratory Factor Analysis results (continued)

Factors	Cronbach's Alpha	Factor Loadings	Eigenvalues	Variance (%)
3. Services	0.745		2.684	15.789
C12. Fully equipped service facilities		0.764		
C10. Science and educational programs and services		0.753		
C9. Flexible and professional tour guide services		0.739		
C17. Welcoming staff		0.531		
C11. Family-oriented services				
4. Transportation	0.751		2.294	13.491
C8. Convenient transportation within the attraction		0.903		
C6. Well-planned viewpoints and travel routes		0.841		
C7. Clear signage including maps and directional signs		0.722		
C1. Reasonable ticket prices		0.669		
Cumulative variance explained by the above four factors (%)				72.639

4.7 Comparison Between Survey Data and Online Data

The comparison between the factors extracted from the questionnaires and the topics derived from tourist reviews was conducted to assess their alignment. The analysis began by mapping the four factors identified through the questionnaire to the eight topics extracted from the online text analysis. This mapping was executed manually, grouping topics based on their content relevance to the factors.

Specifically, Factor 1, labeled "Resources," pertains to the various attributes and elements that enhance the appeal and educational value of the Panda Base. This factor is closely linked with Topic 1, "Panda Superstars and Their Habitat," and Topic 2, "Panda Life and Fascinating Moments." Both topics focus on the core aspects of the Panda Base's offerings related to pandas—their habitat, behaviors, and intriguing moments. The quality

and richness of these panda-related exhibits and experiences form a central part of the attraction's resources, which is why they align closely with Factor 1.

Factor 2, "Visitor Numbers," reflects how the volume of visitors influences the overall experience at the Panda Base. It aligns with Topic 4, "Weather and Timing of Visit," and Topic 5, "Crowd and Waiting Times." Topic 4 examines how factors like weather and the timing of visits affect visitor numbers, impacting when people choose to come. Topic 5 addresses how high visitor numbers can lead to increased crowding and longer wait times, which can affect the quality of the experience. Thus, this factor captures the impact of visitor volume and related issues on the overall satisfaction.

Factor 3, "Services," encompasses the range of service-related aspects provided to tourists. It is connected with Topic 3, "Guided Tours and Knowledge Enrichment," Topic 7, "Facilities and Service Quality," and Topic 8, "Parent-child Experience." Topic 3 focuses on the quality of educational services and informational support offered through guided tours. Topic 7 pertains to the overall standard of amenities and services, such as cleanliness and staff assistance, while Topic 8 addresses the quality of family-friendly services and facilities. This factor highlights the importance of service quality in enhancing tourist satisfaction through various support mechanisms and facilities.

Factor 4, "Transportation," is directly associated with Topic 6, "Transportation and Travel Routes." This topic deals with the infrastructure and ease of navigation within the Panda Base, including signage, travel routes, and internal transport systems. Effective transportation infrastructure is crucial for ensuring that tourists can navigate the site efficiently, which directly impacts their overall experience.

Consequently, the eight topics were organized into four groups, as outlined in Table 4.16 and Table 4.17.

4.7.1 Importance Comparison

To calculate the importance of each factor, the average importance scores for all attributes within the factor were computed from the average ratings provided by respondents. For the topic groups associated with each factor, the importance was determined by averaging the importance scores of the topics within the group. The importance of each topic was assessed by averaging the probability values of the topic across all documents, as derived from the LDA

model, as specified in Equation (3).

Given that the measurement scales for the importance of factors and the importance of topic groups differ, only the rankings of the importance of factors and the corresponding importance of topic groups were compared. Table 4.16 provides an overview of the importance comparison between factors extracted from questionnaires and topics derived from tourist reviews.

Table 4.16 Comparison of importance between extracted factors from questionnaires and extracted topics from tourist reviews, ranked by importance of factors in descending order

Extracted factors from questionnaires	**Importance of Factors**	**Extracted topics from tourist reviews**	**Importance of Topic Groups**
1. Resources	4.574	Topic 1. Panda Superstars and Their Habitat Topic 2. Panda Life and Fascinating Moments	0.206
2. Visitor Numbers	4.320	Topic 4. Weather and Timing of Visit Topic 5. Crowd and Waiting Times	0.120
4. Transportation	4.188	Topic 6. Transportation and Travel Routes	0.094
3. Services	4.049	Topic 3. Guided Tours and Knowledge Enrichment Topic 7. Facilities and Service Quality Topic 8. Parent-child Experience	0.085

The ranking of factors based on questionnaire responses shows that "Resources" holds the highest importance with a score of 4.574. This is

followed by "Visitor Numbers" with a score of 4.320, "Transportation" with a score of 4.188, and "Services," which ranks lowest with a score of 4.049.

In the context of online tourist reviews, the importance rankings of topic groups indicate that "Panda Superstars and Their Habitat" (Topic 1) and "Panda Life and Fascinating Moments" (Topic 2) hold the highest importance with a score of 0.206, corresponding to the factor "Resources." Following this, "Weather and Timing of Visit" (Topic 4) and "Crowd and Waiting Times" (Topic 5) have importance scores of 0.120, aligning with the factor "Visitor Numbers." "Transportation and Travel Routes" (Topic 6) ranks third with an importance score of 0.094, corresponding to the factor "Transportation." The topic group of "Guided Tours and Knowledge Enrichment" (Topic 3), "Facilities and Service Quality" (Topic 7), and "Parent-child Experience" (Topic 8) shows the lowest importance scores of 0.085, corresponding to the factor "Services."

The rankings of the importance of factors extracted from the questionnaires and the importance of the corresponding topics extracted from tourist reviews are consistent. This indicates that the importance of the main aspects of the destination image of the Panda Base is similarly perceived by tourists, regardless of whether assessed through a questionnaire survey or an analysis of online travel reviews.

4.7.2 Performance Comparison

To evaluate the performance of each factor, average performance scores for all attributes within the factor were calculated based on respondents' average ratings. Similarly, the performance of topic groups associated with each factor was determined by averaging the sentiment scores of the topics within those groups.

As with the importance comparison, the measurement scales for factor performance and topic group performance differ; therefore, only the rankings of factor performance and the corresponding performance of topic groups were compared. Table 4.17 provides a comparative overview of performance between factors extracted from questionnaires and topics derived from tourist

reviews.

Table 4.17 Comparison of performance between extracted factors from questionnaires and extracted topics from tourist reviews, ranked by performance of factors in descending order

Extracted factors from questionnaires	Performance of Factors	Extracted topics from tourist reviews	Performance of Topic Groups
1. Resources	4.202	Topic 1. Panda Superstars and Their Habitat Topic 2. Panda Life and Fascinating Moments	0.807
4. Transportation	3.951	Topic 6. Transportation and Travel Routes	0.571
3. Services	3.880	Topic 3. Guided Tours and Knowledge Enrichment Topic 7. Facilities and Service Quality Topic 8. Parent-child Experience	0.700
2. Visitor Numbers	3.153	Topic 4. Weather and Timing of Visit Topic 5. Crowd and Waiting Times	0.481

The ranking of factors based on questionnaire responses indicates that "Resources" has the highest performance score, at 4.202. It is followed by "Transportation" with a score of 3.951, "Services" with a score of 3.880, and "Visitor Numbers," which has the lowest score of 3.153.

In the analysis of online tourist reviews, the performance rankings of topic groups reveal that "Panda Superstars and Their Habitat" (Topic 1) and "Panda Life and Fascinating Moments" (Topic 2) have the highest performance score of 0.807, aligning with the factor "Resources." Next, "Guided Tours and

Knowledge Enrichment" (Topic 3), "Facilities and Service Quality" (Topic 7), and "Parent-child Experience" (Topic 8) show a performance score of 0.700, corresponding to the factor "Services," which ranks third among the factors. "Transportation and Travel Routes" (Topic 6) ranks third in the topic groups with a performance score of 0.571, although the corresponding factor "Transportation" ranks second. Finally, "Weather and Timing of Visit" (Topic 4) and "Crowd and Waiting Times" (Topic 5) have a performance score of 0.481, aligning with the factor "Visitor Numbers," which ranks last among the factors.

Overall, the rankings of factor performance from questionnaires and the performance of corresponding topic groups from tourist reviews are generally consistent. However, discrepancies are noted for the factors "Services" and "Transportation" compared to their corresponding topic groups. The observed discrepancy can be attributed to the timing of data collection. Topic extraction data were sourced from online tourist reviews spanning January 2023 to March 2024, while the factor analysis data were derived from a questionnaire survey conducted in July 2024. Notably, the Panda Base upgraded its internal transportation system in May 2024, and the survey was conducted after this upgrade, which likely contributed to the improved performance of "Transportation and Travel Routes."

The internal transportation system upgrades included several key measures: First, inaccurate road signs and informational markers were corrected to prevent misleading tourists. Second, 118 new green ground spray arrows were applied at key intersections to guide tourists to various attractions, thereby reducing the risk of them becoming lost or retracing their steps. Third, large wooden road signs with increased font sizes were introduced to enhance the clarity of directional information (Qin & Peng, 2024).

4.8 Comparison Between Projected and Perceived Images

From both the importance and performance comparisons, the perceived image of the Panda Base derived from the questionnaire survey closely aligns with the image obtained from the analysis of tourist reviews. This congruence cross-validates the reliability of the

online data analysis. The eight topics extracted from online textual data are more specific compared to the four factors identified through the questionnaire survey. Consequently, a comparative analysis was conducted between the perceived image, which is based on topics derived from tourist reviews, and the projected image, reflected by topics extracted from promotional messages.

The comparison reveals both congruencies and discrepancies in the portrayal of the attraction. Table 4.18 provides a detailed comparison between the projected and perceived images, organized in descending order of the importance of each topic.

Table 4.18 Comparison between projected and perceived images, ranked by importance in descending order

Projected Image		**Perceived Image**	
Topics	**Importance**	**Topics**	**Importance**
Fascinating Updates on Panda Life	0.199	*Panda Life and Fascinating Moments*	0.290
Ticket Reservations and Visitor Capacity	0.164	*Crowd and Waiting Times*	0.159
Notices and Lost Property	0.156	Panda Superstars and Their Habitat	0.121
Transportation and Travel Routes	0.129	*Guided Tours and Knowledge Enrichment*	0.113
Guided Tours and Science Education Programs	0.119	Facilities and Service Quality	0.097
Responsible Tourism and Smoking Awareness	0.093	*Transportation and Travel Routes*	0.094
Events and Activities	0.091	Weather and Timing of Visit	0.080
Biodiversity and Wildlife Conservation	0.050	Parent-child Experience	0.045

(Note: Corresponding topics in the Projected Image and Perceived Image are italicized.)

Four out of the eight projected and perceived topics show a clear correspondence, highlighted in bold in Table 4.18. To explore these corresponding topics further, the trends

in their importance between the projected and perceived images are compared, as illustrated in Figure 4.10.

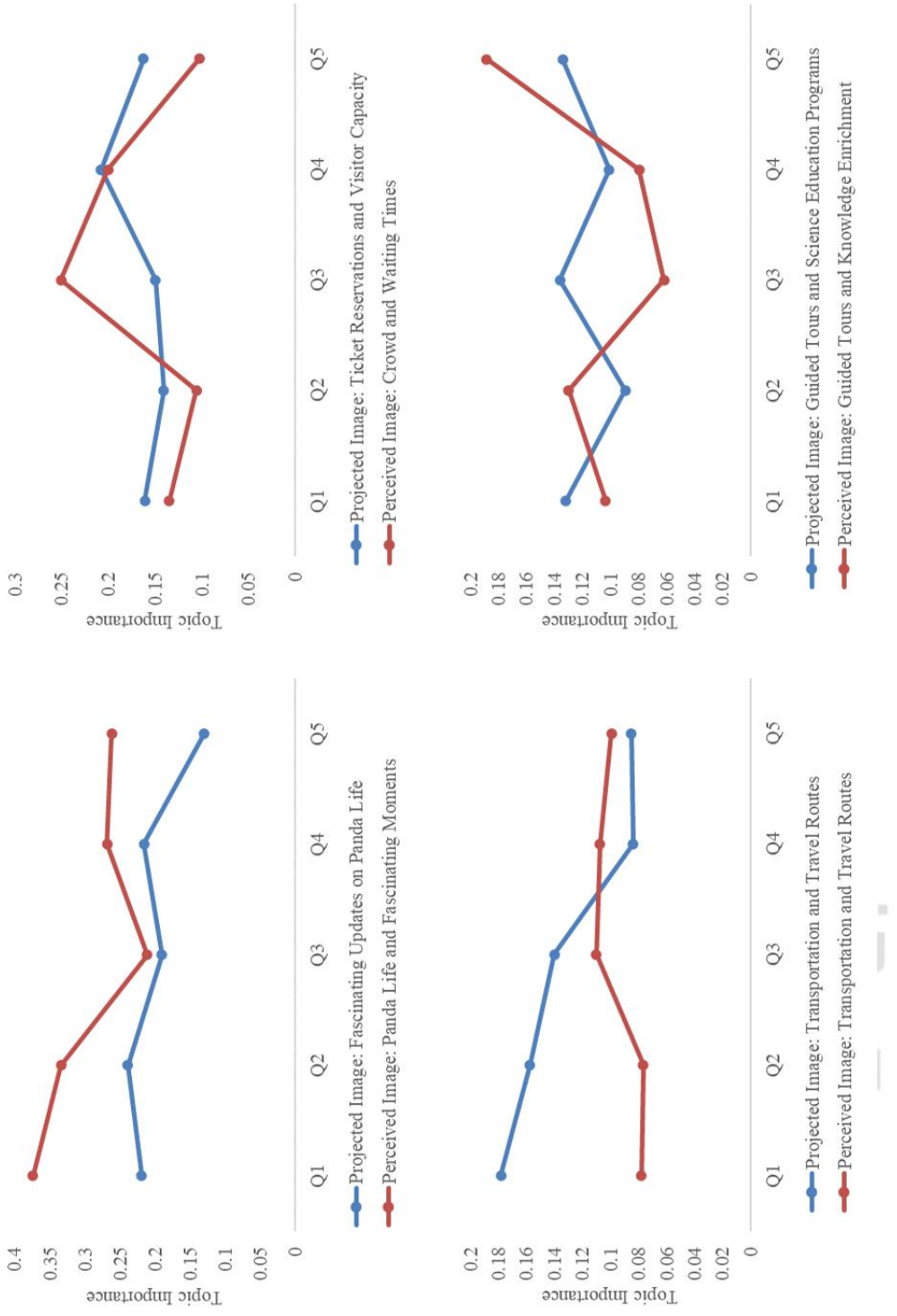

Figure 4.10 Comparison of topic trends in projected and perceived images

4.8.1 Congruencies Between Projected and Perceived Images

"Fascinating Updates on Panda Life" and "Panda Life and Fascinating

Moments": These topics are closely aligned. The projected topic, "Fascinating Updates on Panda Life," has the highest importance score of 0.199, while the perceived topic, "Panda Life and Fascinating Moments," has an importance score of 0.290. The higher importance score of the perceived topic indicates that tourists place greater emphasis on aspects of panda life and intriguing moments than what is highlighted in promotional materials. The trends for these topics are generally similar, with the closest alignment occurring in the third quarter. In other quarters, there is a notable need to enhance the dissemination of information about panda life.

"Ticket Reservations and Visitor Capacity" and "Crowd and Waiting Times": These topics also demonstrate a strong correlation. The projected topic, "Ticket Reservations and Visitor Capacity," has an importance score of 0.164, which closely matches the perceived topic, "Crowd and Waiting Times," with a score of 0.159. This similarity suggests a consistent focus on managing visitor numbers and crowd control in both promotional messages and tourist perceptions. However, a notable discrepancy arises in the third quarter, where tourist attention increased significantly, but this aspect received insufficient coverage in the promotional messages.

"Transportation and Travel Routes": There is a noticeable discrepancy between the importance scores for the projected and perceived topics, with the projected importance score at 0.129 and the perceived importance score at 0.094. This indicates that the emphasis placed on this topic in promotional messages exceeds the level of attention it receives from tourists. Despite this, the gap between projected and perceived importance is gradually narrowing, suggesting an increasing alignment.

"Guided Tours and Science Education Programs" and "Guided Tours and Knowledge Enrichment": These topics exhibit nearly identical importance scores, with the projected topic, "Guided Tours and Science Education Programs," scoring 0.119 and the perceived topic, "Guided Tours and Knowledge Enrichment," scoring 0.113. This similarity reflects a well-aligned focus on educational programs and guided tours between promotional

and perceived images. However, a significant gap is observed between the third and fifth quarters. This discrepancy is largely attributed to fluctuations in tourist attention. In the third quarter, tourists paid the least attention to this aspect, likely due to a stronger focus on issues such as crowding and waiting times. By the fifth quarter, interest in this aspect had increased significantly, but the promotional emphasis did not correspondingly adjust.

4.8.2 Discrepancies Between Projected and Perceived Images

However, no significant correspondence was observed for the remaining topics, indicating discrepancies between the promotional messages and tourists' reviews. Specifically, there was no clear alignment between the projected topics "Notices and Lost Property," "Responsible Tourism and Smoking Awareness," "Events and Activities," and "Biodiversity and Wildlife Conservation," and the perceived topics "Panda Superstars and Their Habitat," "Facilities and Service Quality," "Weather and Timing of Visit," and "Parent-child Experience."

This lack of correspondence suggests that certain aspects of the Panda Base's projected image do not fully reflect tourists' actual experiences and perceptions. It highlights a disconnect between the promotional messages and the topics that tourists find significant, revealing that some concerns and interests of tourists are not adequately addressed or emphasized in the Panda Base's promotional materials.

4.9 Comparison Between Projected and Perceived Channels

Table 4.19 presents a comparison between the projected and perceived channels, examining the alignment between the marketing channels employed for destination promotion and those through which tourists perceive the Panda Base.

The projected channel data is derived from the statistics of online promotional messages (refer to Table 4.1), while the perceived channel data is gathered from tourists' responses in the questionnaire survey (refer to Table 4.10). For ease of comparison, the percentages for both projected and perceived channels have been calculated separately. The percentage calculation

methods are as follows: To understand the marketing importance of each channel, the proportion of promotional messages disseminated through each channel relative to the total number of messages across all channels is calculated. Similarly, to gauge the perceived importance of each channel, the proportion of tourists who selected each channel relative to the total number of all channel selections made by tourists is determined. The channels analyzed include the official website of the Panda Base, the official WeChat account, the official Weibo account, and the official Douyin account.

The data in Table 4.19 reveals significant differences between the projected and perceived channels. The most important channel for projecting the Panda Base's image is WeChat, which accounts for 49.59% of the information released—nearly half of all promotional messages. This is followed by Weibo, Douyin, and lastly, the official website. In contrast, the channels perceived by tourists show a different hierarchy: Douyin is the primary channel, perceived by 34.31% of respondents, followed by WeChat, the official website, and Weibo.

This comparison indicates that Douyin is the main source of information for tourists about the Panda Base, highlighting the need for the Panda Base to strengthen its marketing efforts on Douyin. Additionally, the findings suggest that the Panda Base should consider reducing its reliance on Weibo for promotional activities and instead increase updates on its official website to better align with tourists' perceptions.

Table 4.19 Comparison between projected and perceived channels

Official Marketing Channels	**Projected Channels**		**Perceived Channels**	
	Frequency	Percentage	Frequency	Percentage
Panda.org.cn	127	10.46%	106	19.45%
Wechat	602	49.59%	170	31.19%
Weibo	260	21.42%	82	15.05%
Douyin	225	18.53%	187	34.31%
Total	1,214	100%	545	100%

4.10 Importance-Performance Analysis Results

Before conducting the Importance-Performance Analysis (IPA) on the perceived image, the transformed importance and performance scores for each topic extracted from tourists' reviews were computed using Equations (11) and (12). The resulting values are presented in Table 4.20.

Table 4.20 Transformed importance and performance scores of the perceived image

Perceived Image	Transformed Importance Score	Transformed Performance Score
Panda Superstars and Their Habitat	2.09	3.92
Panda Life and Fascinating Moments	5.00	4.15
Guided Tours and Knowledge Enrichment	1.94	3.52
Weather and Timing of Visit	1.39	2.55
Crowd and Waiting Times	2.74	2.26
Transportation and Travel Routes	1.63	2.85
Facilities and Service Quality	1.68	3.28

In Figure 4.11, the importance and performance values of each attribute in the perceived image are plotted, with importance on the y-axis and performance on the x-axis. The four quadrants, as defined by Martilla and James (1977), provide a framework for evaluating strategic priorities.

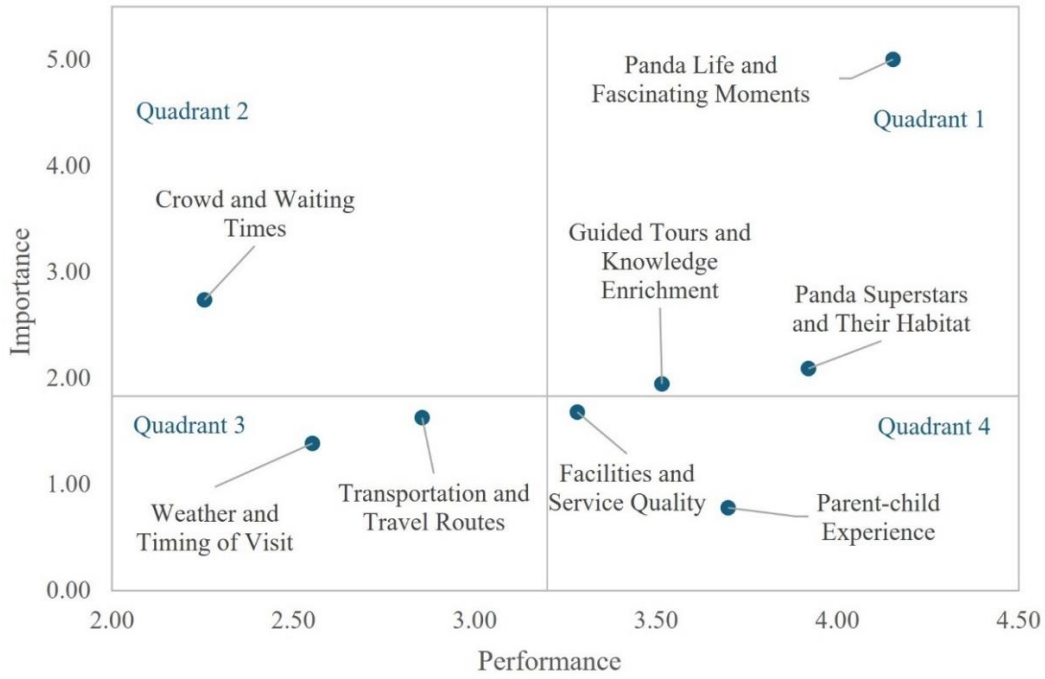

Figure 4.11 Importance-performance analysis of the perceived image

High Importance, High Performance (Quadrant 1): Attributes such as "Panda Life and Fascinating Moments," "Panda Superstars and Their Habitat," and "Guided Tours and Knowledge Enrichment" fall into this quadrant. These attributes are both highly valued by tourists and are currently performing well. The panda base should continue to prioritize these areas, ensuring that high performance is maintained to sustain tourist satisfaction. Marketing strategies should emphasize these strengths to attract and retain tourists.

High Importance, Low Performance (Quadrant 2): The attribute "Crowd and Waiting Times" is positioned in this quadrant. Although it is considered crucial by tourists, it is currently underperforming. Addressing this issue should be a top priority for the panda base. Implementing strategies to manage tourist flow and reduce waiting times will be essential to improve overall satisfaction and meet tourist expectations.

Low Importance, Low Performance (Quadrant 3): "Weather and Timing of Visit" and "Transportation and Travel Routes" are located in this quadrant. These attributes are both underperforming and not deemed critical by tourists. While they are not central to current strategic priorities, minimal improvements should be made to prevent further decline. Resources should be allocated carefully, with primary focus given to more critical areas.

Low Importance, High Performance (Quadrant 4): Attributes such as "Facilities and Service Quality" and "Parent-child Experience" are performing well but are not considered crucial by tourists. The panda base should maintain the high performance of these areas while reallocating resources to address attributes in Quadrant 2, where improvement is needed. Leveraging these strengths in marketing efforts can enhance the destination's overall appeal, but strategic emphasis should remain on addressing higher-priority issues.

Based on the Importance-Performance Analysis depicted in Figure 4.11, the panda base can effectively manage and market the destination image by focusing on the distinct needs and opportunities identified in each quadrant.

CHAPTER 5

Discussion and Suggestions

This chapter provides a detailed discussion of the research findings and practical recommendations. It interprets the results in relation to the research questions and objectives, demonstrating how they address these aspects. It highlights the application of digital innovations in destination image research and discusses the value of the novel methodology proposed in this study. The chapter also compares the findings with previous studies, noting similarities and differences and analyzing possible reasons for the discrepancies. Furthermore, it explores the theoretical and practical implications of the findings, offers actionable suggestions, and outlines how the research can be applied or extended to other areas.

5.1 Destination Image Congruence and Satisfaction Ratings

5.1.1 Empirical Findings

The analysis of the impact of destination image congruence on travel satisfaction reveals several crucial insights. As illustrated in Table 4.11, an overwhelming 95.77% of respondents believe that the alignment between the projected image of the Panda Base and their personal perceptions significantly affects their travel satisfaction. This substantial consensus highlights the pivotal role that image congruence plays in shaping overall tourist satisfaction.

Further analysis presented in Table 4.12 shows that among the 294 respondents who acknowledged the influence of image congruence, a substantial 80.61% either agreed or strongly agreed that a closer alignment between the projected image and their personal perceptions enhances their travel satisfaction. This finding underscores the importance of ensuring that a destination's projected image accurately reflects tourists' expectations to

achieve high satisfaction levels.

Supporting these findings, the Spearman's Rank Correlation analysis in Table 4.13 reveals a correlation coefficient of 0.358, significant at the 0.001 level. This moderate but statistically significant positive relationship suggests that improvements in the alignment between the projected image and personal perception are associated with higher levels of satisfaction. This underscores the importance of maintaining a consistent and accurate representation of the destination to enhance the overall travel experience.

These results align with existing literature, which emphasizes the critical role of matching a destination's projected image with tourists' perceptions to improve satisfaction (Farmaki, 2012; Govers & Go, 2004b; Joppe et al., 2001). Additionally, Y. Li et al. (2023) assert that both the projected image (how the destination is portrayed) and the perceived image (how tourists perceive it) jointly shape satisfaction levels through a process of expectation alignment.

However, it is important to note that 4.23% of respondents indicated that image congruence does not influence their satisfaction. Among the 294 respondents who acknowledged the impact of image congruence, a small minority (6.80%) reported minimal effect, with 3.06% "Strongly Disagreeing" and 3.74% "Disagreeing." Additionally, 12.59% of respondents were neutral. These findings suggest that while image congruence is a significant factor, other elements also contribute to travel satisfaction.

The Spearman's Rank Correlation analysis further corroborates this perspective, revealing that while there is a meaningful relationship between image congruence and satisfaction, the moderate correlation coefficient of 0.358 indicates that additional factors are also influential. Existing literature identifies these factors as including the uniqueness of the destination experience, service quality, cultural influences, and personal preferences, which may not be fully captured by the alignment between the projected and perceived image (Culic et al., 2021; S. S. Huang & Crotts, 2019; Khuong & Phuong, 2017; Prayag & Ryan, 2011). To gain a more comprehensive understanding of the determinants of travel satisfaction and to refine

destination marketing strategies, future research should investigate how these additional factors interact with image congruence.

Based on the empirical evidence, the study has effectively addressed the first research question regarding the impact of destination image congruence on tourists' satisfaction ratings.

5.1.2 Theoretical and Practical Implications

The impact of image congruence on satisfaction can be effectively understood through Expectancy-Disconfirmation Theory. This theory suggests that consumer satisfaction is driven by the gap between pre-consumption expectations and the actual performance of a product or service. When perceived performance aligns with or surpasses expectations, satisfaction occurs; when it falls short, dissatisfaction ensues. In the context of tourist destinations, the projected image sets tourists' expectations, while the perceived image reflects their actual experiences. Often, expectations exceed actual perceptions, and this misalignment between projected and perceived images directly influences tourist satisfaction (Duan et al., 2020; Iordanova & Stainton, 2019; W. Sun et al., 2021).

By analyzing the gap between expectations and actual performance, the theory provides critical insights into the drivers of tourist satisfaction and informs strategies for enhancing the tourist experience and fostering destination loyalty (Cai & Chi, 2021; Hui et al., 2007; Pizam & Milman, 1993; Weber, 1997; Yüksel & Yüksel, 2008; Zehrer et al., 2011).

This empirical study underscores the validity of Expectancy-Disconfirmation Theory within the context of wildlife tourism research. Specifically for the Panda Base, it is critical to ensure that tourists' perceptions align with the projected image communicated through marketing and promotional activities. Discrepancies between anticipated and actual experiences can lead to dissatisfaction, as tourists may perceive a gap between their expectations and the reality of their visit, resulting in feelings of being misled or unfulfilled. To address these issues, it is essential for the Panda Base to present its attributes consistently and accurately in promotional materials. Such

alignment helps set realistic expectations for tourists, thereby reducing the likelihood of disillusionment and improving overall satisfaction.

When a destination adjusts its projected image based on tourists' perceived image, it highlights a dynamic interaction where the perceived image influences the projected image. Traditionally, research has focused on the unidirectional influence of the projected image in shaping tourists' perceptions. As illustrated in Figure 2.2, scholars studying the factors and formation process of perceived destination image generally agree that destination marketing information (the source of the projected image) impacts the perceived image. Other studies similarly assume a static flow, where the destination communicates a specific image that serves as the foundation for tourists' perceptions (Andreu et al., 2000; Farmaki, 2012; Silva & Costa, 2017; Stepchenkova & Morrison, 2006).

This study, however, proposes a reciprocal nature in this relationship, suggesting that tourists' perceptions are not merely passive receptions of the projected image but has the potential to influence how the destination projects itself. This more nuanced understanding highlights an interaction that creates a feedback loop, where the destination continuously adapts its projected image based on ongoing assessments of tourists' perceptions. This adaptive approach allows for a more responsive and accurate representation of the destination, potentially enhancing tourist satisfaction and loyalty.

By recognizing the two-way nature of this relationship, this study advances tourism destination image research by expanding beyond the existing one-way assumption of influence. It enhances the theoretical framework by incorporating mechanisms of image adaptation and dynamic interaction. Additionally, the reciprocal relationship between projected and perceived images fosters innovative approaches to destination marketing research. Real-time analytics and adaptive marketing technologies can be further developed to help destinations continuously adjust their projected image in response to evolving tourist perceptions and emerging trends.

5.2 Destination Image Congruence of the Panda Base

5.2.1 Empirical Findings

The comparative analysis of the projected and perceived images of the Panda Base reveals both congruence and significant differences. This analysis addresses the second research question and achieves the second research goal by demonstrating how to measure the congruence between the projected and perceived images.

1) Attributes with Congruence

Out of the eight topics analyzed, four demonstrate clear alignment between the projected and perceived images. Notably, the emphasis on panda life is evident in both the projected topic "Fascinating Updates on Panda Life" and the perceived topic "Panda Life and Fascinating Moments." Although promotional materials highlight panda life updates, the perceived image suggests that tourists place a substantially higher value on this aspect. This discrepancy implies that while the destination acknowledges the importance of panda life, its promotional efforts may not fully capture the depth of tourists' interest. Furthermore, in all quarters except the third, there is a clear need to strengthen the dissemination of information about panda life.

Similarly, topics related to visitor management, such as "Ticket Reservations and Visitor Capacity" in promotional messages and "Crowd and Waiting Times" in tourist reviews, exhibit a consistent focus, indicating a shared recognition of the importance of managing visitor flow and crowd control. However, a significant discrepancy is observed in the third quarter, where tourist attention increased considerably, yet this aspect was not adequately covered in promotional messages.

The significance of "Crowd and Waiting Times" in the perceived image peaks during the third and fourth quarters, with the highest prominence in the third quarter. This peak is likely due to the summer vacation period, which represents a peak tourist season with a high average daily

number of visitors, leading to increased attention to crowd management. The fourth quarter, which includes the 7-day Chinese National Day holiday, also experiences a smaller peak in tourism, resulting in heightened focus on crowd management, though to a lesser extent than in the third quarter.

In contrast, the importance of "Ticket Reservations and Visitor Capacity" in the projected image is most prominent in the fourth quarter, whereas its importance in the third quarter is comparatively lower. This discrepancy between the projected and perceived images suggests that the emphasis in promotional messages does not align well with the shifting concerns of tourists over time.

Transportation, referred to as "Transportation and Travel Routes" in both promotional messages and tourist reviews, generally shows alignment. However, there is a noticeable discrepancy in the importance scores. Although promotional messages emphasize this topic more than tourists do, the gap in perceived importance is gradually closing, indicating an improving alignment.

Furthermore, the similarity between "Guided Tours and Science Education Programs" in the projected image and "Guided Tours and Knowledge Enrichment" in the perceived image suggests that both the destination and tourists place similar importance on this aspect. Based on the trend, the focus on this topic could be reduced in promotional messages during the third quarter, but it should be strengthened in the fifth quarter.

2) Attributes with Incongruence

Despite these areas of alignment, several significant discrepancies emerge between the projected and perceived images. The promotional topics "Notices and Lost Property," "Responsible Tourism and Smoking Awareness," "Events and Activities," and "Biodiversity and Wildlife Conservation" do not align with the perceived topics "Panda Superstars and Their Habitat," "Facilities and Service Quality," "Weather and

Timing of Visit," and "Parent-child Experience." These mismatches reveal a gap between the aspects emphasized in promotional materials and those valued by tourists.

Several factors may explain these discrepancies. For instance, "Notices and Lost Property" provides basic information such as opening hours and lost-and-found services. Although this information is useful, it lacks the appeal and topicality that might engage tourists, leading to its infrequent mention in reviews. Similarly, "Responsible Tourism and Smoking Awareness" and "Biodiversity and Wildlife Conservation" focus on guiding tourists' behavior and environmental awareness. However, tourists tend to concentrate on their personal experiences rather than these broader guidelines, resulting in limited discussion of these topics in reviews. Additionally, "Events and Activities," such as "Global Nature Day Global Nature Day: Youth Natural Science Knowledge Challenge", was a specialized event with limited participation, which may explain their minimal presence in tourist reviews.

Conversely, the perceived image includes aspects not reflected in the projected image, such as "Panda Superstars and Their Habitat," "Facilities and Service Quality," "Weather and Timing of Visit," and "Parent-child Experience." These discrepancies highlight the need for the Panda Base to refine its promotional strategies to better align with tourists' actual interests and experiences. For instance, if promotional messages comprehensively address the impact of weather conditions and the timing of visits, whether in the morning or afternoon, they would better address tourists' concerns and help set realistic expectations.

The current misalignment suggests that the destination's marketing messages do not fully address the aspects that tourists prioritize, potentially leading to a disconnect between promotional content and tourist expectations. Addressing these gaps could enhance the

coherence between the Panda Base's projected and perceived images, leading to more effective destination marketing and improved tourist satisfaction.

5.2.2 Theoretical and Practical Implications

Since Bramwell and Rawding (1996) introduced the distinction between projected and perceived images of destinations, research on the consistency between these two dimensions has gained prominence. Scholars have made significant efforts to explore and evaluate this consistency using a range of data sources and methods. The sources include questionnaires, travel guides, TV commercials, destination official websites, Online Travel Agencies (OTAs), and social media. Methodological approaches have evolved from traditional questionnaire scale analysis and manual content coding to advanced techniques such as big data mining and machine learning (Andreu et al., 2000; Q. Chen et al., 2023; Farmaki, 2012; Grosspietsch, 2006; Marine-Roig & Ferrer-Rosell, 2018; Silva & Costa, 2017; Wacker & Groth, 2020).

This study employs an innovative methodological approach. Initially, LDA modeling is applied to analyze the projected image. Subsequently, LDA is integrated with sentiment analysis to examine the perceived image. Additionally, the study combines online text mining with questionnaire surveys to cross-validate the data analysis results, thereby assessing the effectiveness of online text analysis and ensuring a more robust and comprehensive evaluation. This approach not only reinforces the applicability of LDA modeling in tourism text mining but also offers a novel perspective on comparing projected and perceived images in the digital era. The methodology of this research can be applied to other destinations, enhancing the reliability and efficiency of destination image congruence research.

For the projected image of the Panda Base, aspects such as "Biodiversity and Wildlife Conservation," "Guided Tours and Science Education Programs," "Events and Activities," and "Responsible Tourism and Smoking Awareness" play a crucial role in educating tourists. This emphasis aligns with existing literature, which underscores the significance of wildlife tourism in raising

awareness about threats to wildlife and the need for environmental protection and biodiversity preservation (Ballantyne, Packer, & Falk, 2011; Ballantyne, Packer, & Sutherland, 2011).

Regarding the perceived image of the Panda Base, derived from tourist reviews, it generally aligns with previous studies (Z. Wang et al., 2024). However, the importance attributed to certain topics has shifted. For instance, this study found that tourists now place greater emphasis on guided tours, while showing less concern for travel routes and weather conditions. This shift may reflect changes in the data collection period, as improvements in the Panda Base's infrastructure and management practices likely influence tourists' evolving perceptions.

Moreover, the findings of this study align well with the conceptual framework for wildlife tourism developed by Reynolds and Braithwaite (2001). Their framework outlines six intrinsic quality factors that define the richness and intensity of wildlife tourism experiences. Four of these factors—authenticity, intensity, uniqueness, and duration—are universal to all tourism experiences, while the remaining two—species popularity (considering attributes like physical attractiveness, size, and danger) and species status (such as rarity and endangered status)—are unique to wildlife tourism.

At the Panda Base, the most important aspect perceived by tourists, "Panda Life and Fascinating Moments," strongly corresponds to the factor of uniqueness and resonates with both species popularity and species status, reflecting tourists' fascination with the charm and rarity of the pandas. The second most significant aspect for tourists, "Crowd and Waiting Times," relates to the factor of duration, emphasizing the impact of the time spent at the destination on the overall experience. These connections underscore the relevance of the Panda Base's offerings to the established wildlife tourism framework, highlighting the importance of these factors in shaping tourist experiences.

The discrepancy between the projected and perceived images of the Panda Base, as identified in this study, highlights a broader dilemma in wildlife

tourism: balancing tourists' desire for increased interaction with wildlife while ensuring the protection of these animals. This challenge is crucial for achieving alignment between the destination's projected image and tourists' actual experiences, and it resonates with concerns discussed in the existing literature.

Higginbottom (2004) developed a model that elucidates the interactions among core components of wildlife tourism experiences, identifying three key factors: wildlife and habitats, tourists, and operators/businesses. Operators are responsible for managing the wildlife tourism destination, wildlife and habitats serve as the tourism resources, and tourists are the participants. A major challenge for managers is to offer tourists opportunities to observe rare or endangered wildlife while minimizing potential negative impacts on these species (Ballantyne, Packer, & Sutherland, 2011; Smith et al., 2011; Sorice et al., 2006). The key to sustainable development in wildlife tourism lies in managing tourist behavior rather than focusing solely on the animals themselves (Rodger & Moore, 2004). For the Panda Base, a key challenge is achieving sustainable development while allowing tourists to engage closely with giant pandas (Cong et al., 2014). Therefore, to enhance the congruence between the projected and perceived images of the Panda Base, it is crucial to prioritize the guidance and education of tourists. Beyond improving tourist satisfaction, fostering greater environmental awareness is essential for advancing the sustainable tourism.

This study pioneers research on projected and perceived images in wildlife tourism destinations, providing valuable empirical evidence on the interests and concerns of Chinese tourists and promoting sustainable tourism practices.

5.3 Issues with the Panda Base's Destination Image

5.3.1 Addressing Incongruence in Destination Image

Achieving congruence between the projected and perceived images of the Panda Base is crucial for effective marketing. To improve the alignment, the Panda Base should enhance its promotional messages around "Panda Life and Fascinating Moments" to better match tourists' interests and expectations.

Moreover, the emphasis on "Ticket Reservations and Visitor Capacity" in promotional messages should be adjusted to reflect shifts in tourists' concerns. Specifically, the largest portion of marketing resources should be allocated in the third quarter, followed by the second largest allocation in the fourth quarter. This approach will ensure that promotional efforts are well-targeted to address peak concerns during these times.

In addition, to further improve destination image congruence, promotional content should integrate the following aspects: "Panda Superstars and Their Habitat," "Facilities and Service Quality," "Weather and Timing of Visit," and "Parent-child Experience." These elements are critical for a comprehensive portrayal of the destination.

To enhance the congruence between projected and perceived images, insights from communication theories such as Agenda-Setting Theory and Two-Sided Persuasion Theory can be highly beneficial.

Agenda-Setting Theory posits that media influence public perception by consistently highlighting certain topics, thereby making them more salient in the public consciousness (M. McCombs & Reynolds, 2002; M. E. McCombs & Shaw, 1972). This theory suggests that the selection and emphasis of particular issues by the media guide audiences to perceive these issues as more significant compared to others. In the context of tourism, this means that by strategically emphasizing specific aspects of a destination, such as unique resources and management measures, destination marketers can shape potential tourists' expectations (Schweinsberg et al., 2017).

For the Panda Base, addressing the four aspects of the perceived image that are not reflected in the projected image is crucial. Strengthening communication around these aspects can help bridge the gap between the projected and perceived images. For instance, if the Panda Base focuses its promotional efforts on specific elements like the lifestyle and behaviors of the star panda "Hua Hua," it can significantly influence how these elements are perceived by potential tourists. This targeted approach ensures that the projected image aligns more closely with the aspects that tourists value most.

Two-Sided Persuasion Theory posits that messages which acknowledge and address opposing viewpoints are more persuasive than one-sided messages. This theory asserts that a communication strategy presenting both sides of an argument, while refuting counterarguments and offering a balanced perspective, enhances message credibility and reduces audience resistance (Hovland et al., 1953). For destinations targeting well-informed and discerning tourists, adopting a two-sided approach can be particularly effective. These tourists, who are likely to conduct thorough research and value transparency, are more responsive to messages that openly discuss both the strengths and limitations of the destination (Ivanov et al., 2018; Min et al., 2013). By constructively addressing potential shortcomings and highlighting positive aspects, destinations can build trust with prospective tourists and manage their expectations more effectively (L. M. Meng et al., 2023; L. R. Tang et al., 2012).

Therefore, by addressing areas such as "Crowd and Waiting Times," where tourists perceive performance shortcomings, and by providing balanced and transparent information, the Panda Base can enhance tourist trust and satisfaction. This approach not only helps in managing expectations but also reduces the likelihood of tourist disappointment by addressing potential criticisms while emphasizing the destination's strengths.

The third quarter is a critical period for the Panda Base to focus on. In addition to concerns about crowding, topics such as "Weather and Timing of Visit," "Transportation and Travel Routes," and "Facilities and Service Quality" saw a modest increase in tourist discussions. However, these topics were not given sufficient emphasis in the promotional messages. Destination managers should enhance their marketing and management strategies to address these areas of concern.

Moreover, comparing the marketing channels used in promotional materials with those perceived by tourists reveals that Douyin is the primary source of information about the Panda Base for tourists. This underscores the need for the Panda Base to intensify its marketing efforts on Douyin. Additionally, the

Panda Base should consider reducing its reliance on Weibo for promotional activities and increasing updates on its official website to better align with tourists' preferences.

5.3.2 Improving Areas of Low Perceived Value

Improving perceived value is crucial, as emphasized by Value Perception Theory, which posits that consumers assess products or services based on their perceived value (Sánchez-Fernández & Iniesta-Bonillo, 2007). In this study, tourists' evaluations of various aspects of the destination's performance are informed by their perceived value. Therefore, it is important to focus on enhancing aspects where perceived value is currently low. Strategies for improving perceived value are derived from a detailed analysis of the perceived image.

Two critical areas requiring enhancement are "Crowd and Waiting Times" and "Weather and Timing of Visit." The issue of "Crowd and Waiting Times" is particularly pressing, as it has the lowest perceived value among tourists despite its high importance. Implementing effective crowd management strategies, such as optimizing tourist flow and improving transparency regarding wait times, is essential for alleviating concerns and enhancing the overall tourist experience.

In contrast, while "Weather and Timing of Visit" also has a low perceived value, its importance is not as high as that of "Crowd and Waiting Times." This allows for a more measured allocation of marketing resources. However, it remains important to include relevant information about weather conditions and timing in promotional materials to help manage tourists' expectations and improve their overall experience.

Analyzing quarterly trends, it is evident that tourists' perceived value of most topics is lowest in the third quarter. This suggests that the third quarter is a critical period for targeted improvements and focused efforts to address these concerns effectively.

5.3.3 Adjusting Strategic Focus Based on IPA Results

Firstly, prioritizing the management of "Crowd and Waiting Times" is essential. This aspect, situated in the second quadrant of IPA, indicates a high level of importance with insufficient current performance. Effective strategies to streamline visitor flow and minimize wait times will not only meet tourists' high expectations but also significantly improve their overall experience.

Secondly, it is crucial to emphasize "Panda Life and Fascinating Moments" and "Panda Superstars and Their Habitat," both of which fall into the first quadrant of IPA. These aspects are highly valued by tourists and should be prominently featured in promotional materials. Special attention should be given to enhancing the visibility of "Panda Superstars and Their Habitat," which is currently underrepresented in promotional efforts.

Thirdly, although "Weather and Timing of Visit" is categorized in the third quadrant and has a lower priority, it still needs to be appropriately reflected in marketing content. Including information about weather and timing in promotional messages and addressing tourists' concerns about these factors are important for enhancing perceived value and maintaining alignment between the destination's image and tourists' experiences.

Fourthly, aspects such as "Facilities and Service Quality" and "Parent-child Experience," which are situated in the fourth quadrant, require only moderate attention to maintain consistency with tourists' perceived image. While these elements do not need to be overemphasized, they represent potential strengths of the Panda Base. Appropriate marketing of these aspects could enhance the destination's appeal and help differentiate it from competitors.

Finally, aspects such as "Guided Tours and Knowledge Enrichment" and "Transportation and Travel Routes" are well represented in the current projected image of the Panda Base. The portrayal of guided tours aligns closely with tourists' perceptions and does not require modification. However, the emphasis on transportation should be slightly adjusted in the projected image to reflect quarterly variations, with particular attention given to this aspect during the third quarter.

5.4 Suggestions

Based on the empirical findings and discussions, this study offers three recommendations for the destination image marketing strategy of the Panda Base. It identifies areas where marketing resources should be increased, reduced, or maintained. These suggestions benefit not only the Panda Base but also serve as a reference for other wildlife tourism destinations.

5.4.1 Enhance Crucial Areas Requiring Increased Marketing Efforts

Firstly, enhancing transparency and effectively managing crowd sizes and waiting times are crucial. Crowding or even overcrowding and long waiting times are identified as aspects with the lowest perceived value yet high importance among tourists, necessitating immediate and significant improvement. While information regarding ticket reservations and visitor capacity is currently included in the Panda Base's projected image, it is evident that this information is insufficient. To address this issue effectively, it is imperative to provide more transparent and detailed information about expected waiting times and visitor flow management.

A two-sided persuasion strategy should be employed to set realistic expectations for potential visitors. This approach involves clearly communicating the current crowd conditions and anticipated delays, while also highlighting the potential impacts these factors may have on the overall travel experience. By doing so, tourists can make informed decisions and manage their expectations more effectively.

In addition to enhance communication, it is crucial to improve crowd management and implement effective strategies to control and guide visitor flow. This could involve several measures: further restricting the number of daily ticket reservations to prevent overcrowding, establishing one-way traffic systems in high-traffic areas to streamline movement, increasing the number and visibility of diversion and guidance signs, and adding more seating areas to reduce the duration of standing in line.

In light of the increasing interest in giant panda tourism, it is advisable for local governments to consider expanding the scenic area of the panda base.

This expansion should not be limited to merely enlarging the physical space but should also encompass enhancements to the surrounding tourism infrastructure. Improvements in transportation, catering, and accommodation facilities are crucial to accommodating a higher volume of tourists. By expanding and upgrading these supporting services, the destination can not only increase its capacity to host more tourists but also enhance the overall tourist experience.

Incorporating these crowd management improvements into marketing efforts can demonstrate the Panda Base's commitment to addressing visitor concerns. By effectively communicating these enhancements, the Panda Base can improve its image and reassure tourists that their concerns are being actively addressed. The third and fourth quarters of each year should be the primary focus for improvement, with particular emphasis on the third quarter.

Secondly, showcasing panda life through engaging media is important. To enhance tourist education, the presentation of panda life can be enriched by highlighting their living habits, spreading knowledge about protecting endangered species, and promoting biodiversity awareness. Given tourists' strong interest in panda dynamics, integrating the topic of "Biodiversity and Wildlife Conservation" into the portrayal of panda life, rather than presenting it separately, may effectively enhance tourists' perceptions.

Establishing a dedicated professional filming team is essential to document intriguing moments in the pandas' daily routines while ensuring minimal disruption to their natural behaviors. This team should focus on capturing a wide range of unique and fascinating behaviors that highlight the pandas' personalities and interactions. The recorded footage should be systematically published on various official platforms, including the Panda Base's website, WeChat, Weibo, Douyin, and other relevant social media channels. To maximize the impact of these publications, it is important to employ engaging video editing techniques, select appropriate and appealing background music, and craft compelling photo captions that enhance the entertainment value of the content.

Furthermore, increasing the frequency of content updates is vital to sustaining tourists' interest in the pandas' lives. By providing regular and diverse updates, the Panda Base can attract and retain tourists who are eager to see new and captivating content. In addition to these efforts, it is essential to prioritize continuous feedback and improvement. By actively seeking tourist input and monitoring engagement metrics, the Panda Base can refine its content strategies and maintain high standards of excellence in its media presentations. This approach will ensure that the dissemination of pandas' daily lives remains dynamic, engaging, and aligned with tourists' interests.

Thirdly, it is essential to emphasize the panda superstars and their habitat. Enhancing the communication coverage of the panda superstars like "Hua Hua" and her habitat is crucial for optimizing tourist engagement and managing congestion. "Hua Hua," a female giant panda born in July 2020, is distinguished by her notably short, rounded body and distinctive posture, which resembles an equilateral triangle without a neck. Her gentle demeanor and unique physical characteristics have endeared her to a broad audience, resulting in significant fan admiration. This appeal has led "Hua Hua" to become a focal point in tourist feedback, with her viewing area often experiencing high levels of congestion.

To address these issues and improve tourist experience, it is essential to leverage advanced digital technologies such as virtual reality (VR) and augmented reality (AR). By offering immersive and interactive virtual experiences of "Hua Hua," these technologies can provide engaging alternatives to physical visits, thus helping to alleviate on-site crowding. VR and AR can simulate the panda's habitat and behaviors, allowing potential tourists to explore and interact with "Hua Hua" virtually before their visit, which can enhance anticipation and reduce the pressure on physical viewing areas. During virtual interactions with "Hua Hua," knowledge about wildlife protection and biodiversity can be shared to raise tourists' environmental awareness.

Furthermore, promotional materials should accurately represent the tourist

experience with "Hua Hua" to ensure that potential tourists have realistic expectations. This includes providing detailed information about the viewing experience, potential congestion, and the steps taken to manage tourist flow. By aligning promotional content with actual tourist experiences, the Panda Base can better manage tourist expectations and improve overall satisfaction.

Fourthly, providing information on how weather conditions and timing of the visit affect the overall travel experience. Based on quarterly changes, this information should receive the greatest emphasis in the third quarter.

Although weather is an uncontrollable external factor, proactive measures can be taken to better prepare tourists for their visit. First of all, provide comprehensive guidance on how various weather conditions—such as rain, snow, or extreme heat—can influence the pandas' behavior and outdoor activities. For example, explain how rainy weather may limit the pandas' time spent in outdoor enclosures and affect their visibility, or how extreme heat might alter their activity patterns. Offering this information helps set realistic expectations for tourists, allowing them to adjust their plans accordingly.

Additionally, develop and communicate contingency plans for different weather scenarios. For instance, advise tourists on alternative indoor activities or sheltered viewing areas available during inclement weather. Detail how tourists can adjust their routes within the Panda Base to avoid congested or less accessible areas during adverse weather conditions. Providing these options can enhance the flexibility and overall enjoyment of the visit.

Moreover, offer insights into how different times of day—morning, noon, or afternoon—can impact the tourist experience. Explain how pandas' activity levels and visibility might vary depending on the time of day, and how peak visitation times could affect crowd levels and wait times. This information allows tourists to choose the optimal time for their visit based on their preferences and priorities.

Currently, the perceived inadequacy of information regarding weather and visit timing highlights a gap in both information dissemination and tourist preparation. To address this, the Panda Base should present practical tips and

recommendations in a clear, engaging, and interactive manner. By doing so, the Panda Base can assist tourists in planning their visits more effectively, manage their expectations, and ultimately improve their overall experience.

5.4.2 To Reduce Marketing in Areas with Lower Immediate Impact

Firstly, optimize resource allocation by scaling back investments in facilities and service quality improvements.

Given the constraints of limited marketing resources, the Panda Base should strategically allocate its investments by prioritizing areas that require immediate enhancement over those with less critical needs. Specifically, the construction of facilities and improvements in service quality are currently performing well, and their relative importance is overshadowed by the more pressing need for effective crowd control. Therefore, it is advisable to reduce investment in these areas and reallocate resources towards addressing more urgent issues, such as managing visitor flow. Enhancing strategies for handling visitor traffic can significantly alleviate problems related to crowding and waiting times, thereby improving overall tourist satisfaction.

Despite reducing investment in infrastructure and service quality, it is essential to maintain and highlight the Panda Base's strengths in these areas within promotional materials. Emphasizing the existing high standards of infrastructure and service quality can serve as a competitive advantage, differentiating the Panda Base from other attractions. Effective communication of these strengths in marketing efforts can reassure potential tourists of the high-quality experience they can expect, even as resources are reallocated to address more urgent priorities.

Secondly, reallocate resources from further development of parent-child facilities, given their current maturity and satisfactory performance.

The current infrastructure for parent-child experiences at the Panda Base is well-established and has garnered positive feedback from tourists, suggesting that additional investment in this area may not yield substantial incremental benefits. Given that the relative importance of enhancing parent-child facilities is lower compared to more pressing needs such as crowd

management, it is advisable to reduce the allocation of resources toward further development in this domain.

However, it remains essential to emphasize the strengths of the Panda Base's existing family-friendly facilities in promotional efforts. Marketing materials should continue to highlight the convenience and appeal of these features, focusing on their suitability for families. By effectively showcasing the current advantages of the parent-child experience, the Panda Base can maintain its attractiveness to family tourists while judiciously managing its limited resources.

Thirdly, it is recommended to streamline the communication of notices and lost property information.

To optimize resource allocation and enhance communication efficiency, the Panda Base should consider limiting the dissemination of notifications and lost-and-found information to its WeChat official account. By concentrating these updates on a single platform, the Panda Base can avoid dispersing marketing resources across multiple channels and ensure a more streamlined communication process.

Currently, the WeChat official account serves as the primary channel for ticket purchases, making it an ideal platform for integrating notifications with ticketing information. This approach not only consolidates communication but also leverages the existing ticket purchasing infrastructure to deliver timely updates. By bundling essential notices with ticket information, the Panda Base can provide a cohesive and user-friendly experience for tourists, thereby improving the efficiency of information dissemination and reducing the potential for confusion.

5.4.3 To Maintain Consistent Marketing Support in Key Areas

Firstly, the dissemination of knowledge about environmental protection and sustainable tourism should be continued, with a focus on integrating this information into content that resonates with tourists. This can be achieved by embedding environmental messages within popular topics, such as the lives of pandas and updates on panda superstars.

Moreover, enhancing tourism literacy is an essential component of this educational effort. This includes informing tourists about responsible travel practices, such as adhering to no-smoking policies and respecting wildlife guidelines. While this focus may not currently be a major concern among tourists, sustained and proactive communication on these topics can raise awareness and foster a more environmentally conscious tourist base. By continuously providing relevant information and guidance, the Panda Base can effectively attract and engage tourists, reinforcing its commitment to environmental stewardship and responsible tourism practices.

In addition to the marketing initiatives undertaken by the Panda Base itself, local governments have a pivotal role to play in advancing the sustainability of local tourism. They can leverage a variety of platforms and resources to enhance tourist guidance and foster a deeper awareness of environmental protection and sustainable tourism practices.

For instance, local governments can develop and implement educational campaigns through diverse media channels, including local news outlets, and public service announcements. These campaigns should aim to inform tourists about the ecological significance of the giant panda and the importance of preserving their habitat. By integrating these messages into various media, governments can reach a broader audience and effectively communicate the values of sustainable tourism. Furthermore, local governments could collaborate with educational institutions and conservation organizations to create and distribute informative materials such as brochures, digital guides, and interactive content that highlight best practices for minimizing environmental impact while visiting.

By integrating these strategies, a comprehensive framework can be established that not only fosters sustainable tourism but also supports the long-term conservation of the giant panda and its habitat. This holistic approach will advance the sustainable development of the local tourism industry, promoting both economic growth and environmental stewardship.

Secondly, the ongoing development and communication of tour guide

services and popular science education programs should be maintained.

These initiatives not only enhance the tourist experience by providing opportunities to observe and interact with pandas but also fulfill tourists' strong interest in acquiring scientific knowledge about panda breeding and feeding. For instance, the "Giant Panda Nutritionist" program, which allows tourists to participate in preparing food for the pandas, has proven to be highly engaging and educational, and has garnered significant discussion in tourist reviews. Implementing activities like Natural Science Knowledge Challenges can further engage tourists, capture their interest, and deepen their understanding of environmental issues and their role in conservation.

Currently, the Panda Base's efforts in communicating such educational content align well with tourists' interests and expectations. To sustain and potentially enhance this positive reception, it is crucial to continue and expand these educational programs, ensuring that they remain relevant and engaging. For example, establishing partnerships with tour operators and travel agencies to integrate sustainability education into their tour packages. By doing so, the Panda Base can further solidify its role as a leading destination for both immersive animal experiences and educational enrichment.

Thirdly, the development and marketing related to transportation and travel routes should be consistently maintained.

The importance placed on transportation and travel routes by the Panda Base is well-aligned with tourists' perceptions. Analysis of textual data and responses from questionnaire surveys reveal a favorable shift in tourist evaluations following recent enhancements in the transportation infrastructure at the Panda Base.

To sustain these positive outcomes, it is crucial to uphold current practices. This includes dynamically adjusting the frequency and routing of sightseeing buses based on variations in tourist numbers, thereby optimizing accessibility and mitigating potential congestion points.

Moreover, the continuous maintenance and regular updating of electronic maps are essential for providing tourists with accurate and timely information.

These maps should be accessible across multiple platforms, including the Panda Base's official website and WeChat account, to ensure comprehensive navigation support. Clear, detailed, and interactive maps will aid tourists in planning their routes effectively and enhance their overall experience at the Panda Base.

By concentrating on these areas, the Panda Base can ensure that its transportation services effectively meet the evolving needs of its tourists, thereby contributing to a smoother and more enjoyable visit.

CHAPTER 6

Conclusion, Contributions and Limitations

6.1 Conclusion

Firstly, this study establishes a significant positive relationship between improved destination image congruence and higher tourist satisfaction ratings, highlighting the importance of managing image congruence in tourism marketing.

Secondly, the analysis of the Panda Base's projected and perceived images reveals both alignment and notable discrepancies. While four topics show general congruence, their importance trends differ, with significant discrepancies in the other four topics.

Thirdly, the findings on destination image congruence offer actionable insights for refining the projected image. Furthermore, the importance-performance analysis of the perceived image provides guidance for enhancement. By improving both projected and perceived images, the gap between them can be effectively narrowed.

Fourthly, marketing efforts should prioritize enhancing transparency, managing crowd sizes and wait times, and providing timely information about weather and visit timing, particularly during the third quarter. Furthermore, there is a need to prominently showcase panda life, with a special focus on panda superstars and their habitats.

Fifthly, resource reductions should concentrate on scaling back investments in facilities and service quality, limiting the development of parent-child facilities, and streamlining communication regarding notices and lost property.

Lastly, areas requiring consistent marketing support should focus on disseminating knowledge about environmental protection and sustainable tourism, alongside the ongoing development of tour guide services, popular science education programs, and transportation and travel routes.

6.2 Contributions

6.2.1 Theoretical Contributions

1) Empirical Validation of Image Congruence and Tourist Satisfaction

By expanding the range of data sources, the study establishes a robust empirical foundation for investigating the relationship between image congruence and tourist satisfaction. This underscores the importance of investigating destination image congruence within the context of tourism marketing.

2) Exploration of the Interplay Between Projected and Perceived Images

This study posits that the relationship between perceived and projected images is reciprocal, creating a feedback loop that allows destinations to adapt their images based on tourists' dynamic assessments. By recognizing this two-way relationship, the study enhances the theoretical framework and encourages innovative marketing strategies that utilize real-time analytics and adaptive technologies to adjust projected images in response to changing tourist perceptions and trends.

3) Integration of LDA Modeling with Sentiment Analysis

This study pioneers the application of LDA modeling to both projected and perceived destination images, introducing a novel analytical framework for measuring their congruence. Additionally, the research integrates LDA modeling with sentiment analysis, providing a more nuanced and comprehensive understanding of a destination's perceived image. This innovation enables a deeper exploration of the thematic and emotional dimensions of tourist perceptions.

4) Enhancement of the Reliability of Perceived Image Analysis

This study advances the methodology by employing a cross-validation approach that integrates both user-generated content and survey data. This innovation addresses the limitations of relying on a single data source, significantly enhancing the reliability and robustness of the analysis of perceived images.

5) Advancement of Research on Specific Attractions

This research shifts from examining broad geographical entities, such as cities or countries, to a focus on a specific attraction, thereby enhancing the literature on destination image congruence. This nuanced approach increases the practical relevance of destination image research, enabling more targeted and actionable marketing strategies that are directly applicable to real-world scenarios.

6) Advancement of Wildlife Tourism Destination Research in China

This study makes a pioneering contribution to the underexplored field of wildlife tourism research in China, particularly within the giant panda tourism market. The findings enhance the understanding of destination marketing in this unique context and offer valuable insights for the development of wildlife tourism.

6.2.2 Practical Contributions

1) Tools for Enhancing Destination Image Congruence

This study provides essential tools for measuring and enhancing destination image congruence, addressing discrepancies between projected and perceived images, and applicable to various destinations.

2) Targeted Marketing Strategies for the Panda Base

The research findings offer actionable marketing strategies tailored specifically for the Panda Base, designed to enhance tourist satisfaction and bolster the destination's competitiveness and sustainability.

3) Policy Recommendations for Local Governments

The study also provides insights for local governments to formulate more effective policies that enhance resource allocation strategies for the sustainable development of wildlife tourism destinations.

4) Insights Applicable to Other Wildlife Tourism Destinations

Wildlife tourism destinations encounter similar challenges, including the need to balance natural resource protection with tourists' needs and

preferences. The findings of this study serve as a reference for other destinations aiming to improve their image management practices.

6.3 Limitations and Future Research

6.3.1 Limitations

Firstly, the study's comprehensiveness is limited by its data collection platforms and the types of data gathered. Promotional messages were sourced exclusively from the Panda Base's four official digital channels, while tourist reviews were limited to two OTAs. These limitations may result in an incomplete analysis of projected and perceived images and introduce potential bias. Furthermore, the focus on textual data excludes multimedia elements such as photos and videos, which means the analysis may not fully capture the rich, multi-sensory aspects of the destination image.

Secondly, the study is confined to Chinese text sources, overlooking promotional messages and tourist reviews in other languages. The travel needs and preferences of international tourists may differ from those of Chinese tourists, leading to distinct perceived images. Effective international marketing strategies require an understanding of diverse tourists from various language backgrounds, necessitating adjustments to the projected image. As a result, this limitation reduces the study's applicability to broader global markets and its effectiveness in attracting international tourists.

Thirdly, the scope of this study is limited to the specific case of the Panda Base. Wildlife tourism is inherently influenced by the species involved, as well as their unique habitats and conservation contexts. Each wildlife tourism site is distinct in terms of its species, conservation status, and tourist interactions, which can significantly shape tourist perceptions. Therefore, applying the results of this study to other wildlife tourism contexts requires careful consideration, and findings should be interpreted with caution when generalizing to different settings.

Fourthly, this study primarily focuses on the congruence of destination image, overlooking other factors that can influence travel satisfaction. By not addressing how these additional factors interact with or impact the

relationship between image congruence and travel satisfaction, the study presents a limited perspective. This narrow focus may hinder a comprehensive understanding of the multifaceted nature of travel satisfaction and the role of image congruence within the broader context of tourist experiences, potentially leading to biases in marketing strategies.

Lastly, the marketing strategy proposed in this study is limited by the data collection timeframe and primarily addresses current conditions. Given that the marketing environment is dynamic, the absence of long-term monitoring of both projected and perceived images restricts the ability to track the evolving nature of tourist perceptions and the necessary adjustments in the destination's projected image. This limitation hinders a comprehensive and nuanced analysis of the bidirectional and dynamic relationship between these images, thereby constraining the understanding of how they interact and develop over time.

6.3.2 Future Research

Firstly, future research should expand the scope of data collection platforms and data types. Utilizing a broader range of digital channels as data sources could provide a more comprehensive understanding of destination image. Additionally, integrating visual data such as photos and videos alongside textual information can enhance the analysis, leading to a deeper and more nuanced understanding of image congruence, potentially requiring the application of digital image processing techniques.

Secondly, future research should investigate perceived images through tourist type classification. Tourists can be categorized into four groups, as suggested by Cohen (1972), highlighting the diversity of motivations and behaviors that influence how different types of tourists engage with destinations. By segmenting tourists based on the characteristics of online reviews, researchers can refine the projected image more effectively. A key segmentation approach involves language; collecting promotional messages and tourist reviews in multiple languages could enhance understanding of international tourists' experiences, facilitating the development of targeted marketing strategies that

resonate with diverse audiences.

Thirdly, expanding the range of study cases and further exploring the practice of sustainable tourism is essential. Future research should encompass a broader spectrum of wildlife tourism destinations to assess the applicability of research methods and the consistency of results across different contexts. Sustainable development is a complex and critical issue for wildlife tourism destinations, where rapidly increasing tourist numbers pose significant challenges, as seen at the Panda Base. Investigating the optimal carrying capacity that balances animal welfare and biodiversity protection with the needs of tourists and local economic development is crucial and requires continuous monitoring and attention.

Fourthly, future research should explore additional factors influencing tourist satisfaction and their interactions with destination image congruence. This approach will provide a more comprehensive understanding of the drivers of satisfaction, expanding the theoretical horizons of both destination image and tourist satisfaction research. Additionally, it will equip destination managers with more effective marketing strategies.

Lastly, future research should develop methodologies for the ongoing assessment of destination image and its changes. Longitudinal studies are essential for gaining a comprehensive understanding of the evolving nature of perceived image and the adjustments made to a destination's projected image. By capturing the bidirectional and dynamic interactions between projected and perceived images over time, researchers can deepen insights into how these images influence one another, thereby advancing the theoretical framework of destination image research.

REFERENCES

Agapito, D., Oom do Valle, P., & da Costa Mendes, J. (2013). The Cognitive-Affective-Conative Model of Destination Image: A Confirmatory Analysis. *Journal of Travel & Tourism Marketing*, *30*(5), 471-481. https://doi.org/10.1080/10548408.2013.803393

Agrawal, A., Fu, W., & Menzies, T. (2018). What is wrong with topic modeling? And how to fix it using search-based software engineering. *Information and Software Technology*, *98*, 74-88.

Al-Azri, H. I., & Morrison, A. M. (2006). Measurement of Oman's destination image in the US. *Tourism Recreation Research*, *31*(2), 85-89.

Al-Natour, S., & Turetken, O. (2020). A comparative assessment of sentiment analysis and star ratings for consumer reviews. *International Journal of Information Management*, *54*, 102132.

Alaei, A. R., Becken, S., & Stantic, B. (2019). Sentiment analysis in tourism: capitalizing on big data. *Journal of Travel Research*, *58*(2), 175-191.

Alarcón-Urbistondo, P., Rojas-de-Gracia, M.-M., & Casado-Molina, A. (2021). Proposal for Employing User-Generated Content as a Data Source for Measuring Tourism Destination Image. *Journal of Hospitality & Tourism Research*, 10963480211012756. https://doi.org/10.1177/10963480211012756

Albalawi, R., Yeap, T. H., & Benyoucef, M. (2020). Using topic modeling methods for short-text data: A comparative analysis. *Frontiers in artificial intelligence*, *3*, 42.

Ali Abd Al-Hameed, K. (2022). Spearman's correlation coefficient in statistical analysis. *International Journal of Nonlinear Analysis and Applications*, *13*(1), 3249-3255.

Ali, T., Marc, B., Omar, B., Soulaimane, K., & Larbi, S. (2021). Exploring destination's negative e-reputation using aspect based sentiment analysis approach: Case of Marrakech destination on TripAdvisor. *Tourism Management Perspectives*, *40*, 100892.

Allen, M. (1991). Meta-analysis comparing the persuasiveness of one-sided and two-sided messages. *Western Journal of Speech Communication*, *55*(4), 390-404.

Andreu, L., Bigné, J. E., & Cooper, C. (2000). Projected and Perceived Image of Spain as a Tourist Destination for British Travellers. *Journal of Travel & Tourism Marketing*, *9*(4), 47-67. https://doi.org/10.1300/J073v09n04_03

Ardito, L., Cerchione, R., Del Vecchio, P., & Raguseo, E. (2019). Big data in smart tourism: challenges, issues and opportunities (Vol. 22, pp. 1805-1809). Taylor & Francis.

Arefieva, V., Egger, R., & Yu, J. (2021). A machine learning approach to cluster destination image on Instagram. *Tourism management*, *85*, 104318. https://doi.org/https://doi.org/10.1016/j.tourman.2021.104318

Arun, R., Suresh, V., Veni Madhavan, C., & Narasimha Murthy, M. (2010). On finding the natural number of topics with latent dirichlet allocation: Some observations. (Ed.),^(Eds.). Advances in Knowledge Discovery and Data Mining: 14th Pacific-Asia Conference, PAKDD 2010, Hyderabad, India, June 21-24, 2010. Proceedings. Part I 14.

Ashfaq, J., Khan, A., Bilal, M., Salman, M., & Shad, F. (2022). The impact of user-generated content (Ugc) on destination image formation and behavior intentions. *Webology*, *19*(2).

Assaker, G., & Hallak, R. (2013). Moderating Effects of Tourists' Novelty-Seeking Tendencies on Destination Image, Visitor Satisfaction, and Short- and Long-Term Revisit Intentions. *Journal of Travel Research*, *52*(5), 600-613. https://doi.org/10.1177/0047287513478497

Assaker, G., & O'Connor, P. (2020). eWOM Platforms in Moderating the Relationships between Political and Terrorism Risk, Destination Image, and Travel Intent: The Case of Lebanon. *Journal of Travel Research*, *60*(3), 503-519. https://doi.org/10.1177/0047287520922317

Avraham, E. (2015). Destination image repair during crisis: Attracting tourism during the Arab Spring uprisings. *Tourism management*, *47*, 224-232.

https://doi.org/https://doi.org/10.1016/j.tourman.2014.10.003

Ballantyne, R., Packer, J., & Falk, J. (2011). Visitors' learning for environmental sustainability: Testing short-and long-term impacts of wildlife tourism experiences using structural equation modelling. *Tourism management*, *32*(6), 1243-1252.

Ballantyne, R., Packer, J., & Hughes, K. (2009). Tourists' support for conservation messages and sustainable management practices in wildlife tourism experiences. *Tourism management*, *30*(5), 658-664.

Ballantyne, R., Packer, J., & Sutherland, L. A. (2011). Visitors' memories of wildlife tourism: Implications for the design of powerful interpretive experiences. *Tourism management*, *32*(4), 770-779.

Baloglu, S., Henthorne, T. L., & Sahin, S. (2014). Destination Image and Brand Personality of Jamaica: A Model of Tourist Behavior. *Journal of Travel & Tourism Marketing*, *31*(8), 1057-1070. https://doi.org/10.1080/10548408.2014.892468

Baloglu, S., & McCleary, K. W. (1999). U.S. International Pleasure Travelers' Images of Four Mediterranean Destinations: A Comparison of Visitors and Nonvisitors. *Journal of Travel Research*, *38*(2), 144-152. https://doi.org/10.1177/004728759903800207

Barreda, A., & Bilgihan, A. (2013). An analysis of user-generated content for hotel experiences. *Journal of Hospitality and Tourism Technology*, *4*(3), 263-280.

Beerli, A., & Martin, J. D. (2004). Factors influencing destination image. *Annals of tourism research*, *31*(3), 657-681.

Bigne, J. E., Sanchez, M. I., & Sanchez, J. (2001). Tourism image, evaluation variables and after purchase behaviour: inter-relationship. *Tourism management*, *22*(6), 607-616.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of machine Learning research*, *3*(Jan), 993-1022.

Bordalo, P., Gennaioli, N., & Shleifer, A. (2013). Salience and consumer choice. *Journal*

of Political Economy, *121*(5), 803-843.

Borlido, T., & Kastenholz, E. (2021). Destination image and on-site tourist behaviour: A systematic literature review. *Revista Turismo & Desenvolvimento (RT&D)/Journal of Tourism & Development*, *1*(36), 63-80. https://doi.org/10.34624/rtd.v1i36.840

Bramwell, B., & Rawding, L. (1996). Tourism marketing images of industrial cities. *Annals of tourism research*, *23*(1), 201-221.

Briciu, V. A., Nechita, F., Demeter, R., & Kavoura, A. (2019). Minding the gap between perceived and projected destination image by using information and communication platforms and software. *International Journal of Computational Methods in Heritage Science (IJCMHS)*, *3*(2), 1-17.

Bui, V., Alaei, A. R., Vu, H. Q., Li, G., & Law, R. (2021). Revisiting Tourism Destination Image: A Holistic Measurement Framework Using Big Data. *Journal of Travel Research*, 00472875211024749. https://doi.org/10.1177/00472875211024749

Cai, R., & Chi, C. G.-Q. (2021). Pictures vs. reality: roles of disconfirmation magnitude, disconfirmation sensitivity, and branding. *International Journal of Hospitality Management*, *98*, 103040.

Cao, J., Xia, T., Li, J., Zhang, Y., & Tang, S. (2009). A density-based method for adaptive LDA model selection. *Neurocomputing*, *72*(7-9), 1775-1781.

Celotto, E., Ellero, A., & Ferretti, P. (2015). Conveying tourist ratings into an overall destination evaluation. *Procedia-Social and Behavioral Sciences*, *188*, 35-41.

CFVG, T. L. H. B. (2011). Congruency between the projected and perceived tourism destination image of Vietnam. *Journal of International Business Research*, *10*(2), 1.

Chan, C.-S., & Zhang, Y. (2018). Matching projected image with perceived image for geotourism development: a qualitative-quantitative integration. *Asian Geographer*, *35*(2), 143-160.

Chang, H. H., Fang, P. W., & Huang, C. H. (2016). The impact of on-line consumer

reviews on value perception: The dual-process theory and uncertainty reduction (*Web Design and Development: Concepts, Methodologies, Tools, and Applications* (pp. 1498-1524). IGI Global.

Chen, C.-F., & Chen, F.-S. (2010). Experience quality, perceived value, satisfaction and behavioral intentions for heritage tourists. *Tourism management*, *31*(1), 29-35.

Chen, C.-F., & Phou, S. (2013). A closer look at destination: Image, personality, relationship and loyalty. *Tourism management*, *36*, 269-278. https://doi.org/https://doi.org/10.1016/j.tourman.2012.11.015

Chen, C.-F., & Tsai, D. (2007). How destination image and evaluative factors affect behavioral intentions? *Tourism management*, *28*(4), 1115-1122.

Chen, J., Becken, S., & Stantic, B. (2022). Assessing destination satisfaction by social media: An innovative approach using Importance-Performance Analysis. *Annals of tourism research*, *93*, 103371.

Chen, J., Kou, G., Peng, Y., Chao, X., Xiao, F., & Alsaadi, F. E. (2020). Effect of marketing messages and consumer engagement on economic performance: evidence from Weibo. *Internet Research*, *30*(5), 1565-1581.

Chen, Q., Xu, S., Liu, R., & Jiang, Q. (2023). Exploring the Discrepancy between Projected and Perceived Destination Images: A Cross-Cultural and Sustainable Analysis Using LDA Modeling. *Sustainability*, *15*(12), 9296.

Chen, X., Li, J., Han, W., & Liu, S. (2021). Urban tourism destination image perception based on LDA integrating social network and emotion analysis: the example of Wuhan. *Sustainability*, *14*(1), 12.

Chi, C. G.-Q., & Qu, H. (2008). Examining the structural relationships of destination image, tourist satisfaction and destination loyalty: An integrated approach. *Tourism management*, *29*(4), 624-636.

Choi, S., Lehto, X. Y., & Morrison, A. M. (2007). Destination image representation on the web: Content analysis of Macau travel related websites. *Tourism management*, *28*(1), 118-129.

Choirisa, S. F., Purnamaningsih, P., & Alexandra, Y. (2021). The effect of e-wom on destination image and attitude towards to the visit intention in Komodo National Park, Indonesia. *Journal of Tourism Destination and Attraction*, *9*(1), 49-60.

Ciriello, R. F., Richter, A., & Schwabe, G. (2018). Digital innovation. *Business & Information Systems Engineering*, *60*, 563-569.

CMBCRTT. (2022). *Chengdu's 14th Five-Year Plan for the Development of Culture, Radio, Television and Tourism*. Chengdu Municipal Bureau of Culture, Radio, Television and Tourism http://www.cdqingyang.gov.cn/wgl/bmwj/2022-09/20/d1a578e2f9a341759d3e598c73f36c1a/files/13e608b176644d6783722ff06947465d.pdf

Cohen, E. (1972). Toward a sociology of international tourism. *Social research*, 164-182.

Cong, L., Newsome, D., Wu, B., & Morrison, A. M. (2017). Wildlife tourism in China: a review of the Chinese research literature. *Current Issues in Tourism*, *20*(11), 1116-1139.

Cong, L., Wu, B., Morrison, A. M., Shu, H., & Wang, M. (2014). Analysis of wildlife tourism experiences with endangered species: An exploratory study of encounters with giant pandas in Chengdu, China. *Tourism management*, *40*, 300-310.

CRBGPB. (2024a). *Introduction to Chengdu Research Base of Giant Panda Breeding*. Chengdu Research Base of Giant Panda Breeding. Retrieved 08-24 from https://www.panda.org.cn/cn/about/

CRBGPB. (2024b). *Official Media of the Panda Base*. Chengdu Research Base of Giant Panda Breeding. Retrieved 2024/05/01 from https://www.panda.org.cn/cn/culture/tiktok/

Crompton, J. L. (1979). An Assessment of the Image of Mexico as a Vacation Destination and the Influence of Geographical Location Upon That Image. *Journal of Travel Research*, *17*(4), 18-23. https://doi.org/10.1177/004728757901700404

Cronjé, D. F., & du Plessis, E. (2020). A review on tourism destination competitiveness. *Journal of Hospitality and Tourism Management*, *45*, 256-265.

Crowley, A. E., & Hoyer, W. D. (1994). An integrative framework for understanding two-sided persuasion. *Journal of Consumer research*, *20*(4), 561-574.

Culic, M., Vujicic, M. D., Kalinic, C., Dunjic, M., Stankov, U., Kovacic, S., Vasiljevic, D. A., & Andelkovic, Z. (2021). Rookie Tourism Destinations-The Effects of Attractiveness Factors on Destination Image and Revisit Intention with the Satisfaction Mediation Effect [Article]. *Sustainability*, *13*(11), 16, Article 5780. https://doi.org/10.3390/su13115780

Curtin, S. (2010). Managing the wildlife tourism experience: The importance of tour leaders. *International journal of tourism research*, *12*(3), 219-236.

De Nisco, A., Mainolfi, G., Marino, V., & Napolitano, M. R. (2015). Tourism satisfaction effect on general country image, destination image, and post-visit intentions. *Journal of Vacation Marketing*, *21*(4), 305-317.

Dolnicar, S., & Grün, B. (2012). Validly Measuring Destination Image in Survey Studies. *Journal of Travel Research*, *52*(1), 3-14. https://doi.org/10.1177/0047287512457267

Dolnicar, S., & Ring, A. (2014). Tourism marketing research: Past, present and future. *Annals of tourism research*, *47*, 31-47.

Dong, X., Ma, J., Zhang, X., Shaalan, A., Chen, Q., & Jia, S. (2023). Revolution trend investigation of tourism destination image with machine learning. *Journal of Vacation Marketing*, 13567667231213152.

Duan, X. L., Marafa, L. M., Chan, C. S., Xu, H., & Cheung, L. T. O. (2020). Measuring the Gaps in the Projected Image and Perceived Image of Rural Tourism Destinations in China's Yangtze River Delta [Article]. *Sustainability*, *12*(12), 16, Article 5121. https://doi.org/10.3390/su12125121

Echtner, C. M., & Ritchie, J. B. (1991). The meaning and measurement of destination image. *Journal of tourism studies*, *2*(2), 2-12.

Echtner, C. M., & Ritchie, J. B. (1993). The measurement of destination image: An empirical assessment. *Journal of Travel Research*, *31*(4), 3-13.

Echtner, C. M., & Ritchie, J. B. (2003). The meaning and measurement of destination image:[Reprint of original article published in v. 2, no. 2, 1991: 2-12.]. *Journal of tourism studies*, *14*(1), 37-48. https://search.informit.org/doi/10.3316/ielapa.200305723

Eid, R., El-Kassrawy, Y. A., & Agag, G. (2019). Integrating Destination Attributes, Political (In)Stability, Destination Image, Tourist Satisfaction, and Intention to Recommend: A Study of UAE. *Journal of Hospitality & Tourism Research*, *43*(6), 839-866. https://doi.org/10.1177/1096348019837750

Elliot, S., Papadopoulos, N., & Kim, S. S. (2010). An Integrative Model of Place Image: Exploring Relationships between Destination, Product, and Country Images. *Journal of Travel Research*, *50*(5), 520-534. https://doi.org/10.1177/0047287510379161

Fakeye, P. C., & Crompton, J. L. (1991). Image differences between prospective, first-time, and repeat visitors to the Lower Rio Grande Valley. *Journal of Travel Research*, *30*(2), 10-16.

Farmaki, A. (2012). A comparison of the projected and the perceived image of Cyprus. *Tourismos*.

Fastdata. (2022). *2021 China Online Travel Industry Report*. 199IT http://www.199it.com/archives/1403775.html

Ferrer-Rosell, B., & Marine-Roig, E. (2020). Projected versus perceived destination image. *Tourism Analysis*, *25*(2-3), 227-237.

Fitzgerald, R., Sandel, T., & Wu, X. (2022). Chinese social media: Technology, culture and creativity (Vol. 48, pp. 100610). Elsevier.

Fotis, J. N. (2015). *The Use of social media and its impacts on consumer behaviour: the context of holiday travel*, Bournemouth University].

Fu, Y., & Timothy, D. J. (2021). Social media constraints and destination images: The potential of barrier-free internet access for foreign tourists in an internet-restricted destination. *Tourism Management Perspectives*, *37*, 100771.

https://doi.org/https://doi.org/10.1016/j.tmp.2020.100771

Gallarza, M. G., Saura, I. G., & García, H. C. (2002). Destination image: Towards a conceptual framework. *Annals of tourism research*, *29*(1), 56-78.

Gartner, W. C. (1989). Tourism image: Attribute measurement of state tourism products using multidimensional scaling techniques. *Journal of Travel Research*, *28*(2), 16-20.

Gartner, W. C. (1994). Image formation process. *Journal of Travel & Tourism Marketing*, *2*(2-3), 191-216.

Gong, T., & Tung, V. W. S. (2017). The impact of tourism mini-movies on destination image: The influence of travel motivation and advertising disclosure. *Journal of Travel & Tourism Marketing*, *34*(3), 416-428. https://doi.org/10.1080/10548408.2016.1182458

González-Rodríguez, M. R., Martínez-Torres, R., & Toral, S. (2016). Post-visit and pre-visit tourist destination image through eWOM sentiment analysis and perceived helpfulness. *International Journal of Contemporary Hospitality Management*.

Goodwin, H. (2011). *Taking responsibility for tourism*. Goodfellow Publishers Limited Woodeaton.

Govers, R., & Go, F. M. (2004a). Cultural identities constructed, imagined and experienced: A 3-gap tourism destination image model. *Tourism (13327461)*, *52*(2).

Govers, R., & Go, F. M. (2004b). Projected destination image online: Website content analysis of pictures and text. *Information Technology & Tourism*, *7*(2), 73-89.

Green, R., & Giese, M. (2004). Negative effects of wildlife tourism on wildlife. *Wildlife tourism: Impacts, management and planning*, 81-97.

Grosspietsch, M. (2006). Perceived and projected images of Rwanda: visitor and international tour operator perspectives. *Tourism management*, *27*(2), 225-234.

Guerreiro, J., & Rita, P. (2020). How to predict explicit recommendations in online reviews using text mining and sentiment analysis. *Journal of Hospitality and*

Tourism Management, *43*, 269-272.

Gunn Clare, A. (1972). Vacationscape: Designing Tourist Regions. *Bureau of Business Research, University of Texas, Austin*.

Guo, Y., Barnes, S. J., & Jia, Q. (2017). Mining meaning from online ratings and reviews: Tourist satisfaction analysis using latent dirichlet allocation. *Tourism management*, *59*, 467-483.

Gurtner, Y. (2016). Returning to paradise: Investigating issues of tourism crisis and disaster recovery on the island of Bali. *Journal of Hospitality and Tourism Management*, *28*, 11-19.

GVR. (2022). *Wildlife Tourism Market Size, Share & Trends Analysis Report*. Grand View Rresearch https://www.grandviewresearch.com/industry-analysis/wildlife-tourism-market-report

Hagen, L. (2018). Content analysis of e-petitions with topic modeling: How to train and evaluate LDA models? *Information Processing & Management*, *54*(6), 1292-1307.

Hahm, J., Tasci, A. D., & Terry, D. B. (2018). Investigating the interplay among the Olympic Games image, destination image, and country image for four previous hosts. *Journal of Travel & Tourism Marketing*, *35*(6), 755-771. https://doi.org/10.1080/10548408.2017.1421116

Haji, S., Surachman, S., Ratnawati, K., & MintartiRahayu, M. (2021). The effect of experience quality, perceived value, happiness and tourist satisfaction on behavioral intention. *Management Science Letters*, *11*(3), 1023-1032.

Hampton, M., & Hampton, J. (2009). Is the beach party over? Tourism and the environment in small islands: A case study of Gili Trawangan, Lombok, Indonesia. *Tourism in Southeast Asia: Challenges and new directions*, *286*.

Hassan, S. B., & Soliman, M. (2021). COVID-19 and repeat visitation: Assessing the role of destination social responsibility, destination reputation, holidaymakers' trust and fear arousal. *Journal of Destination Marketing & Management*, *19*, 100495.

He, J., Liu, D., Guo, Y., & Zhou, D. (2022). Tourism Demand Forecasting Considering

Environmental Factors: A Case Study for Chengdu Research Base of Giant Panda Breeding. *Frontiers in Ecology and Evolution*, *10*, 885171.

Higginbottom, K. (2004). Wildlife tourism: An introduction. *Wildlife tourism: Impacts, management and planning*, 1-14.

Hovland, C. I., Janis, I. L., & Kelley, H. H. (1953). Communication and persuasion.

Huang, L., Ma, J., & Chen, C. (2017). Topic detection from microblogs using T-LDA and perplexity. (Ed.),^(Eds.). 2017 24th Asia-Pacific software engineering conference workshops (APSECW).

Huang, R.-Y., Chang, W.-J., & Chang, C.-Y. (2021). Destination Image Analysis and Its Strategic Implications: A Literature Review from 1990 to 2019. *International Journal of Tourism & Hospitality Review*.

Huang, S. S., & Crotts, J. (2019). Relationships between Hofstede's cultural dimensions and tourist satisfaction: A cross-country cross-sample examination. *Tourism management*, *72*, 232-241.

Huete Alcocer, N., & López Ruiz, V. R. (2020). The role of destination image in tourist satisfaction: the case of a heritage site. *Economic research-Ekonomska istraživanja*, *33*(1), 0-0.

Hui, T. K., Wan, D., & Ho, A. (2007). Tourists' satisfaction, recommendation and revisiting Singapore. *Tourism management*, *28*(4), 965-975.

Hukal, P., & Henfridsson, O. (2017). Digital innovation–a definition and integrated perspective (*The Routledge companion to management information systems* (pp. 360-369). Routledge.

Hunt, J. D. (1971). *Image — A Factor in Tourism*. Colorado State University.

Hunter, W. C. (2016). The social construction of tourism online destination image: A comparative semiotic analysis of the visual representation of Seoul. *Tourism management*, *54*, 221-229.

Iglesias-Sanchez, P. P., Correia, M. B., Jambrino-Maldonado, C., & Heras-Pedrosa, C. D. (2020). Instagram as a Co-Creation Space for Tourist Destination Image-Building:

Algarve and Costa del Sol Case Studies [Article]. *Sustainability*, *12*(7), 26, Article 2793. https://doi.org/10.3390/su12072793

Iordanova, E., & Stainton, H. (2019). Cognition, emotion and trust: A comparative analysis of Cambodia's perceived and projected online image. *Tourist Studies*, *19*(4), 496-519.

Iordanova, E., & Stylidis, D. (2019). International and domestic tourists'"a priori" and "in situ" image differences and the impact of direct destination experience on destination image: the case of Linz, Austria. *Current Issues in Tourism*, *22*(8), 982-1005.

Israel, G. D. (1992). Determining sample size.

Ivanov, B., Dillingham, L. L., Parker, K. A., Rains, S. A., Burchett, M., & Geegan, S. (2018). Sustainable attitudes: Protecting tourism with inoculation messages. *Annals of tourism research*, *73*, 26-34.

Jang, D., Cho, W., & Lee, K. (2020). A Study on the development strategy for marine leisure tourism: Using the Importance Performance Analysis (IPA) method. *Sport Mont*, *18*(1), 39-45.

Jelodar, H., Wang, Y., Yuan, C., Feng, X., Jiang, X., Li, Y., & Zhao, L. (2019). Latent Dirichlet allocation (LDA) and topic modeling: models, applications, a survey. *Multimedia Tools and Applications*, *78*, 15169-15211.

Jenkins, O. H. (1999). Understanding and measuring tourist destination images. *International journal of tourism research*, *1*(1), 1-15.

Jiang, Q., Chan, C.-S., Eichelberger, S., Ma, H., & Pikkemaat, B. (2021). Sentiment analysis of online destination image of Hong Kong held by mainland Chinese tourists. *Current Issues in Tourism*, *24*(17), 2501-2522.

Jiang, Y. (2022). OTA Platforms Online Travel in the Post-Epidemic Era-Case Study of Trip. com Group. *Highlights in Business, Economics and Management*, *2*, 322-326.

Joppe, M., Martin, D. W., & Waalen, J. (2001). Toronto's Image As a Destination: A

Comparative Importance-Satisfaction Analysis by Origin of Visitor. *Journal of Travel Research*, *39*(3), 252-260. https://doi.org/10.1177/004728750103900302

Kaisler, S., Armour, F., Espinosa, J. A., & Money, W. (2013). Big data: Issues and challenges moving forward. (Ed.),^(Eds.). 2013 46th Hawaii international conference on system sciences.

Kanwel, S., Zhou, L. Q., Asif, M., Hwang, J., Hussain, A., & Jameel, A. (2019). The Influence of Destination Image on Tourist Loyalty and Intention to Visit: Testing a Multiple Mediation Approach [Article]. *Sustainability*, *11*(22), 19, Article 6401. https://doi.org/10.3390/su11226401

Khan, A., Ashfaq, J., Bilal, M., Khan, M. H., & Shad, F. (2021). Destination Image Formation through User Generated Content (UGC). An updated Literature Review. *Indian Journal of Economics and Business*, *20*(2).

Khan, S. (2013). Perceived and projected image of India as a tourism destination. *South Asian Journal of Tourism and Heritage*, *6*(1), 97-107.

Kherwa, P., & Bansal, P. (2019). Topic modeling: a comprehensive review. *EAI Endorsed transactions on scalable information systems*, *7*(24).

Khuong, M. N., & Phuong, N. T. (2017). The effects of destination image, perceived value, and service quality on tourist satisfaction and word-of-mouth—A study in Ho Chi Minh City, Vietnam. *International Journal of Trade, Economics and Finance*, *8*(5), 217-224.

Kim, H., & Chen, J. S. (2016). Destination image formation process: A holistic model. *Journal of Vacation Marketing*, *22*(2), 154-166.

Kim, K., Hallab, Z., & Kim, J. N. (2012). The Moderating Effect of Travel Experience in a Destination on the Relationship Between the Destination Image and the Intention to Revisit. *Journal of Hospitality Marketing & Management*, *21*(5), 486-505. https://doi.org/10.1080/19368623.2012.626745

Kim, K., Park, O., Barr, J., & Yun, H. (2019). Tourists' shifting perceptions of UNESCO heritage sites: lessons from Jeju Island-South Korea. *Tourism Review*, *74*(1), 20-

29.

Kirilenko, A. P., Stepchenkova, S. O., & Dai, X. (2021). Automated topic modeling of tourist reviews: Does the Anna Karenina principle apply? *Tourism management*, *83*, 104241.

Kirilenko, A. P., Stepchenkova, S. O., Kim, H., & Li, X. (2018). Automated sentiment analysis in tourism: Comparison of approaches. *Journal of Travel Research*, *57*(8), 1012-1025.

KN. (2024). *Chengdu Ranks Among the Top Three Summer Tourism Destinations in China*. Kandu News https://cdwglj.chengdu.gov.cn/cdwglj/c133185/2024-08/19/content_8975a0e3d38747d4af65d067a99dbbe2.shtml

Kotrlik, J., & Higgins, C. (2001). Organizational research: Determining appropriate sample size in survey research appropriate sample size in survey research. *Information technology, learning, and performance journal*, *19*(1), 43.

Lai, I. K. W., & Hitchcock, M. (2015). Importance–performance analysis in tourism: A framework for researchers. *Tourism management*, *48*, 242-267.

Lai, K., & Li, X. (2015). Tourism Destination Image: Conceptual Problems and Definitional Solutions. *Journal of Travel Research*, *55*(8), 1065-1080. https://doi.org/10.1177/0047287515619693

Laney, D. (2001). 3D data management: Controlling data volume, velocity and variety. *META group research note*, *6*(70), 1.

Lee, B., Lee, C.-K., & Lee, J. (2014). Dynamic Nature of Destination Image and Influence of Tourist Overall Satisfaction on Image Modification. *Journal of Travel Research*, *53*(2), 239-251. https://doi.org/10.1177/0047287513496466

Lee, C.-K., Kang, S., Reisinger, Y., & Kim, N. (2012). Incongruence in destination image: Central Asia region. *Tourism geographies*, *14*(4), 599-624.

Lee, C.-K., Lee, Y.-K., & Lee, B. (2005). Korea's destination image formed by the 2002 World Cup. *Annals of tourism research*, *32*(4), 839-858. https://doi.org/https://doi.org/10.1016/j.annals.2004.11.006

Levy, S. J. (1978). *Marketplace behavior-its meaning for management*. Amacom.

Li, H., Ji, H., Liu, H., Cai, D., & Gao, H. (2022). Is a picture worth a thousand words? Understanding the role of review photo sentiment and text-photo sentiment disparity using deep learning algorithms. *Tourism management*, *92*, 104559.

Li, Q. (2020). *Chengdu Will Build Panda International Tourism Resort*. Xinhua News Agency https://travel.sina.cn/domestic/news/2020-06-03/detail-iirczymk5064602.d.html

Li, Q., Li, S., Zhang, S., Hu, J., & Hu, J. (2019). A review of text corpus-based tourism big data mining. *Applied Sciences*, *9*(16), 3300.

Li, R., Xu, M., Wong, M. H. G., Qiu, S., Li, X., Ehrenfeld, D., & Li, D. (2015). Climate change threatens giant panda protection in the 21st century. *Biological Conservation*, *182*, 93-101.

Li, X. (2023). *How did the giant panda become a "top star" in the era of mobile Internet?* Guangming Daily. Retrieved 2023/12/23 from http://ent.people.com.cn/n1/2023/1223/c1012-40145202.html

Li, X., Zhang, Y., & Mei, L. (2023). Analyzing online reviews of foreign tourists to destination attractions in China: a novel text mining approach. *Asia Pacific Journal of Tourism Research*, *28*(7), 647-666.

Li, Y., He, Z., Li, Y., Huang, T., & Liu, Z. (2023). Keep it real: Assessing destination image congruence and its impact on tourist experience evaluations. *Tourism management*, *97*, 104736.

Li, Z. (2022). *"China's Domestic Tourism Development Annual Report (2022-2023)" Released*. China Travel Network http://www.cntour.cn/h-nd-2491.html

Li, Z., Yuan, F., & Zhao, Z. (2024). Robot restaurant experience and recommendation behaviour: based on text-mining and sentiment analysis from online reviews. *Current Issues in Tourism*, 1-15.

Lin, M. S., Liang, Y., Xue, J. X., Pan, B., & Schroeder, A. (2021). Destination image through social media analytics and survey method. *International Journal of*

Contemporary Hospitality Management.

Lin, Y., Chen, L., & Zhang, C. (2022). Analysis of tourist hotel impression based on snowNLP model. (Ed.),^(Eds.). 2nd International Conference on Internet, Education and Information Technology (IEIT 2022).

Lindberg, K., & Veisten, K. (2012). Local and non-local preferences for nature tourism facility development. *Tourism Management Perspectives*, *4*, 215-222.

Liu, Y., Chiu, D. K., & Ho, K. K. (2023). Short-Form videos for public library marketing: Performance analytics of douyin in China. *Applied Sciences*, *13*(6), 3386.

Liu, Y., Huang, K., Bao, J., & Chen, K. (2019). Listen to the voices from home: An analysis of Chinese tourists' sentiments regarding Australian destinations. *Tourism management*, *71*, 337-347.

Liu, Z., & Park, S. (2015). What makes a useful online review? Implication for travel product websites. *Tourism management*, *47*, 140-151.

Lyu, J., Khan, A., Bibi, S., Chan, J. H., & Qi, X. (2022). Big data in action: An overview of big data studies in tourism and hospitality literature. *Journal of Hospitality and Tourism Management*, *51*, 346-360.

Ma, H., Huang, S., Wang, M., Chan, C., & Lin, X. (2022). Evaluating tourist experience of rural homestays in coastal areas by importance–performance analysis: A case study of homestay in Dapeng new district, Shenzhen, China. *Sustainability*, *14*(11), 6447.

MacKay, K. J., & Fesenmaier, D. R. (2000). An Exploration of Cross-Cultural Destination Image Assessment. *Journal of Travel Research*, *38*(4), 417-423. https://doi.org/10.1177/004728750003800411

Maghrifani, D., Liu, F., & Sneddon, J. (2021). Understanding Potential and Repeat Visitors' Travel Intentions: The Roles of Travel Motivations, Destination Image, and Visitor Image Congruity. *Journal of Travel Research*, 00472875211018508. https://doi.org/10.1177/00472875211018508

Maier, D., Waldherr, A., Miltner, P., Wiedemann, G., Niekler, A., Keinert, A., Pfetsch, B.,

Heyer, G., Reber, U., & Häussler, T. (2021). Applying LDA topic modeling in communication research: Toward a valid and reliable methodology (*Computational methods for communication science* (pp. 13-38). Routledge.

Manosso, F. C., & Domareski Ruiz, T. C. (2021). Using sentiment analysis in tourism research: A systematic, bibliometric, and integrative review. *Journal of Tourism, Heritage & Services Marketing (JTHSM)*, *7*(2), 17-27.

Marine-Roig, E. (2021). Measuring online destination image, satisfaction, and loyalty: Evidence from Barcelona districts. *Tourism and Hospitality*, *2*(1), 62-78.

Marine-Roig, E., & Clavé, S. A. (2016). Destination image gaps between official tourism websites and user-generated content (*Information and communication technologies in tourism 2016* (pp. 253-265). Springer.

Marine-Roig, E., & Ferrer-Rosell, B. (2018). Measuring the gap between projected and perceived destination images of Catalonia using compositional analysis. *Tourism management*, *68*, 236-249. https://doi.org/https://doi.org/10.1016/j.tourman.2018.03.020

Martilla, J. A., & James, J. C. (1977). Importance-performance analysis. *Journal of marketing*, *41*(1), 77-79.

Mayer-Schönberger, V., & Cukier, K. (2013). *Big data: A revolution that will transform how we live, work, and think*. Houghton Mifflin Harcourt.

Mazanec, J. A., & Strasser, H. (2007). Perceptions-based analysis of tourism products and service providers. *Journal of Travel Research*, *45*(4), 387-401.

Mazaruddin, N., & Anuar, F. I. (2019). Panda Tourism: The role of destination image on the relationship between tourists' consumption values and behavioural intention. *Journal of Academia*, *2*(7), 143-151.

Mbaiwa, J. E. (2003). The socio-economic and environmental impacts of tourism development on the Okavango Delta, north-western Botswana. *Journal of arid environments*, *54*(2), 447-467.

McCombs, M., & Reynolds, A. (2002). News influence on our pictures of the world

(*Media effects* (pp. 11-28). Routledge.

McCombs, M. E., & Shaw, D. L. (1972). The agenda-setting function of mass media. *Public opinion quarterly*, *36*(2), 176-187.

McCombs, M. E., Shaw, D. L., & Weaver, D. H. (2018). New directions in agenda-setting theory and research (*Advances in Foundational Mass Communication Theories* (pp. 131-152). Routledge.

MCTC. (2023). *Opinions on Promoting High-Quality Development of the Online Travel Market by the Ministry of Culture and Tourism*. Ministry of Culture and Tourism of China https://zwgk.mct.gov.cn/zfxxgkml/zcfg/gfxwj/202303/t20230327_940941.html

Mehraliyev, F., Chan, I. C. C., & Kirilenko, A. P. (2022). Sentiment analysis in hospitality and tourism: a thematic and methodological review. *International Journal of Contemporary Hospitality Management*, *34*(1), 46-77.

Mele, E., & Cantoni, L. (2019). Analysing Cultural Values in Heritage Promotion by DMO Websites. A Methodological Proposal. *E-review of Tourism Research*, *16*(2/3).

Meng, L., Liu, Y., Wang, Y., & Li, X. (2021). A big-data approach for investigating destination image gap in Sanya City: When will the online and the offline goes parted? *Regional Sustainability*, *2*(1), 98-108.

Meng, L. M., Li, T., & Huang, X. (2023). Double-sided messages improve the acceptance of chatbots. *Annals of tourism research*, *102*, 103644.

Milman, A. (2011). The symbolic role of postcards in representing a destination image: The case of Alanya, Turkey. *International Journal of Hospitality & Tourism Administration*, *12*(2), 144-173.

Min, K. S., Martin, D., & Jung, J. M. (2013). Designing advertising campaigns for destinations with mixed images: Using visitor campaign goal messages to motivate visitors. *Journal of business research*, *66*(6), 759-764.

Mustafa, H., Omar, B., & Mukhiar, S. N. S. (2020). Measuring destination

competitiveness: an importance-performance analysis (IPA) of six top island destinations in South East Asia. *Asia Pacific Journal of Tourism Research*, *25*(3), 223-243.

Naeem, M., & Ozuem, W. (2021). Developing UGC social brand engagement model: Insights from diverse consumers. *Journal of Consumer Behaviour*, *20*(2), 426-439.

Newsome, D., & Rodger, K. (2012). Wildlife tourism (*The Routledge handbook of tourism and the environment* (pp. 345-358). Routledge.

Nghiêm-Phú, B. (2014). A review of destination image studies from 2008 to 2012. *European Journal of Tourism Research*, *8*(1), 35-65. https://doi.org/https://doi.org/10.54055/ejtr.v8i.150

Nguyen, T. T. T., & Tong, S. (2022). The impact of user-generated content on intention to select a travel destination. *Journal of Marketing Analytics*, 1-15.

Nieto, J., Hernández-Maestro, R. M., & Muñoz-Gallego, P. A. (2014). Marketing decisions, customer reviews, and business performance: The use of the Toprural website by Spanish rural lodging establishments. *Tourism management*, *45*, 115-123.

Nikolskaya, E. Y., Zakharova, E. V., Galkin, D. V., Kovaleva, N. I., & Panova, N. A. (2021). The Impact of Digital Technologies on the Transformation of the Tourism and Hospitality Industry. *Revista Geintec-Gestao Inovacao e Tecnologias*, *11*(4), 623-632.

O'connor, P. (2010). Managing a hotel's image on TripAdvisor. *Journal of Hospitality Marketing & Management*, *19*(7), 754-772.

Oliveira, E., & Panyik, E. (2015). Content, context and co-creation: Digital challenges in destination branding with references to Portugal as a tourist destination. *Journal of Vacation Marketing*, *21*(1), 53-74.

Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of marketing research*, *17*(4), 460-469.

Ong, C. E., Xu, S., & Yang, X. (2023). Encountering pandas and their valleys in precarious times: A tourism assemblage perspective. *Tourist Studies*, *23*(1), 25-43.

Orams, M. B. (2002). Feeding wildlife as a tourism attraction: a review of issues and impacts. *Tourism management*, *23*(3), 281-293.

Ozdemir, B., Aksu, A., Ehtiyar, R., Çizel, B., Çizel, R. B., & İçigen, E. T. (2012). Relationships among tourist profile, satisfaction and destination loyalty: Examining empirical evidences in Antalya region of Turkey. *Journal of Hospitality Marketing & Management*, *21*(5), 506-540.

Padlee, S. F., Reimers, V., Mokhlis, S., Anuar, M. M., & Ahmad, A. (2020). Keep up the good work in research universities: An importance-performance analysis. *Australasian marketing journal*, *28*(2), 128-138.

Pandža Bajs, I. (2015). Tourist perceived value, relationship to satisfaction, and behavioral intentions: The example of the Croatian tourist destination Dubrovnik. *Journal of Travel Research*, *54*(1), 122-134.

Park, S., & Nicolau, J. L. (2015). Asymmetric effects of online consumer reviews. *Annals of tourism research*, *50*, 67-83.

PATA. (2023). *PATA's Sustainability Initiatives in 2023*. Pacific Asia Travel Association https://www.pata.org/blog/patas-sustainability-initiatives-in-2023

PD. (2023). *Ticket Sales at the Panda Base Surge Ninefold*. People's Daily https://www.peopleapp.com/column/30038506616-500003519068

Peng, Y., Yin, P., & Matzler, K. (2022). Analysis of Destination Images in the Emerging Ski Market: The Case Study in the Host City of the 2022 Beijing Winter Olympic Games. *Sustainability*, *14*(1), 555.

Picazo, P., & Moreno-Gil, S. (2019). Analysis of the projected image of tourism destinations on photographs: a literature review to prepare for the future. *Journal of Vacation Marketing*, *25*(1), 3-24.

Pike, S. (2002). Destination image analysis—a review of 142 papers from 1973 to 2000. *Tourism management*, *23*(5), 541-549.

Pike, S., & Kotsi, F. (2018). Stopover destination image – perceptions of Dubai, United Arab Emirates, among French and Australian travellers. *Journal of Travel & Tourism Marketing*, *35*(9), 1160-1174. https://doi.org/10.1080/10548408.2018.1476303

Pike, S., & Ryan, C. (2004). Destination positioning analysis through a comparison of cognitive, affective, and conative perceptions. *Journal of Travel Research*, *42*(4), 333-342.

Pizam, A., & Milman, A. (1993). Predicting satisfaction among first time visitors to a destination by using the expectancy disconfirmation theory. *International Journal of Hospitality Management*, *12*(2), 197-209.

Poria, S., Cambria, E., & Gelbukh, A. (2016). Aspect extraction for opinion mining with a deep convolutional neural network. *Knowledge-Based Systems*, *108*, 42-49.

Prayag, G., & Ryan, C. (2011). Antecedents of Tourists' Loyalty to Mauritius: The Role and Influence of Destination Image, Place Attachment, Personal Involvement, and Satisfaction. *Journal of Travel Research*, *51*(3), 342-356. https://doi.org/10.1177/0047287511410321

Purbadharmaja, I. B. P., Setiawan, P. Y., Hayashi, T., & Widanta, A. (2021). How electronic word of mouth (e-WOM) triggers intention to visit through destination image, trust and satisfaction: the perception of a potential tourist in Japan and Indonesia [Article]. *Online Information Review*, *45*(5), 861-878. https://doi.org/10.1108/oir-03-2019-0111

Qin, F., & Peng, X. (2024). *Chengdu Panda Base Completes New Upgrade, Making It Easier to See Hua Hua*. Sichuan Mobile News https://wap.scsjb.cn/news/33206/

Qiuju, L., & Juanjuan, T. (2014). Research on the Communication Effect of Mega-events on National Image Cognition: Based on Agenda-setting Theory. *Tourism Tribune/Lvyou Xuekan*, *29*(6).

Ramkissoon, H., Uysal, M., & Brown, K. (2011). Relationship Between Destination Image and Behavioral Intentions of Tourists to Consume Cultural Attractions. *Journal of Hospitality Marketing & Management*, *20*(5), 575-595.

https://doi.org/10.1080/19368623.2011.570648

Ramseook-Munhurrun, P., Seebaluck, V. N., & Naidoo, P. (2015). Examining the structural relationships of destination image, perceived value, tourist satisfaction and loyalty: case of Mauritius. *Procedia-Social and Behavioral Sciences*, *175*, 252-259.

Rasoolimanesh, S. M., Ringle, C. M., Jaafar, M., & Ramayah, T. (2017). Urban vs. rural destinations: Residents' perceptions, community participation and support for tourism development. *Tourism management*, *60*, 147-158.

Rašovská, I., Kubickova, M., & Ryglová, K. (2021). Importance–performance analysis approach to destination management. *Tourism Economics*, *27*(4), 777-794.

Raza, M. A., Siddiquei, A. N., Awan, H. M., & Bukhari, K. (2012). Relationship between service quality, perceived value, satisfaction and revisit intention in hotel industry. *Interdisciplinary journal of contemporary research in business*, *4*(8), 788-805.

Razović, M. (2013). Sustainable development and level of satisfaction of tourists with elements of tourist offer of destination. *Tourism in Southern and Eastern Europe*, 371-385.

Reid, D. G. (1994). The focus and role of biological research in giant panda conservation. *Bears: Their Biology and Management*, 23-33.

Ren, G., & Hong, T. (2017). Investigating Online Destination Images Using a Topic-Based Sentiment Analysis Approach [Article]. *Sustainability*, *9*(10), 18, Article 1765. https://doi.org/10.3390/su9101765

Reynolds, P. C., & Braithwaite, D. (2001). Towards a conceptual framework for wildlife tourism. *Tourism management*, *22*(1), 31-42.

Rittichainuwat, B., Laws, E., Maunchontham, R., Rattanaphinanchai, S., Muttamara, S., Mouton, K., Lin, Y., & Suksai, C. (2020). Resilience to crises of Thai MICE stakeholders: A longitudinal study of the destination image of Thailand as a MICE destination. *Tourism Management Perspectives*, *35*, 100704. https://doi.org/https://doi.org/10.1016/j.tmp.2020.100704

Rodger, K., & Moore, S. A. (2004). Bringing science to wildlife tourism: the influence of managers' and scientists' perceptions. *Journal of Ecotourism*, *3*(1), 1-19.

Sánchez-Fernández, R., & Iniesta-Bonillo, M. Á. (2007). The concept of perceived value: a systematic review of the research. *Marketing theory*, *7*(4), 427-451.

Schuckert, M., Liu, X., & Law, R. (2015). Hospitality and tourism online reviews: Recent trends and future directions. *Journal of Travel & Tourism Marketing*, *32*(5), 608-621.

Schweinsberg, S., Darcy, S., & Cheng, M. (2017). The agenda setting power of news media in framing the future role of tourism in protected areas. *Tourism management*, *62*, 241-252.

Seo, J.-A., & Oh, I. K. (2017). Destination Image Analysis of Daegu Using Social Network Analysis: Social Media Big Data. *The Journal of the Korea Contents Association*, *17*(7), 443-454.

Serna, A., Gerrikagoitia, J. K., & Alzua, A. (2013). Towards a better understanding of the cognitive destination image of Euskadi-Basque Country based on the analysis of UGC (*Information and communication technologies in tourism 2014* (pp. 395-407). Springer.

Sievert, C., & Shirley, K. (2014). LDAvis: A method for visualizing and interpreting topics. (Ed.),^(Eds.). Proceedings of the workshop on interactive language learning, visualization, and interfaces.

Silva, M., & Costa, R. (2017). How is the Brazil's projected image as a tourism destination perceived by the Portuguese tourist intermediaries: a comparative analysis. *Revista Turismo & Desenvolvimento*, *1*(27/28), 883-897.

Simpson, G. D., Patroni, J., Teo, A. C., Chan, J. K., & Newsome, D. (2020). Importance-performance analysis to inform visitor management at marine wildlife tourism destinations. *Journal of Tourism Futures*, *6*(2), 165-180.

Smith, L. D. G., Ham, S. H., & Weiler, B. V. (2011). The impacts of profound wildlife experiences. *Anthrozoös*, *24*(1), 51-64.

Song, H., & Hsu, C. H. C. (2013). The Image of Taiwan as a Travel Destination: Perspectives from Mainland China. *Journal of Travel & Tourism Marketing*, *30*(3), 253-271. https://doi.org/10.1080/10548408.2013.774919

Song, R., Jin, Z., Zhou, G., & Xu, Y. (2024). *National Tourism Situation: Urban Respondents Love to Travel More, and Women Account for a Large Proportion*. China.com http://travel.china.com.cn/txt/2024-02/21/content_117011682.shtml

Sorice, M. G., Shafer, C. S., & Ditton, R. B. (2006). Managing endangered species within the use–preservation paradox: The Florida manatee (Trichechus manatus latirostris) as a tourism attraction. *Environmental Management*, *37*, 69-83.

Sorokina, E., Wang, Y., Fyall, A., Lugosi, P., Torres, E., & Jung, T. (2022). Constructing a smart destination framework: A destination marketing organization perspective. *Journal of Destination Marketing & Management*, *23*, 100688.

Spenceley, A. (2012). Impacts of wildlife tourism on rural livelihoods in Southern Africa (*Responsible Tourism* (pp. 159-186). Routledge.

Stemler, S. (2000). An overview of content analysis. *Practical assessment, research, and evaluation*, *7*(1), 17.

Stepchenkova, S., & Eales, J. S. (2010). Destination Image as Quantified Media Messages: The Effect of News on Tourism Demand. *Journal of Travel Research*, *50*(2), 198-212. https://doi.org/10.1177/0047287510362780

Stepchenkova, S., & Mills, J. E. (2010). Destination image: A meta-analysis of 2000–2007 research. *Journal of Hospitality Marketing & Management*, *19*(6), 575-609.

Stepchenkova, S., & Morrison, A. M. (2006). The destination image of Russia: From the online induced perspective. *Tourism management*, *27*(5), 943-956.

Stepchenkova, S., & Morrison, A. M. (2008). Russia's destination image among American pleasure travelers: Revisiting Echtner and Ritchie. *Tourism management*, *29*(3), 548-560.

Stylidis, D. (2022). Exploring resident–tourist interaction and its impact on tourists' destination image. *Journal of Travel Research*, *61*(1), 186-201.

Stylidis, D., Belhassen, Y., & Shani, A. (2017). Destination image, on-site experience and behavioural intentions: Path analytic validation of a marketing model on domestic tourists. *Current Issues in Tourism*, *20*(15), 1653-1670.

Stylidis, D., Shani, A., & Belhassen, Y. (2017). Testing an integrated destination image model across residents and tourists. *Tourism management*, *58*, 184-195. https://doi.org/https://doi.org/10.1016/j.tourman.2016.10.014

Stylos, N., Vassiliadis, C. A., Bellou, V., & Andronikidis, A. (2016). Destination images, holistic images and personal normative beliefs: Predictors of intention to revisit a destination. *Tourism management*, *53*, 40-60. https://doi.org/https://doi.org/10.1016/j.tourman.2015.09.006

Sun, M., Ryan, C., & Pan, S. (2014). Using Chinese travel blogs to examine perceived destination image: The case of New Zealand. *Journal of Travel Research*, *54*(4), 543-555.

Sun, W., Tang, S., & Liu, F. (2021). Examining Perceived and Projected Destination Image: A Social Media Content Analysis. *Sustainability*, *13*(6), 3354.

Taecharungroj, V., & Mathayomchan, B. (2019). Analysing TripAdvisor reviews of tourist attractions in Phuket, Thailand. *Tourism management*, *75*, 550-568.

Tang, J., Meng, Z., Nguyen, X., Mei, Q., & Zhang, M. (2014). Understanding the limiting factors of topic modeling via posterior contraction analysis. (Ed.),^(Eds.). International conference on machine learning.

Tang, L. R., Jang, S. S., & Morrison, A. (2012). Dual-route communication of destination websites. *Tourism management*, *33*(1), 38-49.

Tasci, A. D., & Gartner, W. C. (2007). Destination image and its functional relationships. *Journal of Travel Research*, *45*(4), 413-425.

Tasci, A. D., Gartner, W. C., & Tamer Cavusgil, S. (2007). Conceptualization and operationalization of destination image. *Journal of Hospitality & Tourism Research*, *31*(2), 194-223.

Tse, S., & Tung, V. W. S. (2021). Measuring the Valence and Intensity of Residents'

Behaviors in Host–Tourist Interactions: Implications for Destination Image and Destination Competitiveness. *Journal of Travel Research*, 0047287521997576. https://doi.org/10.1177/0047287521997576

Tseng, S.-Y., & Wang, C.-N. (2016). Perceived risk influence on dual-route information adoption processes on travel websites. *Journal of business research*, *69*(6), 2289-2296.

UNWTO. (2021). *UNWTO/Chimelong Initiative on Wildlife Conservation and Sustainable Tourism in Africa & Asia and the Pacific*. UN Tourism https://www.unwto.org/asia/chimelong-Initiative-wildlife-conservation

Vayansky, I., & Kumar, S. A. (2020). A review of topic modeling methods. *Information Systems*, *94*, 101582.

VG, G., Park, E., & Lee, C. K. (2021). Testing the influence of destination source credibility, destination image, and destination fascination on the decision-making process: Case of the Cayman Islands. *International journal of tourism research*, *23*(4), 569-580.

Wacker, A., & Groth, A. (2020). Projected and perceived destination image of tyrol on Instagram (*Information and Communication Technologies in Tourism 2020* (pp. 103-114). Springer.

Wang, A., Zhang, Q., Zhao, S., Lu, X., & Peng, Z. (2020). A review-driven customer preference measurement model for product improvement: sentiment-based importance–performance analysis. *Information Systems and e-Business Management*, *18*(1), 61-88.

Wang, J., Li, Y., Wu, B., & Wang, Y. (2021). Tourism destination image based on tourism user generated content on internet. *Tourism Review*, *76*(1), 125-137.

Wang, R., Hao, J.-X., Law, R., & Wang, J. (2019). Examining destination images from travel blogs: A big data analytical approach using latent Dirichlet allocation. *Asia Pacific Journal of Tourism Research*, *24*(11), 1092-1107.

Wang, T.-L., Tran, P. T. K., & Tran, V. T. (2017). Destination perceived quality, tourist

satisfaction and word-of-mouth. *Tourism Review*, *72*(4), 392-410.

Wang, Y., Li, X., & Lai, K. (2017). A Meeting of the Minds: Exploring the Core–Periphery Structure and Retrieval Paths of Destination Image Using Social Network Analysis. *Journal of Travel Research*, *57*(5), 612-626. https://doi.org/10.1177/0047287517706262

Wang, Z., Udomwong, P., Fu, J., & Onpium, P. (2023a). Big Data in Tourism Destination Image Measurement: A Review between 2013 and 2022. (Ed.),^(Eds.). 2023 International Conference on Computer Applications Technology (CCAT).

Wang, Z., Udomwong, P., Fu, J., & Onpium, P. (2023b). Destination image: A review from 2012 to 2023. *Cogent Social Sciences*, *9*(1), 2240569. https://doi.org/10.1080/23311886.2023.2240569

Wang, Z., Udomwong, P., Fu, J., & Onpium, P. (2024). Destination image analysis and marketing strategies in emerging panda tourism: a cross-cultural perspective. *Cogent Business & Management*, *11*(1), 2364837.

Weber, K. (1997). The assessment of tourist satisfaction using the expectancy disconfirmation theory: A study of the German travel market in Australia. *Pacific Tourism Review*, *1*(1), 35-45.

Wei, F. (2020, 2020/11/17). *The giant panda: a successful conservation story the world needs to hear*. Global Times. Retrieved 2020/11/17 from https://www.globaltimes.cn/content/1207140.shtml

Wei, F., Swaisgood, R., Hu, Y., Nie, Y., Yan, L., Zhang, Z., Qi, D., & Zhu, L. (2015). Progress in the ecology and conservation of giant pandas. *Conservation Biology*, *29*(6), 1497-1507.

Wen, S. (2023). *Tourism bounces back rapidly, contributing to 11% of China's GDP*. Global Times https://www.globaltimes.cn/page/202312/1303989.shtml

Wohlfart, O., Adam, S., & Hovemann, G. (2022). Aligning competence-oriented qualifications in sport management higher education with industry requirements: An importance–performance analysis. *Industry and Higher Education*, *36*(2),

163-176.

Woosnam, K. M., Stylidis, D., & Ivkov, M. (2020). Explaining conative destination image through cognitive and affective destination image and emotional solidarity with residents. *Journal of Sustainable Tourism*, *28*(6), 917-935. https://doi.org/10.1080/09669582.2019.1708920

WTO. (2005). Making Tourism More Sustainable-A Guide for Policy Makers (English version). World Tourism Organization.

WTTC. (2019). *THE ECONOMIC IMPACT OF GLOBAL WILDLIFE TOURISM*. World Travel & Tourism Council (WTTC) https://wttc.org/Portals/0/Documents/Reports/2019/Sustainable%20Growth-Economic%20Impact%20of%20Global%20Wildlife%20Tourism-Aug%202019.pdf

Wu, L. M., Dong, C., & Xiong, G. X. (2020). A Big-Data-Based Analysis on the Impact of Cruise Tourism Image on Chinese Tourist Satisfaction and Behavioral Intentions [Article]. *Journal of Coastal Research*, 314-318. https://doi.org/10.2112/si106-073.1

WWF. (2015). *Population Growth and Habitat Expansion: Insights from the Fourth National Giant Panda Survey*. wwfchina.org https://www.wwfchina.org/news-detail?id=1588&type=3

Xiao, X., Fang, C., Lin, H., & Chen, J. (2022). A framework for quantitative analysis and differentiated marketing of tourism destination image based on visual content of photos. *Tourism management*, *93*, 104585.

Xu, D., Cong, L., & Wall, G. (2019). Tourists' spatio-temporal behaviour and concerns in park tourism: Giant Panda National Park, Sichuan, China. *Asia Pacific Journal of Tourism Research*, *24*(9), 924-943.

Xu, H., & Lv, Y. (2022). Mining and application of tourism online review text based on natural language processing and text classification technology. *Wireless Communications and Mobile Computing*, *2022*(1), 9905114.

Xu, Y. (2024). *Hong Kong Media: China's Panda Tourism Economy is Booming*. South China Morning Post http://news.china.com.cn/2024-08/13/content_117364105.shtml

Yan, X. (2022). *Chenghua District, Chengdu: Strive to Create a New Highland for the Integrated Development of Culture, Business, and Tourism*. Sichuan Economic Network https://travel.sohu.com/a/592412866_120364846

Yan, Y., Chen, J., & Wang, Z. (2020). Mining public sentiments and perspectives from geotagged social media data for appraising the post-earthquake recovery of tourism destinations. *Applied Geography*, *123*, 102306.

Yang, B., Hu, Y., Cheng, X., Bao, Y., & Chen, W. (2023). Exploring the factors affecting content dissemination through WeChat official accounts: a heuristic-systematic model perspective. *Electronic Commerce Research*, *23*(4), 2713-2735.

Yang, J. (2024). *Tourism industry on way to full recovery*. China Daily https://www.chinadaily.com.cn/a/202404/30/WS66304045a31082fc043c4c1e.html

Yi, G. (2023). *The Explosive Growth of the 'Panda Economy's' Appeal*. thecover https://www.thecover.cn/news/0urwKQZh2xiH90qSdq8Jkw

Yüksel, A., & Yüksel, F. (2008). Consumer satisfaction theories: a critical review. *Tourist satisfaction and complaining behavior: Measurement and management issues in the tourism and hospitality industry*, 65-88.

Zehrer, A., Crotts, J. C., & Magnini, V. P. (2011). The perceived usefulness of blog postings: An extension of the expectancy-disconfirmation paradigm. *Tourism management*, *32*(1), 106-113.

Zhai, Y., & Chen, P. (2020). Sentiment analysis on tourist satisfaction with rural homestay inns based on reviews from the website of online travel agency. *International Journal of Sustainable Development and Planning*, *15*(5), 705-712.

Zhang, J. C., Xie, C. W., Morrison, A. M., & Zhang, K. (2020). Fostering Resident Pro-Environmental Behavior: The Roles of Destination Image and Confucian Culture

[Article]. *Sustainability*, *12*(2), 17, Article 597. https://doi.org/10.3390/su12020597

Zhang, L. (2022). *On New Year's Day, the Expansion Area of the Chengdu Panda Base Opened for Trial Operation*. 163.com https://m.163.com/dy/article/GSNE8L6R0519814N.html?spss=adap_pc

Zhang, S.-N., Li, Y.-Q., Ruan, W.-Q., & Liu, C.-H. (2022). Would you enjoy virtual travel? The characteristics and causes of virtual tourists' sentiment under the influence of the COVID-19 pandemic. *Tourism management*, *88*, 104429.

Zhang, T., Li, B., & Hua, N. (2022). Chinese cultural theme parks: text mining and sentiment analysis. *Journal of Tourism and Cultural Change*, *20*(1-2), 37-57.

Zhong, L., Liu, J., Morrison, A., Dong, Y., Zhu, M., & Li, L. (2023). Destination image: a consumer-based, big data-enabled approach. *International Journal of Contemporary Hospitality Management*.

Zhou, L., Pan, S., Wang, J., & Vasilakos, A. V. (2017). Machine learning on big data: Opportunities and challenges. *Neurocomputing*, *237*, 350-361.

Zhu, H. (2022). Accounting of air pollution on tourism economic loss in fuzhou based on big data analysis. *Mathematical Problems in Engineering*, *2022*(1), 2715872.

Zou, Y. (2020). *Ctrip Releases Data: Chengdu Research Base of Giant Panda Breeding Ranks Third in China in Terms of Online Bookings*. Red Star News https://www.yangtse.com/zncontent/885834.html

LIST OF PUBLICATIONS

1) Wang, Z., Udomwong, P., Fu, J., & Onpium, P. (2024). Destination image analysis and marketing strategies in emerging panda tourism: a cross-cultural perspective. *Cogent Business & Management*, 11(1), 2364837. https://doi.org/10.1080/23311975.2024.2364837

2) Wang, Z., Udomwong, P., Fu, J., & Onpium, P. (2023). Destination image: A review from 2012 to 2023. *Cogent Social Sciences*, 9(1), 2240569. https://doi.org/10.1080/23311886.2023.2240569

3) Wang, Z., Udomwong, P., Fu, J., & Onpium, P. (2023). Big Data in Tourism Destination Image Measurement: A Review between 2013 and 2022. In *Proceedings of the 2nd International Conference on Computer Applications Technology (CCAT 2023)*. September 15-17, 2023, Guiyang, China.

4) Wang, Z., Udomwong, P., Fu, J., & Onpium, P. (2023). Unveiling the Interplay between e-WOM Image and Perceived Image: A Case Study of Chengdu, China. In *Proceedings of the 3rd International Joint Conference on Hospitality & Tourism 2023 (IJCHT-23)*. July 18-20, 2023, Bangkok, Thailand.

APPENDIX A

Questionnaire

The Chengdu Giant Panda Breeding Research Base: Tourism Image Survey

Dear Participants,

We extend a warm invitation to you to take part in the Tourism Image Survey for the Chengdu Giant Panda Breeding Research Base (referred to as "the Panda Base"). This survey is conducted by the International College of Digital Innovation at Chiang Mai University, Thailand. Be assured that your anonymity and privacy are guaranteed. Your responses will be used solely for scientific purposes. Completing the questionnaire will take only about 3-5 minutes of your time. Your participation is entirely voluntary, and you may withdraw from the survey at any time.

If you are willing to participate in this survey, kindly ensure that you have already carefully read the **Participant Information Sheet** and signed the **Informed Consent Form** before proceeding. Thank you very much for your cooperation.

Part 1: Participant Demographics

A1. Have you visited the Chengdu Research Base of Giant Panda Breeding (referred to as "the Panda Base") between January 2023 and July 2024?

A. Yes

B. No (If "No," skip to the end of the questionnaire)

A2. Age:

A. Under 20 years old (If "Under 20 years old," skip to the end of the questionnaire)

B. 20-29 years old

C. 30-39 years old

D. 40-49 years old

E. 50-59 years old

F. 60 years old and above

A3. Gender:

A. Male

B. Female

C. Don’t want to mention

A4. Education level:

A. Junior high school or below

B. High school or technical secondary school

C. Junior college

D. Undergraduates

E. Postgraduates

A5. Place of residence:

A. Chengdu city

B. Other areas in Sichuan province except Chengdu city

C. Other areas in Chinese mainland except Sichuan province

D. Overseas

Part 2: Destination Image Congruence and Travel Satisfaction

B1. Which official communication channels of the Panda Base have you followed? (Select all that apply)

A. Official website of the Panda Base

B. Official WeChat account of the Panda Base

C. Official Weibo account of the Panda Base

D. Official Douyin account of the Panda Base

E. Other (Please specify)

B2. How closely does the image of the Panda Base projected on the platforms mentioned above align with your perception? (Ranking from 1 to 5, where 1 represents the least consistent and 5 represents the most consistent)

A. 1 - Not consistent at all

B. 2 - Somewhat inconsistent

C. 3 - Neutral

D. 4 - Somewhat consistent

E. 5 - Completely consistent

B3. Does the degree of congruence between the projected image of the Panda Base and your perception affect your travel satisfaction?

A. Yes

B. No (If "No," skip to Part 3)

B4. To what extent do you agree with the statement: "If the image projected by the Panda Base is more aligned with my perception, my travel satisfaction is higher"? (Ranking from 1 to 5, where 1 represents strongly disagree and 5 represents strongly agree)

A. 1 - Strongly disagree

B. 2 - Disagree

C. 3 - Neutral

D. 4 - Agree

E. 5 - Strongly agree

B5. Please rate your overall satisfaction with your visit to the Panda Base. (Rate from 1 to 5, where 1 indicates strongly dissatisfied and 5 indicates strongly satisfied)

A. 1 - Strongly dissatisfied

B. 2 - Dissatisfied

C. 3 - Neutral

D. 4 - Satisfied

E. 5 - Strongly satisfied

Part 3: Perceived Destination Image Measurement

The table below is utilized to evaluate the destination image of the Panda Base, with each indicator rated for both importance and performance based on your travel experience to the Panda Base. Please use a scale from 1 to 5, where:

- 1 indicates the indicator is very unimportant to your travel experience or the actual performance is very poor.

- 5 indicates the indicator is very important to your travel experience or the actual performance is very good.

Destination Image Attributes	Evaluation	Values				
		1	2	3	4	5
C1. Reasonable ticket prices	Importance					
	Performance					
C2. Good habitat conditions for giant pandas	Importance					
	Performance					
C3. A plentiful number of giant pandas	Importance					
	Performance					
C4. Observe diverse behaviors of giant pandas	Importance					
	Performance					
C5. See superstar giant pandas like "Hua Hua"	Importance					
	Performance					
C6. Well-planned viewpoints and travel routes	Importance					
	Performance					

C7. Clear signage including maps and directional signs	Importance					
	Performance					
C8. Convenient transportation within the attraction	Importance					
	Performance					
C9. Flexible and professional tour guide services	Importance					
	Performance					
C10. Science and educational programs and services	Importance					
	Performance					
C11. Family-oriented services	Importance					
	Performance					
C12. Fully equipped service facilities	Importance					
	Performance					
C13. Reasonable visitor capacity limits	Importance					
	Performance					
C14. Advance notice of the pandas available for viewing	Importance					
	Performance					
C15. Advance notice of potential visitor numbers	Importance					
	Performance					
C16. Efficient crowd flow management	Importance					
	Performance					
C17. Welcoming staff	Importance					
	Performance					

This marks the conclusion of the questionnaire. Thank you for your time and participation!

Note: This questionnaire will be translated into Chinese before distribution.

APPENDIX B

Ethics Approval Letter

สำนักงานคณะกรรมการจริยธรรมการวิจัยในคน มหาวิทยาลัยเชียงใหม่
Chiang Mai University Research Ethic Committee Office
239 Huay Kaew Road, Suthep Sub-district, Mueang Chiang Mai District, Chiang Mai Province 50200
Tel. (66) 53-943565 e-mail: cmurec.cmu@gmail.com, cmurec.cmu2@gmail.com

Ref. No.: 8392(10).E.1/786 9 July 2024

RE: Certificate of Approval

Dear Zuo Wang,

Regarding to your research proposal entitled "Enhancing Destination Image Congruence for Tourist Satisfaction Ratings", research project code CMUREC 67/191, Chiang Mai University Research Ethic Committee (CMUREC) has approved the research project and issued the Certificate of Approval as attachment.

Note that 1. The researcher must use the research protocol and other related documents that approved and certified from Chiang Mai University Research Ethic Committee only.

2. Researcher must submit a progress report and renew the ongoing research project within 30 working days before the expiry of the certificate. (Before 26th May 2025)

3. If there is an amendment to the research protocol or other documents. Please submit a request for protocol amendment and must obtain an endorsement of the amendments before conducting research.

4. If any adverse event occurs, the researcher must report the adverse events or changes in research activities to CMUREC within the time period according to the standard operation procedures (SOPs)

5. When the research is completed, the research must submit a final report to CMUREC within 60 working days.

If the research carry out in foreign countries, the researcher must conduct human research ethics in accordance with the laws of that country.

Furthermore, it is the researchers' responsibility to translate the documents approved by the Committee into a language that the participants can understand.

Yours sincerely,

Chaiyun Sakulsriprasert

(Assistant Professor Dr.Chaiyun Sakulsriprasert)
Acting Chairperson, Chiang Mai University Research Ethics Committee

CURRICULUM VITAE

Author's Name	Ms. Zuo Wang
Place of Birth	Sichuan, People's Republic of China
Education	2021-2024, Doctor of Philosophy, Digital Innovation and Financial Technology, Chiang Mai University
	2004-2007, Master of Arts, Advertising, Communication University of China
Publications	Wang, Z., Udomwong, P., Fu, J., & Onpium, P. (2024). Destination image analysis and marketing strategies in emerging panda tourism: a cross-cultural perspective. *Cogent Business & Management*, 11(1), 2364837. https://doi.org/10.1080/23311975.2024.2364837
	Wang, Z., Udomwong, P., Fu, J., & Onpium, P. (2023). Destination image: A review from 2012 to 2023. *Cogent Social Sciences*, 9(1), 2240569. https://doi.org/10.1080/23311886.2023.2240569
	Wang, Z., Udomwong, P., Fu, J., & Onpium, P. (2023). Big Data in Tourism Destination Image Measurement: A Review between 2013 and 2022. In *Proceedings of the 2nd International Conference on Computer Applications Technology (CCAT 2023).* September 15-17, 2023, Guiyang, China.
	Wang, Z., Udomwong, P., Fu, J., & Onpium, P. (2023). Unveiling the Interplay between e-WOM Image and Perceived Image: A Case Study of Chengdu, China. In

Proceedings of the 3rd International Joint Conference on Hospitality & Tourism 2023 (IJCHT-23). July 18-20, 2023, Bangkok, Thailand.

Experience 2015 – Present, School of Tourism and Cultural Industries, Chengdu University