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指導教授:苑守慈博士

運用隱喻計算於特色結盟之企業夥伴推薦研究

- 以區域觀光產業為例

Metaphor-Based Alliance Partners Recommendation for
Unique and Attractive Destination Image Building

研究生：葉又誠

中華民國 100 年 6 月
致謝

終於撐到寫致謝了，這段日子實在是……，唉！我說不下去了。總之，我必須感謝很多人，最重要的，當然是苑老師。苑老師是我在大學以來見過對學生付出最多的老師，不論是論文上的細心指導、英文上聽說讀寫的訓練、甚至設法支援有經濟困難的我，受到老師幫助的事項真的多不勝數，因此，我在心底給苑老師深深的一鞠躬，感謝她在這兩年來對我的栽培與協助。

我感謝同實驗室的夥伴們。我感謝 Alfred 與 Mika 學長，在研究上他們著實了給我很多寶貴的建議。特別感謝淳雅，她大概我這兩年來最密集互動的夥伴，我們一起解決同樣的困難與問題，有她的陪伴，讓我感覺我不是一個人孤軍奮戰。我感謝 Claude、Claire、Sherry、Diana 跟 Kenny，雖然我們只有相處一年，但你們的加入讓我們實驗室增加許多活力與歡笑，讓我苦悶的研究生活多了許多樂趣。

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研究所大概是我最後一段學生生活，我感謝在家人們以及我成長過程中所遇到所有的朋友們跟老師們，沒有你們，沒有今天的我。

葉又誠
於台北家中
2011 年 7 月
論文提要內容:

對於結盟的建立而言，如何選擇夥伴是相當重要的議題。許多的學術研究著重於建立一些選擇夥伴的框架或準則，以求達到資源分享、節省成本的效果。在旅遊產業中，許多文獻舉出了意象建立的重要性，也點出了意象的有效建立有賴於企業體彼此緊密的合作，然而，較少研究探討如果要建立獨特且具有吸引力的意象效果，應該選擇哪些夥伴才能到達目標。因此，本研究提出一系統化的方法能幫助使用者分析並找出合適的合作夥伴，以建立獨特且具有吸引力的意象。此一方法利用隱喻計算作為工具，嘗試找出創新的解決方案。本研究所提出的系統架構，並輔以相關的演算法與情境來說明方法上的可用性。從理論上的觀點來看，本研究嘗試透過自動化的方式找出隱喻的意涵，並將之整合到一現已解決的方法上。從實務面來看，本研究提供了中小型企業一個有用的方法能幫助他們找到合適的合作夥伴。透過建立更高品質的夥伴關係，我們期盼在旅遊產業的中小型企業能夠進一步增加其競爭優勢、存活與獲利能力。此外，研究也發現，一個區域的意象多樣性直接影響到中小型企業透過合作來建立市場利基的可能性。
Abstract

Partner selection is an important issue in alliance formation. A lot of research works have been done in developing the framework or criteria for selecting partners from the views of resource complement, cost reductions and knowledge sharing. However, research to date suggests relatively little is known about how to select partners for attractive and unique image building, which is essential to the developments of tourism especially for SME owners in the tourism sector. In this paper, we propose a systematic approach for service providers in tourism to identify appropriate partners to form alliances and build their attractive and unique images. This approach employs metaphors as a tool to generate innovative and creative solutions. The system architecture is then provided and elaborated with algorithms and the system scenario. From the theoretical perspective, we attempt to excavate the meaning of metaphors from the web in order to propose a new frame of problem-solving. From the practical perspective, we provide SME owners with a useful approach for managing partner selection and attractive and unique image building. By forming better alliances, SMEs in tourism sector can gain competitive advantages and improve their sustainability and profitability. In addition, the image diversity of a tourism destination is an important factor on market niche creation through alliance formation.

Keywords: SMEs, destination image building, computing metaphor, alliance partner selection
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CHAPTER 1. INTRODUCTION

Image building serves as a significant positioning strategy in the tourism industry. The research conducted for this dissertation uses computing metaphor to lay emphasis on developing a systematic approach for forming alliances in order to build attractive and unique images. This chapter introduces the core topics addressed in this dissertation: alliance partner selection, image building and computing metaphors. It offers an overview of interrelationships between these concepts and elucidates research background, motivations, questions, method and contributions.

1.1 Research Background

In tourism industry, Small- and Medium-sized enterprises (SMEs) are those actors who account for a significant proportion of tourism service providers. For example, 99% of tourism achievements in Austria are constituted by SMEs (OECD 2008). Tourism SMEs usually have poor resources for human resource development, limited budget for marketing and lack of knowledge in recognizing their important roles in tourism development. Due to these facts, researchers and governments still keep asking “what can we do for them to make them be more sustainable?”

In an effort to answer this question, the research suggests that SMEs in tourism to join a co-operative scheme in order to increase their performance and profitability. Tourists usually expect to attain a holistic experience from a destination, but such an experience often cannot be satisfied by a single small business service provider (OECD 2008). Therefore, there have been numerous studies in the literature about the prominence of cooperation and partnerships in the tourism sector (OECD 2008; Smeral 1998; Reid 2008). The report from Organization for Economic Co-operation and Development (OECD) indicates the success of an individual business often
depends on the success of a destination which can be derived from greater cooperation between tourism SMEs in the specific context of local networks and clusters (OECD 2008). Through cooperating with others, SMEs are capable to diversify tourism product portfolios to attract tourists and, in turn, improve their sustainability and profitability by making it possible for tourists to stay longer and consume more.

In addition, it has been widely recognized that it is important to build unique and attractive destination images for tourism development (e.g., Mackay & Fesenmaier 1997; Vanolo 2004). Destination image might be thought of as “an impression of a destination (Echtner& Ritchie 2003).” The more attractive a destination image is built, the more chances tourists select the destination. Thus, positive, appealing and charming image-building of a destination can serve as a policy and strategic tool in order to attract tourists, economic actors and investments (Vanolo 2004).

However, a gap has been identified between proposed destination images and supplied tourism products (Camprubı’re 2008) because destination images are too extensive to be built or provided by only one single SME business. In order to reduce this gap, cooperation between businesses is needed. In the context of all of the above, the key means to further ongoing tourism development in a regional area will be to form highly integrated destinations with flexible operating network alliance. In alliance formation process, partner selection is undoubtedly an important task for future success (Medcof .1997).

1.2 Research Motivations and Questions

A number of literatures have investigated how to select appropriate partners in order to form a prosperous alliance. Brouthers proposed a framework for analyzing the likely success of strategic alliances, called ‘the 4 Cs’, which involves complementary
skills, cooperative cultures, compatible goals, commensurate levels of risk (Brouthers et al. 1995). Several studies (e.g., Pesa’maa et al. 2007; Shah et al. 2008) have also identified a series of criteria (e.g., trust, loyalty, complementarity, financial payoff) for selecting partners.

While considerable attention has been paid in the past to research issues related to develop the partner selection criteria for the intentions of resource complement (Lin et al. 2009; Shah et al. 2008), cost reductions (Geringer 1991; Lin et al. 2009; Medcof 1997) and knowledge sharing (Brouthers et al. 1995; Dacin et al. 1997), there is no work on establishing a systematic approach to identify partner portfolios with the attractive and unique features (e.g., image building in tourism).

In fact, partner selection is inherently time-consuming process. When practitioners deal with this kind of potential partnership discovering process, it’s burdensome for them to identify every possibility of partner compositions. Nevertheless, very few studies attempt to develop an information system to facilitate this process in an automatic way.

For image building, it is inherently a value co-creation process as indicated in the service-dominant logic (Vargo & Lusch 2008). It involves pre-visit and post-visit stages. When a tourist visits a tourism destination, he/she would have intensive interactions with the destination. The image of a destination is then co-created both by tourists and service providers within the destination.

However, past research in image building often reflects a goods-dominant orientation of value creation (Kotler et al. 1999; Yu’ksel & Akgu’l 2007; Mackay & Fesenmaier 1997). They viewed the customers as operand resources and focus on making use of different marketing approaches to influence and change how the customers perceive the image of a destination in their image building processes. This
perspective somewhat limits the value co-creation opportunities. Therefore, we would like to develop an approach in the form of an information system enacts as an operant resource which can be leveraged by the SME owners co-creating the value with tourists (i.e., the other operant in destination tourism) in order to identify appropriate partners so as to integrate resources more effectively and propose the compelling value propositions (i.e., destination images).

In sum, we recognized the importance of cooperation between SMEs in tourism industry and briefly reviewed partner selection criteria. We also noticed that image building play a critical role in tourism success and its interdependency with business cooperation. However, we finally discovered that there is a valuable research question still remains unanswered. That is, how do we help SMEs identify their alliance partners in order to build attractive and unique images? Is there any mechanism that can be designed to aid SME owners to choose partners for image building? To what extent is the proposed mechanism leveraged to establish market niche for the SME owners? These questions then lead to the following research objectives.

1.3 Research Objectives

The overall goal of this research is to develop a creative and automatic approach that can facilitate partner selection process in order to build attractive and unique images. Through erecting differential images and forming novel partnerships, new niche markets and new tourism products could be explored and developed. To achieve this goal, the following list of more specific objectives is established.

(1) To identify a way for innovative partner composition discovery.

(2) To develop a system architecture and a series of algorithms that forms a basis for facilitating this alliance partner recommendation service.
(3) To implement a prototype system to demonstrate the feasibility and practicability of the proposed method.

By successfully forming a unique and attractive image, SMEs can seek to build promising alliances together, and thus improve their sustainability and profitability.

1.4 Research Method

In this study, the proposed approach employs metaphor as a starting point. Metaphor is a structure of our cognitive system (Lakoff 1987) and affects the way we perceive the world, categorize experiences, and organize our thoughts (Casakin 2007). For example, the metaphor “my lawyer is a shark” entails that the lawyer is aggressive or terrifying. A metaphor usually highlights certain aspects of the concept (i.e. aggressive) and downplays others (i.e. a creature). One of the utilities of metaphors is to help people to define abstract concepts into a more concrete level (Hill 1995). Metaphors are thus a great form to represent abstract concepts like images.

Metaphors have been used to foster creative and innovative thinking in different domains. For example, metaphors were applied to product design and architectural design (Casakin 2007; Wang 2009). In product design, metaphors are used to explore the possibilities of product design solutions, and the product designers make their design to reflect the characteristics of metaphors to products on visual level, action level and image level (Wang & Liao 2009). Additionally, researcher and practitioners often make analogy between business environments and ecosystem so as to develop a series of strategies (Iansiti & Levien 2004). We have seen evidences of the usefulness of metaphors to reinforce innovative thinking. Therefore, we believe it can be applied to solve our research questions.

Furthermore, computing metaphor is one of interesting topics in natural language
processing domain. Fruitful researches have produced lots of techniques to excavate the meanings behind metaphors (Abe & Nakagawa 2006; Baumer et. al. 2009; D'Harris 2002; Jones 1992; Mason 2004; Martin 1990; Slack 1980; Veale & Hao 2007; Weiner 1984; Zhou et al. 2007). These researches provide a solid basis for us to be able to develop a metaphor-based partner recommendation system.

In general, the main reasons why we employ computing metaphors as the kernel of our approach are as follows.

1. Metaphors are great meaning carriers which help us to define abstract concepts like images.
2. Metaphors have been widely recognized that its ability to foster unconventional solutions discovering.
3. Computing metaphor theory provides us a solid basis to analyze metaphors automatically.

In the scenario of using metaphor-based partner recommendation system, the users will be asked to provide a metaphorical statement which signifies the images they want to build. Then the system starts to analyze the metaphor and finally generate a series of partner candidates. Through integrating computing metaphors, we are able to develop a generative of discovering alliance partners for building the unique and attractive destination images.

1.5 Research Contributions

This dissertation presents the following key contributions:

1. From the theoretical perspective, we attempt to adopt computing metaphor to propose a new frame of problem-solving.
2. From the practical perspective, we provide SME owners with a useful approach
for managing partner selection and attractive and unique image building.

(3) From service science perspective, we develop a systematic approach to facilitate value network development and service integration.

1.6 Content Organization

The research framework of this study is presented in Figure 1.1. In this chapter, the environment where the problem space resides is briefly described in terms of people, organizations and technology. SME owners and tourists are two kinds of people who play active roles in this research. Businesses usually have scarce resources and limited capabilities. Such calls provide motivations for SMEs into how to leverage information technology to improve their sustainability and profitability. In order to finely investigate and design innovative artifacts to tackle this challenging problem, related literatures addressing alliance partner selection, destination image and metaphors will be provided in chapter two. The chapter serves as the fundamental knowledge for us to further extend the human and organizational capabilities by creating new artifacts. Chapter 3 then delineates the whole picture of our research work and demonstrates the role of the proposed mechanism in the application context. Next, Chapter 4 elaborates our metaphor-based alliance partner recommendation approach including the conceptual framework that guides the system design and the technical detail of system architecture. For the purpose of validating the effectiveness and quality of the new artifact, Chapter 5 provides a detailed scenario and Chapter 6 offers a set of experiments to manifest its utility and performance. Finally, the research findings, implications and future research are addressed in Chapter 7 for researchers and practitioners to extend and implement.
Figure 1.1 Research framework (Source: Hevner et al, 2004)
CHAPTER 2. LITERATURE REVIEW

Chapter 2 reviews relevant research from alliance partner selection, destination image and metaphors. First, justification for a growing need of a systematic approach in partner recommendation is offered by examining current research on alliance partner selection. The literature regarding this issue is discussed to provide (1) a review of partner selection criteria and (2) a primary justification for establishing a creative method to excavate innovative partner composition. Following this discussion, a review of the destination image literature is provided to justify the importance of image building in tourism sector and amplify the interrelationship between image building and alliance formation. Finally, the introduction of metaphors is given to justify the application of computing metaphor as a sound tool to facilitate the innovative partner selection process.

Chapter 2 has three objectives and it serves as the theoretical foundation specified in research framework in Figure 1.1. The first is to review common approaches used for alliance partner selection. The second is to provide theoretical justification for sustainability improvements by the aid of image building and cooperation. The third is to provide the evidence that metaphors have great potential for tackling partner recommendation problem with the purpose of attractive and unique image building.

2.1 Alliance Partner Selection

Alliance can provide firms with new source of competitive advantages (Bierly and Gallagher, 2007). A number of studies have sought to identify the underlying
motivations for the alliance formation. These motivations majorly include resource complement (Lin et al. 2009; Shah et al. 2008), transaction cost reductions (Geringer 1991; Lin et al. 2009; Medcof 1997) and knowledge sharing (Brouthers et al. 1995; Dacin et al. 1997). In the resource complement perspective, it is innately superior to have partners with different resources that can provide absent ingredients or capabilities so as to leverage and integrate them to create synergies (Lin et al. 2009; Shah et al. 2008). On the other hand, transaction cost can be an important concern (Geringer 1991; Lin et al. 2009; Medcof 1997). Organizations tend to seek the partners who can reduce their business transactions in order to do more with less efforts and money. Meanwhile, knowledge sharing can be another consideration. Learning through cooperation could be one of the efficient and effective ways to gather additional expertise and skills of specific areas (Brouthers et al. 1995; Dacin et al. 1997). However, despite the growing numbers and increasing significance of alliances, considerable proportions of alliances performed ineffectively (Inkpen & Ross, J 2001).

The reasons behind the ineffectiveness of alliance are complex. Two common causes are inappropriate partner selection and poor alliance management (Holmberg & Cummings 2009). In this study, we focus on partner selection. The rich body of literature thus have explored and developed the partner selection approaches, checklists and criteria for partner selection (Brouthers et al. 1995; Dacin et al. 1997; Geringer 1991; Lin et al. 2009; Medcof 1997; Shah et al. 2008; Wu et. al. 2009). The paper in Wu (2009) provided a review of the partner selection criteria developed by numerous studies (see Table 2.1). The common criteria include characteristics of the partner, marketing knowledge capability, intangible assets, complimentary
capabilities and degree of fitness. These criteria can be further subdivided into minor aspects for evaluating the fitness of partners.

Table 2.1 Criteria and sub-criteria for the partner selection (source: Wu et. al. 2009)

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Sub-criteria</th>
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<td>Characteristics of the partner</td>
<td>Unique competencies, compatible management styles, compatible strategic objectives, higher or equal level of technical capabilities between manufacturers and distributors</td>
</tr>
<tr>
<td>Marketing knowledge capability</td>
<td>Increased market share, better export opportunities, and knowledge of local business practices</td>
</tr>
<tr>
<td>Intangible assets</td>
<td>Trademarks, patents, licenses, or other proprietary knowledge, reputation, previous alliance experiences, technically skilled employees among partners</td>
</tr>
<tr>
<td>Complimentary capabilities</td>
<td>Partners owned managerial capabilities, wider market coverage, diverse customer, the quality of distribution system to those of the strategic partners</td>
</tr>
<tr>
<td>Degree of fitness</td>
<td>Compatible organization cultures, willingness to share expertise, equivalent of control</td>
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Such criteria contributes to the research works for developing systematic methods in partner selection. Above-listed criteria are often integrated into the development of partner selection methods. Table 2.2 presents the methods for partner
selection and their criteria used. In fact, most methods are concentrating functional aspects (i.e., cost, quality, performance, etc) of partner selection, especially those used in developing production network or supply chain management (Amid et. al. 2006; Chang 2006; Feng et. al. 2010; Fischer et. al. 2004; Hacklin et. al. 2006; Jung 2010; Yeh & Chuang 2010). These methods also demonstrate product-centric perspectives, which regard products as the starting point of planning process and focus on performance, efficiency and utility (Sheth et. al. 2000).

However, we argue that customer-centric perspective should be bought into partner selection issue, particularly for service industry like tourism, which inherently involves cross-industries relationships resulting in alliances because tourists need various kinds of service (i.e., transportation, accommodation, entertainment and so on) during a journey. To best practice the customer-centric perspective, the intrinsic value (i.e., psychological or emotional value) should not be ignored. As observed in Table 2.2, these psychological and emotional aspects are also neglected in current methods for partner selection. The problem regarding how to select partners in order to create superior service experiences remains unanswered.

Table 2.2 Methods for partner selection

<table>
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<th>Target</th>
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<td>product quality, performance history, reputation, production capacity</td>
<td>Production network</td>
</tr>
<tr>
<td>Authors and Year</td>
<td>Methodology</td>
<td>Criteria</td>
<td>Application</td>
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</tr>
<tr>
<td>(Hajidimitriou and Georgiou, 2002)</td>
<td>Linear programming (goal programming model)</td>
<td>rapid market entry, compatible management styles, political advantage, compatible strategic objectives, distribution network quality, willingness to share expertise, compatible organization cultures, better export opportunities, technological level, quality of local personnel, knowledge of local business practice, location of joint venture facilities</td>
<td>International Joint Venture</td>
</tr>
<tr>
<td>(Feng et al., 2010)</td>
<td>Fuzzy multiple attribute decision-making (FMADM) approach</td>
<td>individual utility (technology capability, financial health, knowledge and managerial experience, capability to access new market), collaborative utility (Resource complementarity, overlapping knowledge bases, motivation correspondence, goal correspondence, compatible cultures)</td>
<td>New product development</td>
</tr>
<tr>
<td>(Ye, 2010)</td>
<td>TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution)</td>
<td>cost, time, trust, risk, quality</td>
<td>Virtual enterprise</td>
</tr>
<tr>
<td>(Wang &amp; Chen, 2007)</td>
<td>Fuzzy preference programming (FPP) method</td>
<td>price, quality, financial stability, customer service</td>
<td>Virtual Enterprise</td>
</tr>
<tr>
<td>(Chang, 2006)</td>
<td>Fuzzy linguistic quantifier</td>
<td>R&amp;D, cost, quality, service, response</td>
<td>Supply Chain</td>
</tr>
<tr>
<td>(Amid et al., 2006)</td>
<td>Fuzzy multiobjective linear model</td>
<td>cost, quality, service, capacity</td>
<td>Supply Chain</td>
</tr>
<tr>
<td>(Fischer et al., 2004)</td>
<td>Ant colony optimization algorithms, AHP</td>
<td>number of offer, date of delivery, price, social competence</td>
<td>Production Network</td>
</tr>
</tbody>
</table>
On the other hand, the research indicates that partner selection is time-consuming process and the decisions of alliance formations are often made in the limited time and information (Holmberg & Cummings 2009; Bierly and Gallagher, 2007). For tourism SMEs, the business owners rely on the knowledge of their social network to form the alliances. The search base of the list often is limited to those companies they have known, and the opportunities for innovation consequently are constrained. Such calls provide motivation for us to develop an information rich platform with a set of semi-automatic and manageable mechanisms that can enlarge the potential partner base and facilitate the process.

Therefore, for recent study, researchers have produced conceptual partner selection framework, checklists criteria and methods for partner selection, but little is known how to select partners in order to bring emotional value to their customers. To further facilitate partner selection process, our study intends to develop an alternative approach characterized by the ability to search in a wider candidate base automatically and the ability to evaluate partner portfolios while considering emotional value brought to customers.
2.2 Destination Image

In past decades, considerable concern has arisen over destination image building in the field of tourism research (Smeral 1998; Mackay & Fesenmaier 1997). This trend is basically derived from the fact that destination image has profound influence on tourists’ decision making process so that it can serve as a source of differentiation. Destination image, by definition, can be regard as the perceptions, beliefs, impressions, ideas and understandings that a person has of a destination (Tuohino 2001; Echtner & Ritchie 2003). That is, destinations with attractive, unique, compelling, positive images have more chances to be selected by the tourists during travel decision process (Woodside & Lysonski 1989). This phenomena implies that understanding the images embedded in the mind of tourists is highly beneficial to explain tourists behaviour and develop effective destination marketing strategy.

According to Echtner and Ritchie (2003), destination image can be interpreted in terms of three dimensions – attributes to holistic, functional characteristics to psychological characteristics and common to unique – as indicated in Figure 2.1. Destination image is intrinsically impressions of place. In attribute-based perspective, these impressions may refer to different attributes of a destination such as climate, price level, infrastructure, friendliness and so on. Alternatively, destination image can be described in holistic view. For example, Paris is commonly regarded as one of most romantic cities in the world. Among those image attributes, some of them are closer to functional characteristics, associated with tangible aspects of the destination, such as natural attractions and others are closer to psychological characteristics, tied with intangible aspects of the destination, such as atmosphere. Moreover, some of destination images may be very unique or common in comparison to other destinations. Unique attributes somewhat have a tourism destination better positioned
to compete with other destinations. By identifying the characteristics of a destination, tourism development agencies are able to manage and propose a compelling image to make a destination more sustainable. Above all, this framework pinpoints three dimensions that are genuinely useful for capturing the tourism-related elements which can serve as a starting point for considering tourism development.

![Figure 2.1. The dimensions of destination image](image)

Recent research has shown the significance of marketing alliance for image building and tourism development. This concern mainly derived from the argument that it is always possible to find the gap between the destination image the marketers are trying to make and supplied tourist products (Camprubí 2008). That is, the proposed destination image may not reflect the reality of a destination owing to the low degree of collaboration and cohesion between businesses which supply the tourism products. This gap may have substantially negative impact on customer satisfaction. One possible explanation regarding this issue is that some destination images are too extensive to be formed or provided by only one single business. For example, if a destination is promoted as a paradise resort, it seems unlikely to exhibit
this image only by the efforts of one business. To create this image, it is supposed to involve different actors (i.e. accommodation service provider, outdoor activities provider, government, tourism development agencies, etc) within this area to cooperate with each other for offering the holistic experience of a destination to tourists. SMEs are those actors with scarce resources and limited capacity, but for major participants in tourism industry, it would be innately superior to engage them in developing a high level of cohesion, cooperation and coordination network (OECD 2008), which can be achieved by the efforts of multiple alliance relationships within a destination. The image gap thus can be reduced. In spite of the importance of marketing alliance for image building being identified in the literature, scant research specifically proposed systematic approaches to identify the appropriate partner compositions for image building.

In our study, we further extend the notion of destination image to business image. Attractive and unique business image building is assumed to be a differentiation strategy in tourism context. In examining previous research regarding image measurement, it should be noted that no matter it is a product, store or business, there is a certain image perceived by customers and this image strongly influences customer’s decision making process (Echtner & Ritchie 2003; MacInnis & Price 1987; Hampton et al. 1987; Jain & Etgar 1976; Stell & Fisk 1986). Hence, through creating positive images and forming successful alliances, SMEs are capable of launching more alluring tourism products and then improve their capacity and profitability.
2.3 Metaphor

Metaphors might be thought of as “understanding and experiencing one kind of things in terms of another (Lakoff & Johnson 1980).” For example, we understand abstract ideas of friendship in terms of our experience in taking care of flowers. The metaphor, “Friendship (i.e., target) is a flower (i.e., vehicle),” entails the ideas that friendship is beautiful and vulnerable and it can grow and bloom. These attributes of flower can be applied to the target “friendship”. The ideas from the attributes of flower influence the way “friendship” is understood. Therefore, metaphors are broadly considered to be a conceptual mapping of properties between two knowledge domains, the target domain and the source domain (Lakoff & Johnson 1980; Mason 2004). The target domain provides dimensions for attribution, whereas the source domain (or vehicles) offers properties that may be applicable to the target (McGlone & Manfredi 2001).

A metaphor, as a result, is an effective manner for defining abstract concepts on more concrete level. The abstract nature of friendship is made clearer by defining more concrete characteristics of flower like beauty and vulnerability. Destination image, in essence, is an abstract concept, which is suitable to be described in the form of metaphor. By analyzing metaphors, the characteristics of abstract concepts are able to be embodied.

Metaphors have been widely applied to many areas, such as computer science, psychology, the corporate world, and one of the most interesting applications is in design problem solving due to its potential on enhancing creative and innovative thinking (Casakin 2007; Lubart & Getz 1997; Weick 2003). When designers want to develop an innovative solution to a specific problem, the critical first step is to perceive the world in an unorthodox and unconventional way. Morgan once stated “metaphors provide some different ways of thinking about things (Morgan 2006).”
That means metaphors can help us uncover the complex and paradoxical characteristics of things, we then are able to manage and design the solutions that we may have not thought possible before.

These ideas have appeared in the vast literature. For instance, in architectural domain, one of the most impressive metaphors ‘less is more’ makes reference to the engineering idea of reducing architectural design to its minimal and basic nature (Casakin 2007). In product design, metaphors are used to explore the possibilities of product design solutions, and the product designers make their design to reflect the characteristics of metaphors to products on visual level, action level and image level (Wang & Liao 2009). In business administration, metaphors are regarded as a tool to describe “visions” or organization mission and strategy to gain novel concepts for innovation (Hill & Levenhagen 1995). In our study, due to the capabilities of metaphors in creative thinking, we believe it is promising to apply metaphors to design partner configurations for attractive and unique destination images building.

In the previous examples, most of the metaphors were interpreted and created by human being. In most cases, people can understand the metaphor, but they are usually unable to speak out all the specific meanings behind the metaphors (Zhou et al. 2007). Additionally, we often need to come up with an insightful metaphor before we really enjoy the advantages of metaphors. These are two important tasks we have to tackle when we are using the metaphors.

As a result, a number of studies have investigated on how to support the above tasks in an automatic way, that is, computing metaphor. These studies can be generally classified into two categories. One is metaphor comprehension and the other is metaphor generation. Both tasks are designed to be done automatically by the aid of information technology.
Metaphor comprehension is defined as a process of mapping between the target and vehicle concepts in order to identify some similarities for metaphor interpretation (Slack 1980; Zhou et al. 2007). There are two general ways that dominate the metaphor comprehension task. One is the rule-based approach and the other is statistics-based approach (Zhou et al. 2007). Approaches based on rules are usually involving hand-coded rules or knowledge base (D'Harris 2002; Martin 1990; Weiner 1984). The level of applicability in these system is limited to the predefine knowledge base. Notice that it is rather difficult to define all the rules or knowledge by human beings. Statistic-based approaches, alternatively, could be implemented by dynamically mining documents or corpus on the fly to understand the metaphor components (Mason 2004; Veale & Hao 2007). The corpus from web serves as a plentiful knowledge source that implicitly represents a different perspective in the world.

Similar to metaphor comprehension, metaphor generation process involves identifying the vehicles associated with shared common attributes (Abe & Nakagawa 2006). The approaches for metaphor generation are relatively few because generating a novel metaphor is more complex. However, there were still some approaches, e.g. Sardonicus (Veale & Hao 2007) and transparently-motivated (T-M) (Jones 1992). These approaches also can be classified into two categories, statistic-based approaches and rule-based approaches. Statistic approaches are normally developed based on leveraging statistic method in mining the corpus to establish a probabilistic model or identify the concept patterns (Abe & Nakagawa 2006;Veale & Hao 2007). Rule-based approaches can be implemented as building knowledge base through framing grammatical or hierarchical structure relationships between target and source domains (Baumer et. al. 2009; Jones 1992).
Although a substantial body of research studies are now available to shed light on automatically understanding or generating metaphors, the application of computing metaphors is still at early stage. We can observe metaphors have been used in vast domain like mentioned above. We also can notice that, in natural language processing domain, there are paramount studies on processing metaphor automatically (Abe & Nakagawa 2006; Baumer et. al. 2009; D'Harris 2002; Jones 1992; Mason 2004; Martin 1990; Slack 1980; Veale & Hao 2007; Weiner 1984; Zhou et al. 2007). Nevertheless, scant research deals with integrating computing metaphor approaches to solve the problem in specific industries. In this study, we aim to take advantages of metaphors to explore innovative solutions for alliance partner selection in a heuristic and automatic manner in the regional tourism industry.

This chapter has reviewed literature from several issues – alliance partner selection, destination image and metaphor – relevant to the goals of this dissertation. This review included discussions on traditional way of partner selection, influential accounts of destination image building and the utility of metaphors. We can then summarize three points as follows.

(1) For partner selection, there is growing need on a systematic and automatic approach to uncover partner compositions with market niche potentials.

(2) For SMEs in tourism industry, it is beneficial for them to make successful alliances by building attractive and unique images.

(3) For image building, metaphor is a great meaning carrier and its power on creativity contributes to innovative solutions discovery. Computing metaphor theory here forms a sound basis for analyzing metaphor automatically.
Through connecting these concepts and theory, we are able to develop a methodology to solve our research problem in an unconventional way.
CHAPTER 3. MOTIVATION APPLICATION

The purpose of this chapter is to give a brief introduction of our research project called “uVoyage” that led to the development of proposed approach. This chapter describes the design of uVoyage conceptual framework, the rationales behind various aspects of the design and the role of alliance partner recommendation approach in this framework. This chapter focuses solely on giving the big picture of our research project and it serves as the designed artifact specified in research framework in Figure 1.1. The following chapter presents the technological details of the proposed partner recommendation approach.

3.1 The uVoyage Conceptual Framework

At the heart of uVoyage conceptual framework is to improve the collective health of the SMEs in tourism regions/clusters that can assist the creation and delivery of service products by a set of particularly designed mechanisms leveraging information and communication technology (ICT). Under this proposition, the main issues are including as follows.

(1) For businesses, how do service providers share resources and capabilities in order to improve collective sustainability?

(2) For customers, how do people discover the unknown but desired services matched with their emotional needs?

(3) For tourism development, how do administrators develop highly cooperative value network and assess the health of regional tourism ecosystem?
The uVoyage conceptual framework consists of four tiers as shown in Figure 3.1. At the bottom of the cube is the first tier indicating three basic elements of regional tourism. Among them, destination refers to a certain tourism location and its environment that many tourism-related service providers live by. Within a destination, technology plays a significant role in facilitating tourism services. The relationships between B2B, B2C and C2C are also focused. These three basic elements set up an ideological foundation for us to consider region/cluster tourism development.

In the second tier, image modeling and sheltering operations enable service providers to manage their images, and control risks and unwanted fluctuation in current or future business. Image modeling is an automated and adaptive mechanism for modeling the image features of destinations, customers and businesses. As described in chapter 2, destination and business images reflect the thoughts or feelings of customers towards a destination or business. Customer images, on the other hand, are modeled to reflect the personalities, preferences and emotional needs of a customer. Once these three kinds of images are modeled, we are able to manage images for businesses or destinations and match customers’ needs to desired businesses or destinations. In addition, sheltering operations provide a series of tools...
that relieve certain marketing or managerial operations performed by businesses. By getting additional resources or capabilities, the performance or productivity of business can be further enhanced.

In third tier, common assets and third party services are included. Based on image models in the second tier, we are able to perform alliance network design and assessment by integrating computing metaphor technique. A mechanism for evaluating service diversity of regional tourism ecosystem is also provided. Furthermore, Third party service providers, such as transportation, logistics, raw material suppliers, or other independent software vendors, enact as auxiliary enablers built on top of the common assets in order to facilitate or enrich the service operations. On the all the tiers mentioned above, the destination ecosystem health can be measured and improved.

In general, uVoyage conceptual framework includes a set of systematic approaches that focus on fostering regional tourism development and improve its sustainability. The core values of the framework are described in terms of the following 3P (Protective, Proactive and Prosperous).

Protective : Protective means that it is designed for SMEs in order to create a financial safety net. That is, protect SMEs against failures and then improve their survivability.

Proactive : Proactive implies that SMEs can keep being alerted the changes of environments and customer needs based on the image modeling. SMEs then can proactively take actions to response the ever-changing environments.

Prosperous : Prosperous denotes the ideal outcome of regional tourism service system. The underlying framework encourages SMEs to design better value
propositions to make an attractive change that contributes to making a destination more prosperous and improving collective sustainability.

With the proposed uVoyage conceptual framework, we will implement it in the form of web-based platform called “uVoyage”. The following section illustrates the system architecture and modules of uVoyage platform.

3.2 uVoyage System Architecture

There are mainly six modules in uVoyage as shown in Figure 3.2. The modules of image modeling and image mixing are related to the first two tiers of the framework. These two modules attempt to capture destination, business and customer images in order to have a protective mechanism that senses the dynamic environment and customer needs. The sheltering service management module is designed for realizing the sheltering operations for SMEs mentioned above. Additionally, SME alliance service formation and alliance feasibility management module are designed for assisting business cooperation and value sharing. Finally, destination service module is developed to match tourists’ expectation and the tourism services available on the platform.
Both tourists and regional tourism SMEs are the target users of uVoyage. Tourists search for desired services, whereas SMEs search for potential partners to cooperate. In essence, the overall system process is to model image, recommend alliance partners, measure alliance feasibility, form alliances, match customer needs to desired service and finally offer sheltering service. More specifically, the system begins from capturing images of destination, businesses and tourists. Tourists’ preferences, regional SMEs’ and environment data are used as the primary input for the image modeling. Image mixing module here aims at making image model more representative. We assume the interaction between tourists, SMEs and the environments will influence their images. Thus, the image mixing module is designed for reflecting these interactions to image modules. Besides, in order to reduce computation complexity, we use colors as the uniform representations of images.

After images have been modeled, alliance partner recommendation can be performed. The mechanism of alliance partner recommendation is main focus of this study. It will be elaborated in the following chapter. Next, every cooperation
A suggestion coming from the alliance service formation module will be evaluated by the alliance feasibility measurement module for assessing the possibility of cooperation success. Afterward, the destination service matching module recommends services to tourists by matching images of tourists to SMEs’ services. Finally, with the sheltering service management module that fulfills related electronic cooperation management and marketing functions, tourism SMEs can deliver their services more effectively.

In summary, the uVoyage conceptual framework and the uVoyage service system design architecture was proposed for creating an innovative tourism service platform. The conceptual framework emphasizes the importance of value creation and value sharing with different stakeholders in the ecosystem. Regional tourism SMEs can create their attractive services through cooperation services to fulfill tourists’ needs and obtain sheltering services from the uVoyage platform. Tourists can also more easily discover services which are more closely related to their thoughts/feeling and compose the desired journey. Tourism SMEs on the uVoyage platform then keeps getting feedback from tourists and find more potential partners to cooperate and design more innovative services. Consequently, the sustainability of SMEs can be improved and the development of region/cluster tourism can also be fostered.
CHAPTER 4. METAPHOR-BASED ALLIANCE PARTNER RECOMMENDATION MECHANISM

This chapter describes the implementation details of metaphor-based alliance partner recommendation system and it serves as an artefact in terms of algorithms as specified in research framework in Figure 1.1. The primary purpose of this chapter is twofold. First, it elaborates the connections between different concepts including computing metaphor, image building and alliance partner selection and how to integrate them into the system architecture. Second, it offers a comprehensive description of system modules and exhibits its ability to provide a solution to manage partner selection and attractive and unique image building. Throughout this chapter, we will provide several examples to demonstrate the required data and related computations in terms of algorithms and formula performed at each step in the process so as to justify the feasibility and creativity of the system.

4.1 Conceptual Framework

The underlying conceptual framework of this study is shown in Figure 4.1 prescribing the basic concept guiding our system design. The primary goal of our method is to identify possible alliance partner compositions for attractive and unique image building. The aim of this implementation, then, is to support this process by leveraging computing metaphor technique. By integrating different existing computing techniques, we further pursue a new metaphor-based frame for problem solving.
As described in Chapter 2, image building can serve as a positioning strategy directly contributing to the success of tourism destination and businesses. Image building, in essence, highly depends on the capabilities and resources possessed by business owners. To comprehensive image building, business owners can acquire the missing elements from partnerships. Additional benefits coming from partnerships include integrative tourism products portfolio development, information and knowledge sharing, and better customer service (Hamel et. al. 1989). With successful alliance formation, alluring images are likely to build and more tourism products are able to be developed. Through this positive and iterative process, a highly collaborative value network of a local area is built and thus drives this area being more successful and prosperous.

![Figure 4.1 The conceptual framework](image)

Nevertheless, there exists a huge gap between the image building and partner selection. How do business owners know which partners they should choose in order to build a specific image? Is there any easier and systematic way that can help them
complete this job? Our study is intended to answer these questions. Metaphor here serves as a good starting point to reduce this gap owing to the following reasons.

First, metaphors are genuinely useful in defining abstract concepts like images. In fact, destination images are often depicted in the form of metaphors (Vanolo 2004). For example, Hawaii is just like a paradise. Second, the notion of metaphor as an excellent facilitator for the design idea creation and innovative thinking is gaining credence. On the top of this, we believe metaphors have great potentials to discover unfamiliar solution to partner compositions problem. Third, available computing metaphor theory forms a theoretical grounding that the analysis of metaphors can be automatically completed. As mentioned above, the employment of metaphor is then justified.

This conceptual framework can be summarized by pointing out six interrelationships that delineate the nature and contributions between concepts. These interrelationships consist of following:

(1) Metaphors are wonderful meaning carriers that help people understand abstract concept (e.g. images) on more concrete level.

(2) Computing metaphor technique forms a sound basis for us to analyze metaphors exploringly and automatically.

(3) The true power behind metaphors is the ability to explore unfamiliar design alternatives and establish novel associations with the problem so that new possible partner compositions may be uncovered.

(4) Through using our recommendation system, business owners are able to identify partners to form a featured alliance.
(5) By forming alliance, the lacking capabilities or resources can be complemented to build attractive and unique images.

(6) With highly development of local partnership network, the tourism destination will have more chances to succeed.

The framework described in Figure 4.1 provides a guide that demonstrates the big picture of this study. Next, a brief introduction of image model is provided. Based on the conceptual framework, the system architecture is developed and exhibited in the following subsections. However, prior to the presentation of our system architecture, the assumed modelling of images for destinations, businesses and customers will be briefed first.

### 4.2 Image Model

Image model is a model which is developed to capture emotional perceptions of a destination or business. There are three kinds of image model in our system – destination image model, business image model and customer image model. The meanings of destination image model and business image model are the same – the emotional perceptions of destination or business. One the other hand, the meaning of customer image model has a slight difference; that is, customer image model is used to describe their psychological preference or emotional needs towards businesses or destinations.

The structure of an image model involves adjectives used to describe the target (a destination, business or customer) and an intensity value of each adjective. Intensity value is the percentage of people who think a specific adjective is appropriate to describe the target. Table 4.1 illustrates an example of destination
image model in which people think it’s charming, fascinating and enjoyable when they travel around this tourism site. The image element “enjoyable” with higher image intensity value imply this destination gives people relatively strong feeling of “enjoyable”. In our research, image model serves as a basis for us to further collect, present and analyze image data in a systematic way.

Table 4.1 An example of destination image model

<table>
<thead>
<tr>
<th>Image element No.</th>
<th>Adjective</th>
<th>RGB value</th>
<th>Number of people</th>
<th>Image intensity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>charming</td>
<td>(255,18,204)</td>
<td>300</td>
<td>0.3</td>
</tr>
<tr>
<td>2</td>
<td>fascinating</td>
<td>(176,119,72)</td>
<td>200</td>
<td>0.2</td>
</tr>
<tr>
<td>3</td>
<td>enjoyable</td>
<td>(216,128,0)</td>
<td>500</td>
<td>0.5</td>
</tr>
</tbody>
</table>

In order to make image model be easily analyzed and processed, all of the image elements (i.e., adjectives) can be represented by a color if necessary. A significant amount of research on color psychology has disclosed that colors are often associated with feelings or emotions (Kobayashi, 1981; Nijdam, 2005; Ou et al., 2004; Suk and Irtel, 2010; Xin et al., 1998). For example, the color red has been associated with excitement and the color yellow has been associated with cheerfulness. Kobayashi provided an excellent model relating colors to emotions, called color image scale (see Figure 4.2 and 4.3). Through adopting this scale, every adjective manifesting the emotion perception of a target in image models can be associated a color with a RGB value. One of important considerations for mapping adjectives onto colors is that a quantitative method can analyze or compute those image data after the adjectives are replaced with RGB values. Under the constraint of mapping every word onto a color, the number of image elements in an image model is limited to 122 words, which can be found in Color Image Scale.
Figure 4.2 Single Color Image Scale (Kobayashi, 1992)

Figure 4.3 Key Word Image Scale (Kobayashi, 1992)
4.3 The System Architecture

As mentioned before, the goal of this system is to leverage computing metaphors to excavate the meaning behind proposed images and further identify possible partner candidates. In order to help users to get desired outcomes, market niche assessment of different recommendation choices will be evaluated during the system process. To achieve these ends, the system architecture is designed and presented as Figure 4.4.

In essence, the overall system process is to comprehend the goal, identify the missing image elements to achieve the goal, generate new metaphors, map these metaphors to a manageable set of candidates, and evaluate and prioritize the alternatives. Therefore, this system architecture consists of four main modules – goal comprehension module, candidates generation module, niche assessment module and image classification module. As the names of modules imply, each module represents the basic goal that the process needs to be completed in order to achieve the desired end. Before the details of these modules are provided, the structures of image model should be formulated.
(1) Goal comprehension module

- **Purpose:** comprehend the meaning of the goal and identify the missing image elements for goal achievement.
- **Major Input:** a goal in the form of a metaphorical statement
- **Components:** metaphor comprehension and gap identification
- **Major Output:** gap image elements

(2) Candidates generation module:

- **Purpose:** conduct metaphor generation and comprehension process to generate a series of partner composition choices
- **Major Input:** gap image elements
- **Components:** metaphor generation, metaphor comprehension, candidate discovery and goal fulfillment analysis
- **Major Output:** a series of partner composition choices

(3) Niche assessment module:
• **Purpose**: evaluate the market niche potential for different choices

• **Major Input**: a series of partner composition choices

• **Components**: attractiveness analysis and uniqueness analysis

• **Major Output**: attractiveness score and unique score

4.4 Image classification module:

• **Purpose**: process image data in advance to reduce the computation complexity of niche assessment

• **Major Input**: customers’ image preferences and business images

• **Components**: customers’ preferences classification and business images classification

• **Major Output**: customer image preference clusters and business image clusters

We will describe each of the modules in additional process details and provide the algorithm and formula of these modules.

4.4 Goal Comprehension Module

An assumption of our partner recommendation system is that the users have an ability to clearly define their image they would like to build. For instance, a SME may want to make its customers think they’re so happy and just like in paradise when they visit. Then, a SME user needs to have an ability to think of the word “paradise” and input it into our system. After that, the system would start from analyzing the goal “paradise” and identify its latent meanings in order to find the most appropriate partners for collectively achieving the goal. The goal comprehension module is designed to perform this task.

In order to comprehend metaphors, e.g., a SME (target) is just like a paradise (vehicle), we adopt a web-driven, case-based approach called the Sandonicus approach (Veale & Hao 2007), which leverages the text of web as a plentiful knowledge source to identify what properties are most contextually appropriate to
apply to both sides of target and vehicle. This approach employs Google search engine as a retrieval mechanism for finding properties of words by using Google supported APIs, which allow the search of wildcard term * as any possible words. For example, if you send a query “as * as paradise” to Google, you may get a series of words, such as beautiful, gorgeous, wonderful. That implies paradise can be beautiful, gorgeous and wonderful. More specifically, these words can be considered as the properties of paradise. We treat these properties as the meaning of paradise.

However, there are few points that need to be addressed for benefiting from the Sandonicus approach. First, this system will operate in Chinese environment and the Sandonicus approach is basically designed for English environment. To employ the Sandonicus approach, the words need to be translated from Chinese into English. We adopt unofficial Google dictionary API to do so (source: http://code.google.com/p/google-api-translate-java/). Second, given a user is assumed to input a phrase to describe the goal, the phrase should be decomposed into processable lexical units. This task is performed by using Chinese word segmentation API from Sinica (source: http://ckipsvr.iis.sinica.edu.tw/). For example, if the user input (in Chinese form: 電影巨片) is “blockbuster movie” instead of “paradise”, then this phrase is first decomposed to two lexical units (i.e., blockbuster and movie) and then they are separately sent to Google dictionary to translate them from Chinese to English. After translation, the system then starts to send “as * as blockbuster movie” to Google Web query and gets a series of adjectives. Finally, it’s unavoidable to attain undesired results when we employ the sentence pattern “as * as vehicle” in Google. To settle this issue, we develop a two-step process to ensure we can get the quality results. The first step is to establish an exception word list. Any word in this list will be filtered out from the search results. For example, when we send a query “as * as
paradise”, we may get the result like “as well as paradise”. The word “well” is obviously not a result we would like to get. Then, all we need to do is add the word “well” to the exception word list, and the program would automatically filter it out. We create the list during the test runs. The second step is to leverage SentiWordNet to keep the positive words in the results. SentiWordNet is a lexical resource of opining mining (Baccianella et al. 2010; Esuli & Sebastiani 2006). One of its ability is to determine a word whether has positive or negative meaning. A word determined positive means that the word demonstrates good side of a thing. For example, happy is a positive word and sad is a negative word. Only the positive words are the words that we care about because the words are used to describe goal and only positive aspects of the goal are important in building good images.

All the details mentioned above are the design logic of the component “metaphor comprehension”. The input of this component is a goal in the form of metaphorical statement and the output is a set of adjectives, which are the meanings of the goal. For more details of metaphor comprehension process, see the algorithm in Figure 4.5.

Thereafter, the gap identification component attempts to catch the missing part of existing images of the SME for achieving the goal. As describe in section 4.2, our system also collected the images of SMEs (i.e., business image model). The collected images are basically adjectives (i.e. image elements) used for describing a SME. Through comparing the collected image elements of SMEs and identified images elements from the goal, the image gap then can be identified.
During the comparison process, the semantic similarity analysis is conducted to evaluate how close the meanings of two words are, given that the images elements are adjectives. We use DISCO (extracting DIstributionally related words using CO-occurrences) is a Java class that allows to retrieve the semantic similarity between arbitrary words (Kolb 2008, 2009). It will output a semantic similarity score. Higher score indicates higher semantic similarity. If any of wanted images cannot be found in the existing images of SME or cannot be found in the existing image with a high level of similarity, that image would be considered as one of the gap images. In other words, gap images are those which are not able to be fulfilled by existing images.

Table 4.2 presents an example of gap image analysis. Assume that there are three adjectives (wonderful, beautiful and gorgeous) identified by metaphor comprehension process. This means the SME would like to deliver a service experience that makes people think it’s wonderful, beautiful and gorgeous. In order to understand which
image element is missing, the system would start to compare the goal images (wonderful, beautiful and gorgeous) with the image model of the SME. The table 4.2 shows that the SME give people charming, pleasant and gorgeous images. If any goal image element can be found an exactly same adjective or can be found an adjective with similar meaning in business image model, then this goal image element is determined “fulfilled”. In this example, the goal image “wonderful” cannot be fulfilled because there are no words with similar semantic meaning. On the other hand, the goal image “beautiful” can be fulfilled owning to similar word “charming” and the image “gorgeous” can be fulfilled because of the exactly same word in the image model of the SME. Those unfulfilled adjectives are the gap images. The algorithm of gap identification is specified in Figure 4.6. In sum, the identified gap images will entail what are the elements that should be complemented by others for achieving the goal so that they can serve as the good starting point for partner candidate generation.

Table 3.2 An example of gap image analysis

<table>
<thead>
<tr>
<th>Adjectives from analyzing the goal</th>
<th>Adjectives from the business image model</th>
<th>Fulfilled or not</th>
</tr>
</thead>
<tbody>
<tr>
<td>wonderful (gap image)</td>
<td>pleasant</td>
<td>No</td>
</tr>
<tr>
<td>beautiful</td>
<td>charming</td>
<td>Yes</td>
</tr>
<tr>
<td>gorgeous</td>
<td>gorgeous</td>
<td>Yes</td>
</tr>
</tbody>
</table>

However, there is one important thing needed to be noticed. Setting an appropriate goal is relevant to success. If the goal setting is either undesirable or the users do not take features (i.e., environmental, cultural, social aspect) of the destination where the service is offered into account, the users may not get the optimal results. Therefore, in this study, we assume the users can come up with an appropriate
goal, which involve considering the customer desirability of the goal and the environmental, cultural and social features of a destination.

**Gap Identification Component**

1. Take the image model of a specific SME
2. Conduct the semantic similarity analysis
   - For each element of salient properties vector (goal image elements), examine its semantic similarity relative to the images of SME.
   - Set MaxSimilarity = the highest level of similarity of specific salient property
   - FOR i To total number of salient properties
     - MaxSimilarity = 0
   - FOR j To total number of images of SME
     - TempSimilarity = Compute the semantic similarity index between Salient and ImgSME
     - IF MaxSimilarity  <  TempSimilarity  THEN
       - MaxSimilarity = TempSimilarity
   - END
   - NEXT
   - IF Maxsimilarity > specific threshold THEN
     - Tag Salient with “fulfilled”
   - ELSE
     - Tag Salient with “unfulfilled”
   - END
   - NEXT
3. Save all of the properties tagged with “unfulfilled” as the Gap vector

**Figure 4.6. Gap identification algorithm**

### 4.5 Candidates Generation Module

Candidates generation module aims to attain possible partner lists. The process is briefly described as follows. Base on the gap images identified in the last module, hereafter named “supertype”, this module uses it to generate a collection of new metaphors. These metaphors are then analyzed by the metaphor comprehension process to ensure every metaphor we generate makes sense and then each metaphor
can also be projected to specific business types for possible cooperation accordingly. Once these candidates are identified, goal fulfillment analysis is executed to ensure that cooperating with those candidates can achieve the user’s goal, attaining a series of business types for potential cooperation.

The basic idea behind the abovementioned process is to generate the new metaphors that best describe the possible partners. For example, if a new metaphor is generated like “your partner is as wonderful as flower”, the system will try to find a partner who can be best described as flower. The reason to do so is that metaphor usage in design problems has been a primary inspiration for our study of analogy. We believe analogy to the design field can give a heuristic problem solving strategy in which a problem solving method can be carried over to another new problem. In the first module, metaphor comprehension is brought into our approach for understanding the goal. In this module, metaphor generation is for generating possible partners who have potential to collectively achieve the goal with the initiator.

Similar to what the metaphor comprehension process does, the metaphor generation process (see Figure 4.7) uses the “gap images” as salient properties of metaphors and send the query “as gap image as *” to Google. It will return a collection of vehicles that have the “gap image” properties. This process involves the filtering work as well. For instance, if the gap properties include sweet and delicious, it will send two queries, “as sweet as *” and “as delicious as *”, to Google and then gathers collections of vehicles that can be depicted as sweet and delicious. The vehicles with those two properties in the same time are preferred. After collecting a series of vehicles, this module combines the topic and vehicles to form a complete set of metaphors and uses the metaphor comprehension process to examine the suitability of the metaphor configurations. Once this step is completed, the module then projects
the vehicles to some real business types and investigates the level of fulfillment of the user’s goal.

<table>
<thead>
<tr>
<th>Metaphor Generation Component</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Step 1:</strong> Take the Gap image vector</td>
</tr>
<tr>
<td><strong>Step 2:</strong> Generate vehicles by the aid of Google API</td>
</tr>
<tr>
<td>For i To the total number of elements in the Gap vector</td>
</tr>
<tr>
<td>Send the query “as Gap_i as *” to Google</td>
</tr>
<tr>
<td>Save the results in the Vehicle_{ij} vector</td>
</tr>
<tr>
<td>For j To the total number of elements in the Vehicle vector</td>
</tr>
<tr>
<td>Send the query “as Gap_i as Vehicle_{ij}” to Google</td>
</tr>
<tr>
<td>IF the number of returned results higher than a specific threshold</td>
</tr>
<tr>
<td>THEN</td>
</tr>
<tr>
<td>Keep Vehicle_{ij}</td>
</tr>
<tr>
<td>ELSE</td>
</tr>
<tr>
<td>Remove Vehicle_{ij}</td>
</tr>
<tr>
<td>END</td>
</tr>
<tr>
<td>NEXT</td>
</tr>
<tr>
<td>NEXT</td>
</tr>
<tr>
<td><strong>Step 3:</strong> call metaphor comprehension to identify the properties of each vehicle</td>
</tr>
<tr>
<td><strong>Step 4:</strong> Compute gap image coverage rate for each vehicle</td>
</tr>
<tr>
<td>Gap image coverage rate of a given vehicle =</td>
</tr>
<tr>
<td>the number of gap image contained in the properties of a vehicle</td>
</tr>
<tr>
<td>the number of gap images</td>
</tr>
<tr>
<td>For each Vehicle_{ij}</td>
</tr>
<tr>
<td>Compute the number of gap image are contained in Vehicle_{ij}</td>
</tr>
<tr>
<td>Record the maximum gap image coverage rate</td>
</tr>
<tr>
<td>Next</td>
</tr>
<tr>
<td><strong>Step 5:</strong></td>
</tr>
<tr>
<td>For each Vehicle_{ij}</td>
</tr>
<tr>
<td>If gap image coverage rate of Vehicle_{ij} = maximum gap image coverage rate among Vehicle_{ij}</td>
</tr>
<tr>
<td>Save the valid vehicles in Vehicle_{ij} as the Candidate vehicle vector</td>
</tr>
<tr>
<td>Next</td>
</tr>
</tbody>
</table>

Figure 4.7. Metaphor generation algorithm

One major limitation of the Sandonicus approach is that the sentence pattern used for generating new metaphors is improper to deal with multiple salient properties at a time. As we noted earlier, the sentence pattern we employed in metaphor generation is “as salient property as *”. Google search would return a set of words modified by the salient property. Imagine if we attempt to send a statement to Google
like this, “as property1, property2, property3… as *”, it is obviously that the results would not be desired because people do not use language like that. Apparently, we’d better to try it on the other way around.

In this research, we extend the Sandonicus approach so as to generate the metaphors with multiple properties following terms of a three-stage process. At first, the each property is put into the sentence “as property as *” and separately sent to Google search. Different sets of words then are returned. In this stage, different words (i.e., vehicles) with a given property are the new metaphors generated. Second, use metaphor comprehension technique to contrarily identify the properties of vehicles. Accordingly, a set of vehicles are generated and the properties of each vehicle are identified as well. The primary principle to find the most appropriate vehicles is that the properties of the vehicle should contain gap images as many as possible. Finally, the vehicle contained the most gap properties will be chosen in order to form the new metaphor.

After a set of metaphors are generated, candidate discovery component then attempts to match the metaphors to real businesses. More specifically, if a new metaphor “your partner is just like a flower (vehicle)” is created, the component will try to find out which business entity is just like a flower. To do so, the image model similarity analysis will be executed. The design logic of image model similarity analysis is very similar to gap image analysis introduced in section 4.4. Table 4.3 presents an example of image model similarity analysis. In the previous step, the properties of the vehicles have been identified and these properties are also adjectives. Therefore, the first column in the table shows the properties of the vehicle and the second column presents the major image elements of a given business model. The only difference between gap image analysis and image model similarity analysis is
that gap image analysis tries to understand which image element cannot be fulfilled but image model similarity analysis is focusing on the image elements that can be fulfilled. Figure 4.8 shows a simple formula is developed for indicating the level of similarity between two different image element sets. In general, a vehicle will be matched to the business model with the highest similarity score.

Table 4.3 An example of image model similarity analysis

<table>
<thead>
<tr>
<th>Adjectives from analyzing the vehicle</th>
<th>Adjectives from the business image model</th>
<th>Fulfilled or not</th>
</tr>
</thead>
<tbody>
<tr>
<td>wonderful</td>
<td>pleasant</td>
<td>No</td>
</tr>
<tr>
<td>beautiful</td>
<td>charming</td>
<td>Yes</td>
</tr>
<tr>
<td>gorgeous</td>
<td>gorgeous</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Image model similarity score

\[
\text{Image model similarity score} = \frac{\text{the number of image element that can be fulfilled}}{\text{the number of image element in a given image model}}
\]

Figure 4.8 the formula of image model similarity score

The computation complexity would be high if the system tries to perform image similarity analysis for every image business model in the system. For example, if there are 1000 business image models in our system, and then it will be 1000 times of image similarity analysis to be conducted in order to find the best match for a vehicle.

For the purpose of reducing computation complexity, the image classification module is developed and will be elaborated in a later section. Put simply, if these 1000 image models can be grouped into several classes (e.g., 100 classes) according to their image configuration, then the image similarity analysis only need to perform 100 times.
Once the best match of image class is identified, the image models belonging to this class are all matched because we assume that the image models in the same class have similar image configurations. For more details, please reference Figure 4.9 and 4.10.

**Candidate Discovery Component**

Step 1: Match vehicles to real businesses

For each Candidate vehicle, examine its similarity relative to the image models of business classes.

Set MaxSimilarity = the highest level of similarity between a specific vehicle property and a specific image of a specific business class

Set CountFulfilledProperty = the number of fulfilled properties (the initial value of CountFulfilledProperty = 0)

Set MaxFulfilledProperty = the maximum number of fulfilled properties.
Set Flag = the index of Business image class
Set SimilarityLevel = the level of similarity of specific vehicle and real business image class

FOR i To total number of 0 Candidate vehicles

MaxFulfilledProperty = 0

FOR j To total number of Business image class

CountFulfilledProperty = 0

Set \( P_k \) = Read the properties of a specific candidate vehicle from CandiVehicleProperties

Set \( B_{1m} \) = Read the images of a specific business image class

FOR k To total number of \( P_k \)

MaxSimilarity = 0

Figure 4.9. Candidate Discovery algorithm (1)
Candidate Discovery Component (Cont.)

FOR m To total number of BI
    TempSimilarity = Compute the semantic similarity index between pk and BI
    IF MaxSimilarity < TempSimilarity THEN
        MaxSimilarity = TempSimilarity
    END
    NEXT

IF MaxSimilarity > specific threshold THEN
    Tag Gap_i with “fulfilled”
    CountFulfilledProperty = CountFulfilledProperty + 1
END
NEXT

IF MaxFulfilledProperty < CountFulfilledProperty THEN
    MaxFulfilledProperty = CountFulfilledProperty
    Flag = j
END

Figure 4.10.Candidate Discovery algorithm (2)

For each matched real businesses, compute its level of goal fulfillment. Since the goal of the SME is to convey a specific image to public through the aid of cooperation, it’s essential to have the anticipated effect of cooperation forecasted when different partner compositions are formed. To this end, the image model mixing API is accordingly adopted. The image model mixing API belongs to color mixing APIs which are developed by our research team. The basic idea of image model mixing is to integrate the image elements of two image models to form a new one. After a new image model is formed, image model similarity analysis is executed to compare the goal images with the new image model. According to the results of
image model similarity analysis, the fulfilled images can then be identified. Then, goal fulfilment score can be computed. The formula is showed in Figure 4.11. The denominator is the number of goal images and the numerator is the number of goal images which are fulfilled. The higher score indicates the higher level of goal fulfilment and its value will between 0 and 1. For more details of goal fulfilment analysis, reference Figure 4.12. Finally, the output of candidate generation module will be the candidates list with the highest goal fulfilment score.

\[
\text{Goal fulfillment score} = \frac{\text{the number of goal images that can be fulfilled}}{\text{the number of goal images}}
\]

Figure 4.11 The formula of goal fulfilment score

4.6 Niche Assessment Module

Niche assessment module is built for evaluating the market potential of each likely partner composition. While the candidate generation process in the previous module is completed, several partner choices would be generated. It is beneficial if more information can be provided to make proper decision for partner selection. Recall from the research claim in chapter one, the proposed mechanism also can help users to increase the possibilities of building attractive and unique image. We certainly need to have a way of analyzing this part. This is the purpose of niche assessment module.
Niche assessment here involves attractiveness analysis and uniqueness analysis. Attractiveness analysis is to measure the consumer desirability and uniqueness analysis is to examine the degree of differentiation (Yu˘ ksel & Akgu˘ l 2007). The
true meanings behind the attractive and unique analysis components are to evaluate how attractive or unique the predicted image are for the possible new alliances. For the sake of assessing attractiveness and uniqueness, we have to predict the image configuration of a new alliance when a new partnership is built. Similar to goal fulfilment analysis, image model mixing is also adopted to generate a new image model of a new alliance. The following parts address the respective mechanisms about attractiveness analysis and uniqueness analysis.

The notion of attractiveness here refers to the extent of allurement and capacity that can satisfy the needs of customers (Yuksel & Akgul 2007). As mentioned in Chapter 3, uVoyage system provides a destination recommendation service that offers an opportunity for users to uncover the tourism destinations and business entities fulfilled their emotional needs. The basic logic of this recommendation system is to match the customer emotional preferences and needs to the images of a destination or business entities. Simply put, if the images possessed by a destination or business entity can match the customer preference and needs, the matching relationship is built and a recommendation is generated. Therefore, when we want to measure how attractive images a new alliance possesses, we can compute how many emotional preferences can be matched to the predicted alliance images. The more customers can be matched, the higher level of attractiveness is measured.

Customer emotional preferences are presented in the form of customer image model. We prescribe that if the configuration of customer image model is similar to the configuration of alliance image model, then these two image models are matched. This comparison can be easily accomplished by leverage image similarity analysis introduced in the previous sections. The higher image similarity score indicates higher
level of good match. This score is definitely between 0 and 1, but to which level can be determined “matched”? This issue will be examined in the section 6.3.1.3 in chapter 6.

The algorithm of attractiveness component is then presented in Figure 4.13. For computation simplicity, the collected customer preferences information has been classified into several customer preference classes. The reason for classifying customer image model into several classes is that it may take too much time to find the best match by image similarity analysis if considering all the image models in the system. The alternative way is only to perform image similarity analysis for the representative image model of each class. The image models in the same group mean they have similar image configurations. If an image class is matched, that indicates all the image models in this class are all matched. The computation complexity of finding best match will be significantly reduced. More information regarding preference classification is provided in the next section.

Attractiveness analysis technically follows two steps. The first step is to use image model mixing API to predict the image model of new alliance. The second step is to compute attractiveness score. According to the formula of attractiveness score in Figure 4.14, the denominator indicates the total number of customer image models and the numerator refers to the total number of matched image model. In simpler terms, the system calculates how many percentage of preferences can be matched based on the new alliance image model.
**Attractiveness Analysis Component**

Step 1: Generate the image model of a new alliance

Step 2: Compute the image model similarity score between the alliance image model and the image model of each customer preference class.

Set $score_i = \text{the image similarity score of the new alliance and customer preference class}_i$

Set $\text{sumOfMatchedImgModels} = \text{the number of matched image models}$

Initially, $\text{sumOfMatchedImgModels} = 0$

If ($\text{score}_i > \text{threshold}$) then

Set $\text{numOfImgModel} = \text{Get the number of image models belonging to customer preference class}_i$

$\text{sumOfMatchedImgModels} = \text{sumOfMatchedImgModels} + \text{numOfImgModel}$

End if

Compute the attractiveness score

$$= \frac{\text{the number of matched image models (i.e., sumOfMatchedImgModels)}}{\text{the total number of customer image model in the system}}$$

Figure 4.13 The algorithm of attractiveness analysis component

On the other hand, uniqueness here signifies the extent of image differences between a new alliance and existing business entities (Cracolici & Nijkamp 2009). An alliance image model is determined as “unique” when its image configuration is substantially varied from other image models. Similarly, uniqueness analysis also leverages pre-processed image clusters to reduce computation complexity. The only difference is that attractiveness analysis uses customer preference clusters and uniqueness analysis employs business image clusters.

To understand the extent of image difference between two image models, all need to do is to examine the differences of intensity values in two image models. The reasons are as follows. All of image models, no matter which kind, are composed of the same 122 image elements (e.g., pleasant, charming and gorgeous…etc.) with their quantity
values and intensity values. The quantity value of each element denotes the number of people who think the target (i.e., business or destination) demonstrates the image elements and the intensity value refers to the percentage of quantity value in the image model. If people think a business or destination is not “charming”, then the quantity and intensity value of image element “charming” in the image model will be zero. Given that the image elements in a model are completely the same and the only difference rests on their quantity and intensity values, the comparison of image models in uniqueness analysis merely involves examining the differences of the quantity or intensity values among different models. However, we would like to treat image models equally without discrimination on the popularity of the target (i.e., business or destination) so only intensity value is considered in this analysis. Above descriptions can be verified in the following example.

Table 4.4 An example of two image models

<table>
<thead>
<tr>
<th>Image element No.</th>
<th>Adjective</th>
<th>Quantity</th>
<th>Intensity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Image model 1</td>
<td>Image model 2</td>
<td>Image model 1</td>
</tr>
<tr>
<td>1</td>
<td>charming</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>fascinating</td>
<td>500</td>
<td>4000</td>
</tr>
<tr>
<td>3</td>
<td>enjoyable</td>
<td>400</td>
<td>6000</td>
</tr>
<tr>
<td>…</td>
<td>…</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>122</td>
<td>…</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Sum</td>
<td>1000</td>
<td>10000</td>
<td>9200</td>
</tr>
</tbody>
</table>

Table 4.4 presents an example of two image models. These two image models are composed of the same 122 image elements and each element is along with a quantity and intensity value. For image model 1, 100 people think the target (business,
alliance or destination) is charming, 500 people think it’s fascinating and 400 people think it’s enjoyable. Everyone can have multiple feelings against the target. The intensity value is computed according to each quantity value and the sum of them. For instance, the intensity value of charming in image model 1 is 0.1 (100/1000). Because the image elements in both models are the same and the measure for examining the image configurations should be independent of popularity of the target, only intensity value is considered.

The algorithm of uniqueness analysis is provided in Figure 4.14. Uniqueness analysis is designed for measuring how different the new alliance image model is. The initial step for uniqueness analysis is the same as attractiveness analysis- generate the image model of the new alliance. Next, to address the extent of difference between existing business image models and the new alliance image model, the dissimilarity indexes against different business image classes are computed. The dissimilarity index indicates the degree of dissimilarity between two given image models. The formula of dissimilarity index is that sum of intensity difference between two image models divided by 2, which is the maximum value of intensity difference in extreme case that the image elements with non-zero intensity values are completely different in any given two image models. The index will be hence limited in 0 to 1. For example, table 4.4 shows the sum of intensity difference is 0.4.

After all the dissimilarity indexes for each business class are computed, the minimum value of the dissimilarity indexes is selected as the final uniqueness score because the minimum value means the most conservative estimate. To put it more clearly, the new alliance image model should be compared with the representative image models of each business cluster. Each comparison generates one dissimilarity value. Assume that there are three image business clusters (e.g., BC1, BC2, BC3) and
therefore three dissimilarity values are generated (e.g., 0.2 for BC1, 0.4 for BC2 and 0.8 for BC3). The dissimilarity value 0.2 will be chosen as the final uniqueness score. Hence, uniqueness score can be used to demonstrate the level of uniqueness of a given image model.

<table>
<thead>
<tr>
<th><strong>Uniqueness Analysis Component</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Step1:</strong> Generate the image model of a new alliance</td>
</tr>
<tr>
<td><strong>Step2:</strong> Compute the dissimilarity index between the alliance image model and the image model of each business classes</td>
</tr>
<tr>
<td>Set BusinessImgCluster(_i) = the representative image model of business image cluster (_i)</td>
</tr>
<tr>
<td>Set A(_\text{Intensity}_j) = the intensity value of image element (_j) in image model of the new alliance</td>
</tr>
<tr>
<td>For each business cluster (_i)</td>
</tr>
<tr>
<td>Calculate the uniqueness index on the basis of business cluster (_i)</td>
</tr>
<tr>
<td>Set (<em>\text{Intensity}</em>{ji}) = the intensity value of image element (_j) in image model of business image cluster (_i)</td>
</tr>
<tr>
<td>Dissimilarity index = [ \frac{\sum_{j=1}^{\text{the number of image elements}}</td>
</tr>
<tr>
<td>Next</td>
</tr>
<tr>
<td><strong>Step 3:</strong> Choose the minimum value of uniqueness index as the final uniqueness score</td>
</tr>
<tr>
<td>Uniqueness Score = [ \text{Min}{\text{Uniqueness Index}} ]</td>
</tr>
</tbody>
</table>

Figure 4.14 The algorithm of uniqueness analysis component

However, even though those scores can indicate the level of attractiveness and uniqueness of a new alliance, the users may be not able to understand whether it is good enough, especially compared to other business in the same destination. Therefore, the implementation of the system would involve offering some reference
points which can help user understand its position among the businesses in the same
destination. For instance, after an attractiveness score is computed, the system than
starts to examine how many percentage of business whose attractiveness score is
below the newly generated score and the new alliance would fall into any of five
ranks (i.e., A,B,C,D,E) (see Table 4.5). The users will be able to see the level of
attractiveness in terms of the rank and the meanings of the ranks will be also
elaborated. Then, it would be much clear to users when they appreciate the meanings
of these indicators.

Table 4.5 The reference points for attractiveness and uniqueness score

<table>
<thead>
<tr>
<th>Rank (the level of attractiveness or uniqueness)</th>
<th>How many percentage of business whose score is below your score</th>
</tr>
</thead>
<tbody>
<tr>
<td>A (high)</td>
<td>80~100%</td>
</tr>
<tr>
<td>B (relatively high)</td>
<td>60~80%</td>
</tr>
<tr>
<td>C (medium)</td>
<td>40~60%</td>
</tr>
<tr>
<td>D (relatively low)</td>
<td>20~40%</td>
</tr>
<tr>
<td>E (low)</td>
<td>0~20%</td>
</tr>
</tbody>
</table>

In sum, when the image of a new alliance is evaluated as attractive and unique,
this new alliance would be considered to have a market potential. By appraising the
niche of each possible partner composition, this module is able to identify the novel
partnerships with high desirability and differentiation.
4.7 Image Classification Module

For the purpose of reducing computation complexity in niche assessment module, image classification module is developed because the niche assessment module involves intensive computation and comparison processes. For example, when evaluating the level of uniqueness, it’s possible to compare the image configuration of a new alliance to all of existing business entities. This process would take considerable time due to the magnitude of data entries.

Hence, this module processes the required inputs in advance (e.g., the preferences of tourists and the images of businesses) for the niche assessment module. SOM cluster analysis (Kohonen 1990; Samsonova et. al. 2006) is adopted in order to classify both the needs of tourists and the images of businesses. Unlike k-mean cluster analysis, SOM cluster analysis does not need to specify how many clusters to be classified. That’s the main reason why SOM cluster analysis is preferred, given that we don’t know how many clusters should be generated at all. After image classification, the system does not have to compute all the data entries in the database and it only needs to compare the characteristics of several identified classes when computing the level of uniqueness. To put it the other way around, if the images of business entities are not classified beforehand, the predicted images of new alliance are then need to be compared with all existing business entities when assessing how unique the image configuration of the new alliance is. While classification has been done, the predicted images of new alliance are then compared with only the identified classes.

Image classification analysis takes advantages of Java-ML (Machine Learning) API (Abeel et al. 2009), which includes a collection of machine learning and data
mining algorithms. Before utilizing this API, image model data need to be converted to numerical data in order to successfully implement cluster analysis. An image model includes its image elements, quantity value and intensity value. Among them, image elements are adjectives and they cannot be input to cluster analysis because they are in semantic form. Luckily, each adjective are able to be replaced by a color with RGB value. However, it’s much easier to perform cluster analysis if each image model can be represented by only one color instead of multiple colors. To reach this end, color mixing API developed by our research team is employed to mix multiple colors into one color. The rationale of color mixing API is that get the center of gravity of input colors. If an image model have similar configuration, it would be mixed into the similar RGB value.

While perform image color mixing, it’s unnecessary and impossible to input all the 122 image elements to be mixed. Otherwise, the mixed color will always be the same color. The basic idea is that only important image elements (i.e., the image elements with higher intensity values) be involved in color mixing. For simplicity, 80/20 principle is applied. We believe 80 percents of a business image can be represented by 20% image elements of an image model. Therefore, to decide which colors should be mixed, we first sort the image elements of an image model according to their intensity values in descending way. By sorting, the first image element will be the element with the largest intensity value and it’s also the most important one. We then calculate the cumulative percentage of intensity value from the first element to the last one. When the cumulative percentage is reached 80%, the colors already taken into account are those colors which need to be involved in color mixing. By doing so, every image model can be converted to a RGB value and put into a three dimension coordinate system. Cluster analysis can then be readily executed.
Finally, the computation task in the niche assessment module can be done more efficiently and effectively by leveraging image clusters.

In this section, we illustrate the four main modules which form the basis of the system architecture for partner recommendations. In next section, we would like to offer an example to demonstrate the usage scenario of this system architecture and its practicability.
CHAPTER 5. Application Scenario

In previous chapters, we presented a metaphor-based alliance approach that integrates computing metaphor and image model to generate partner candidates. This chapter attempts to demonstrate the application context and the service journey of the application in order to embody the proposed mechanism in a concrete example. This chapter also serves as one of evaluation approach as specified in research framework in Figure 1.1

5.1 An overview of application context

The main focus of this study is to facilitate regional tourism development. Tourism brings together people of different interests and creates bonds between the various actors. The tourists seek to attain the holistic experiences of a tourism destination and they’re involved in intensive interactions between residents and environments where nature, culture and society converge. The businesses in tourism devote themselves to satisfy the customer functionally and emotionally needs. The regional governments also endeavour to increase the contribution of tourism to the economy by encouraging competitive and profitable tourism development in regions. These players play very important roles in developing the tourism industry.

We argue that it’s time for the tourism industry to consider image-based innovations owing to the dominant power of image in the tourism decision process. For businesses, they can start to appraise creating attractive and unique images in order to entice more customers. For tourists, they are able to obtain the right services according their emotional needs and preference in an unconventional way.
Uvoyage system serves as a bridge to connect businesses to customers and make image-base innovation become possible.

5.2 The service journey of the application

Business and customer are two kinds of stakeholders who are directly involved in our research project. Figure 5.1 demonstrates the service journey of business and customer. A business (business A) will start from registering in the uVoyage platform. It needs to fill out a form specifying some fundamental information (i.e., company name, address, e-mail…etc.) as shown in Figure 5.2. Next, it will be asked to offer image-related information to initialize its business image model before it can leverage any of image-related functions in the platform. As illustrated in Figure 5.3, the business owners may need to select the adjectives that can best describe the feelings customer may have when customers enjoy its services. These adjectives are selected from Kobayashi’s color image scale (Kobayashi, 1981) as mentioned in Section 4.2, Chapter 4.
Figure 5.1 The Service journey of business and customer
Figure 5.2 The business registering form

Figure 5.3 The questionnaire for initializing business image model
After a business image model is initialized, business A is able to employ metaphor-base partner recommendation mechanism. However, only when the business image models can actually reflect the images of business, the recommendations will be more useful and accurate. To pursue this end, the business image models will evolve over time according to the interactions between business and customers. For instance, after customer visited the business, feedback information can be collected as the basis for adjusting business image models.

Assume business A chooses “the service experience is like a blockbuster movie” as the goal image to build. All it needs to do is to input “blockbuster movie” to the partner recommendation system as observed in Figure 5.4. Afterwards, several suggestions will be generated and the goal fulfilment score, uniqueness score and attractiveness score of each suggestion are provided to help users make their decisions.

![Figure 5.4 the interface of metaphor-based partner recommendation system](image-url)
Table 5.1 An example of metaphor-based partner recommendation process

<table>
<thead>
<tr>
<th>System Module</th>
<th>Input</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Goal Comprehension (metaphor comprehension and gap analysis)</td>
<td>blockbuster movie</td>
<td>Goal images: enjoyable, dramatic, engaging, exciting, grand, cool, entertaining</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Gap images: enjoyable, dramatic, engaging, exciting</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Vehicles: game, story</td>
</tr>
<tr>
<td>Candidate Generation</td>
<td>Gap images:</td>
<td>Choices:</td>
</tr>
<tr>
<td></td>
<td>enjoyable, dramatic, engaging, exciting</td>
<td>(1) Business B</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2) Business C</td>
</tr>
<tr>
<td></td>
<td>Vehicles: game, story</td>
<td></td>
</tr>
<tr>
<td>Niche Assessment</td>
<td>Choice 1~5</td>
<td>Choice</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
</tr>
</tbody>
</table>

Table 5.1 offers information that reflects the process of metaphor-based partner recommendation mechanism. After the goal “blockbuster movie” is input, the goal comprehension module is evoked to understand the image elements embedded in the goal statement. The identified images are enjoyable, dramatic, engaging, exciting, grand, cool and entertaining. The gap images are then determined by comparing the identified images and the image model of the target business. If any identified image
cannot be fulfilled by any of the existing image element in the image model, then the identified image element will be determined as one of gap images. For more information regarding gap analysis, please reference section 4.4 goal comprehension module in Chapter 4. Next, two vehicles (i.e., game and story) are generated and mapped to two business image classes. Then, several businesses are randomly selected from these two business image classes and they forms partner choices. Finally, attractiveness score and uniqueness score of each choice are computed and provided. Higher attractive score means the new alliance has higher attractiveness to customer and higher uniqueness score indicates the images of the new alliance are highly different from the existing business image model in the platform. For more information, please reference Section 4.6 niche assessment model in Chapter 4. According to the scores of attractiveness and uniqueness, the business owner can prioritize his/her choices. Through the above-mentioned process, a business owner is capable of identifying business partners who have potential to collectively create the goal images in a systematic and simple way.

In this chapter, we demonstrate the role of proposed mechanism in the tourism platform. In the next chapter, the evaluation part of the proposed mechanism is provided.
Chapter 6 Evaluation

This chapter describes the experiments utilized to evaluate the proposed mechanism in chapter 4 and to respond to the research objectives and contributions set forth in chapter 1. To reiterate, the purpose of this research was to develop a systematic approach that can facilitate partner selection process in order to build the images proposed by SME owners. Research questions addressed in the study were:

1. What mechanism can be designed to aid SME owners to choose partners for image building?
2. To what extent is the proposed mechanism leveraged to establish market niche for the SME owners?

This chapter serves as the evaluation part in research framework in Figure 1.1 and it is, therefore, presented in four sections. The first section delineates the hypotheses that will be examined in this research. Next, the details of experimental data and assumptions are provided. Third, the results of experiments performed for optimizing the parameters and answering the research questions are presented. In the final section, the results are summarized and discussed.

6.1 Hypotheses

As noted in previous chapter, the mechanism starts from analyzing the goal statement from the user in order to discover the partner candidates who can assist the image building process. Hence, the first step we need to take is to ensure it indeed can improve the level of goal fulfilment. While a SME owner would like to build a certain image (i.e., the goal) for his/her business, he/she can identify the possible partners
who have great potential to co-create the image successfully through the aid of proposed mechanism. Thus, we have the first hypothesis formed.

- **Hypothesis 1**: The proposed mechanism can help SMEs to identify the partners who have great potential to jointly build the goal images.

However, the image diversity of a destination may have significant impact on the level of difficulties in goal achievement. The term “image diversity” is used to describe how diverse are business images of a destination. Considering partner selection case, forming a new promising alliance is inherently limited to partner search base. The more multifarious the partner search base is, the more opportunities service innovation will have. In this idea, if there are abundant SMEs with diverse images in a destination, then it’s much easier for SMEs to find the appropriate partners to cooperate because the basic concept of this research is to find the partners who have the missing image elements. We then have the following hypotheses.

- **Hypothesis 1-A**: In the context of high image diversity, a SME would have more chances to improve the level of goal fulfilment through cooperating with others.
- **Hypothesis 1-B**: In the context of low image diversity, a SME would have few chances to improve the level of goal fulfilment through cooperating with others.

For the same reason, we believe the level of image diversity would influence the level of attractive and unique image building. The following hypotheses have formed as well.

- **Hypothesis 2**: In the context of high image diversity, a SME has more chances to build unique image through cooperating with others and vice versa.
- **Hypothesis 3**: In the context of high image diversity, a SME has more chances to build attractive image through cooperating with others and vice versa.
After validating the ability of the proposed mechanism to improve goal achievement, we can further test whether it can help SMEs to create their market niche. As mentioned earlier, there are two indicators regarding market niche assessment in this study (i.e., the level of uniqueness and level of attractiveness for a given alliance). We then have the following performance indicator as showed in Figure 6.1. If the coefficient is greater than 1, it means the proposed mechanism can effectively help SMEs to find appropriate partners for the sake of creating market niche. Moreover, the hypothesis for this issue is put forward.

\[
\text{Market Niche Coefficient} = \frac{\text{the level of uniqueness} + \text{the level of attractiveness} \ (\text{after cooperating with other SMEs})}{\text{the level of uniqueness} + \text{the level of attractiveness} \ (\text{before cooperating with other SMEs})}
\]

Figure 6.1. Market Niche coefficient formula

- Hypothesis 4: The proposed mechanism can effectively help SMEs to form a new alliance with market niche.

In the next section, it outlines the assumptions made for revealing the limitations of the mechanism as well as the experimental data set to test the hypotheses depicted in the previous section.

6.2 Assumptions and Experimental Data

6.2.1 Assumptions

Before the experiments are performed, several assumptions should be addressed.

- Assumption 1: When the system goes through partner discovering process, the search base for partners is limited in the same destination where the SME is located. In this research, we only try to tackle the problem of local tourism development. Nevertheless, it is still worth bearing in mind that the opportunities
for service innovation would become restricted if the search base is limited in a destination. Once this restriction is lifted, cooperation across destinations becomes possible. It is more likely to find the appropriate partners for goal achievement because more possibilities are opened up.

- Assumption 2: The image models of SMEs in the system are quite representative. The proposed approach heavily relies on the image model data. If the quality of image models does not reach the acceptable level, then the outcomes of recommendations would not be reliable.

- Assumption 3: The user’s inputs (the goal statement) should at least include one noun. The goal statement should be in the form of metaphorical statement. Every metaphor needs to have a vehicle which is a noun.

- Assumption 4: The performance of language translation API is good enough. The adopted technique of metaphor comprehension was designed for English context. In order to apply this technique to Chinese context, we need language translation API to translate Chinese statement into English. However, if the statement is too complex, then the quality of translation would not good enough.

- Assumption 5: The cultural difference is ignored. After the Chinese metaphorical statement has been translated into English. The context for metaphor comprehension would switch from eastern to western. That is not so promising in real application.

6.2.2 Experimental data

Given that it’s intrinsically impossible to acquire real image model of SMEs before the system is put into practice. Alternatively, we use the computer program to automatically generate the testing data. In total, 140 business image models and 140
customer image models are separately generated.

For the purpose of testing the hypotheses, two different levels (higher and lower) of image diversity context should be formulated. A destination with higher level image diversity indicates the SMEs within the destination give people diversified feelings. We can understand the level of image diversity by examining the number of image clusters and the distance between image clusters. The details are provided as below.

As mentioned in Chapter 4, every image model in the form of colors can be mixed into one RGB value. If an image model have similar configuration, it would be mixed into the similar RGB value. Through this conversion process, every image model can be converted to one RGB value and projected to a three-dimension (RGB) space. The cluster analysis then can be performed. In this regard, the RGB values in the same cluster means these image model have the similar image configuration.

In addition, the number of clusters implies the variety of image models. More image clusters reflects the wide difference in image models. On the other hand, if there is a tendency for the clusters to flock together, then it means the image models are relatively homogeneous (i.e., lower image diversity). If the clusters in the three-dimension space are located in a scattered fashion, it represents that the image models are relatively heterogeneous (i.e., higher image diversity). We believe it is strategically important to appreciate that healthy tourism ecosystem should exhibit higher image diversity, the ability to offer comprehensive experiences.

In order to automatically generate image models creating two different image diversity settings, the image model generation program should be able to manipulate the configuration of an image model. We know that the level of image diversity is decided by the number of clusters and the distance between each cluster. We also know that each cluster is formed from several nearby dots in the RGB space. If we
can ensure each generated image model can be converted to its designated RGB value, then the results of image cluster analysis can be deftly manipulated. In this regard, this program needs to have an input that is a RGB value. According to the given RGB value, the program will start to find the closest five colors of image elements. It will give these five image elements larger image quantity value and the rest of them get smaller value. The reason to do so is that the color mixing mechanism will only select the image elements that their intensity values are high enough to perform the color mixing. If the selected colors are those colors which are close to the given RGB value, then the color mixing result will be also close to it because the color mixing mechanism is basically to get the center of gravity of input colors.

After the program is developed, it can be used to generate image models, 140 for customers and 140 for businesses. The only problem is how to decide the input RGBs for generating image models. Regarding this issue, we adopt the random way to do so because the image model just is developed by our research team, and there are no practical image model data for us to reference. Therefore, if we want to generate the image models that fit image lower diversity setting, all we need to do is to input fewer number of colors to generate 140 image colors and vice versa. For example, if we input one color to generate 10 image models, then these image models would have similar image configurations; contrariwise, if we input ten different colors to separately generate 10 image models, then these image models would have different image configurations. According to this characteristic of image model generation program, the fewer colors are input and then the level of image diversity of image models will be smaller.

Figure 6.2 and 6.3 demonstrate the results of cluster analysis of 140 business image models for context setting of experiments. The blue circles represent the centers of each cluster. In a lower image diversity context, the number of clusters is
relative few (i.e., 5 image clusters) and the distance between the centers of each cluster is relatively short. Contrary to Figure 6.2, Figure 6.3 demonstrates the results for higher image diversity context (i.e., 11 image clusters) in similar manner. With different context settings, we are able to examine the impact of image diversity.

Figure 6.2 concentrated centers of image clusters (lower image diversity)

Figure 6.3 scattered centers of image clusters (higher image diversity)
6.3 Experiments and Results

The experiments are divided broadly into two parts. The first part was conducted to find a set of design parameters that can optimize the performance of the mechanism. The second is to evaluate the above-mentioned hypotheses.

6.3.1 Design parameters

In the mechanism, there are three key parameters (the number of metaphors, the number of Google queries and the similarity threshold for attractiveness analysis) that need to be finely tuned in order to ensure a near optimal system performance. Following are the descriptions of the parameters and the experiment results.

6.3.1.1 The number of metaphors

One of the fundamental principles for partner selection is to find the partners who have the complimentary capabilities and resources, which are embodied in terms of the images in our system. Considering the system process, an initial step is to find the image gap between the goal and the status quo. The gap analysis results will suggest what are the missing elements required to complement by others. The identified partners should be able to fill this image gap.

It is worth noting that the system would not generate possible partner candidates until the new metaphors have been made. During partner generation process, the system attempts to metaphorize the partners to something and then tries to match the something to the real business partners. The gap images are supposed to be embedded in these metaphors in order to ensure the image gap can be filled.

However, there is one thing we should bear in mind. That is, one of the most troubling aspects of these metaphors generation is that it cannot be always to find the metaphors embedded all the gap image elements. Sometimes they are just hardly to
find. Furthermore, considering the efficiency of generating the final output, it is practically unacceptable to find the best metaphor because it may take too much time. Therefore, we settle for the second option that we seek a metaphor with the highest gap image coverage index under a limited number of metaphors generated. The gap image coverage index formula is showed in Figure 6.4.

\[
gap \text{image coverage index} = \frac{\text{the number of gap images embedded in the metaphor}}{\text{the number of gap images}}
\]

Figure 6.4.gap image coverage index formula

In this experiment, what we would like to know is how many metaphors should be generated in order to keep the image coverage index and the system efficiency performance in acceptable level. The results are shown in Figure 6.5. The system efficiency performance here refers to the execution time of the proposed mechanism and its value has been normalized (e.g., 1 indicates high performance and 0 indicates low performance). The results appeared to suggest that the number of metaphor should be set to 3 because it reaches the balanced state between system efficiency performance and the gap image rate; however, for the research purpose, we decide to set the number of metaphors to 8 since it would be better to have a higher gap coverage rate. When the system is put into practice, this parameter would be change to 3.
Figure 6.5 The test run for deciding the number of metaphors required to ensure acceptable system efficiency performance

6.3.1.2 The number of Google queries

Google search ajax API is adopted when the system sends a query to Google. It’s quite a powerful tool and it’s convenient to use, but it only return up to 64 results at a time. We found that many of the returned results are often duplicated or useless. For the sake of getting the wanted results, performing queries several times are unavoidable. This experiment was then designed to understand how many times queries have to be sent in order to get the wanted words.

For example, while the system sends a query like “as * as a noun”, a sets of words that can replace the wildcard character would be returned. Only some of results are desirable because all we need are meaningful adjectives. We may also get the results like “as long as a noun...”. These kinds of results are those needed to be filtered out. The unwanted word list should be prepared to automatically do so. Furthermore, assuming that we want to get 10 meaningful adjectives in this example, if the system finally gets 8 adjectives, we would say that we get a result with 80% image element discovery rate. The simple formula of image element discovery rate is
provided as follows. The optimal is the result with the highest image discovery rate.

\[
\text{image discovery rate} = \frac{\text{the number of images we actually get}}{\text{the number of wanted images}}
\]

Figure 6.6. Image discovery rate formula

The results are illustrated in Figure 6.7. The horizontal axis indicated the number of queries sent to Google while the vertical axis depicted the image discovery rate. The results highlights that the number of Google queries should be set to 4 because this setting would make image element discovery rate be close to 100%. It’s already high enough. The system performance has been significant improved after the setting was adopted.

Figure 6.7 The number of Google queries

6.3.1.3 The image similarity threshold for attractiveness analysis

In the final module of the proposed mechanism, attractiveness analysis is performed to evaluate the power to attract people by the given image configuration of a new
alliance. This process involves the comparison of image models. Let’s assume there is a predicted image model of a new alliance. This new image model would be compared with each representative image model of customer image clusters and a image similarity score would be generated for each cluster. The image similarity score denotes the level of similarity between image models and its value will be between 0 and 1(e.g., 1 represents two image models have similar image configuration and 0 indicates they have nothing in common). For more details of image model similarity, please reference section 4.5 in chapter 4.

We also assume that customer image model represents their preference and behavior at some level. If an image model configuration of an alliance is really similar to an image model of a customer (i.e., high similarity score), we believe this customer will be attracted by the feeling presented by this new alliance. However, to what extent is the level of similarity that we think it higher enough to say that the customer will be attracted by a specific alliance? It is clearly that a similarity threshold is needed and its value is undefined for now. This experiment was set up to determine the value of similarity threshold.

There are two important considerations to properly set this parameter. The first consideration is that this parameter should be higher enough to reflect the idea that the similarity score is supposed to be high when the customers are attracted. That’s why the thresholds we tested started from 0.71. The second is that the thresholds can not to be set too high or too low. To explain this, consider the process of attractiveness analysis.

The attractiveness analysis is to calculate the percentage of customers who are attracted by a specific alliance in our platform. We determine whether the customers are attracted by the alliance according to the level of similarity between the image models of customers and the alliance. If the similarity threshold is set too high, then
no customer would be determined “being attracted”. For example, assume that there are three customer image models (C1, C2, C3) and an alliance image model (A1). The attractiveness analysis would start by computing the level of similarity of image models for each pair, that is, the level of similarity between C1 and A1, C2 and A1, and C3 and A3. Assume that the levels of similarity are 0.75, 0.82 and 0.87 respectively. If the similarity threshold is set to 0.9 (too high), then the attractiveness score becomes 0 because no customer can be attracted; conversely, if the similarity threshold is set to 0.72 (too low), then the attractiveness score becomes 1 because all customers can be attracted. In either case, there is a possible side effect – the attractiveness scores usually remain the same score (0 or 1) for different alliances. Then, we are not able to know the level of attractiveness differences between alliances. That makes the attractiveness analysis out of function.

According to the important considerations mentioned above, the goal of this experiment was designed to ensure the threshold setting can make the attractiveness score effective. Simply put, it can tell the differences of the attractiveness level between different cases. As observed in Figure 6.8, the vertical axis indicates the percentage of cases which have different attractiveness score by setting a given threshold and the horizontal one denotes the value of threshold. The results suggested that the threshold should be set to 0.84. About 90% cases have different attractiveness score.
Figure 6.8 The similarity threshold for attractiveness analysis

After all the parameters are well settled, we can further validate the usefulness of the proposed mechanism and test the hypotheses.

6.3.2 Evaluate the hypotheses

In this subsection, the hypotheses are tested through the experiments in order to answer the research questions mentioned earlier. The experiment setting is summarized below. The parameters are set according to the results of previous section. 12 goals are also prepared for the experiments.

Table 6.1. The parameter setting for the experiments

<table>
<thead>
<tr>
<th>Parameters</th>
<th>values</th>
</tr>
</thead>
<tbody>
<tr>
<td>the number of metaphors</td>
<td>8</td>
</tr>
<tr>
<td>the number of Google queries</td>
<td>4</td>
</tr>
<tr>
<td>the similarity threshold for attractiveness</td>
<td>0.84</td>
</tr>
<tr>
<td>analysis</td>
<td></td>
</tr>
</tbody>
</table>
Table 6.2. The testing goals prepared for the experiments

<table>
<thead>
<tr>
<th>Goals</th>
<th>Input</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Heaven</td>
<td>the service experience is just like being in Heaven</td>
</tr>
<tr>
<td>2</td>
<td>fascinating game</td>
<td>the service experience is just like playing fascinating game</td>
</tr>
<tr>
<td>3</td>
<td>shining fireworks</td>
<td>the service experience is just like watching shining fireworks</td>
</tr>
<tr>
<td>4</td>
<td>romantic wedding</td>
<td>the service experience is just like attending romantic wedding</td>
</tr>
<tr>
<td>5</td>
<td>childhood fantasy</td>
<td>the service experience is just like fulfill childhood fantasy</td>
</tr>
<tr>
<td>6</td>
<td>magical show</td>
<td>the service experience is just like watching magical show</td>
</tr>
<tr>
<td>7</td>
<td>nostalgic village</td>
<td>the service experience is just like being in nostalgic village</td>
</tr>
<tr>
<td>8</td>
<td>blockbuster movie</td>
<td>the service experience is just like watching blockbuster movie</td>
</tr>
<tr>
<td>9</td>
<td>Olympics</td>
<td>the service experience is just like attending Olympics</td>
</tr>
<tr>
<td>10</td>
<td>Dreamy Island</td>
<td>the service experience is just like being in Dreamy Island</td>
</tr>
<tr>
<td>11</td>
<td>Bali Island</td>
<td>the service experience is just like being in Bali Island</td>
</tr>
<tr>
<td>12</td>
<td>cultural festival</td>
<td>the service experience is just like attending cultural festival</td>
</tr>
<tr>
<td>13</td>
<td>Hawaii</td>
<td>the service experience is just like being in Hawaii</td>
</tr>
<tr>
<td>14</td>
<td>Paris</td>
<td>the service experience is just like being in Hawaii</td>
</tr>
</tbody>
</table>

6.3.2.1 The level of goal fulfillment

The first step to evaluate the proposed mechanism is to guarantee it indeed can improve the level of goal fulfillment. The followings are the relevant hypotheses.
Hypothesis 1: The proposed mechanism can help SMEs to identify the partners who have great potential to jointly build the goal images.

Hypothesis 1-A: In the context of high image diversity, a SME would have more chances to improve the level of goal fulfilment through cooperating with others.

Hypothesis 1-B: In the context of low image diversity, a SME would have few chances to improve the level of goal fulfilment through cooperating with others.

Figure 6.9 The level of goal fulfillment under low level image diversity context
In this experiment, business image models were randomly selected from business image classes as the target businesses who want to discover partners by metaphor-based partner recommendation mechanism. Two different levels of image diversity contexts were formulated to test the impact of this factor on goal fulfillment under high level image diversity context.
achievement activity. Specifically, there were five image business classes in low diversity context. Each business class represented one possible image type of businesses. Therefore, five business image models were separately selected from five business image classes in a random manner. We are able to understand the performance of goal fulfillment for each different business image types. After the target businesses were selected, we started to input 14 goals separately to gain 70 results (i.e., 5 target businesses x 14 different goals) and their fulfillment scores. This step was taken in both context settings, and then we’re able to examine the difference between them.

The complete results are shown in Figure 6.9, 6.10 and 6.11. In Figure 6.9 and 6.10, the solid line indicates the level of goal fulfillment after the target businesses cooperates with the partners our system recommended and the dotted line refers to the level of goal fulfillment before the target businesses cooperates with others. The goal fulfillment scores are averaged base on the different goal settings. According the formula of goal fulfillment score provided in section 4.5, the goal fulfillment scores in these two Figures will be between 0 and 1. The higher value means the higher level of goal fulfillment and vice versa. The detail of the goal fulfillment score and its rationales are provided in chapter 4, goal fulfillment analysis.

In general, as observed in these three Figures, the level of goal fulfillment can be improved through cooperating with the partners the system recommended, no matter in which context. This improvement is reflected in gaining higher goal fulfillment score. Figure 6.9 and 6.10 highlights the differences between cooperating with partners (i.e., the solid line) and doing business by the SME itself (i.e., the dotted line). Cooperating with partners may have more chance to improve their images.

However, it has to be stressed that image diversity is a particularly important variable in considering the likelihood of improving the level of goal achievement. In
Figure 6.11, it demonstrates level of improvement on goal fulfillment for each goal in two different context settings. These results support the idea that the image diversity of a destination would impact on the level of difficulties in goal achievement. That is, in higher image diversity context, businesses are much easier to find the appropriate partners to collectively achieve the goal. In sum, hypotheses 1 (The proposed mechanism can help SMEs to identify the partners who have great potential to jointly build the goal images), 1-A (In the context of high image diversity, a SME would have more chances to improve the level of goal fulfilment through cooperating with others) and 1-B (In the context of low image diversity, a SME would have few chances to improve the level of goal fulfilment through cooperating with others) are supported by these results.

6.3.2.2 The level of uniqueness

- Hypothesis 2: In the context of high image diversity, a SME has more chances to build unique image through cooperating with others and vice versa.

The hypothesis 2 is constructed in order to examine the impact of image diversity on creating differentiation feature through alliance. In Figure 6.12, the horizontal axis denotes different goal settings and the vertical axis indicates the uniqueness score which is between 0 and 1 as well. The higher score means the new image configuration of a new alliance is quite different from others. The formula of the uniqueness score and its rationales are already offered in chapter 4, uniqueness analysis. The process of this experiment is very similar to previous one. It began by randomly selecting businesses as the target businesses and then generated different partner suggestions separately according to those 14 goals settings. The uniqueness
scores are computed and averaged in the end for each goal setting.

Figure 6.12 The level of uniqueness under different level of image diversity setting

The Figure 6.12 and 6.13 demonstrate that the image diversity would influence the businesses to create unique feature. The difference between Figure 6.12 and 6.13 is that they are presented in different perspectives. The former one presents the original uniqueness score and the latter exhibits the level of improvement on uniqueness reflected in higher uniqueness score. As observed in Figure 6.12, the original uniqueness scores in higher image diversity context are greater than the scores in lower image diversity context. However, the level of improvement on uniqueness in higher image context is lower than in low image context. Obviously, it is more difficult to improve the level of uniqueness for business in high level context.

A partial explanation for these results may lie in the fact that the businesses in a high image diversity context are already unique enough. To address that, please see table 6.3, the distribution of uniqueness scores before cooperating with partners in
different image diversity context. In the table, the uniqueness scores above 0.5 account for 82 percent (18%+64%) of the businesses in a higher image diversity context. It seems challenging to further improve the uniqueness given that the business is already very unique.

The other more likely explanation rests in the nature of the effect of partnerships. If the business image model is really unique, which means this business has higher intensity of special image elements that others don’t. Consider one of our assumptions of this study is that business can acquire mixing image elements for goal achievement through partnerships. If the missing image elements that are brought in are the common image elements, then it is likely to decrease the level of uniqueness. Such effect is relatively evident when the original business is quite unique. In sum, the hypothesis 2 (In the context of high image diversity, a SME has more chances to build unique image through cooperating with others and vice versa) is not supported.

Figure 6.13 The level of uniqueness improvement under different level of image diversity setting

Table 6.3 The distribution of uniqueness scores before cooperating with partners in...
different image diversity context

<table>
<thead>
<tr>
<th>the interval of uniqueness score</th>
<th>lower image diversity</th>
<th>higher image diversity</th>
</tr>
</thead>
<tbody>
<tr>
<td>0~0.25</td>
<td>20%</td>
<td>18%</td>
</tr>
<tr>
<td>0.25~0.5</td>
<td>60%</td>
<td>0%</td>
</tr>
<tr>
<td>0.5~0.75</td>
<td>20%</td>
<td>18%</td>
</tr>
<tr>
<td>0.75~1</td>
<td>0%</td>
<td>64%</td>
</tr>
</tbody>
</table>

However, there is one thing worth noting that the image diversity is not the only factor influencing the level of uniqueness. Sometimes the goal setting matters, especially when the goal is too common. That is, the images we are trying to create are already to be seen everywhere. Then, it would become harder to build unique feature through the common goal.

6.3.2.3 The level of attractiveness

- Hypothesis 3: In the context of high image diversity, a SME has more chances to build attractive image through cooperating with others and vice versa.

The hypothesis 3 was designed to examine the impact of image diversity on building attractive images. Similar to the previous experiment, the ways to perform this experiment have nothing different. As showed in Figure 6.14, all of the level of improvement on attractiveness scores in both contexts are greater than 0. This means businesses are able to improve their attractiveness level through partnerships. The detailed information regarding the meaning of attractiveness score and its rationale are available in chapter 4, attractiveness analysis.

The results also suggested that the higher level of image diversity might have potential impact on improving attractiveness. In the Figure 6.14, the solid line indicates the level of improvement on attractiveness in a lower diversity context and
the dotted line refers to the level of improvement on attractiveness in a higher diversity context. The solid line almost lies above the dotted line. One possible implication is that businesses have more chances to become more attractive by cooperating with others in higher image diversity context. Therefore, the hypothesis 3 (In the context of high image diversity, a SME has more chances to build attractive image through cooperating with others and vice versa) is also supported.

![Figure 6.14 The level of attractiveness improvement under different level of image diversity setting](image)

Figure 6.14 The level of attractiveness improvement under different level of image diversity setting

6.3.2.4 Market niche creation

- Hypothesis 4: The proposed mechanism can effectively help SMEs to form a new alliance with market niche.

This experiment was devised to simulate the condition that the users use the proposed mechanism repeatedly with different goal settings in order to find the partners who have the greatest potential to jointly create market niche. It is crucially important to
note that the design logic of the proposed mechanism does not guarantee to find the partners who can improve the level of goal fulfilment, uniqueness and attractiveness in the same time. Instead, the mechanism only identifies the partners that potentially could help improve the level of goal fulfillment, even though it cannot always be done. The rest of analysis, such as attractiveness analysis or uniqueness analysis, is just complimentary information to help users make more appropriate choices in market niche creation perspective. The design logic of this experiment is described as follows.

First, there are 11 business image clusters in our testing data. We then randomly and separately picked one business image model from each image cluster. Which means there were 11 different kind of business picked as the targets. These 11 cases are presented as horizontal axis in Figure 6.15. The basic idea is that we attempts to prove the business image type is irrelevant to getting the benefits from the proposed mechanism. Regardless of what kinds of businesses, they can create market niche by employing the mechanism.

Second, there are 14 different goal settings prepared for 11 businesses to test. We then chose the best of partner recommendation results for each business as the final decision. This action implies that sometimes a business may not get the most appropriate results from a given goal. This situation may cause either by the following two reasons. One reason is that the goal setting may be too common or undesirable. The other one might be that the destination where the business located belongs to low level image context. The potential business partners are too limited to find the appropriate ones in order to improve the level of goal achievement as well as the possibility of market niche creation. Normally, it’s hard to change the context where the businesses are located, but they do can change their goals. Through changing the goal repeatedly, businesses can find the best solution for them.
Finally, compute the market niche coefficient for each 11 cases with the best goal setting and the choice. As mentioned in section 6.1, if market niche coefficient is greater than 1, it indicates that the possibility of creating market niche is improved by forming a new alliance relationship. The results reflected in Figure 6.15 indicate that almost any kind of business can benefit from employing the proposed mechanism. The hypothesis 4 (The proposed mechanism can effectively help SMEs to form a new alliance with market niche), therefore, is supported as well.

![Figure 6.15 Market niche coefficient](image_url)

**6.4 Discussion of Findings**

The goal of this study is to integrate metaphors with destination image theory to develop a mechanism that features partner recommendations for building attractive and unique images. Although the experiment results of this study provide overall support for the utility of the proposed mechanism, some of them reveal a few
unexpected relationships that are not consistent with what we hypothesized. We hypothesize that businesses have more chances to build unique and attractive image in a higher diversity context. Our results confirm that businesses in higher diversity context would have more opportunities to find appropriate partners to enhance their attractiveness (i.e., hypothesis 3). However, the influence of image diversity context on uniqueness level improvement is not the case that we expected. In a higher diversity context, it becomes much difficult to improve the level of uniqueness (i.e., hypothesis 2).

A plausible explanation for the opposite results gained from testing hypothesis 2 is that partnership sometimes neutralizes the level of uniqueness if the business image is already very unique before cooperating with others. This relationship leads us to hold an opinion that if a business already has unique images but cooperates with businesses with common images, then the uniqueness of new alliance might not be as high as before.

Here are some results are worth summarizing:

1. The proposed mechanism does have ability to help business improve the level of goal achievement on image building.
2. The image diversity of a destination has paramount impact on the goal achievement, and attractive and unique image building.
3. The business image type is irrelevant to getting the benefits from the proposed mechanism. Regardless of what kinds of businesses, they can create market niche by employing the mechanism.

The results of these experiments also have implications for businesses while employing the proposed mechanism. First, the mechanism can be easily used to find potential partners in order to create market niche. However, this method should still
be used with caution. For example, inappropriate goal setting will lead to an increase in difficulty of creating market niche. As indicated in experiments for testing hypotheses 2 and 3, if the goal is set too common or not desirable, then it’s hard for business to build attractive and unique features. Second, the results of experiments for testing hypotheses 1, 3 support the idea that the businesses in higher image diversity context have more opportunities to find the most appropriate partners to create service innovation. If the government can provide more incentives for businesses to move in to a low image diversity destination, then regional tourism development might be fostered. Finally, these findings of all the experiments lead us to believe that cooperation with partners could be an efficient way to build attractive and unique images.

In the next chapter, the research implications, conclusions and future directions are provide as the end of this research.
Chapter 7 Conclusion

This research was initiated with two broad research questions. The first question is related to designing a new mechanism in order to aid SME owners to choose partners for attractive and unique image building. The remaining one is to understand to what extent the proposed mechanism can be leveraged to establish market niche for the SME owners. The results have been presented in details in chapter 6. This chapter summarizes the research contributions first. Next, the managerial implications of the research are discussed. Finally, the limitations of this study, future research and conclusions are presented.

7.1 Contributions

First, building on the destination image theory in the tourism domain, we explore how metaphors can be integrated into partner selection mechanism. Destination image, by definition, can be regard as the perceptions, beliefs, impressions, ideas and understandings that a person has of a destination (Tuohino 2001; Echtner & Ritchie 2003). Such perceptions and impressions are abstract concepts, which can be represented in the form of metaphor. Metaphor also demonstrates its ability to foster innovative solution generation in the design discipline. By combining three streams of literature regarding destination image, metaphor and computing metaphor, we extend the applicability of metaphor to real world problem solving. Using the groundwork laid in this study, researchers might gain some insights to apply metaphors to other problem domains.

Second, our study also contributes fresh perspectives to tourism and natural language processing research, in particular, designing a new artefact adopting the perspectives from the two disciplines. Although computing metaphor has been
studied extensively in natural language processing (NLP) domain (Abe & Nakagawa 2006; Baumer et. al. 2009; D'Harris 2002; Jones 1992; Mason 2004; Martin 1990; Slack 1980; Veale & Hao 2007; Weiner 1984; Zhou et al. 2007), their applications in the tourism literature is rare. In this research, we enrich this stream of literature through extending the Sandonicus approach and applying it on image analysis and metaphor generation in the tourism context. The extension of the Sandonicus approach is unfolded with a three-stage process so as to generate the metaphors with multiple properties. By demonstrating the promising application, we may bring out new insights for researchers of both disciplines.

Third, this study fulfils the research gap derived from the argument that there exists an image gap between the proposed image and supplied tourism products (Camprub i ́ 2008). That is, the proposed destination image may not reflect the reality of a destination owing to the low degree of collaboration and cohesion between businesses which supply the tourism products/services. The proposed mechanism encourages businesses to find the appropriate partners to form alliances and develop new services that fit the proposed images. In this way, the inconsistency between what customers perceived from the proposed image and what they experienced from the real service would be reduced owning to the higher degree of collaboration between businesses in a destination.

Overall, this study contributes to the tourism literature by providing a manageable tool for businesses to choose partners in order to create images. This research also enriches the natural language processing studies through establishing a new real world application for metaphor comprehension and generation techniques. Finally, this exploration of an interdisciplinary approach exemplifies the viewpoints
from service science that focuses on studying, designing and implementation of service system with a set of systematic approaches.

7.2 Managerial Implications

Base on the destination image theory in tourism domain, our research offers an operationalized tools for companies to select partners while considering image building. We conclude that SMEs in tourism industry should cooperate with each other in order to compliment each others’ limited resources and co-develop new services that fit the proposed images. As identified in the hypothesis 4, the underlying efforts would make them be able to create market niche. In particular, our hypothesis 1 justified that the proposed mechanism could improve the level of goal achievement on image building for businesses. However, hypotheses 1-A, 1-B and 3 also point out that the level of image diversity is a relevant factor that influences the opportunities of improving goal achievement and attractiveness on image building. Such facts imply it is beneficial to create a simulating environment of a destination (i.e., higher diversity context) where business have more chances to successfully build different image and improve attractiveness to benefit tourists by the efforts of alliances. We argue higher image diversity is worth to pursue because it also entails that tourists can have more diversified and comprehension experiences in a destination.

To pursue this end, we suggest two ways of actions should be taken. On one hand, businesses should be told that the images they proposed should be not similar to others. This would result in the reduction of opportunities in creating market niche and negative impact on image diversity of a destination. On the other hand, the
government can provide some incentives to attract diversified businesses to move to the lower image diversity destinations for the sake of satisfying various customer needs.

According to the results of testing hypothesis 2, our research offers evidence echoing the real world phenomenon that businesses already have unique features would not be necessarily to cooperate with partners. If these businesses cooperate with partners with common image attributes, they may suffer from the abatement of uniqueness level owing to the common images brought into the entire services. Nevertheless, if this abatement on uniqueness can contribute to gain higher attractiveness in return, then it becomes a trade-off for businesses to decide. Our market niche assessment module provides both indicators (i.e., attractiveness and uniqueness) for businesses to reference. Hence, businesses need to consider all the possible results before they take their actions.

Finally, one point should be made clearer for businesses who intend to leverage metaphor-based partner recommendation mechanism. That is, the appropriate goal setting is relevant to create their market niche. More specifically, if the proposed goal is neither attractive nor unique to people, it is unlikely to form a new service with attractive or unique feature. By setting the appropriate goals, businesses are able to enjoy the benefits brought from the propose mechanism.

7.3 Limitations and Future Works

We note several limitations to our work that should be taken into account when leveraging our approach. First, sometimes it’s difficult for SME owners to come up with an appropriate or innovative goal setting to take the best advantages of the proposed mechanism. If this situation happens, the utility of the proposed approach might be might be reduced. Second, we are not able to gain practical usage data of the
proposed mechanism because the implementation of uVoyage platform would not be finished until mid June, 2010. It takes time to invite participants to use the platform and the evolvement of image model also needs time. Only when the image models of target entities (e.g., customer, business, destination) can actually represent the real images of them, it is more likely to generate meaningful results from metaphor-based partner recommendation mechanism. We believe the way we used to justify the performance and utility of the proposed mechanism represents a considerable simplification of the real world context. A practical field experiment in which participants can gain more realistic experiences of using metaphor-based partner recommendation approach will certainly produce more reliable and meaningful results.

Third, partner selection for image building is only the beginning. The rest of activities, how to co-develop a new service, how to manage the operations and so on, are even of decisive importance to successfully build images. These issues remain unaddressed in this study.

Finally, as the summary of above-mentioned limitations, the future research could move beyond the initial development of the proposed mechanism to gain more data from practical world and further examine the effect of image-driven service innovation. Also, the new mechanism could be developed to encourage SME owners to discover or come up with appropriate goals for using partner recommendation mechanism. Finally, the current study is only focusing on local/regional tourism development. Future research may extend the focus to across regions level or even national level.
7.4 Conclusion Remarks

In this paper, we address the problem of how to assist the tourism SME owners with a useful approach for managing partner selection to build the attractive and unique image. By leveraging the operant resources (i.e., skills, knowledge and technology) from others, SMEs are able to gain competitive advantages and eventually improve their sustainability and profitability. To this end, this paper identifies the interrelationships between computing metaphor, attractive and unique image building and alliance formation and then presents a novel and systematic approach to solve the problem.

We also offer a system scenario and experiments for this method to show its practicability. We believe the method can SME owners in managing the partner selection tasks for attractive and unique image building in a more efficient and effective way.
REFERENCES


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Press Professional, Inc. San Diego, CA, USA.


