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Unveiling Technological Innovation in Hospitality and Tourism through Patent Data: Development Perspective and Competition Landscaping

Abstract

This study fills a gap in the literature by focusing on hospitality and tourism technology development (supply-side perspective) rather than technological adoption (demand-side perspective). Drawing on US patent data, we focus on three main technology areas: travel agencies, hotels and restaurants, and online reservations. With a dataset of 88,344 patents granted to 13,696 assignees since 1966, we study hospitality and tourism-related technologies under the three fields. Using the machine learning-based text analytics, we analyze the classes of patents invented in each sector. We also map technological competition landscapes in the three domains in terms of innovation quality (PageRank centrality) and quantity (patent volume) and discover leading/following firms.

Keywords: technology innovation; patent; competitor mapping; resource-based theory; machine learning

1. Introduction

Innovation has been considered a key competitive advantage factor for hospitality and tourism management (HTM) (Nicolau & Santa-María, 2013; Hameed et al., 2021; Lim & Ok, 2021; Kim et al., 2022; Shin & Perdue, 2022a). Of the various types of innovations, technological innovation is deemed a critical driving force of growth in HTM-related industries (Iranmanesh et al., 2022; Jayawardena et al., 2022; Song et al., 2022; Shin et al., 2022). Given the importance of technology innovation in HTM-related sectors, most previous literature has mainly focused on the benefits of leveraging technological innovation in the industry (Shin & Perdue, 2022a); specifically, this focus has revolved around the technology adoption (i.e., demand-side) perspective and investigated its effect on customer satisfaction (Wang et al., 2017). Interestingly, in contrast to the technology adoption standpoint, the technology development stimulated by the needs per se (i.e., supply-side) of HTM industry stakeholders (e.g., tourists, tourism distribution channels, and service suppliers) (Baki, 2021, 2022; Cook et al., 2018) have been relatively under-addressed as an individual research area. Our study fills in the research gap by focusing on HTM technology development (from *a supply-side perspective*) by leveraging patent-related data, as opposed to the adoption of technological innovation to the HTM industry (*a demand-side perspective*). The debate about *demand-pull* and *technology-push* has been longstanding in the innovation research area (Di Stefano et al., 2012), which can be seen as the key driving force of technological innovation. However, rather than arguing whether demand or supply comes first, this study intends to define technology development from the *supply-side* as follows: technologies developed by the internal/external HTM service suppliers to engender efficient service management (e.g., crowd/queue management, yield management)". As it has evolved around the HTM industry, the supplier's aspect will be highlighted. As a proxy for technological innovation, we utilize patented information because the only novel and valuable inventions distinctive from extant technologies are granted a proprietary property right by issuing patents. Drawing on the patented technologies, our research question is examined in the view of HTM technology development.

Note that in-house technology developments in HTM-related industries (e.g., Priceline bases its booking systems on its own patents) have accelerated with the advent of information technologies, especially in key competitive factors such as real-time information (e.g., schedules, fares, rates, and availabilities) (Benckendorff et al., 2019; Knani et al., 2022) and strategic revenue management (Talón-Ballestero et al., 2022). These factors encourage HTM firms' in-house technology development for their proprietary rights to use their own software. In particular, stemming from the resource-based view of firms (RBV), intangible sources (e.g., specific market needs, decision-making techniques, or management systems) can also provide a competitive advantage to a firm's idiosyncratic capabilities (Mowery et al., 1998; Haldorai et al., 2022). In other words, a firm's competitive positioning can be determined based on its resources (Liu et al., 2020), so we argue in this study that firms can be defined in terms of their technology resources, such as patents. Note that patents reflect technological innovation changes (Archibugi & Planta, 1996), and the analysis of the keywords associated with patents can be used to unearth technology-related opportunities (Lee et al., 2009). Therefore, given the increasing gravity of HTM technology innovation, firms in HTM-related sectors are also aware that they may lose their market competitiveness if they lag behind technology development competitions (Zach, Nicolau & Sharma, 2020). Consequently, the competition between firms has become more intense to take the lead in the market.

In this context, patents become a crucial element in supporting innovation. Firms patent to protect their intellectual properties, monopolize the technological advantage against competitors (Mazzoleni & Nelson, 1998), and eventually prevent unauthorized copycats. Also, firms with a strong patent portfolio can build high barriers to entry and earn licensing fees from followers who need to utilize patented key technologies for their own businesses (Gallini, 2002). In this regard, technological pioneers take strong market positions by limiting the inflow of competitors and securing specific niches (Mazzoleni & Nelson, 1998).

Despite the significance of HTM technology innovation and intense interfirm competitions in practice, the HTM literature, however, has relatively understudied the technology development standpoint. Such a lack of focus may be attributed to 1) ambiguous definitions of what types of technologies are seen as HTM-related and 2) the absence of reliable data sources for academic research.

In fact, previous studies have mainly focused on interpreting and explaining HTM firms' innovation activities (Dang & Wang, 2022; Lee et al., 2022; Shin & Perdue, 2022b; Yang et al., 2021). In comparison, our study aims to delve into the HTM technology development perspective, contributing to the technological innovation literature in HTM sectors in at least three different ways. First, this study may be one of the earliest HTM innovation studies to leverage a large scale of up-to-date patent data from the Google Patents database.

We obtain 88,344 patents and their specific meta-information and conduct a series of analyses, which are clearly articulated to encourage future studies on the technology development standpoint in the HTM literature. Second, based on the Cooperative Patent Classification (CPC) system that presents granular and reliable patent categorizations, we focus on patents about 1) *travel agencies*, 2) *hotels and restaurants*, and 3) *online reservations*. This clearly delineates the boundary of HTM-related technologies. Moreover, we analyze in-depth HTM-related patents in the three patent groups based on textual data, categorizing their content into several latent topic categories. Third, we provide a strategic viewpoint by which firms can discover their competitors or benchmark firms in terms of HTM technology development and reasonably realize their standings in the technology competitions.

More specifically, we first use unsupervised machine learning-based text analytics (i.e., LDA) to derive latent categories in the three patent subgroups “travel agencies”, “hotels and restaurants”, and “online reservations”. We then characterize the topic categories based on several main terms. Second, as an extension of the first analysis, we examine the competitive standings of firms in the HTM industry based on the firm-level citation networks and patenting volume with visual representations. The results show that several firms outside the HTM industry (*external entities*), such as Google and IBM, have taken leading positions over some conventional travel agencies, including Priceline (*internal entities*). Their specific standings are represented based on innovation quality and quantity, i.e., PageRank centrality and patent volume, respectively. Consequently, to conceptually position our work in the literature, we present Figure 1 with visual clarification of our research angle. While much extant HTM literature on technology innovation focuses on the technology adoption of internal HTM entities (third quadrant), few studies cast light on the development viewpoint (first and fourth quadrants). We fill in the research gap by analyzing reliable patent-related data and then categorize HTM-related patents into several groups. Moreover, in our second analysis of technology competition at the firm level, we show that external firms outside the HTM industry, e.g., IBM and Google, are the leading firms (first quadrant), followed by several internal players, e.g., Priceline (fourth quadrant).

This study continues with the following section surveying the literature on technological innovation in HTM with foci on three broad topics: technology innovation for competitive advantage, interfirm networks and innovation in HTM industries, and landscaping interfirm competition for HTM-related technologies. Then, we describe our unique dataset's configuration in data collection and preprocessing. Subsequently, we introduce key methods used for primary analyses and present the results. Lastly, we discuss the implications of this study from both theoretical and managerial perspectives, followed by concluding remarks.

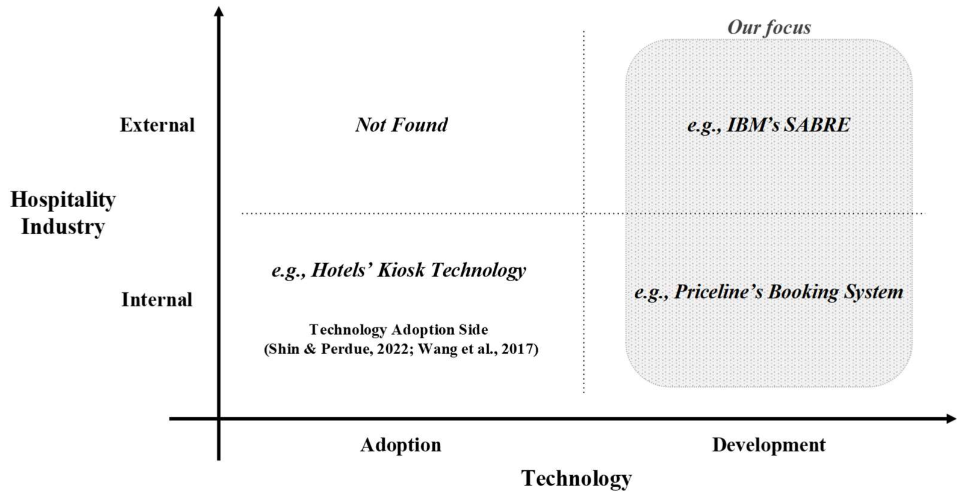

Figure 1. Conceptual Research Framework

2. Technological innovation in HTM

Value creation for customers is vital in today's hospitality business environment, and HTM has used technological innovation to flourish their businesses and upgrade customer experience. Such attempts have been made either via redesigning their services or by incorporating new devices to gather automated data, thereby providing services tailored to each customer, adjusting the service, or implementing corrective measures (Knani et al., 2022). As described, the impact of new technologies on the HTM industry is crucial. Since Barras' (1986) theory of innovation in services, HTM innovation research has built up since the mid-1980s, reinforcing the role of innovation as a vital competitive force for HTM companies and destinations (Hall, 2009; Ottenbacher, 2007; Gomezelj, 2016). Among various innovations, technological innovation has obtained considerable attention from previous studies. Specifically, some scholars noted that HTM firms introduced new technologies to improve service quality and operational performance (Blake, Sinclair & Soria, 2006; Sirirak et al., 2011). Over time, this research interest has evolved to the effect of information and communication technologies (ICT) on HTM-related sectors, beginning with internet network technology and virtual reality and recently progressing to artificial intelligence and robots (Orfila-Sintes & Mattsson, 2009; Guttentag, 2010; Tussyadiah, 2020; Ivanov & Webster, 2020). Mainly, the technology demand-side viewpoint has focused on technology acceptance from extrinsic drivers in comparison to technology development based on intrinsic motivations. This viewpoint considers HTM-related technologies as a tool for effectively refining services. As such, the previous technological innovation research stream has shed light mostly on the application of innovative technologies (i.e., *demand* or *adoption*) to the HTM industry and their effect on firms' products, services, and operating performance. In addition, most theory-driven studies have mainly addressed the adoption of technology innovation in HTM industries and its effect on customer satisfaction or changes in travel behavior. In comparison to the focus on the adoption side, the empirical literature on HTM technology development per se has been limited in scope and volume (Jacob & Groizard, 2007; Buhalis & Law, 2008), although the need for them has been continuously suggested (Hjalager, 2010; Hall & Williams, 2019; Williams & Shaw, 2011). The following sections articulate important prior literature.

2.1. Technology innovation for competitive advantage

Technology advances have long been recognized as a crux of innovation (Coombs, Saviotti, & Walsh, 1987), and this is no exception in the HTM literature (Kim et al., 2022). Technology innovation is a key driver of competitive advantage in many industries, as it enables companies to create new products and services, improve existing offerings, and reduce costs. By investing in R&D and implementing cutting-edge technologies, firms can gain a significant edge over their competitors, improve their operational efficiency, and enhance their overall competitiveness. By leveraging technology innovation, companies can create new sources of value for their customers, improve their operational efficiency, and achieve a sustainable competitive advantage (Porter, 1985).

In this context, the resource-based view is an essential theoretical framework to characterize those companies that are able to gain competitive advantages (Seo et al., 2021). Note that if firms have resources that are "valuable, rare, inimitable and non-substitutable" (Barney, 1991), the resulting competitive advantages make the firms able to distinguish from competitors and occupy a stable position in the market. This differentiation via resources was already put forth by Porter's (1985) value chain model, featuring the advantageous actions that firms can carry out by using their resources instead of employing the resources per se. In this regard, this author goes as far as to say that "resources are not valuable in and of themselves" and even claims that it is the value created through the actions conducted by using these resources that are relevant to securing competitive advantages. Regarding technological innovation, Porter (1985) stated that the relationship between technological change and competition is intricate because having new technologies alone may not guarantee a company's future success. In addition, Lengnick-Hall (1992) added evidence to Porter's argumentation by stating that four preconditions (imitability, a reflection of market realities, timing, and requisite capabilities for exploitation) are required for innovation activities to lead to competitive advantages. Importantly, in addition to the effect of intrinsic factors, various external determinants, including buyers, distribution channels, and suppliers, build the company's value chain, and the interfirm network among such stakeholders maximizes the interdependent technology value (Shank & Govindarajan, 1992; Dekker, 2003). Theoretically, Hjalager (2010) articulated that institutional innovation is a singularity of HTM innovation, indicating that enterprises' networks are a key component of HTM innovation research.

2.2. Interfirm networks and innovation in HTM industries

Networks can refer to a variety of relationships and connections between different actors in the HTM industry, such as suppliers, customers, competitors, and regulators. These networks can play a critical role in facilitating knowledge transfer, collaboration, and the development and diffusion of new technologies and practices (Hjalager, 2010). The literature has shown that innovation in the HTM industry is often the result of collaboration and coordination among various actors in the industry, including hotel chains, technology companies, and government agencies (Gomezelj, 2016). By leveraging their networks, these actors can certainly pool resources, share expertise, and overcome the challenges that are associated with developing and implementing new technologies. For example, hotel chains may work with technology companies to develop and implement new systems for managing guest data and enhancing the guest experience. Government agencies may collaborate with hotels and technology companies to promote the adoption of sustainable practices and technologies that are more environmentally friendly.

Still, among travel service providers, a successful paradigmatic example of an interfirm network stands out: Global Distribution System (GDS) spanning heterogeneous sectors. An exemplar is *Sabre*, the reservation system of American Airlines developed in the 1960s. It allowed travel agencies, hotels, and other airline firms to use their platform even beyond for inside scheduling, ticketing, and issuing boarding passes (Porter, 1985; Sabre (n.d)). Based on the innovative computerized system, the value chain among those stakeholders was established. Beginning with *Sabre*, computerized GDSs such as *Galileo*, *Worldspan*, and *Amadeus* were set as standard inventory management systems in the travel and tourism industry (Kärcher, 1996). The generalization of the new inter-operating system in the HTM industry spawned opportunities for firms to deliver services innovatively, thereby becoming a critical component of today's hospitality providers (Andriotis & Paraskevaidis, 2021; Christ-Brendemühl, 2022). This process was called process innovation (Hjalager, 2010) and created an entirely different business model (Bower & Christense, 1995; Bieber et al., 2017). With the internet revolution in the early 1990s, online transactions of HTM-related services matured, enabling customer-to-customer (C2C) transactions as well as business-to-customer (B2C) or business-to-business (B2B) trading. Price comparison websites, peer-to-peer platforms (e.g., Airbnb), and social media are critical technologies as well. However, on their origins, GDS and early computer reservation systems are the fundamental technological development in HTM-related sectors invigorated by the evolution of information and communication technology (Stamboulis & Skayannis, 2003).

In summary, enterprises' networks play a critical role in HTM innovation research by enabling collaboration, knowledge transfer, and the development and diffusion of new technologies and practices.

2.3. Landscaping interfirm competition for HTM-related technologies

The literature that focuses on the strategic value of identifying and monitoring current or potential competitors has conducted this task based on the product perspective, leading to myopic or biased analyses. However, competitors can be identified not only in terms of firms' products but also of other resources (e.g., intellectual properties) (Markman, et al., 2009; Bergen & Peteraf, 2002; Chen, 1996), such as information technology (Wu et al., 2006). Hence, drawing on the literature, we view patents as firms' key capital in technology innovation. We conjecture that the resource-based approach at the firm level may serve as an appropriate landscape on which technology competitors can be discovered and provide a new list of competitors beyond the product boundary. In particular, not only do we look at firms' innovation quantity, i.e., patenting volume, but we also utilize the inter-firm patent citation networks to better understand their relative standings between firms in terms of innovation quality.

In summary, following the resource-based view (RBV) (Barney, 1991; Barney & Arikan, 2001), we view firms in the HTM industries as a collection of their patents, the proxy for innovation. We then map such firms based on the two innovation performance metrics of quality and quantity. In doing so, we provide useful business intelligence for HTM firms to understand their standings and detect their competitors in terms of technology development. Such a landscape of technology competition in the HTM-related industries has been unexplored in the literature.

3. Research Design

This study investigates in-depth specific HTM industries by focusing on patents, widely used in the literature as the proxy for innovation. Also, the use of patents to anticipate new technological innovation is well-established in the literature (Daim et al., 2006; Tseng et al., 2007). We utilize patents first by selecting HTM-related patents categories according to the Cooperative Patent Classification (CPC) system (Figure 2). In detail, starting from patent subclass "G06Q" representing "Data Processing Systems or Methods", two main groups include "G06Q10 (Administration; Management)" and "G06Q50 (Systems or methods specially adapted for specific business sectors, e.g., utilities or tourism)". We then drill down into three subgroups: G06Q10/02 (reservations for tickets, services, or events), G06Q50/12 (hotels and restaurants), and G06Q50/14 (travel agency). The focus on three patent subgroups defined by CPC provides a reliable boundary of HTM-related

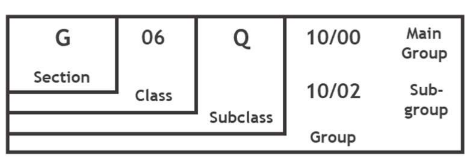

Figure 2. Hierarchical Taxonomy of the CPC Structure

innovation.

The second step categorizes technologies invented as HTM-related patents by using machine learning-based text analytics, which has proven to be a method with accurate results in tourism (Ahmed et al., 2008; Afsahhosseini & Al-Mulla, 2020; Cankurt & Subasi, 2015; Claveria et al., 2016; Li et al., 2021; Nilashi et al., 2017; Xie et al., 2021). Also, firm-level patent citation network analysis is conducted to explore which firms are leading technology frontiers in terms of technology development. The overall research flow is summarized in Figure 3.

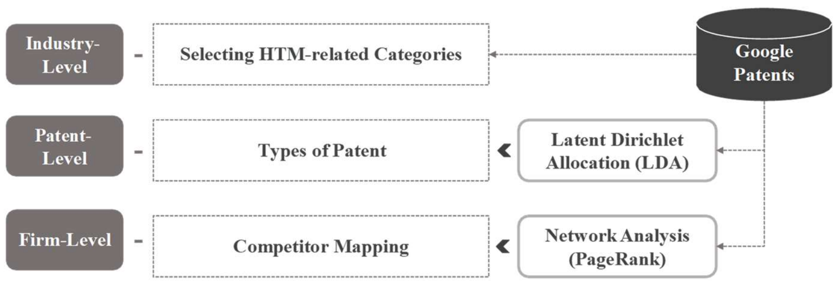

Figure 3. Research Flow (referenced from Geum, Kim & Lee, 2017)

3.1. Data

We seed our data from the Google Patents database as of December 2020. One reason for choosing the database is that, unlike datasets used in most of the innovation literature, it provides up-to-date patent information quarterly, guaranteeing the recency and timeliness of our study. Second, Google Patents translates the textual information of non-US patents to English and broadens the scope of our dataset beyond the US patents. Third, the database is based on the new CPC system jointly designed by the United States Patent and Trademark Office (USPTO) and European Patent Office (EPO), offering a more updated classification scheme.

Under the CPC system, this study is focused on three technology fields associated with HTM industries: 1) travel agencies (G06Q50/14), 2) hotels and restaurants (G06Q50/12), and 3) online reservations (G06Q10/02). After obtaining the main seed patents in those categories until December 2020, we then expand the seed patent set by incorporating their one-hop neighbors in terms of backward and forward citations. Consequently, patent-related information of the enlarged patent set, including assignees, patent titles, and abstracts, is collected from the Google Patents database.

Before proceeding to the main analyses, we resolve several issues in our data. As to the assignees of the patents, in some cases, patents are reassigned to a new firm or inventor from the initial assignee. Nevertheless, the Google Patents database does not completely reflect the transfer records. Given that one of the main goals of this study is to provide the current standings of firms in terms of technological innovation, this gap is an issue because patent assignees in our initial dataset do not represent the current assignees. To address the problem, we update the assignees by using a web scraper that searches through the Google Patent search engine[1], instead

[1] https://patents.google.com/

of the Google Patents database. To automate this update process, we use the Beautiful Soup[2] library, one of the most popular modules for web scraping. Specifically, we do so first by examining the HTML structure of a Google Patent page and then locating the tag for the "current assignee" of patents in the HTML tree. Second, we build a web scraper with the help of the Beautiful Soup library and search for the current assignees of all the patents in our analysis. Through this process, we successfully update assignee information before conducting the network centrality analysis. In addition, we find that identical patent assignees have different names on multiple patents. For instance, International Business Machines (IBM) appears as assignees with variants in name, such as "IBM," "International Business Machines Corp.," or "International Business Machines Corporation." We thoroughly examine such variations and unify the identifiers over multiple rounds of investigations.

Table 1. Summary Statistics

Variable	Obs	Mean	Stdev.	Max	Min
Number of patents	88,344	.	.	.	.
Number of assignees	13,696	.	.	.	.
Patent filing year	88,344	2006	8.65	2017	1966
CPC – Travel agency (binary)	88,344	0.004	0.061	1	0
CPC – Hotels & Res. (binary)	88,344	0.012	0.109	1	0
CPC – Online res. (binary)	88,344	0.035	0.183	1	0
Length of patent title	88,344	64.69	31.78	500	3
Length of patent abstract	88,344	780.94	296.21	14444	36

Consequently, our dataset contains 88,344 granted patents with 13,696 assignees, mostly firms, or inventors since 1966. Only granted patents by US Patent Office are retained. Hence, our coverage of patents and firms is substantial. We note that filed patents but not granted are excluded from our dataset since it is a common practice in the innovation literature. As to the patents with multiple patent subgroup CPC codes, they are weighted equally. For example, if a patent assigned to Priceline has G06Q50/14 (Travel Agency) as well as G06Q10/02 (Online Reservations), Priceline has 0.5 of G06Q50/14 and 0.5 of G06Q10/02. For LDA training, the patent is used twice for topic categorization in the two areas.

[2] https://pypi.org/project/beautifulsoup4/

Table 2. Example of the Patents used in Our Study

Patent Number (Granted Year)	Patent Title	Patent Abstract	Related CPC	Patent Assignee
US10318903B2 (2019)	"Constrained cash computing system to optimally schedule aircraft repair capacity with closed loop dynamic physical state and asset utilization attainment control"	"A method of providing the first set of computer systems with access to a recommendation about operation of one or more assets based on the one or more assets being in revenue service or in repair is disclosed. Operations data and inspection data is collected at the first set of computer systems…."	G06Q50/14 Travel agencies	General Electric Co.
US9922345B2 (2015)	"Increased visibility during order management in a network-based supply chain environment"	"A system, method and article of manufacture are provided for a first business entity to provide a network-based supply chain framework for collaborative order management between at least a second and a third independent business entity, such as a service provider, vendor, reseller, manufacturer, and the like…"	G06Q50/12 Hotels or restaurants	Accenture Global Services Ltd.
US8135650B2 (2012)	"Method and apparatus for a cryptographically assisted commercial network system designed to facilitate buyer-driven conditional purchase offers"	"The present invention is a method and apparatus for effectuating bilateral buyer-driven commerce. The present invention allows prospective buyers of goods and services to communicate a binding purchase offer globally to potential sellers, for sellers conveniently to search for relevant buyer purchase offers, and for sellers potentially to bind a buyer to a contract based on the buyer's purchase offer…"	G06Q10/02 Reservations, e.g., for tickets, services, or events	Priceline com LLC.

3.2. Methods

Latent Dirichlet Allocation (LDA)

We leverage LDA (Blei, Ng & Jordan, 2003) by using the Gensim[3] module in Python to discover latent topic categories out of patent textual data for the three patent subgroups (travel agencies, hotels & restaurants,

[3] https://radimrehurek.com/gensim/

and online reservations). LDA has been well-known to reasonably classify a wide range of documents, such as scientific articles and survey data (Blei, 2012). Specifically, given a set of documents about a particular domain, e.g., patent documents in the technology innovation context, LDA identifies latent groups with their specific terms in an unsupervised manner, offering transparency and interpretability. Building on the latent topic categories derived from LDA, our study casts light on 1) what types of tourism-related patents are developed, and 2) how they are categorized to understand tourism technological innovation.

As a generative statistical model that derives latent topics out of a collection of documents, LDA assumes that 1) a document is represented by a probability distribution of multiple topic categories and 2) a topic category is defined by a probability distribution of terms. Using Gibbs sampling, the method then estimates the posterior probability of a Bayesian structure (Casella & George, 1992). The expectation-maximization algorithm is used to converge on the two probability distributions. Lastly, the LDA algorithm generates a probability distribution of categories per document and a collection of terms with weights on the categories. In our study, documents are the aggregates of patent titles and abstracts. According to Arts et al. (2018), combining patent titles and abstracts to form the main text of the patent is a common practice in management and innovation literature when dealing with patent text data. So, the combined patent titles and abstracts are considered a document, and it is used for training the LDA model. Consequently, we create three topic models for the three patent subgroups.

Ranking firms based on the PageRank centrality

In network analyses, network centrality indicates the relative importance of nodes in a network. Of the various centrality measures, we utilize the PageRank (PR) algorithm developed by Google to quantify the importance of nodes (Brin & Page, 1998) since PageRank considers both the number and quality of links with a node to approximate how central the node is in a network. The key idea is that nodes linked by other nodes of a higher centrality are considered more central. Thanks to the property, PageRank is widely used in literature to measure the impact of scientific articles or researchers (Ding et al., 2009). The algorithm ranks such entities in citation networks based on their knowledge propagation to subsequent papers or authors (Senanayake et al., 2015). Following the literature, we apply the PageRank centrality to our dataset's firm-level patent citation network to rank firms in HTM industries in terms of innovation quality.

More specifically, in our patent citation networks, firms serve as nodes in the graph, and links between firms represent their patent citations. We compute the PageRank centrality of the firms around HTM industries by using the python library NetworkX[4] as below.

$$PR(f_i) = \frac{1-d}{N} + d \sum_{f_j \in M(f_i)} \frac{PR(f_j)}{L(f_j)},$$

[4] https://networkx.org/documentation/stable/reference/algorithms/generated/networkx.algorithms.link_analysis.pagerank_alg.pagerank.html

where f_i and f_j denotes the firm i (cited firm) and firm j (citing firm). $PR(f_i)$ indicates PageRank value of firm i. j is a firm that cites patents of the focal firm i, and N represents the number of firms in the citation network. $L(f_j)$ is the total count of backward citations of firm j when developing its own patents, and d is the damping factor that models the likelihood of citing an arbitrary patent. Following the default settings in Brin and Page (1998), we set d to 0.85. Under this setting, PageRank centrality is calculated until it converges through enough iterations. In doing so, we measure each firm's PageRank centrality based on the interfirm patent citation network.

4. Results

The LDA algorithm needs a hyperparameter, the number of topic categories. To derive a reasonable number of categories, we conduct cross-validations with different numbers of categories and then compare the in-sample coherence score. The coherence score quantifies the co-appearance of two terms for a category using a scoring function. Hence, the models with a greater number of categories have a higher coherence value (Mimno et al. 2011; Newman et al. 2010). Nevertheless, a redundant number of topic categories may reduce interpretability and leads to over-fitting, e.g., worst topic categories do not allow guessing a general topic category (Röder et al., 2015). Therefore, a reasonable number can be chosen by considering both interpretability and coherence values. As shown in Figure 4, we choose eight categories for travel agencies with a coherence value of 0.339, ten for hotels and restaurants (coherence value = 0.338), and six for online reservations. Given that models have a marginal increase in coherence value or even underperform the best parameters, we select these numbers for the topic categories. For online reservations, we choose six categories (coherence value = 0.278) instead of twelve to obtain more prominent distinctions between categories at the expense of a small coherence decrease. Several main terms represent each topic category, thereby allowing us to obtain a more detailed categorization of the three patent subgroups.

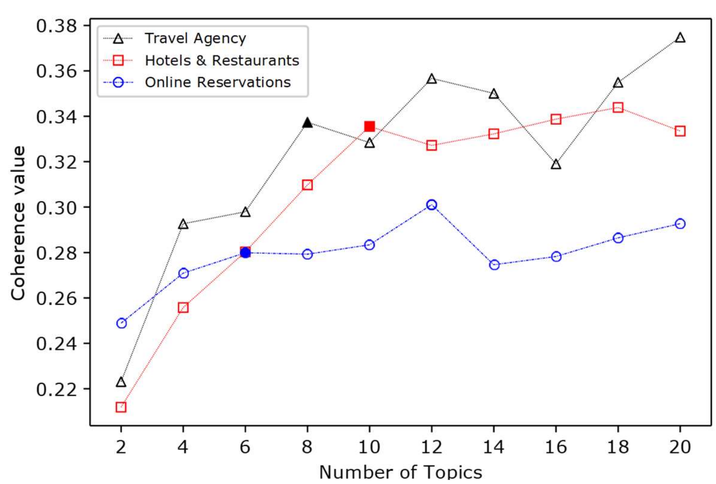

Figure 4. Coherence Plot for Each Category. (The filled markers are indicative of the parameters chosen)

Travel Agencies

Based on the topic category and main terms in Figure 5, we infer proper labels for each topic category. It is a standard practice in the use of LDA to label categories based on the main terms for a topic category (Liu et al., 2020). These labels are, from Category 1 to 8 in order, “Destination Route Optimization (e.g., a travel scheme to minimize travel costs for an organization)”, “Reservation Search Query”, “Event Reservation (e.g., online transactions/events processing system for an individual customer/entity)”, “Itinerary Scheduling (e.g., a system for creating a travel plan and ticketing based on input information)”, “Conditional Purchase Offer (e.g., a method to match buyer’s purchase offer to seller)”, “Information Interface for Traveler”, “Location-based Trip/Accommodation Search”, and “Transaction Search Module”. Most travel agencies’ technologies relate to travel planning, itinerary, and destinations. In addition, we note that a conditional purchase offer (CPO) in the HTM industry refers to a transaction setting contingent on certain conditions between travel distribution channels and service providers.

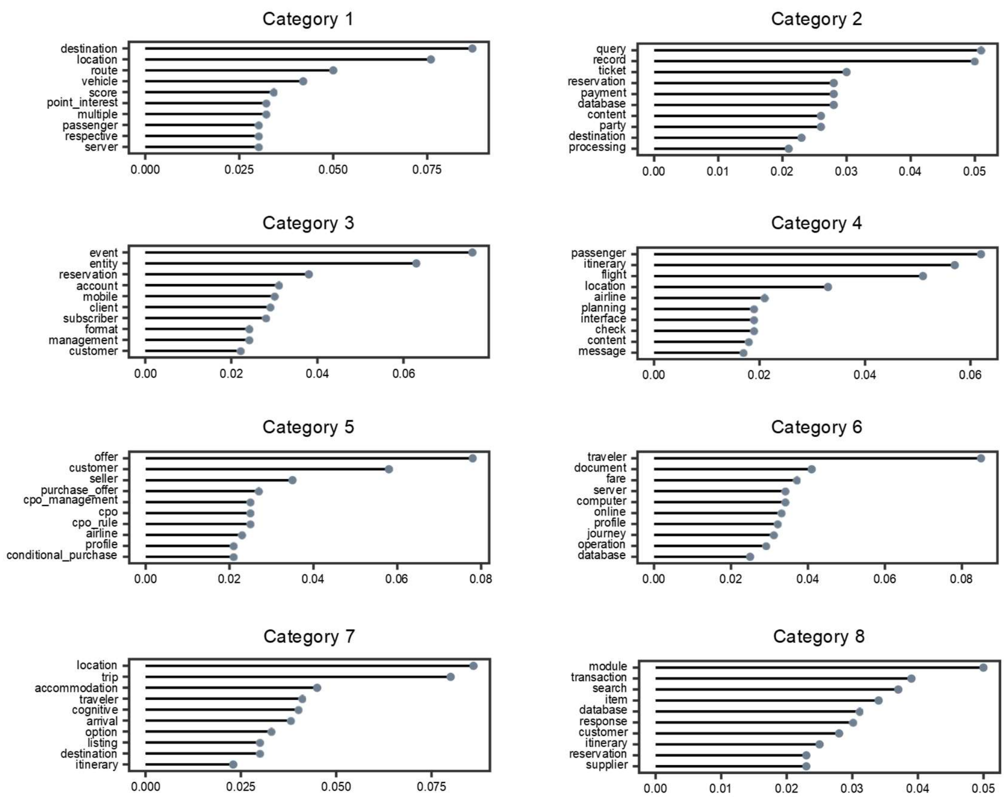

Figure 5. Topic Category by Term Distribution – Travel Agencies (G06Q50/14)

Hotels and Restaurants

Ten topic categories for hotels and restaurants (G06Q50/12) are labeled in Figure 6. We assign the following labels from Category 1 to 10 in order: “Content Displaying System (e.g., displaying technology for order/reservation and inventory information)”, “Mobile Communication Server for Restaurants”, “Electronic Menu System”, “Table Order System (e.g., Self-order using mobile devices on the table)”, “Delivery Management Systems (e.g., systems for delivery time estimation and customized recipes)”, “Merchant (Service Provider) Support System”, “Customer Ordering Management (e.g., queue management, ordering platform-related)”, “Patron Management System (e.g., database for customer food preferences)”, “Automated Cooking

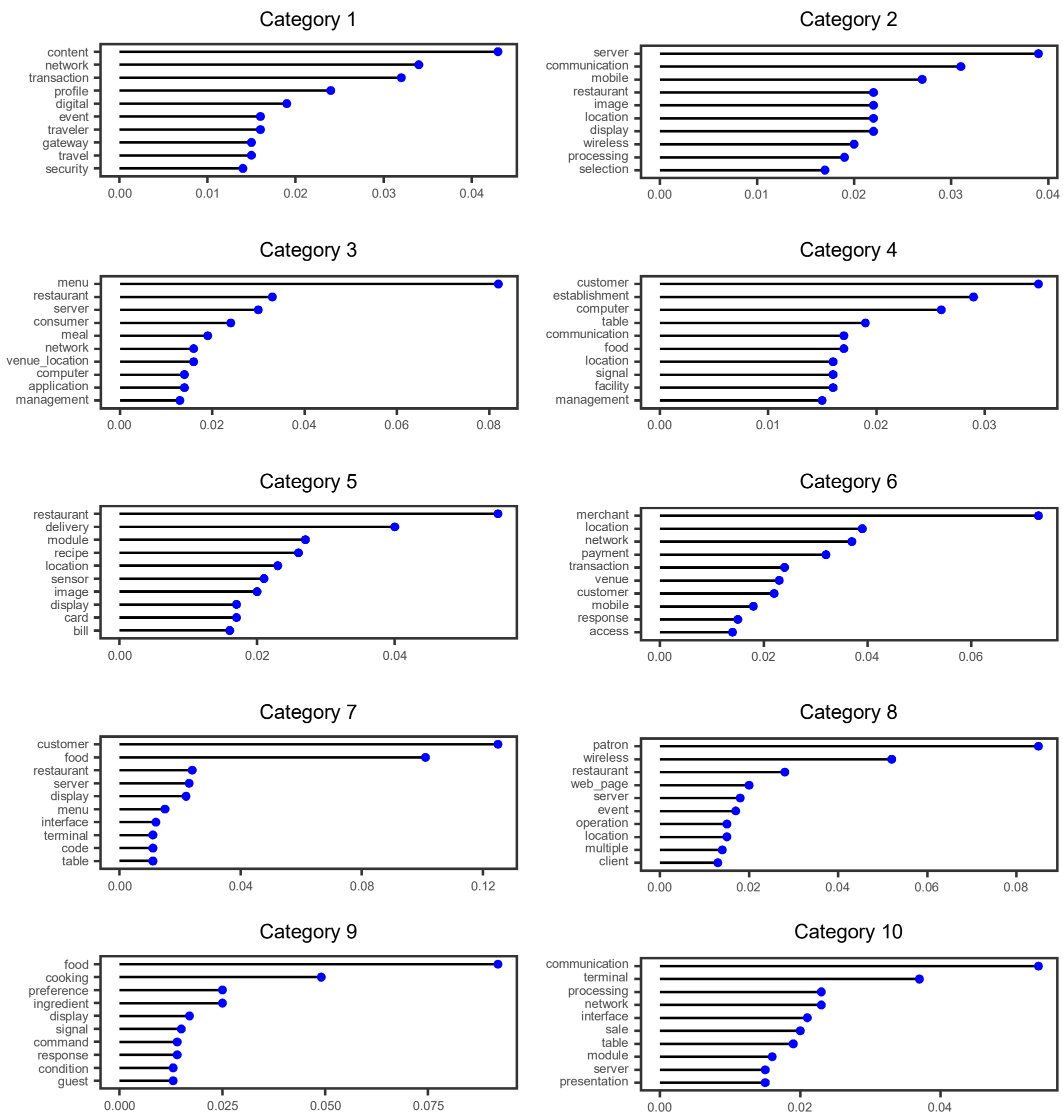

Figure 6. Topic Category by Term Distribution – Hotels and Restaurants (G06Q50/12)

System (e.g., customized food preparation and management system)”, and “Communication Terminal for Sales Management (for both hotels and restaurants)”. In addition, a self-service ordering system, including mobile devices and kiosks, can promptly process transactions between customers and employees. These technologies have built up technological innovation in the hospitality industry.

Online Reservations

For online reservation-related patents, we obtain six topic categories (Figure 7). Given the terms and their weights in each topic category, we assign the following labels from Category 1 to 6 in order: "Online Parking Reservation (e.g., valet parking management system)", "Ticket Issuance Management (e.g., ticket issuance system from travel, accommodations to event and activity)", "Computerized Reservation System", "Traffic/Transaction Processing (e.g., systems for status updates, including reservation confirmation by integrating multiple data sources)", "Sharing/Rental Vehicle Reservation (Vehicle Availability Monitoring System)", and "Travel Itinerary Optimization Algorithm (e.g., optimizing individual itinerary conforming to customer selection – hotel, flight, and rental car)". Tourism service suppliers can manage reservations via their own websites, but travel intermediaries' platforms (e.g., online travel agencies or metasearch engines) provide integrated reservation services for hotels, flight tickets, rental cars, cruises, and package tours. Thus, the LDA outcome about online reservation comprehensively includes diverse patent technologies related to online reservation management technologies, benefiting tourism service suppliers and intermediaries.

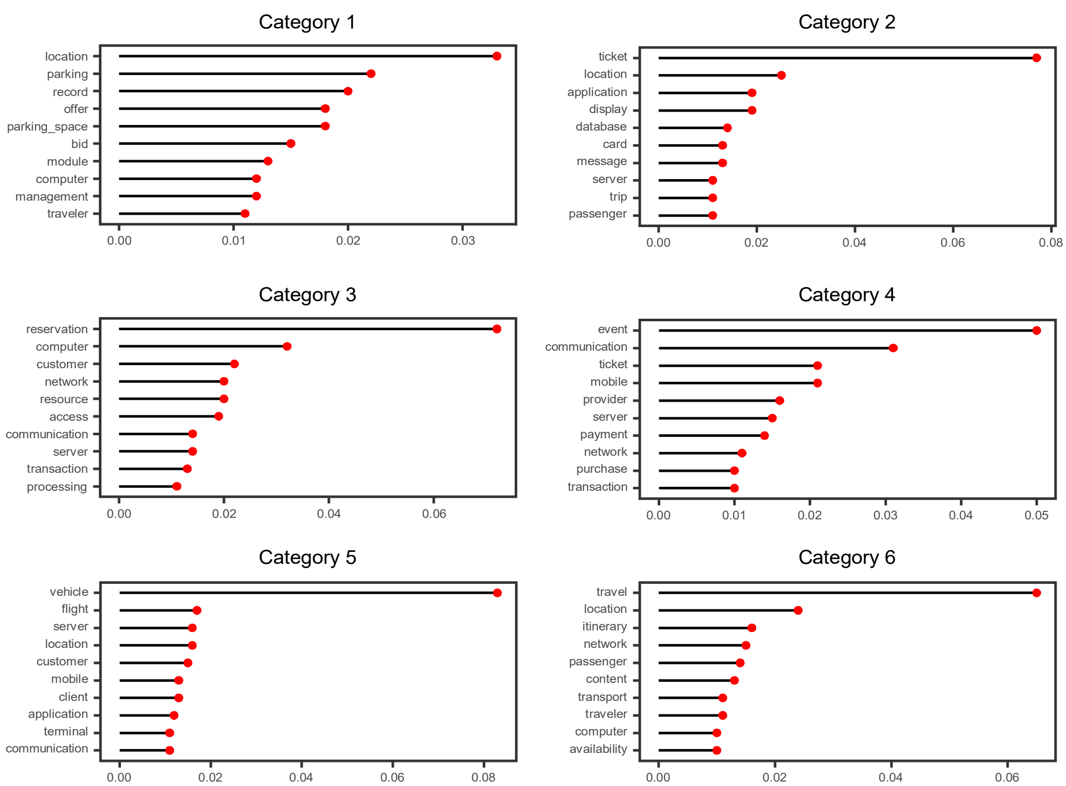

Figure 7. Topic Category by Term Distribution – Online Reservations (G06Q10/02)

We summarize the results of topic category labeling in the three patent subgroups in Table 3. We note that 1) these labels are derived based on a set of main terms with their weight, as well as a collection of patent documents in each subgroup. As shown in LDA plots and in Table 3, labels in Travel Agency and Online

Reservation subgroups have some semantic overlaps. However, in the Travel Agency category, labels focused explicitly on travel itineraries, customer management, and agency platform, whereas in the Online Reservations category, labels are mainly related to overall travel services and methods for data processing and optimization. In addition, hotels and restaurants are largely differentiated from the other two sectors. In particular, "Table Order System," "Electronic Menu System," "Delivery Management System," and "Automated Cooking System" are unique to hotels and restaurants. Such technology terms appear neither in travel agencies nor in online reservations.

Table 3. Summary of Topic Category Labels

Category	Travel Agency	Hotels & Restaurants	Online Reservations
1	Destination Route Optimization	Content Displaying System	Online Parking Reservation
2	Reservation Search Query	Mobile Communication Server for Restaurants	Ticket Issuance
3	Event Reservation	Electronic Menu System	Computerized Reservation System
4	Itinerary Scheduling	Table Order System	Traffic/Transaction Processing
5	Conditional Purchase Offer	Delivery Management System	Sharing/Rental Vehicle Reservation
6	Information Interface for Traveler	Merchant (Service Provider) Support System	Travel Itinerary Optimization Algorithm
7	Location-based Trip/Accommodation Search	Customer Ordering Management	
8	Transaction Search Module	Patron Management System	
9		Automated Cooking System	
10		Communication Terminal for Sales Management	

Consequently, we present a data-driven exploration of HTM-related technologies based on a large volume of patent text data by using a popular topic modeling algorithm (LDA). We expect future studies on technology innovation in the HTM context to refer to our detailed technology categorizations for in-depth case studies on specific HTM-related technologies. In such a way, our analysis will contribute to the literature.

Competitor Analysis – Landscaping Technology Competitions

Drawing on the resource-based view (RBV) (Barney, 1991), strategic management literature has long stated that competitors can be recognized in terms of particular resources that firms have, as well as their products in markets (Peteraf & Bergen, 2003; Liu et al., 2020). In line with the literature, we follow the framework for competitor identification by Peteraf and Bergen (2003) so as to landscape innovation competition in the context of tourism-related technologies. We do so by evaluating firms' innovation resources in terms of innovation quantity (patents) and quality (citations).

Figure 8 presents the conceptual distinctions of patenting firms based on their innovation quality and quantity. Valentini (2012) suggested that measuring a firm-level innovation outcome in terms of patent quantity and quality could provide comprehensive aspects of patent innovativeness. In particular, measuring patent quality by citations, has long been encouraged in interdisciplinary research fields as an essential dimension of innovation resources (Hall et al., 2001; Valentini, 2012; Mariani et al., 2019). Recent literature suggests that a key method to quantify the technological importance (patent quality) is PageRank Centrality indicating how often an impactful patent is cited by "other important patents" (Mariani et al., 2019; Yoo & Lee, 2022). Drawing on such literature, we illustrate the four quadrants describing patenting characteristics of firms, thereby serving as a useful tool to understand firms' standings in innovation competitions, as in the cases below.

In Figure 9, several leading firms in each industry are represented in terms of PageRank centrality (*y-axis*) and patent volume (*x-axis*), which quantifies innovation quality and quantity, respectively. The patent citation network for PageRank centrality in our study is reliable for measuring firms' innovation quality since valuable upstream knowledge is leveraged by downstream inventions (Hall et al., 2005). Such use of patent citation is well demonstrated in the innovation literature (Jaffe & De Rassenfosse, 2019). We note that the two metrics are normalized between 0 and 1. Also, the quadrants are divided based on the medians of each axis.

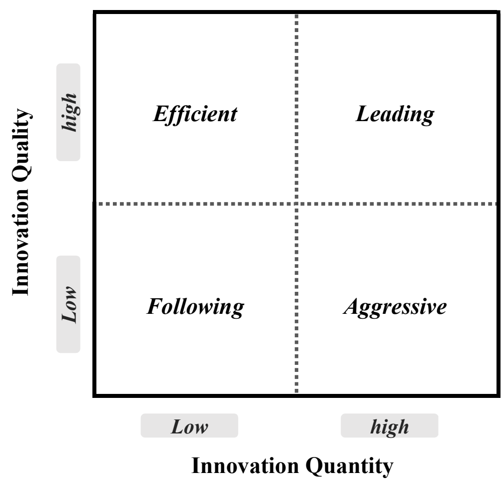

Figure 8. Conceptual Competitor Map

Travel Agencies

For *travel agencies* in Figure 9, the first quadrant representing *leading* firms (i.e., high quality – high quantity) is mostly positioned by *external* firms outside HTM industries, such as Google and IBM. However, it is worth noting that some internal players, including Priceline and Amadeus are also located in the first quadrant. Hence, these two firms can be seen as *internal* leaders inside the HTM industries in terms of technology development. As an illustration, Google invented a patent titled "*Selecting destinations or points of interest*" [5] for a travel location based on the geographic data store, and Amadeus owns a patent "*Device and methods for reserving travel products*" [6], a computerized system for processing travelers' request.

[5] US9454544B1

[6] US8428980B2

In the second quadrant (i.e., high quality – low quantity), a mixed group of external and internal firms is observed, including AT&T, Microsoft, Uber (external), and Airbnb (internal). Specifically, these firms show efficient PageRank centrality relative to their patenting volume; in other words, the impact of their patents is relatively higher than patenting volume. In the case of AT&T, despite its below-median patenting volume, its PageRank centrality ranks second following Google in the first quadrant, indicating that the technology development by AT&T is seen as efficient. Hence, it is reasonable to view such firms as *efficient* firms. In addition, we note that Microsoft, as a founder of Expedia in the mid-1990s, holds several impactful patents deployed in the travel agency industry, explaining in part that Microsoft falls into the efficient group.

The third quadrant representing the *follower* firms (i.e., low quality – low quantity) exhibits several businesses distant from the HTM industries: Rakuten, Liberty Peak Ventures, Pennar Software, and Hipmunk, a travel metasearch platform. Specifically, Rakuten specializes in online retail services away from travel agencies, and Liberty Peak Ventures specifically focuses on the development and licensing of intellectual properties, such as patents. Hipmunk started as an airfare search engine firm for business travelers but closed in 2020 due to low market demand. Hence, for *following* firms in the third quadrant, it appears that travel agencies-related patents are of less technological focus in comparison to other quadrants.

In the fourth quadrant for firms with *aggressive* patenting, several online travel agencies, including Kayak and Bookit, appear with a couple of outside HTM firms, such as Mastercard and Cognitive Scale. Despite their lower innovation quality relative to quantity, their high patenting intensity is indicative of high engagement with technology development to prevent unauthorized technology copycats and amortize from patent licensing with other firms. Also, aggressive patenting (quantity) may lead to more citations and PageRank centrality (quality) in the long run, so these firms can move up to leading firms potentially.

Hotels and Restaurants

For *hotels and restaurants* (Figure 9), we map a set of patenting firms over the four quadrants. Similar to travel agencies in the previous section, the first quadrant is mainly dominated by external firms, such as IBM, AT&T, and Microsoft, but also Doordash and GuestTek as internal firms are located in the leading group.

The second quadrant is taken by Accenture, GrubHub, and NEC Corp. Especially, Accenture ranks second in PageRank centrality despite its below-median patenting volume, showing highly efficient technology development in hotels and restaurant-related patents. As an internal enterprise, GrubHub, a food order and delivery platform, also shows efficient performance. An example of GrubHub's patent is "*Utility for creating heatmaps for the study of competitive advantage in the restaurant marketplace*" [7], a tool for visualizing competing restaurants.

The third quadrant identifies a combined group of external and internal firms. For externals, big-tech companies, e.g., Amazon, Intel, and Paypal, appear in the group of followers, whose patents are mostly associated with facilitating transactions and payment. Along with the externals, online reservation platforms for

[7] US8880420B2

restaurants and hotel businesses – OpenTable and AMEX Travel – represent the internals as *following* firms. One of the key patents of OpenTable for guest monitoring is "*Computer based guest monitoring and identification system and method"*[8], by utilizing radio-frequency identification (RFID) tags through which guest information is transmitted.

The fourth quadrant contains Mastercard, Panera, and Restaurant Technology as aggressively patenting firms. In particular, Panera turns out to be the only restaurant business inventing patents to analyze and facilitate their restaurant operations, as illustrated in their patent "*Techniques for analyzing operations of one or more restaurants*"[9], which is invented to diagnose malfunctions in restaurant operations based on operational data or video footage.

Online Reservations

Major firms in the online reservation sector present significant overlap with travel agencies and hotels and restaurants. Specifically, IBM, Google, and Microsoft show in the first quadrant outstanding PageRank centrality and patenting volume, followed by booking platforms, such as Priceline and Bookit. We note that IBM appears as a leading firm in all sectors, and Priceline and Microsoft also belong to the leading groups in travel agencies and hotels and restaurants, respectively. For the other quadrants, firms are compactly distributed near the two medians, compared to travel agencies and hotels and restaurants. Such a dense distribution makes a less clear distinction between *efficient*, *following*, and *aggressive* patenting firms in the technology competition landscape.

By and large, in all three areas, IT companies (i.e., external) mostly have central standings in terms of technology competition, compared with the HTM firms (i.e., internal). This implies that when HTM-related firms search for their technology competitors, they may need to look beyond their industry to discover the competitors in the blind spot (non-HTM sectors or external). Several entities can benefit from this competitor analysis. For example, chief technology officers may utilize this framework when their firms initiate a new technology development to be differentiated from extant technologies of competitors. Consequently, our descriptive analysis of the technology competition can provide useful intelligence for firms around HTM-related industries to understand their standings and detect technology competitors in different positions. Such a competitor discovery in terms of HTM technology development is our contribution to the literature.

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[8] US9904895B2

[9] US9336830B1

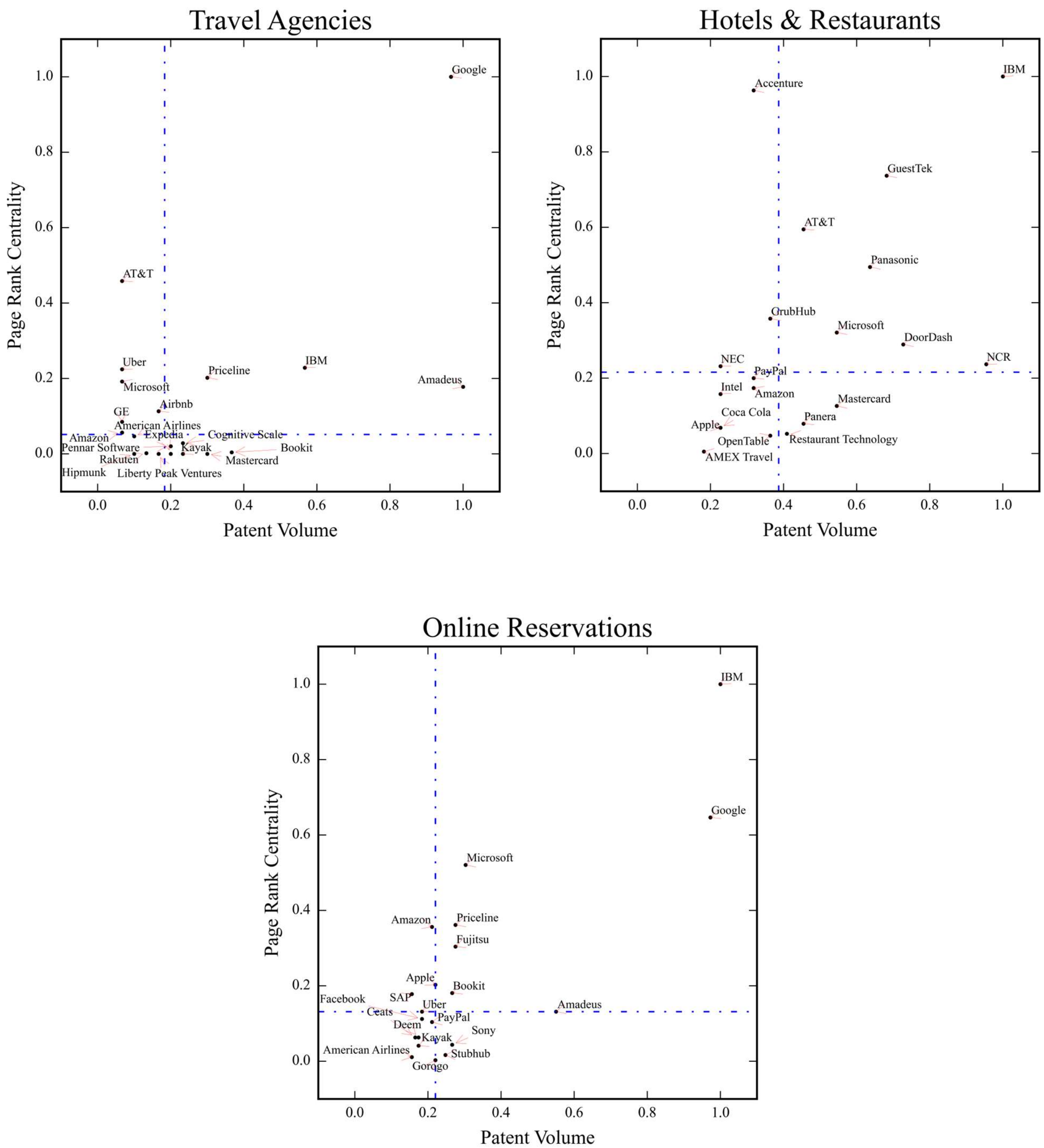

Figure 9. Competitor Landscape Mappings

5. Conclusion and Implications

This study has focused on the technology development (i.e., supply-side) in the HTM industry, while the prior HTM innovation literature has studied mainly the technology adoption (i.e., demand-side) standpoint. By leveraging the Google Patents database that provides up-to-date and reliable patenting records, we analyze over 80,000 HTM-related patents with 13,696 assignees (firms) in the areas of 1) travel agencies, 2) hotels and restaurants, and 3) online reservations. Such categorization is based on the CPC system jointly developed by the USPTO and EPO.

Our first analysis employs unsupervised machine learning text analytics (i.e., LDA) to derive granular categorizations of the patents. We present a different number of categories for each area with specific main terms representing each category. Specifically, we derive eight categories in the travel agencies, ten in hotels and restaurants, and six in online reservations. We also introduce the key terms and their corresponding weights to describe a collection of technologies in each sector and their relative importance. Labeled key terms seem highly relevant to each sector. For example, itinerary scheduling and conditional purchase offer are unique technologies in travel agencies. Automated food preparation, table order, and delivery management system are necessary for process optimization in the kitchen and restaurants. The food service industry invests heavily in technology and has a high demand for automated equipment for productivity improvement and reducing labor costs (Cook et al., 2018), explaining why technologies in this sector are mostly related to restaurants. Patents in the online reservations category also include comprehensive reservation technologies (in hotels, tour packages, tickets, and rental vehicles). In summary, we show that technologies have been developed in response to the needs of HTM stakeholders in each sector, and this implication highlights a supply-side perspective in HTM technology innovation research.

The second analysis utilizes a network analysis by using the patent citation records in the three areas, respectively, as well as patenting volume. We formulate interfirm citation networks to investigate the relative standings (i.e., rankings) in technology development. For this purpose, we leverage PageRank centrality (quality) and patenting volume to map popular patenting firms in the three areas. Our visualizations with the two metrics show that major IT firms outside the industries (e.g., Google, Microsoft, and IBM) form the technology frontier group. This group is followed by insiders, such as 1) Priceline and Amadeus in travel agencies, 2) DoorDash and Grubhub in hotels and restaurants, and 3) Kayak and Bookit in online reservations. In brief, in terms of knowledge transfer based on the patent citation, the outsiders take the technology leader positions, while the insiders are seen as relatively the followers. From the RBV theoretical viewpoint, firms' competitive positioning in the market can be determined by their internal resources, including a firm's knowledge of market needs (Liu et al., 2020; Mowery et al., 1998). Drawing on the RBV literature, this study views firms as an aggregate resource of technologies they have. In particular, based on patent data as a proxy for a firm's technology development, we identify competitive standings among companies retaining core technologies in the HTM-related markets. Therefore, the results of the second analysis unveil the competitive relationships drawn from companies' own technology capabilities, potentially expanding firms' knowledge about rivalries or benchmarks in terms of technology development.

Throughout the two series of analyses, we have examined three HTM-related technology categories quite separately. However, we also would like to highlight two main commonalities across the three sectors. First, the majority of the HTM-related technology categories aims to enhance customer service and increase efficiency in business operation, such as, in Table 3, "Destination Route Optimization" in travel agencies, "Content Displaying System" in hotels and restaurants, and "Travel Itinerary Optimization Algorithm" in online reservations. Second, such technologies are mostly computer-based systems that are integrated with other systems, for example, payment processing and inventory management. The integrative features require real-time updates based on internet connectivity so as to provide customers or steps with up-to-date information on availability, pricing, and other relevant details. Taken together, incorporating the three HTM-related technology sectors enables us to understand the user-centric goal of technology development on a real-time basis. In addition, the second analysis of landscaping technology competitions (Figure 9) commonly shows that technology frontiers in all three domains are mostly external software firms outside the HTM industries, such as Google, IBM, and Microsoft.

Regarding managerial implications for firms, first, our firm-level patent citation analysis can be a useful precursor for their competitor studies. Given the legal disputes for the intellectual properties in the HTM industry, pre-emptively determining potential technology competitors and strategizing their patenting portfolios are imperative for firms. On the one hand, firms can avoid unintended patent infringement and reduce the risk of engaging in lawsuits. On the other hand, they can detect unauthorized copycats of their patented technologies and charge them reasonable licensing fees. Prior to such in-depth competitor analysis, our analysis can provide a list of potential competitors in advance.

Second, decision-makers visualizing the map of rivals can, apart from identifying the closest competitors, establish a rank-order for the other companies operating in the sector; thus, they can design and potentially implement technology innovation-related actions included in their strategic plans for each of those companies in the map, thereby distinguishing different levels of actions. In other words, not only can firms prioritize actions to the closest rivals, but they can determine different intensities in the application of their strategic actions—either to defend themselves or to make the most of their position.

Third, a dynamic analysis can be conducted so that decision-makers not only see their current situation on the map in terms of their technology innovation status but also the evolution of their positions. This way, they can figure out the causes that led their own company to the current position and, additionally, they can ascertain the reasons their rivals evolved the way they did. Accordingly, by looking at the trends of each firm, they can foresee the future potential position and, consequently, take actions to either pursue a trend or apply corrective measures.

Fourth, coopetition strategies. As firms can see their own position on the map with respect to their rivals, they can also opt for coopetition strategies. Certainly, competitors that cooperate enhance their innovation capabilities (Köseoglu et al., 2021), which is especially significant for small and medium-sized firms (Gnyawali & Park, 2009; Kallmuenzer et al., 2021); note that, as they share strengths, they put together their distinct advantages in such a way that this synergetic relationship benefits the firms involved even though they remain competing against each other. Also, they have the capacity to distribute the potential workload that a technological innovation project may entail, which could be too much—financially or in terms of the number of workers needed—for a firm alone. Obviously, working together has the potential to team up and implement actions to compete against larger rivals. Small and medium-sized firms, particularly startups which are related to technology tend to not only compete against each other but also against well-established, powerful firms;

thus, if they ally and join forces, they can better compete again the 800-pound gorillas in the market, whether they are outsiders or insiders as pointed out in the results. To sum up, as firm identify their best allies on the map, they can initiate coopetition relationships that help set up industry standards. As these rivals within the industry share information and bring about new technologies, they can establish requirements and standards that will assist the sector with no risk of jeopardizing a single firm's core competency or its intellectual property.

Concerning theoretical implications, first, the articulation of the data collection and analytic methods. As indicated previously, this work is one of the earliest attempts in the literature to shed light on the technology development perspective in the areas of HTM. We introduce the fact that specific patent categories are highly relevant to HTM-related areas based on the CPC system. To our knowledge, none of the prior HTM literature has taken advantage of such reliable categorizations for empirical analysis. To encourage follow-up studies regarding HTM technology development, we have articulated the data collection process and analytic methods used in this study. We note that they are all publicly available and expect future studies to leverage such free resources. More importantly, this study emphasizes the technological capabilities of firms having HTM-related technologies from a resource-based perspective. Firms' difficult-to-imitate technologies (i.e., granted patents) can provide a competitive advantage and become fundamental driving forces for technology innovation. Along with newly adopted data sources and perspectives on technological innovation in this research, we expect that research on the capabilities of RBV—and the value chain model for that matter—can be expanded in subsequent HTM studies. Recall that Porter (1985) claims that the resources per se do not have value, but what firms do with them is what really counts. Consequently, derived from the results of this study, technology innovations measured through patents can be used as an operational component to analyze whether firms are making the most of their resources and find the optimal level to maximize performance.

Second, rivalry analysis in the context of strategic groups. The results show the interlaced technology competition between internal/external firms around HTM industries. The innovation perspective with patents building on the theory of strategic groups can offer insightful theoretical perspectives. Considering that this theory is built upon the structure–conduct–performance theoretical framework proposed in Industrial Economics—with the core component being the strategic group defined as a set of firms that, within an industry, show similarities in terms of key strategic dimensions (Hunt, 1972)—strategies implemented through technological innovation can be analyzed to detect the strategic groups operating in the industry. Recall that in this theory, the strategic dimensions lead to differential effects on performance; thus, the definition of strategic groups through the lens of the theoretical contribution of this study that proves the interlaced competition among insiders and outsiders can bring critical insights into the analysis of rivalry intra-group as well as between groups. In this regard, beyond the traditional analysis of strategic groups conducted in the HTM literature (Hesford et al., 2020; Park & Jang, 2022; Want et al., 2022), an additional element that would add further accuracy to the predictive ability of strategic groups is (1) whether the members of the groups rely on outsiders as opposed to insiders when it comes to innovation and (2) the types of patents that seem to better represent the inter-industry rivalry.

This work is not without limitations. We currently focus on only the three HTM-related patent subgroups in the CPC, including travel agencies (G06Q50/14), hotels and restaurants (G06Q50/12), and online reservations (G06Q10/02). However, many additional HTM-related patents do not belong to the three categories. Given these undiscovered patents, future studies could propose data-driven frameworks that automatically landscape HTM-related patents using text or other methods. Also, the lack of qualitative information means that there is a gap to be filled, opening up first new research avenues. For example, implementing coopetition-related surveys addressed to decision-makers would help unearth the reasons why some firms tend to resort to innovations performed by outsiders rather than insiders. A second research line would consist of the assessment of the use of outsiders' vs. insiders' innovation through the market value of the firms involved. In line with Nicolau and Sharma (2022), we could perform an analysis of the firm value to determine which option—outsiders vs. insiders—the market value the higher. Finally, in line with the aforementioned theory of strategic groups, the definition of strategic groups via patents would be a novel approach to the analysis of rivalry in the context of the HTM literature that could bring in relevant information about the competition/cooperation patterns that hospitality and tourism firms follow. All this future research avenue should be implemented by using updated databases that extend the 1966-2020 period used in this study, even more so considering that it might take a long time—minimum 18 months (Popp et el, 2003)—years between filing and obtaining the patent.

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